


UNIVERSITY OF BIRMINGHAM

# Development of a flood risk assessment framework for railway drainage infrastructure assets at component-level

by

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# Abstract

Inadequate performance of the railway drainage system has detrimental effects on the performance of the various other systems in a railway section including track superstructure, substructure, earthworks, electric, and operational equipment. Flooding incidents in railway drainage systems are exacerbated as severe rainfall events are becoming more frequent due to climate change. Drainage asset interventions need optimised to improve resilience of the railway to flooding. Given the time and money limitations, asset management decision-making needs to rely on targeted and evidence-based approaches for optimised resource allocations. Since the drainage infrastructure of many railways is old and often buried, there is a paucity of detailed inspection and maintenance history data and available data suffers from being subjective, inconsistent and incomplete. Such data introduces uncertainty into the decision-making process, which is aggravated by the uncertain future impacts of land-use and climate change. Therefore, there is a need for approaches that can deal with these uncertainties, such as risk management, to support established asset management techniques.

This research was conducted to provide railway drainage infrastructure managers with a decision-support framework for quantitative assessment of flood risk associated with drainage assets at a component level. The developed framework consists of four modules that utilise data-driven technologies to obtain elements required for a quantitative risk score. The first module looks at condition modelling of railway drainage assets using Machine learning (ML) algorithms. The second module proposes the use of two-dimensional hydraulic modelling of railway drainage assets for simulation of flooding scenarios. The third module quantifies flood damage through the development of an economic damage costing model which considers both tangible and intangible impacts of a flooding incident. The damage quantification entails an uncertainty analysis to account for uncertainties in costing and exposure parameters. The fourth module quantifies risk in monetary terms using probabilities of the flooding scenarios and their respective economic damage. Applicability of the proposed tools for each of the modules is demonstrated through three case studies. The first case study entailed training and testing of a variety of ML algorithms for modelling

the structural and service condition of railway drainage pipes using asset records provided by the UK railway infrastructure manager, Network Rail. The best-performing model of the trained ML algorithms was the Boosted Trees algorithm which achieved 88% overall accuracy for structural condition prediction and 72% overall accuracy for service condition prediction. The second case study involved the use of a two-dimensional hydraulic modelling software to model flooding scenarios at a case-study railway section in the UK, with asset data provided by Network Rail. The flood exposure outputs for the various tested scenarios were used in the third case study to demonstrate the damage quantification module through running Monte Carlo simulations using the developed cost model at two locations within the studied railway section. The damage was presented with monetary damage charts for the various scenarios at either locations. The sensitivity of cost model was largest towards the parameters: Length of flooded track, number of passenger trains passing the site, train cancellation cost and renewal work possession time. Larger uncertainty in these parameters will result in larger uncertainty in the damage quantification and subsequently risk quantification. The damage quantification followed with a risk quantification for the two locations, reflecting the monetary risk level for each. The risk was demonstrated with uncertainty envelopes at the two locations. At one location the expected risk value was £1.21M and at the other it was £2.41M, although the second location entailed larger uncertainty in the quantified damage. This demonstrates the applicability of the framework to support operational level of drainage infrastructure management. It enables streamlining risk-informed decision-making for scheduling and prioritisation of proactive intervention activities. Thereby, it allows optimal resource allocations, building resilience within the railway drainage system against extreme rainfall events and evaluation of future flood risk mitigation measures.

# Dedication

الحَمْدُ لله الَّذي يَسَّرَ البِداياتْ وَ أَكْمَلَ النِهايات
الحَمْدُ لله الَّذي بِنِعْمَتِهِ تَتِمُّ الصَّالِحاتْ
الحَمْدُ لله حَمْداً كامِلاً..الحَمْدُ لله دائِماً وَ أَبَداً

إلى مَنْ أعْطوا و أجْزَلو بِعَطائِهِمْ
إلى مَنْ كانو مَصْدَرْ القُوّة والثَّباتْ في طَريقي
إلَيْكُمْ يا مَنْ لَو أنَيْتُ بِالتَّقْديرِ كَلِمة ما وفَّى بِبَعْضِ قَدْرِكُمْ
والِدَي العَظيمَيْنْ..نَبيل و نابِغة

إلى أخي الغَالي..سَنَدي وَ قُرَّةَ عَيني و مَصْدَرْ فَخْري
..الدُكتور عَدْنانْ

و أخيراً..إلى الْغائِبْ الْحاضِرْ ..إلى مَنْ فارَقَني جَسَداً وَ لَمْ يُفارِقْ خاطري
إلى روحِكَ النَّقِيَّة..أخي غَيْثْ

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# List of Abbreviations

3D CFD Three-dimensional Computational Fluid Dynamics
AEP Annual Exceedance Probability
AHP Analytic Hierarchy Process
AI Artificial Intelligence
AUC Area Under the Curve

BsT Adaptive Boosted Trees

BT Bagged Trees
CBM Condition based maintenance
CEH Centre for Ecology and Hydrology
CI Consistency Index
CM Corrective maintenance
CORINE Coordinated Information on the European Environment
CR Consistency Ratio
CWA Connection Weight Analysis
DEM Digital Elevation Models
DS Downside

DT Decision Trees
DTM Digital terrain Model
EAD Expected Annual Damage
EM East Midlands
ETA Event tree analysis
FMEA Failure Mode and Effect Analysis
FMECA Failure Mode and Effect and Criticality Analysis
F-N Frequency-Number diagram
FPR False Positive Rate
FTA Fault Tree Analysis
GIS Geographic information system
GLOFRIS GLObal Flood Risk with Image Scenario
GPR Ground Penetrating Radar
HACCP Hazard analysis and critical control points
HAZOP Hazard and Operability studies
HEC-RAS Hydrologic Engineering Center–River Analysis System
HN Hidden Neurons
HSR High Speed Rail
IDF Intensity-Duration-Frequency
IML Interpretable ML
IPMS Proactive Maintenance System
IQL Information Quality Levels

KNN K-Nearest Neighbours
LandIS Land Information System
LNE London North Eastern

LNWN London North Western North coast
LNWS London North Western South coast
LOPA Layers protection analysis
M&R Maintenance and Repair
MCA Multi-criteria analysis
MCDM Multi-Criteria Decision Making
MCs Monte Carlo simulation
MILP Mixed Integer Linear Programming
ML Machine Learning
NN Neural Networks
NR Network Rail's
OS Ordnance Survey
PM Preventative maintenance
RAIL Rail Infrastructure Loss
RASOR Rapid Analysis and Spatialization of Risk
RI Random Index
ROC Receiver Operator Characteristic curve
RP Return period
RPA Return Period Analysis
S&C Switch and Crossing
SMOTe Synthetic Minority Over-sampling Technique
SRVC Service condition prediction
STRC Structural condition prediction
SWE Shallow Water Equations
SWIFT Structured What-If
SWMM Storm Water Management Model
TMI Thornthwaite Moisture Index
TPSS Traction Power Supply System
UDS Urban Drainage System
US Upside
VaR Value at risk
WLCC Whole Life Cycle Costing
WPHM Weibull proportional hazards model

# Chapter 1: Introduction

## 1.1 Background

The railway drainage system (including surface and buried components) is embedded within with other railway track elements like earthworks, ballast, sub-ballast. Its purpose is to efficiently divert water away from the track (track drainage) or to keep water from reaching the track elements (off-track drainage). Therefore, an improperly performing drainage system can have severe impacts on the performance of the railway track. Poor, or inadequate, railway drainage of a section of railway track occurs where the influx of water exceeds the drainage capacity of the track's drainage assets. Exposure to water leaves the various elements of the railway infrastructure at a risk of damage, including the track substructure (ballast, track-bed layers, embankment and cutting slopes), track superstructure (rails, fastenings and sleepers), and operational elements (point assets, signalling, electric equipment) (Sañudo et al., 2019, Le Pen and Powrie, 2022). Flood damage experienced by these elements may manifest in various forms, including ballast fouling (Anbazhagan et al., 2012), softening and therefore differential settlement of the subgrade soil (Rushton and Ghataora, 2014), track settlement (Kaewunruen and Chiengson, 2018), subgrade washout (Tsubaki et al., 2017), earthwork failures (Martinović et al., 2016), interference with electrical power supply (Sañudo et al., 2019, Palin et al., 2021) and damage to structures such as bridges and culverts (Benn, 2013). Depending on the severity of impact, such damage can result in unplanned track maintenance, speed restrictions, track closures and even derailments (Spink et al., 2014). In the UK, flooding incidents are reported to cost around £23m per year in delay compensations alone, aside from the costs of cancellations and timetable changes (Network Rail, 2017). Furthermore, in the UK, drainage renewals alone have cost £69m in 2019/2020 (Network Rail, 2021). Likewise in China, the average annual spending on the flood-related maintenance in the Chinese Railway System was about $15m in addition to $37.5m annual average of indirect operational disruption losses (Hong et al., 2015). On a global scale a study by Koks et al. (2019) estimated the expected annual damage caused by surface flooding to transport systems to be around 4 billion USD. Additionally, poor drainage can

cause surrounding environments to be flooded and require the payment of third-party damage compensation (Sañudo et al., 2019).

Poor drainage may be due to asset degradation, inadequate routine maintenance (e.g., clearing debris), and/or insufficient design capacity. The design capacity of many drainage assets is determined from predicted return periods of rainfall events of a particular intensity and duration. For example, in the UK a return period of 50 years is typically used as a design event for railway drainage assets in primary or secondary routes, according to the design standards of Network Rail (2018), the infrastructure manager of the majority of the UK's heavy railway infrastructure. However, climate change in many countries is resulting in higher severity and frequency of severe rainfall events. Therefore, existing drainage infrastructure designed according to standards conceived before the impact of climate change was apparent, may not now, or in the future, be adequate. Rational drainage design should also consider runoff from adjacent land. Runoff can increase during the life of a drainage asset, not only because of climate change, but also due to land use change, for example, deforestation or urbanisation. Some railway track owners and operators, however, do not normally consider within drainage design standards third party land when calculating the catchment area (e.g. Network Rail (2018)). This evidently can also lead to miscalculations when designing an adequate drainage system. The combinations of these factors increase the risk of flooding. For example, on the UK's major railway network, over the past 5 years there have been 450 flooding incidents on average per year, most of which occurred at a rainfall event of a return period less than 1 in 10 (Wu et al., 2021b). Thus, highlighting the inadequacies of the present UK heavy railway drainage system. Similarly, European railways are subjected to extreme rainfalls and resulting floods which are becoming more frequent as a result of climate-change (Sañudo et al., 2019). European standards, Austria, Spain, Norway, Germany and the UK have all identified the need for adaptation and mitigation planning against climate change (Sañudo et al., 2019). However, despite its importance in maintaining the functionality of the railway system, there is a relative paucity of studies on asset management tools and techniques for drainage systems.

Given the restricted budgets and the operational nature of the railway environment, both time and money resources for interventions are often limited. Therefore, railway infrastructure managers need to improve decision making to make cost-effective investments in drainage maintenance, renewal and in building resilience of drainage networks. In this regard, Preventative Maintenance (PM) is a form of proactive asset management wherein maintenance takes place, when necessary, according to bespoke performance thresholds. It aims to ultimately reduce the likelihood of a failure occurrence and increase reliability while reducing the maintenance costs during an asset's lifecycle (Stenström et al., 2016). However, effective PM decision-making requires tools to understand the asset's condition degradation during its lifecycle.

The drainage infrastructure in countries with well-established railway systems is often old and buried, and therefore drainage asset knowledge from inspections is subjective, inconsistent and incomplete (i.e., rogue data). Such poor-quality information introduces uncertainty into the decision-making process, which is exacerbated by the uncertain future impacts of land use and climate change. Therefore, there is a need for approaches that can deal with these uncertainties, such as risk management, to support established asset management techniques.

There are three levels of infrastructure asset management at which budgeting, and resource allocation takes place. These are strategic, tactical, and operational levels. At the strategic level, network-level, long-term (>10 years) planning of budgets and standards takes place. At the tactical level, medium-term (1-5 years) programming of route-level works takes place, with consideration of objectives and performance indicators. Operational level of management addresses the short-term (<1 year) budgeting at section-level as well as the ongoing daily/weekly operational works at subsection- or component-level.

In this regard, Rezaei (2020) developed a risk-informed drainage asset management tool using Monte Carlo simulations and historic network data to support the network-level planning of railway investment. The research supports strategic decision making but not operational/ tactical levels of decision making. This work is not available for further investigation. Wu et al. (2021b) develops condition degradation Markov Chain matrices for estimation of drainage network asset condition,

thus supporting the network-level budget planning of maintenance and renewal schemes. The work doesn't look at analysing risk associated with drainage system and therefore doesn't support prioritisation decision making. Usman (2020) devised a risk-informed approach to identify railway track sections at greatest flood risk. Usman (2020) used Fault Tree Analysis to estimate the probability of poor drainage based on historic data and expert opinion. The assessment of damage as a consequence of poor drainage was based on historic data. It doesn't look at site-specific flood likelihood and consequence as a result of rainfall events, asset condition and site-specific catchment properties. There is yet a need for a digitally-driven tools to comparatively assess flood risk associated with drainage components to support preparation/operational level of management. Such a tool will support cost-effective decision-making regarding optimal scheduling and prioritisation of various risk-reduction interventions in the short-term.

## 1.2 Problem statement

For improved short-term operational planning of drainage interventions, infrastructure managers need to improve asset performance monitoring in order to support continual prognosis of problem areas and thereby carry out proactive maintenance, where needed. Such tasks require the development of predictive condition modelling for drainage assets at the component level. In conjunction, infrastructure managers require user-friendly methods for the transparent and robust identification of drainage asset performance gaps (i.e., gap between capacity of asset and the runoff influx) under various scenarios of flood risk sources and drivers (E.g., climatic factors, catchment, and asset condition). Furthermore, since asset data and the impacts of climate change on railway track drainage requirements are uncertain, there is a need to quantify flood risk to improve the scheduling and prioritisation of drainage asset maintenance decision making. This requires the quantification of consequence and associated likelihood of a drainage component failure. Understanding flood risk enables the evaluation of various mitigation plans for flood risk reduction (e.g., planting vegetation, land use planning, increasing drainage asset capacity, structural flood protection measures).

## 1.3 Aim and objectives

In order to address the problem stated above, this research project aims to develop a risk assessment framework for component-level quantitative evaluation of flood risk associated with drainage assets to inform operational asset management.

This aim is achieved through the following research objectives:

1. Identify railway drainage system components, performance, and approaches to intervention planning.
2. Identify methods for infrastructure asset condition modelling.
3. Review literature on railway asset management.
4. Identify requirements for risk assessment and techniques for quantitative analysis.
5. Identify appropriate methods for modelling flood risk and impacts.
6. Design a theoretical framework to obtain components for a quantitative flood risk assessment, employing methods identified from literature review.
7. Perform case study demonstrations of designed theoretical framework for component-level railway drainage quantitative flood risk assessment.

## 1.4 Novelty

This research addresses the need for approaches to support risk-informed operational level drainage asset management through the development of a four-module framework for quantitative flood risk assessment of railway drainage asset components. The following summarises the main contributions of this research towards this end.

1. Introduction of the use of data-driven Machine Learning (ML) methods for predictive structural and service condition modelling of drainage assets. A journal paper has been published by Aljafari 2022, which reports the novel condition modelling work carried out in this research (attached in Appendix A)

2. Identification of the most appropriate ML algorithm for both structural and service drainage condition prediction.
3. Identification of input factors most significant towards structural and service condition prediction of railway drainage pipes.
4. Utilisation of 2D hydraulic modelling platforms as an agile computational tool for scenario analysis of railway drainage flood risk sources and drivers (e.g., rainfall event, asset condition, land use). Thus, enabling the visual assessment of localised flooding at drainage component flooding and associated flood exposure of the various asset systems in the vicinity of the flooding component.
5. Development of a customisable cost model which monetises both tangible and intangible damage as a consequence of localised flood exposure experienced by the various track assets, third parties and environment.
6. Use of the statistical Monte Carlo simulations tool for an uncertainty analysis in flood damage quantification. Thereupon, the production of damage charts with uncertainty envelopes as a visual representation of economic flood damage scenarios.

## 1.5 Benefit to industry

This research provides drainage asset management teams with a robust framework for quantitative drainage risk assessment that leverages data from their existing asset records. To enable early warnings of maintenance needs, the framework introduces the use of ML methods for predictive condition modelling utilising drainage asset databases. Thereby, promoting improved asset knowledge and early warnings of maintenance needs. The proposed use of 2D hydraulic modelling offers infrastructure managers a user-friendly and agile platform for visual depiction of localised flood modelling. Furthermore, the use of 2D modelling for the representation of the as-built drainage system and its interaction with the surrounding environment under a scenario analysis serves as a demonstrative application of digital twins for railway drainage systems. Railway industry decision makers can integrate this framework (including the proposed tools) into their operational drainage

asset management practice (and associated standards) in order to streamline risk-informed scheduling and prioritisation of proactive maintenance interventions for optimal resource allocations at both preparations/operations levels of drainage asset management. During the preparation of annual intervention plans, understanding the economic flood risk levels associated with drainage components enables infrastructure managers to perform Cost/Benefit analyses for balancing Preventative Maintenance (PM) against Corrective Maintenance (CM) schemes. Furthermore, understanding the necessary maintenance needs ahead of time enables simultaneous scheduling of necessary activities for various assets in a specific track section such that to optimise the use of intervention windows and reduce track downtime, thus improving operational reliability and availability of track. Additionally, the framework supports ongoing operations management of drainage components in order to mitigate against extreme weather events by performing a scenario analysis to evaluate resilience of the system, thus, enabling early warnings of potential problem areas and timely decision making for protective intervention measures.

## 1.6 Thesis structure

Chapter 1 provides the background to the research, a problem statement and summarises the aim, objectives, and novelty of work.

Chapter 2 provides a description of the drainage system, its components, potential problems, current performance characterisation, approaches to intervention planning and a review of condition modelling applications for drainage infrastructure. Furthermore, the chapter reviews asset management principles and studies on railway infrastructure asset management.

Chapter 3 reviews the concept of risk-informed asset management and railway infrastructure studies thereof. The chapter also reviews risk standards and literature on flood risk modelling.

Chapter 4 describes the research methodology.

Chapter 5 describes the developed theoretical framework.

Chapter 6 demonstrates an application of Machine Learning algorithms modelling drainage asset condition.

Chapter 7 demonstrates a flood modelling case study application.

Chapter 8 demonstrates impact quantification and risk quantification case study applications.

Chapter 9 provides a discussion of the case studies and the applicability of the developed theoretical framework.

Chapter 10 highlights findings, conclusions and future work.

# Chapter 2: Railway drainage systems and asset management

## 2.1 Introduction

This chapter provides background on railway drainage systems, drainage asset performance and approaches to intervention planning. It then provides a review of condition modelling applications in both urban and rail drainage infrastructure to identify gaps in research. Thereafter, the chapter reviews principles of asset management and literature studies on railway systems asset management to then establish the need for risk-informed asset management approaches in railway drainage assets. Thereby, the chapter achieves the first three objectives of the research (see Section 1.3).

## 2.2 Railway drainage system

The quality of the railway track (in terms of its structural integrity and subsequent impact on track life and service quality) is directly dependent on the condition of the ballast, earthwork formation and track drainage (Spink et al., 2014). The presence of water on the track is detrimental to the performance of these and other components of the track (see Section 2.2.6). Therefore, it is important that the drainage system keeps or drains water away from track. The railway track substructure receives water from multiple sources (see Figure 2.1), including: directly from rainfall and snowfall, runoff from rain or snowmelt from adjacent land, and via ground water seepage and upwards through capillary action (Li et al., 2015).

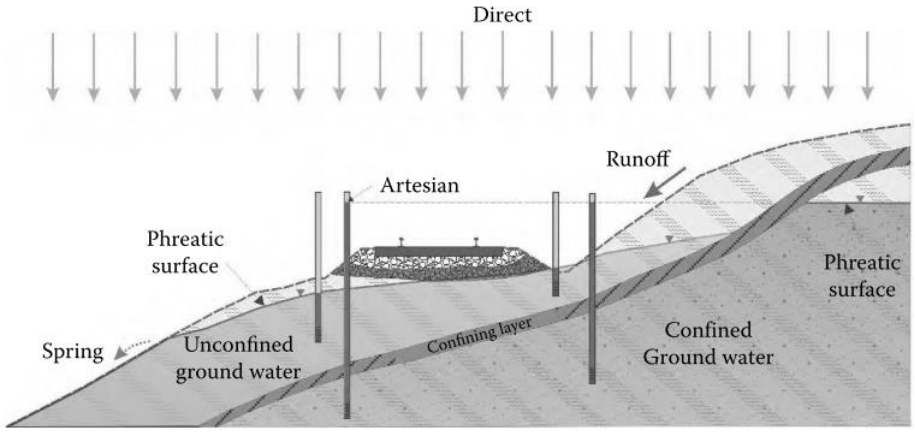



*Figure 2.1. Sources of water into the track substructure (Li et al., 2015)*

The drainage system is defined as a series of interlinked components that conducts surface or subsurface water away from sensitive structures such as the railway track or earthworks to ensure effective track support and performance and associated earthwork safety (Spink et al., 2014). 'Track' drainage serves to remove water away from track and is placed adjacent to it, whereas 'off-track drainage' is distant from the track and serves to keep catchment runoff away from it (Spink et al., 2014). Table 2.1 categorises railway drainage assets into two main categories depending on their function, namely surface and subsurface drainage assets. The following sections further describe these.

*Table 2.1. Categorisation of railway drainage asset types (Spink et al., 2014)*

| Asset category | Geometry | Function | Construction | Example asset types |
|---|---|---|---|---|
| Ditches and channel drains | Linear asset | Surface water collection and transfer | Lined or unlined surface channels. | Ditch, grassed surface water channel, combined pipe and channel drain, linear drainage channel, cascade, flume, aqueduct, catch drain, cess drain, mitre drain |
| Pipes | Linear asset | Subsurface water transfer and water collection | Below ground pipework, | Pipework, culvert, perforated pipe, collector drain, carrier drain |
| Filter drains | Linear asset | Surface and/or subsurface water collection and transfer | A vertical gravel or synthetic filter medium with or without a basal pipe | French drain, counterfort drain, combined surface and groundwater filter drains |
| Chambers | Point asset | Subsurface water transfer and maintenance point<br>Connecting linear assets<br>sump to trap sediment | Concrete, masonry or plastic chambers with cover and incoming/outgoing pipe connections | Manhole, catchpit, inspection chamber |
| Inlet and outlets | Point asset | Transition point between surface and subsurface drainage | The point at which below ground pipe flows from or discharges into surface water course with or without a headwall structure | Outfall, inlet, outlet |
| Miscellaneous | Point linear or polygonal asset | Water transfer away from track | Blankets placed within earthworks, vertical or horizontal placement.<br>Ballast laid over track formation | Earthwork drainage blanket<br>Ballast |

### 2.2.1 Surface drainage

Surface drainage serves to remove surface runoff before it enters the track system as well as to collect water percolating out of track structures (Tzanakakis, 2013). The main types of surface drainage are cess drains, catch drains, and mitre drains as shown in Figure 2.2 (Tzanakakis, 2013, RailCorp, 2009).

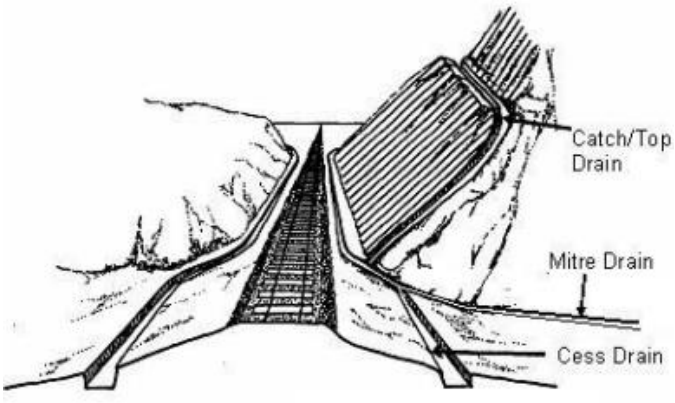



*Figure 2.2. Surface drainage types (RailCorp, 2009)*

Cess drains are typically located at the subgrade level at the side of the track (Figure 2.3). They serve to remove from the track water that has infiltrated through the ballast (Tzanakakis, 2013). They are most commonly found in cuttings where water cannot freely move away from track (Tzanakakis, 2013).

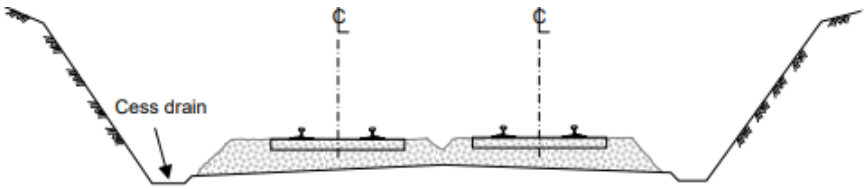



*Figure 2.3. Typical location of cess drain (RailCorp, 2009)*

Catch drains, on the other hand, intercept runoff before it enters the track or earthwork structures (Tzanakakis, 2013). Catch drains are often located on the crest of a cutting to divert water away from the cutting face to prevent its erosion (Tzanakakis, 2013, DPTI, 2018). They can also be located at the uphill side of an embankment to divert water away from the embankment toe (DPTI, 2018, Tzanakakis, 2013). Figure 2.4 illustrate the setting of catch drains in an embankment and a cutting.

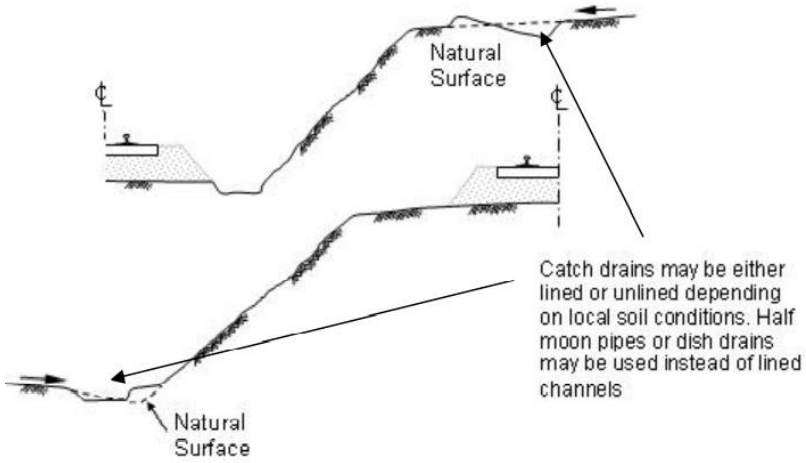



*Figure 2.4. Typical catch drains (RailCorp, 2009)*

Mitre drains are connected to catch and cess drains along the track length to remove excess water (RailCorp, 2009). Figure 2.5 illustrates the role of mitre drains.

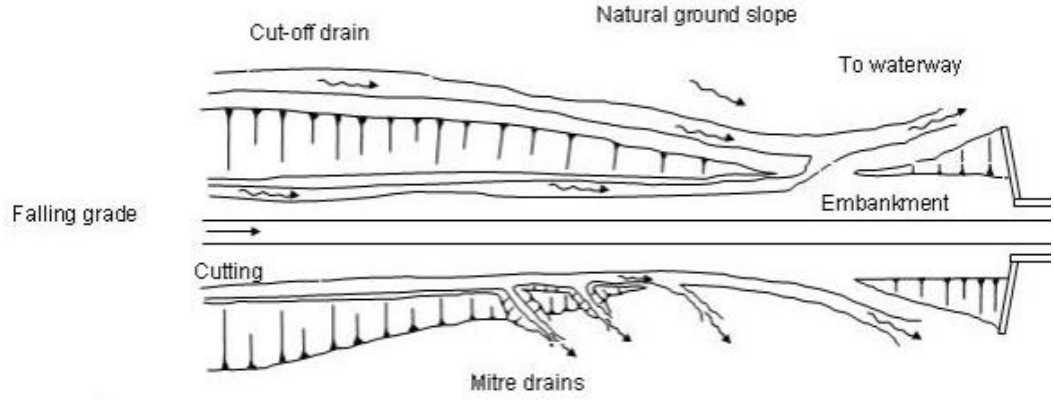



*Figure 2.5. Mitre drains (RailCorp, 2009)*

### 2.2.2 Subsurface drainage

Subsurface drainage is necessary to maintain the stability of the track subgrade and to ensure the stability of earthworks (Tzanakakis, 2013). Its roles are to drain track structure where water seeps through ballast into subgrade (Figure 2.6), control/lower the water table (Figure 2.7) and drain earth slopes (Figure 2.8) (Tzanakakis, 2013).

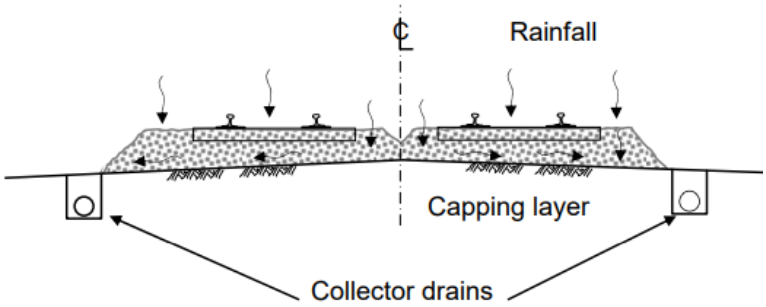



*Figure 2.6. Collection of water seeping into ballast structure (RailCorp, 2009)*

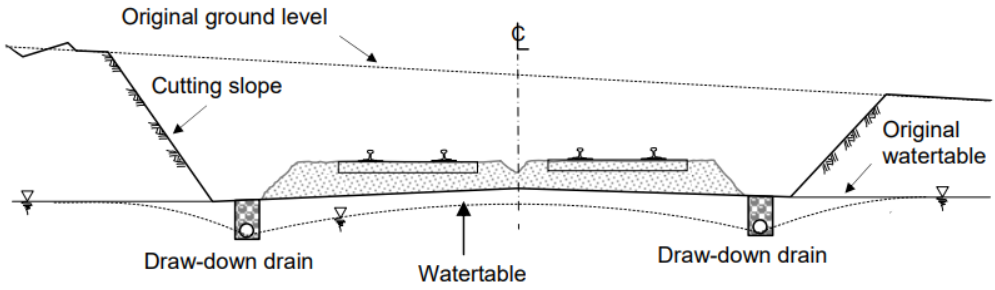



*Figure 2.7. lowering water table (RailCorp, 2009)*

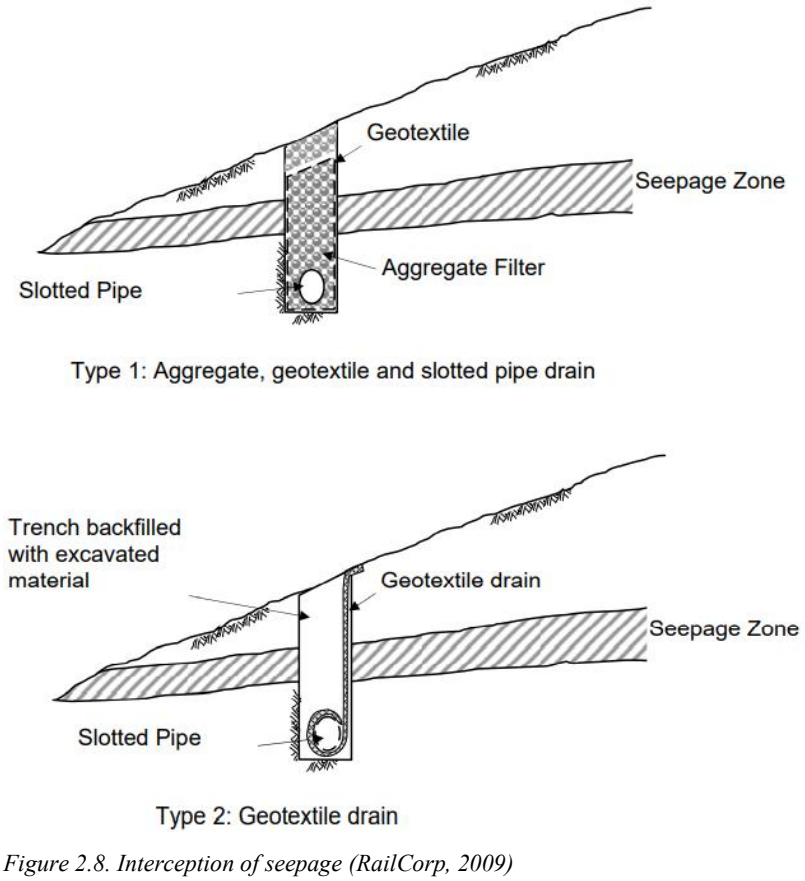



*Figure 2.8. Interception of seepage (RailCorp, 2009)*

Subsurface drains are of three main types, namely longitudinal drains (collector drains) (Figure 2.9), transverse drains (Figure 2.10) and drainage blankets (Figure 2.11) (RailCorp, 2009). Carrier drains

are a type of subsurface drains. Their purpose is to carry large water volumes from the subsurface collector drains into the outlet. This is to ensure the water in collector drains doesn't infiltrate again into subgrade at any point downstream (RailCorp, 2009). Figure 2.12 illustrates the role of a carrier drain.

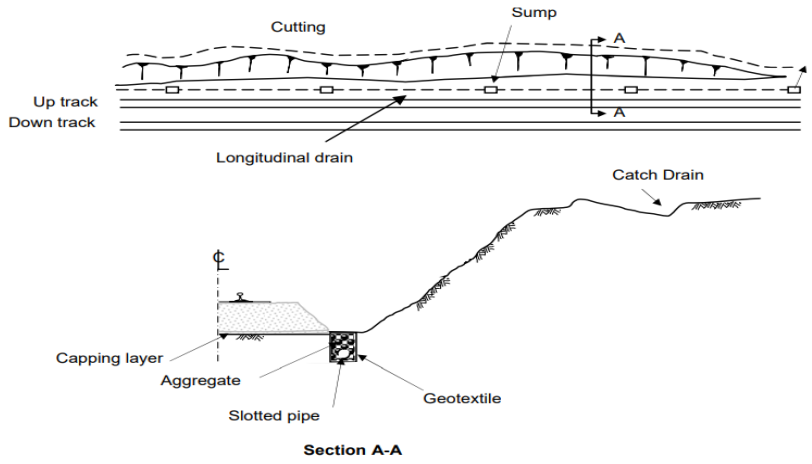



*Figure 2.9. Longitudinal drain arrangement (RailCorp, 2009)*

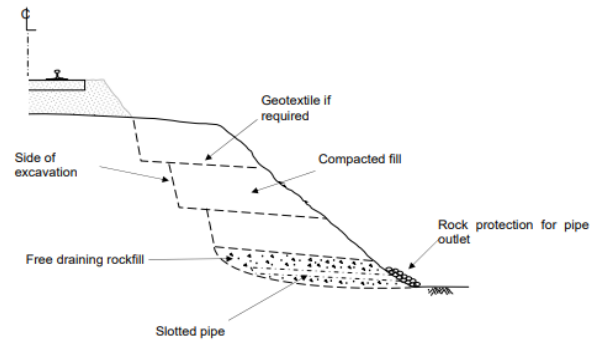



*Figure 2.10. Typical transverse drain (RailCorp, 2009)*

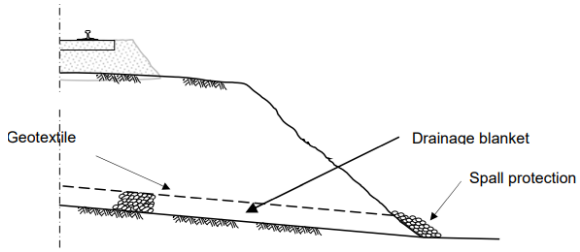



*Figure 2.11. Typical drainage blanket (RailCorp, 2009)*

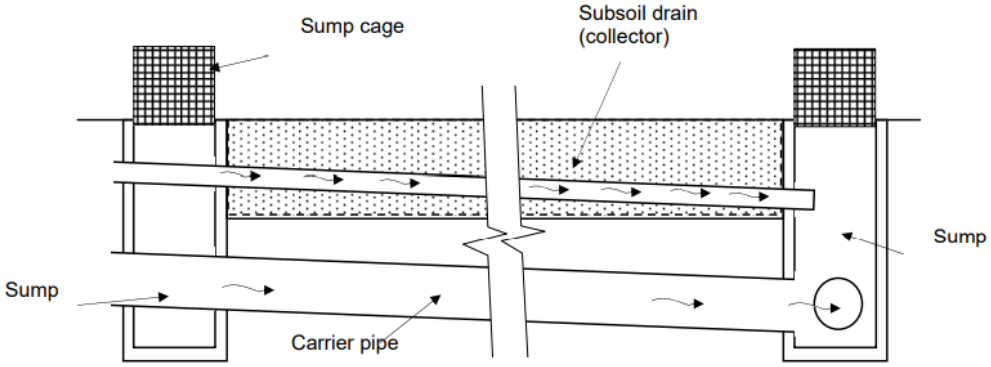



*Figure 2.12. Subsoil collector drain and a larger carrier pipe (RailCorp, 2009)*

Subsurface drains can consist of combinations of pipes, aggregate, and geotextiles (RailCorp, 2009). Aggregate drains consist of permeable aggregate as shown Figure 2.13 (RailCorp, 2009). Pipe drains consist of perforated/slotted pipes made of various materials, like steel, uPVC and Cast iron, installed in an aggregate-backfilled trench as shown in Figure 2.14 (RailCorp, 2009). Geotextiles can be wrapped around the backfill in an aggregate drain (Figure 2.13) or around a pipe (Figure 2.14) to prevent fines from clogging the backfill in aggregate drain or the pipe perforations in a pipe drain (RailCorp, 2009). Geotextiles can also be used as stand-alone horizontal or vertical drainage blankets to collect and convey water along its plane away from the track bed and into an outlet (see Figure 2.11).

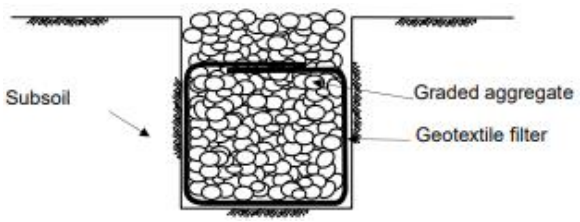



*Figure 2.13. cross section of a typical subsurface aggregate drain with geotextile (RailCorp, 2009)*

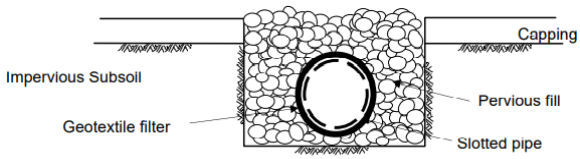



*Figure 2.14. cross section of a typical subsurface pipe drain with geotextile surrounding pipe (RailCorp, 2009)*

### 2.2.3 Inlet and outlets

Where the water enters the drainage system, there should be provision of appropriate screens and sumps to prevent debris and silt from entering the system and causing blockage (Network Rail, 2018). For outlets, where sediment in flow is high, a silt trap should be provided prior to water exist into outlet water body as shown in Figure 2.15 (RailCorp, 2009). Furthermore, energy dissipators are required where outlet velocities are high to reduce the risk of scour at outlets (RailCorp, 2009).

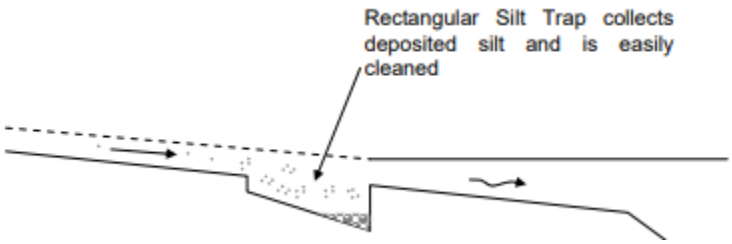



*Figure 2.15. Silt trap in drains with high sediment loads(RailCorp, 2009)*

### 2.2.4 Drainage asset condition degradation

The condition of a drainage asset is characterised by its structural and service condition. Structural condition reflects the severity of physical defects that affect the integrity of asset's fabric (Spink et al., 2014). Such defects require repair or replacement of the asset. Service condition is associated with the asset's water-carrying capacity in relation to the asset's design capacity (Spink et al., 2014). Typically, poor service condition is addressed through routine maintenance activities such as cleaning the asset or clearing vegetation. All assets degrade over time due to a variety of factors as summarised in Table 2.2. Figure 2.16 schematically compares rates of degradation of hard (e.g. pipes, channels and chambers) and soft assets (e.g. ditches). The impact of drainage asset degradation is manifested as, loss of flow capacity, loss of flow velocity and blockage, which can cause flooding, damage to other assets and third party damage (Spink et al., 2014).

*Table 2.2. Modes of drainage asset degradation (Spink et al., 2014)*

| Deterioration | Location | Surface | | | Subsurface | | | |
|---|---|---|---|---|---|---|---|---|
| | Asset category | Ditches | Channels | Inlets and outlets | Filter drains | Chambers | Pipes and culverts | Pumped systems |
| | Construction / Mode | soft | Hard | | Soft | Hard | | E&M |
| Service | Sediment | X | X | | X | X | X | X |
| | Debris accumulation | X | X | X | | | | |
| | Vegetation growth | X | X | | X | | | |
| | Root growth | | | | X | X | X | |
| Structural | Bank failure | X | X | | | | | |
| | Animal burrowing | X | | | | | | |
| | Compression and collapse | | | | | | X | |
| | Cracking and spalling | | X | X | | X | X | |
| | Misalignment of components | | X | | | X | X | |
| | Time-dependent brittleness | | | | | | X | |
| | Accidental damage | X | X | X | X | X | X | X |
| | Corrosion of components | | | X | | X | X | X |
| | Mechanical failure of moving parts | | | X | | X | | X |
| | Electrical failure | | | | | | | X |

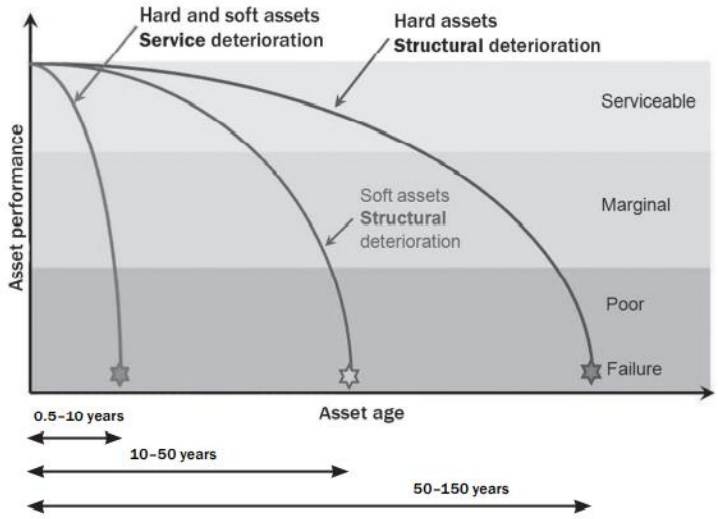



*Figure 2.16. Rates of asset degradation (Spink et al., 2014)*

### 2.2.5 Parameters affecting pipe condition degradation

A series of studies have been conducted on degradation of urban drainage/water-supply pipes in urban areas as will be discussed in Section 2.3.5. due to relative abundance of studies on pipe assets compared to other drainage assets, this section focuses on parameters affecting pipe drainage. However, the parameters are applicable to be considered when extending the work to other drainage assets. From these studies, Davies et al. (2001a) highlights that there is no single parameter, or even small group of parameters, which stand out as having a particularly strong influence on pipe condition. Rather, it is a process resulting from the interaction of many factors. These factors can be categorised into four groups according to Ana and Bauwens (2010), Davies et al. (2001a), Rajani and Kleiner (2001), as follows:

- physical factors: pipe age, pipe shape, pipe size, pipe depth, pipe length, pipe material, pipe slope, pipe type, joint type and material;
- environmental factors: groundwater level infiltration/exfiltration, presence of trees, traffic and surface loadings and soil condition including soil type, pH, density, resistivity, aeration;
- operational factors: sediment level, sewage characteristics of flow, maintenance, and repair strategies. water pressure, surge pressures, summer and winter air and water temperatures, wheel loads, vehicle impact factor and frost load factor; and

- installation factors: installation method, standard of workmanship, laying condition, load factor, coefficient of horizontal stress at rest, coefficient of sliding friction.

### 2.2.6 Effects of poor drainage

Improperly performing drainage assets can lead to water ponding within the track substructure (Selig and Waters, 1994). Excess water in the substructure can cause significant increase in maintenance costs of other assets such as the track structure, earthworks, power and communications systems (Selig and Waters, 1994, Spink et al., 2014). The permeable nature of the track substructure actively promotes water entry into the subgrade from both surface water infiltration through ballast and sub-ballast, and through groundwater seepage (Spink et al., 2014, Li and Selig, 1995). The prolonged presence of water in the subgrade can reduce the strength and stiffness of subgrade soils (Li and Selig, 1995). Major associated problems include progressive shear failure of embankments, subgrade attrition with mud pumping leading to formation of wet beds, consolidation settlement of the track, swelling/shrinkage leading to a rough track surface (and thereby poor ride quality), cutting slope erosion and soil collapse in the form of earthwork washouts (Li and Selig, 1995). These issues are particularly prevalent in fine-grained (cohesive) soils. Figure 2.17 and Figure 2.18 show examples of wet bed and earthwork washout, respectively. Blockage or lack of catch drains at the top of a cutting slope can result in the erosion of cutting slope faces or internal erosion and stability failures (Spink et al., 2014, Li et al., 2015). Furthermore, in coarse-grained (loose) soils, subgrades are subjected to liquefaction failures resulting from increased pore pressure under repeated loadings which leads to track vertical profile degradation and track settlements (Li et al., 2015). Ballast fouling results from mud pumping from the subgrade into the granular layers (Li et al., 2015). This impedes the permeability of the granular layers which is a major enabler of water flow into collector drains away from the track, hence further exacerbating the water ponding problem (Spink et al., 2014). Furthermore, extensive presence of water in the ballast layer leads to premature ballast degradation and sleepers attrition through the combination of slurry abrasion, chemical action and water freezing (Selig and Waters, 1994). As for other assets, high water levels and/or ponding can

cause signalling problems and interfere with power supply (Spink et al., 2014). Furthermore earthwork movements may result in the movement of gantries supporting overhead cables and affect transmission of power to trains in addition to damage or destruction of sections of the communications networks (Spink et al., 2014). Signalling , cameras and signage that are located within earthworks can also be damaged (Spink et al., 2014). Therefore, maintaining adequacy of drainage can prevent or minimise theses problem, thus reducing the associated maintenance and repair (M&R) costs in addition to costs associated with safety and operational disruptions (Selig and Waters, 1994, Spink et al., 2014).

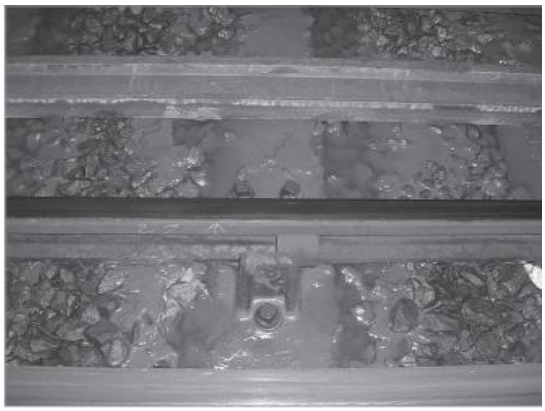


*Figure 2.17. Wet bed (Spink et al., 2014)*



*Figure 2.18. earthwork washout (Tzanakakis, 2013)*

## 2.3 Drainage asset performance and interventions

### 2.3.1 Asset performance

Drainage asset performance describes the effectiveness of drainage components during wet weather (Spink et al., 2014). According to Spink et al. (2014) drainage performance is assessed by the combination of asset condition and design capacity of the asset. The capacity of the asset is given by its size, gradient and roughness (Spink et al., 2014). These depend on design assumptions like the size of the design event (i.e. rainfall intensity) and the catchment area served (Spink et al., 2014). Drainage condition is usually observed from regular visual inspections carried out by trained inspectors and requires dry weather. Performance evaluation, however, requires wet weather for the visual inspection of the effectiveness of an asset in conveying water (Spink et al., 2014).

A performance gap is the difference between required and actual performance. It is usually induced by either condition degradation of the asset or where the design capacity is insufficient due to subsequent changes in catchment size, land use or climate (Spink et al., 2014). Drainage design standards usually specify the size of a rainfall event to which the asset is designed. Typically railway drainage assets are designed to withstand a 1 in 50 event without flooding and critical drainage infrastructure assets should be capable of dealing with a 1 in 200 event at (Spink et al., 2014). Criticality of various components of the railway drainage system depend on the importance of the assets in terms of flood impact across assets and the strategic importance of the route (Spink et al., 2014). Establishing performance gaps identifies locations which will require intervention over the short or long-terms (Spink et al., 2014). A robust evaluation enables the optimisation of intervention activities over the life cycle of an individual asset as well as the asset system.

### 2.3.2 Intervention activities

The types of intervention activities throughout an asset's lifecycle can be categorised as one of three types, i.e. maintenance, refurbishment or renewal (Spink et al., 2014). Maintenance interventions

are small scale work that does not materially change the drainage infrastructure. The types of maintenance activity are (Spink et al., 2014):

- Cyclical (routine) maintenance: these are routine activities scheduled regularly to ensure performance level.
- Non-cyclical (periodic) maintenance: these are planned targeted works scheduled following an inspection or a condition assessment.
- Emergency maintenance: these are unplanned reactive works in response to a flooding or pollution event or to rapidly address a safety related issue.

Refurbishment are non-routine works which address defects in drainage assets to restore performance. Renewal is the replacement of an asset at the end of its useful life or the redesign of the asset (Spink et al., 2014). Table 2.3 summarises intervention activities to remedy various potential defects in railway drainage assets.

*Table 2.3. Drainage asset intervention activities (adapted from (Spink et al., 2014, Network Rail, 2018))*

| Asset type | Defect | Cause | Maintenance | Refurbishment | Renewal |
|---|---|---|---|---|---|
| **Channels and ditches** | Blockage | Channels blocked by ingress of rubbish | Clean out and reprofile | | |
| | | Soil tipping | | | |
| | Vegetation | Overgrowth | | | |
| | Collapse | Bank instability<br>Scour | | Line channel/ditch to preserve cross-section and reduce maintenance<br>Protect against bank erosion on slopes by using 500 mm wide grass strips<br>On steep slopes, reduce the flow velocity using baffles | |
| | | Burrowing animals | Control vermin and fill burrows | | |
| **Pipes** | Silt and debris build-up | Normal operation | Clean regularly by:<br>Pressure jetting<br>Rodding | | |
| | | Filter medium absent or unsuitable for the ground | Clear silt and replace filter and/or porous fill | | |
| | Root blockage | Trees or hedges | Root cutting using a jetter equipped with a flail | | |
| | Partial collapse | Major pipe cracking or deformation | | Local open cut and/or replacement<br>Patch repair or local relining | |
| | | Holes and collapses of less than one pipe length | | | |

| Asset type | Defect | Cause | Maintenance | Refurbishment | Renewal |
|---|---|---|---|---|---|
| | Complete collapse | Structural failure of more than one pipe length | | | Renew by open cut |
| **Piped collector drains** | Blockage | Surface washing in of fines<br>Migration of fines from surrounding ground<br>Wet-beds<br>Ballast attrition | | Dig out and replace filter surround | |
| | Hydraulic | Uneven pipe gradient from disturbance of surrounding ground | | Replace filter surround to improve drawdown from surrounding ground | Renew by open cut |
| | | Inadequate capacity for catchment runoff | | | |
| **Carrier drains** | Blockage | Capacity reduced by material ingress, poor pipe alignment | Rodding: by hand for clearing of small local blockages and locating larger obstructions<br>Water jetting/rodding/dragging relies on ability to pass cable through pipe | Open excavation: dig up pipe, cleanout/repair/replace | |
| | | Root intrusion | Vegetation management to restrict spread of trees, and<br>Drag scraping<br>Flail jetting | Pipe replacement | |
| | Hydraulic surcharging | Poor fall or pipe alignment | | Replace filter surround to improve drawdown from surrounding ground | Renew by open cut |
| | | Inadequate pipe capacity | | Relay by open cut or increase diameter of pipe-size if a compromise between flow capacity and self-cleansing velocity | |
| **Culvert** | Blockage | Debris | Check/clear trash screen | | |
| | | Silt | Clear non-man entry culverts by rodding, drag scraping or water-jetting<br>Clear man-entry culverts by water jetting, hand excavation drag scraping or , of sufficient headroom, by mini digger<br>Remove obstructions from downstream body of water | | |
| | | Rubbish or trash | Fit trash screens | | |
| | Structural | General deterioration | Local repairs: replace missing bricks/repoint mortar joints<br>Fill voids/repair lining | | |
| | | Scour voids | | Reline conduit<br>Extend headwall or training walls, flumes and aprons | |
| | | Collapse | | | Reconstruct |
| | Insufficient flow capacity | Change in upstream catchment<br>Outlet smaller than inlet | | Remediation to increase capacity | |
| **Catchpits and manholes** | Silting | Normal operation | Clean out by:<br>Hand excavation<br>Mechanical jetting or vacuuming | | |
| | | Adjacent recently ploughed fields | | | |
| | | Persistent silting due to adjacent land drainage problems | Bespoke solution required | | |
| | Blockage/material ingress/ chambers filled or buried | Damaged or missing covers<br>Poor maintenance practices, e.g. Re ballasting | Remove ballast in sump and replace damaged or missing covers to keep ballast out | | |

| Asset type | Defect | Cause | Maintenance | Refurbishment | Renewal |
|---|---|---|---|---|---|
| | | | Raise catchpits before ballast drops and/or clean chambers on completion of track work | | |
| | Collapse | Damage by ground movement or vehicle | | | Rebuild catchpit |
| Outfall | Structural | General deterioration | Local repairs: repair missing bricks. Repair mortar joints | | |
| | | Scour | | Extend headwall or training walls, flumes and aprons | |
| | Blockage | Seized flap valve | | Repair or replace valve | |
| | Restricted flow | Problems outside ownership boundary | Liaise with the relevant third party to resolve | | |

### 2.3.3 Current approaches to intervention planning

Traditionally, drainage interventions are scheduled based on condition appraisals; wherein an intervention would be warranted only if the asset has already failed or is expected to fail (Spink et al., 2014). In the first case, a reactive intervention is required, whereas in the second case a proactive trigger-based intervention is warranted. An optimal maintenance planning strategy occurs when employing both reactive and proactive maintenance as shown in Figure 2.19. The optimal economic zone for scheduling interventions is the point where the sum of proactive and reactive maintenance costs is a minimum (Elcheikh and Burrow, 2017). If the asset is maintained prematurely, following a fully proactive maintenance plan, then the maintenance cost exceeds any benefit incurred (Elcheikh and Burrow, 2017). Conversely, if the asset is not maintained in time and a reactive approach is adopted, the consequent maintenance cost will be greater than optimal (Elcheikh and Burrow, 2017). Currently in the UK the drainage asset management choice of a reactive or proactive approach is decided based on the importance of the route (Spink et al., 2014). The importance of a route depends on the volume of traffic, speed on the route and the strategic importance in terms of income it generates/penalty incurred (Spink et al., 2014).

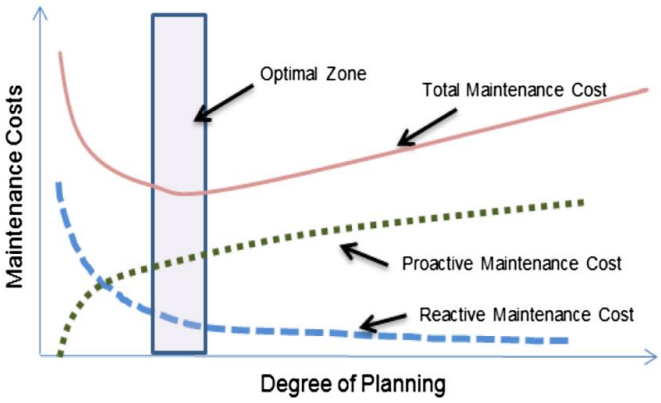



*Figure 2.19. Balance of planned and unplanned maintenance (Elcheikh and Burrow, 2017).*

### 2.3.4 Condition-based maintenance

Proactive approaches have traditionally been linked to Condition-based maintenance (CBM). CBM is a form of non-cyclical proactive approach to maintenance scheduling where decision making is based on the observed condition of the asset (Su et al., 2017). Condition-based maintenance enables effective maintenance practices which extend useful life while reducing operational interference associated with cyclic maintenance, thus reducing associated maintenance costs (Van der Westhuizen and Gräbe, 2013). In recent years, CBM has received growing attention in various industries (Su et al., 2017). In the railway systems, Jamshidi et al. (2018), and Vale and Ribeiro (2014) developed CBM approaches for track quality degradation using Mixed Integer Linear Programming (MILP) for optimisation of long-term maintenance planning and short-term crew scheduling based on stochastic deterioration models. Wang et al. (2020b) developed an Intelligent Proactive Maintenance System (IPMS) to support CBM of Traction Power Supply System (TPSS) in the Chinese High Speed Rail (HSR) using sensor-collected traction health and load data combined with health assessment machine learning algorithms and subsequent algorithms for maintenance planning optimisation. Firlik et al. (2023) used thermal imaging cameras at point of contact of wheel-rail interface to monitor wheel-rail interaction, identify flange climbing, rolling noise generation and longitudinal creepage during traction or breakage. Zanelli et al. (2023) deployed wireless sensor nodes for monitoring freight train infrastructure condition using geo-

localised vibration measurements. La Paglia et al. (2023) used acceleration measurements from in-service high-speed trains to monitor condition of rail track vertical alignment. Wu et al. (2023) developed a method for estimation of structural fatigue degradation of bogie frames using axle box accelerations measurements. Harrington et al. (2023) proposed the use of three-dimensional (3D) laser-based machine vision scans and machine learning Neural Networks (NN) for condition assessment of track spikes and fasteners as an alternative to the costly human visual inspections.

Currently in the UK, planned drainage maintenance is based on condition appraisals that traditionally rely on field inspections, which suffer from a lack of repeatability and reproducibility (Spink et al., 2014). To improve monitoring of drainage railway assets there is therefore a need to develop automated inspection processes. For example, Kovacevic et al. (2016) developed a methodology to asses railway infrastructure using Ground Penetrating Radar (GPR), seismic refraction and drones to evaluate measures of track performance features including ballast fouling, soil water content, slope geometry and drainage condition. Furthermore, Gong et al. (2023) proposed the use of three-dimensional Computational Fluid Dynamics (3D CFD) simulations to study the drainage condition within the ballast layer following various ballast cleaning interventions.

Cost-effective railway infrastructure intervention planning requires, in addition to improved regular performance monitoring, the use of reliable condition prediction models (Jovanovic et al., 2015). Such models enable the continual prognosis of potential failures (Xie et al., 2020). In literature, there are studies which were aimed at predicting the condition of various railway assets. Some examples from other railway studies include Furtado and Ribeiro (2023) in which they developed a degradation prediction model for railway bridges using a Markov model to support long-term maintenance planning. Sresakoolchai et al. (2023) used automated machine learning recognition to recognise and classify railway turnout deterioration following extreme weather events. Wang et al. (2023) developed a data-driven machine learning approach for evaluating the occurrence of track geometry defects based on substructure condition. There is a paucity in such studies for the railway drainage system. Those pertinent to this research are discussed in Section 2.3.5.

### 2.3.5 Overview of existing condition models for drainage assets

Infrastructure condition models can be divided into physical, statistical and Machine Learning (ML) models (Yang, 2004). All three model types have been used to model storm water/wastewater pipe condition, predominantly for urban and road drainage systems. The applications of the three types of models in literature are reviewed in this section, with a focus on physical empirical models, particular types of statistical models, known as a Markov models, and ML models. The applications of various prediction techniques and models gathered from the literature are summarised in Table 2.4. The studies are categorised based on the type of the used model, with a specification of the studied assets and the asset properties considered in the condition modelling application.

*Table 2.4. Summary of existing drainage asset condition models*

| Method | Study | Asset | Asset Properties [a] | | | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | $P_1$ | $P_2$ | $P_3$ | $P_4$ | $P_5$ | $P_6$ | $P_7$ | $P_8$[b] | $P_9$ | $P_{10}$ | $P_{11}$ | $P_{12}$ | $P_{13}$ | $P_{14}$ | $P_{15}$ | $P_{16}$ | $P_{17}$ | $P_{18}$ | $P_{19}$ | $P_{20}$ | $P_{21}$ | $P_{22}$ | $P_{23}$ | $P_{24}$ | $P_{25}$ |
| Homogeneous Markov Chains | Wu et al. (2021b) | Rail drainage assets [c] | X | X | X | | | X | X | X | | | | | X | | | | | | | | | | | |
| | Micevski et al. (2002) | Storm water pipes | X | X | | | | | | | X | | | | | X | X | | | | | | | | | | |
| | Meegoda et al. (2004) | Urban Drainage Culverts | X | | | | | X | | | | | | | | | X | X | | | | | | | | | |
| | Wirahadikusumah et al. (2001) | Sewers | | X | | | | | | | | | | | | | | | X | X | X | | | | | | |
| | Altarabsheh et al. (2016) | Sewers | | | | | | | | | | | | | | | | X | | | | | | | | X | |
| | Baik et al. (2006) | Sewers | X | X | | | | | | | | | | | | | | X | | | | X | X | | | | |
| | Tran et al. (2008), Tran et al. (2010) | Stormwater pipes | X | | | | | X | | | | | | | | | | X | X | | | | X | | | | |
| Non-homogenous Markov chains | Le Gat (2008) | Urban drainage pipes | X | | | | | | | | | | | X | X | | | | | | | | | | | | |
| | Kleiner et al. (2006) | Water mains | X | X | | | | | | | | | | | | | | X | | | | | | | | | |
| Deterministic Linear model | Vollersten and König (2005) | Concrete sewer pipe | | | | | | | | | | | | X | | | X | | X | | X | | | | | | |
| Cohort Survival model | Baur and Herz (2002) | Sewer pipes | X | X | X | | | X | | X | | | | X | X | | | | | | | | X | | | | |
| | Xu and Sinha (2021) | Water mains | X | | | X | X | | | | | | | X | | | X | | | | | X | | | | | |
| Fuzzy method | Xu et al. (2020) | Water mains | X | X | | X | | | | | X | | X | | | | X | X | X | | X | | | | | | |
| Ensemble Classifier | Mohammadi et al. (2020) | Sewer pipes | X | X | | | | | | | | | | | | | X | X | X | | X | X | X | | | | |
| Neural networks | Tran et al. (2008), Tran et al. (2007), Tran et al. (2006), Tran et al. (2009), Tran et al. (2010) | Stormwater pipes | | | | | | | | | X | X | | | | X | | | | | | | | | | | X |

[a] $P_1$: Pipe size (diameter); $P_2$: Pipe material; $P_3$: Pipe shape; $P_4$: Pipe lining; $P_5$: Pipe Protection; $P_6$: Location; $P_7$: Route; $P_8$: Asset subclass; $P_9$: Type of subgrade; $P_{10}$: Presence of trees; $P_{11}$: Traffic load; $P_{12}$: Construction period; $P_{13}$: Type of effluent; $P_{14}$: Serviceability condition; $P_{15}$: Corrosion related properties; $P_{16}$: Age; $P_{17}$: Cover depth; $P_{18}$: Backfill material; $P_{19}$: Groundwater level; $P_{20}$: Length; $P_{21}$: Gradient; $P_{22}$: Land use; $P_{23}$: Maintenance; $P_{24}$: Sojourn time; $P_{25}$: Thornthwaite Moisture Index (TMI)

[b] For chambers and channels

[c] channel, chamber, culvert, pipe

Physical empirical condition models (such as linear and exponential models) are based on physical mechanisms that govern pipe deterioration (Tran et al., 2007). They require relatively large amounts of specific types of data to fully capture deterioration behaviour, but such data is often unavailable (Ana and Bauwens, 2010). Moreover, failure mechanisms of pipes are very complex as they are the result of interaction between numerous factors (see Section 2.2.5), often with stochastic damage propagation (Rajani and Kleiner, 2001, Madanat et al., 1997). An example of these empirical model is the ExtCorr linear model developed by Konig (2005), which gives an estimate of the external corrosion of concrete pipes due to environmental factors. The validation of the model was not reported in the article and hence it is not possible to comment on its accuracy. Furthermore, Vollersten and König (2005) stated that in such a model there is high level of uncertainty associated with the 'external conditions'.

Statistical models on the other hand allow for randomness in the behaviour of deteriorating pipes. They assume a stochastic behaviour where predictions are based on past distribution of condition degradation occurrences. The most commonly used statistical pipe condition model is the Markov chain model (Wu et al., 2021b). A Markov model assumes that the current state of the asset fully captures all the information regarding the factors that influence future condition and hence, future condition depends solely on current condition (Ana and Bauwens, 2010, Meegoda et al., 2004). There are two main types of Markov models; Homogeneous Markov chains which are time-independent and non-homogeneous Markov chains in which transition probability from one condition to the other changes with the age of an asset (Ana and Bauwens, 2010). Wu et al. (2021b) used a Markov model for simulations of service condition transition probabilities of railway drainage assets at network level. However, as discussed in section 2.2.4, to determine maintenance needs, it is essential to assess structural condition in addition to service condition. Moreover, in addition to network-level strategy evaluation, individual-asset condition assessment is crucial for effective asset management (Fecarotti and Andrews, 2017).

A Cohort survival model is another form of statistical model and is based on statistical regressions methods utilising survival probability (Xu and Sinha, 2021). The method estimates the duration that

an asset remains in a certain condition until it moves to the next condition, which is presented as a survival curve (Baur and Herz, 2002). For example, Baur and Herz (2002) utilised this approach to forecast the date when a sewer asset would enter a critical condition based on the asset's characteristics. Xu and Sinha (2021) used Weibull proportional hazards model (WPHM) for survival analysis based on records of pipe breaks to predict a pipe's' mean time to failure. Xu and Sinha (2020), Xu and Sinha (2021) found that for their work a main issue with using survival analyses for pipes was to do with missing data points in historical records, i.e., statistical left truncation problem. To address this, Xu and Sinha (2021) used Artificial Neural Networks for data imputation. This procedure was followed by the survival analysis which observed an error reduction in estimation of pipe mean time to failure from 14% to 2%. This is sensible because calibration of the WPHM without considering the left-truncated break records can introduce bias into inferences and predictions. Therefore, integrating data-driven imputation as a pre-analysis step will reduce this bias.

ML models, a subsection of Artificial Intelligence (AI), are data-driven models, which are meant to complement or replace knowledge-driven models when describing a physical phenomenon, such as deterioration of an asset (Solomatine and Ostfeld, 2008). ML simulates the acquisition of knowledge similar to human brain learning which enables continuous improvement of model performance (Liu et al., 2019). They learn the hidden patterns behind the observed data, which enables them to make predictions (Tran, 2007). ML methods are suitable for identifying complex non-linear relationships between input and output data (Lee et al., 2021). They are tolerant of imprecise, subjective, and limited noisy data and can handle both real values and categorical/ordinal input (Tran et al., 2007, Ellis et al., 2008). Unlike statistical methods, ML methods make no assumptions about the data distribution or the required explanatory variables (Asnaashari et al., 2013, Tran, 2007, Solomatine and Ostfeld, 2008). There is a wide range of successful applications of ML methods in the literature, these mainly use Artificial Neural Networks (ANN), Support Vector Machine (SVM), K-Nearest Neighbours (KNN) and Ensemble Classifiers which include Decision Trees (DT), Bagged Trees (BT), Random Forests (RF), Gradient Boosted Trees (GBT)

and AdaBoost. Table 2.5 summarises the ML applications and their measures of performance. The achieved model performances in these studies highlight the suitability and success of ML algorithms as condition prediction models. Furthermore, with recent developments in digital technologies, models which incorporate the use of Big Data for railway infrastructure condition assessment, such as Machine Learning (ML), are likely to become indispensable decision support tools for infrastructure managers (Thaduri et al., 2015, and Mcmahon et al., 2020). Big data refers to the large and diverse datasets collected on physical assets at an increasing rate as sensors, processing abilities, software and technologies are used to facilitate the exchange of asset data. This includes the management of railway drainage as there is an increasingly large amount of data being collected by railway organisations on railway drainage assets. TrackWater is an example where sensors are leveraged in railway drainage to collect information on siltation and flooding within the a piped drainage system (Devan, 2019).

*Table 2.5. Applications of ML for various infrastructure assets*

| **Study** | **ML** | **Application** | **Data split** | **Measure of performance** |
|---|---|---|---|---|
| Ahmed et al. (2021) | KNN<br>NN<br>SVM<br>RF | Prediction of tunnel condition | 80% training/validation<br>20% testing | Accuracy=<br>KNN 80.12%<br>RF 85.38%<br>NN 56.14%<br>SVM 56.73% |
| Alawad et al. (2020) | DT | Safety analysis of railway stations | 80% training<br>20% testing | Accuracy= 88.7% |
| Allah Bukhsh et al. (2019) | DT<br>RF<br>GBT | Predict maintenance needs of railway switches | 70% training<br>30% testing | Accuracy= 84%<br>F-score=86% |
| Arshad and Ahmed (2021) | LR<br>GBT<br>DT<br>RF | Prediction of train delay due to weather impact | Not available | Accuracy=<br>LR 90%<br>GBT 92%<br>DT= 94%<br>RF 96% |
| Asadi et al. (2019) | AdaBoost | Quantification of deterioration in concrete bridge deck | unspecified | Precision Vs. Recall trade-off curve, described as “very good results” |
| Asnaashari et al. (2013) | NN | Forecasting watermain failure rate | 50% training<br>25% validation<br>25% testing | $R^2$=0.94 |
| Assaad and El-adaway (2020) | ANN<br>KNN | Prediction of bridge deck condition | 80% training/validation<br>20% testing | Accuracy= 91% |

| Study | ML | Application | Data split | Measure of performance |
|---|---|---|---|---|
| Caradot et al. (2018) | RF | Sewer pipe condition | 60%training<br>40% testing | Recall of pipes in bad condition=67% |
| Fathi et al. (2019) | ANN<br>RF | Pavement deterioration prediction of Alligator Deterioration Index (ADI) | 75% training<br>25% testing | $R^2$ =0.79<br>RMSE=14.43 |
| Ferreño et al. (2021) | Multiple Linear Regression (MLR)<br>KNN<br>Regression Tree (RT)<br>RF<br>GBT<br>ANN<br>Support Vector Machine (SVM) | Prediction of rail pads stiffness | 80% training<br>20% testing | $R^2$=<br>MLR 0.452<br>KNN 0.628<br>RT 0.923<br>RF 0.965<br>GBT 0.995<br>ANN 0.990<br>SVM 0.060 |
| Harvey and McBean (2014) | RF | Pipe condition prediction | 70% training<br>30% testing | Recall=82% |
| Kalathas and Papoutsidakis (2021) | DT<br>RT | Maintenance prediction of railway traction/braking system | Not specified | Accuracy= 80%<br>Weighted Precision= 0.8<br>Weighted Recall= 0.8 |
| Lee et al. (2018) | ANN<br>SVM | Prediction of Track deterioration as Track Quality Index | 85% training<br>15% test | $R^2$ =0.86 MSE=0.03 |
| Liu et al. (2018) | RF | Quantify susceptibility of railway to rainfall-induced hazards | 60% testing<br>40% validation | Accuracy=95% |
| Mazari and Rodriguez (2016) | RF | Pavement deterioration prediction (IRI) | unspecified | $R^2$= 0.994and<br>RMSE= 0.049 |
| Mittal and Rao (2017) | NN | Detection of track defects, switches and signals and monitor track health | 80% training<br>20% testing | Defect detection:<br>Precision= 95%<br>Recall= 25%<br>Signal detection:<br>Accuracy= 93%<br>Precision= 99%<br>Switch Detection:<br>Precision= 94%<br>Recall= 83% |
| Moghtadernejad et al. (2021) | NN<br>KNN<br>RF | Conversion of condition from old scheme to new rating scheme for railway supporting structures | 66% training<br>33% testing | F-score= 0.5-0.8 |
| Mohammadi et al. (2020) | GBT | Prediction of sewer pipe condition | 80% training<br>20% testing | Accuracy=87% |

| Study | ML | Application | Data split | Measure of performance |
|---|---|---|---|---|
| Piryonesi and El-Diraby (2021) | Gradient Boosted Trees (GBT) | Prediction of International Roughness Index (IRI) and Pavement condition index for pavement deterioration | 90% training<br>10% testing | Accuracy=88% |
| Rokstad and Ugarelli (2015) | RF | Structural condition of sewers | Unspecified | ROC Area under curve=60% |
| Tran et al. (2008), Tran et al. (2007), Tran et al. (2006), Tran et al. (2009), Tran et al. (2010) | NN | Storm water pipe condition | 60% training<br>15% validation<br>25% testing | Accuracy=81% |
| Wang et al. (2020a) | NN<br>DT<br>RF | Prediction of road roughness (IRI) | 10-fold cross validation | $R^2$ =0.92 NN<br>$R^2$ =0.9 DT<br>$R^2$ =0.93 RF |
| Wu et al. (2015) | RF | Pipe defect classifications | Four-fold cross validation | Accuracy=80% |
| Xu and Sinha (2021) | ANN | Imputation of pipe failure records for pipe failure occurrence (classification) and year of failure (regression) | 70% training<br>30% testing | AUC=0.88<br>MSE=29.79 |

## 2.4 Asset management

### 2.4.1 Definitions

Asset management is defined as the "systematic coordinated activities and practices through which an organisation optimally and sustainably manages its assets and asset systems, their associated performance, risks and expenditures over their life cycles for the purpose of achieving its organisational strategic plan" (IAM, 2008a). The organisational plan is defined as "the overall long-term plan for the organisation that is derived from, and embodies, its vision, mission, values, business policies, stakeholder requirements, objectives and the management of its risks" (IAM, 2008a). Each asset has value to the organisation in relation to achieving its organisational objectives. The generated value is usually achieved when individual assets are managed as part of an asset system or an asset portfolio (IAM, 2015). The asset system is the set of assets that are interrelated to deliver a function like the railway drainage system conducting water away from the track and earthworks (IAM, 2008a). An asset portfolio is the complete range of assets and asset system owned by the organisation (IAM, 2008a). Within the portfolio, the asset systems may be highly interdependent or may deliver independent parallel contributions to the organisation's total objectives (IAM, 2008a). In the case of railways, the drainage system is highly integrated within the track and earthwork systems, where an improperly performing drainage system affects the performance objectives of the railway system over both the short and long-term as described above. Therefore, railway track owners and operators need to make significant and cost-effective investment in track drainage design, construction, performance monitoring and maintenance, taking into account future needs associated with climate and land use change. To support such decision making it is necessary for these organisations to follow a systematic asset management approach that recognises the importance of drainage assets in ensuring the integrity of all other infrastructure. Accordingly, organisations need to have appropriate plans that can realise corporate polices, strategies and objectives as well as asset management strategies and associated objectives that can realise these polices.

### 2.4.2 Hierarchy

There are three tiers of asset management decision making hierarchy (Spink et al., 2014):

- Strategic management. This is the high-level translation of organisational strategic plans to specify asset management policy which informs the production of asset management strategy, objectives, targets and plans (Spink et al., 2014, IPWEA, 2011).
- Tactical management. This addresses resource allocations (natural, physical, financial, etc.) according to detailed asset management procedures and standards to achieve strategic goals through meeting defined levels of service (Spink et al., 2014, Kiritsis et al., 2009).
- Operational management: This entails detailed short-term implementation plans that aim to provide organisation annual or bi-annual direction for operation, maintenance, renewal, and retirement lifecycle decisions (Spink et al., 2014, Kiritsis et al., 2009).

Each of these levels of management is associated with specific management functions. Figure 2.20 describes the scope of each level of management. In the railway drainage context, to support organisations in realising their corporate policies, strategies and objectives, a track owner, or operator, needs to carry out appropriate drainage asset management at the planning, programming, preparation and operations levels of management. Planning is to do with the management of the entire network of drainage assets as a whole, by which strategic, long-term expenditure requirements of drainage assets are determined that take into account the impact of drainage on the performance of all railway assets. Programming involves the development of multi-year drainage asset expenditure requirements in the medium term. Preparation identifies actual drainage construction and maintenance projects, and operation management concerns the in-depth assessment of the condition of short sections of longitudinal drainage assets (e.g. drainage pipes) and their components over the immediate and short term.

Furthermore, the quality of the management decisions made depends on the quality of asset information inputted. There are four main Information Quality Levels (IQL) specified by The World Bank (Sasidharan et al., 2022):

- IQL I: Most comprehensive level of detail that is mainly used as a benchmark for other measurement methods and research purposes.
- IQL II: Sufficient level of detail to distinguish the performance and economic returns of different technical options. It is typically used for project design, supervision and testing.
- IQL III: Summary details with categorised or aggregate values for the route and is typically used for preliminary design, programming, and budget preparations.
- IQL IV: The basic summary statistics of inventory, performance, and utilisation, of interest to infrastructure providers and users; typically used for network statistics and strategic planning.

For example, to enable proactive asset management at an operational level, IQL I/II is required. In railway drainage, this level consists of validated inventory data and asset condition data (Spink et al., 2014).

| Decision making level | Strategic | Tactical | Operational | |
|---|---|---|---|---|
| Management functions | Planning | Programming | Preparation | Operations |
| Length of cycle | Long term (>10 years) | Medium term (1-5 years) | Budget year (<1 year) | Ongoing (days/weeks) |
| Spatial coverage | Network-level | Route-level | Section-level | Object or sub-section where works take place |
| Application to the policy framework | Vision & mission statement | Objectives/performance indicataors | Standards | Standards |
| Application to the planning framework | Corporate plan | Business plan | Operational plan | Systems and procedures |
| Application to the operations | Rail standards and budgets | Developing work programme | Work design and contracts | Operations and management |

*Figure 2.20. Scopes of railway asset management levels (adapted from Sasidharan et al. (2022)).*

There are three levels of value creation for an asset portfolio in support of the organisational objectives (IAM, 2015). Figure 2.21 shows the lowest level is value creation for individual assets over their lifecycle where capital investment decision-making and operations and maintenance decision making are optimised for an individual asset to achieve efficiency and effectiveness (IAM,

2015). Realisation of value at an asset system level requires consideration of each asset's contribution at a system level, where the whole life costs, risks and performance are aggregated across all assets in the network to observe and optimise the capability of the asset system (IAM, 2015, IAM, 2008a). The management of asset portfolios concerns return on investment, compliance and sustainability which contributes to achievement of organizational objectives (IAM, 2015).

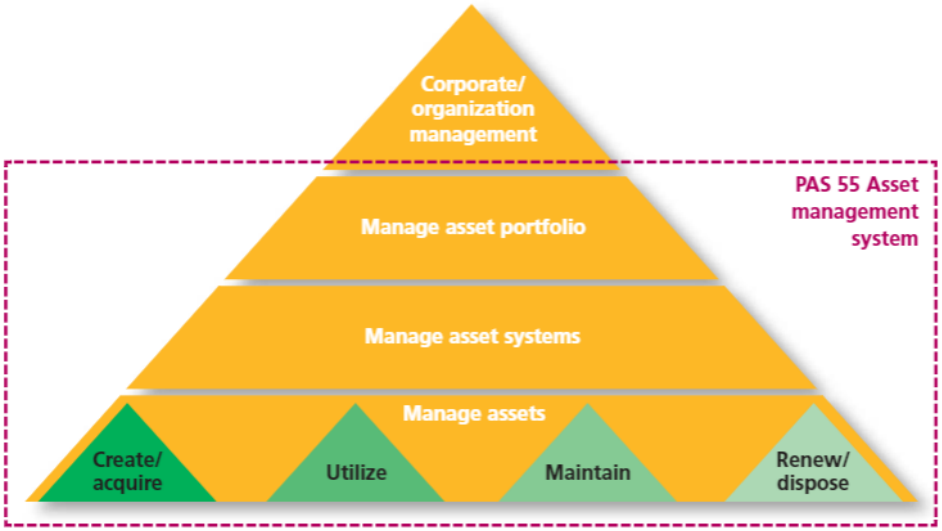



*Figure 2.21. Levels of assets and their management (IAM, 2008a)*

Optimisation of asset management activities in an asset management strategy should follow a bottom-up approach starting with optimisation of individual asset interventions and building up to activity programming for asset portfolio (IAM, 2008b). Figure 2.22 illustrates optimisation of intervention activities entailed at the three levels of value creation. Optimisation of activities for individual assets requires weighing the feasibility and benefit of a specific intervention against the cost and performance criteria at a specific time (IAM, 2008b). Asset lifecycle optimisation achieves value realisation at a component level through coordination of activities across the lifecycle of the asset with the purpose of maintaining level of performance, reducing costs and ensuring sustainable delivery of activities (IAM, 2008b). At an asset system level, coordination of activities should consider interdependencies between components (IAM, 2008b). Activity programme delivery across the asset portfolio owned by the organisation looks at work bundling across assets to ensure minimal

operational disruption, resource levelling within budget constraints and the identification of critical paths (IAM, 2008b).

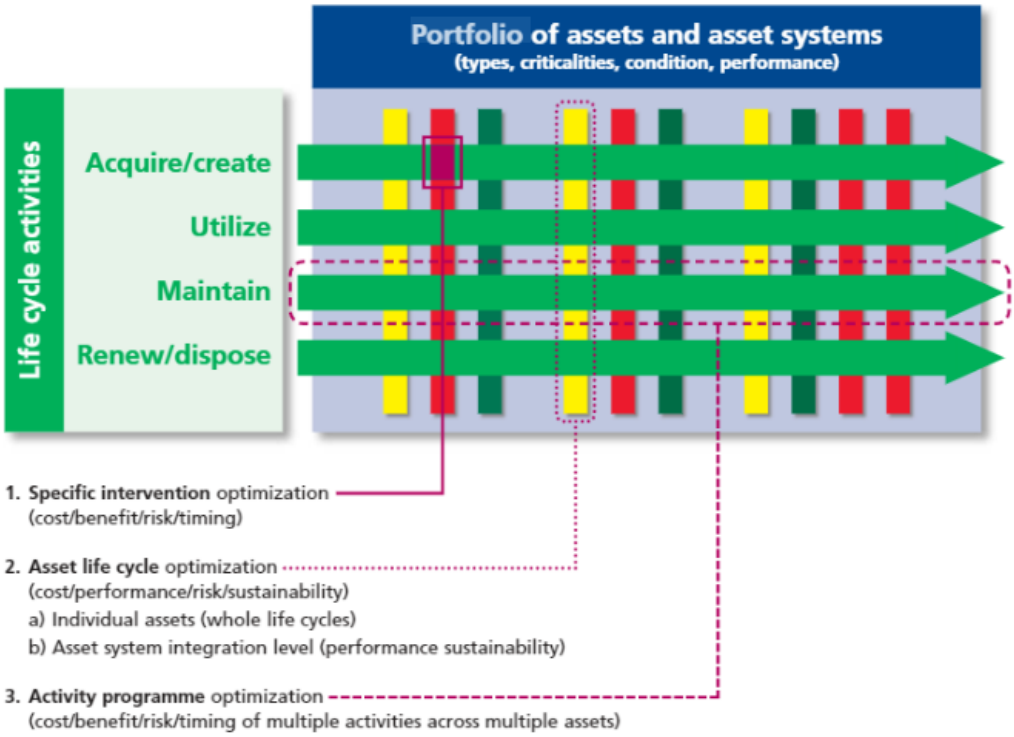



*Figure 2.22. Primary requirements for optimisation of asset management activities (IAM, 2008b).*

### 2.4.3 Railway asset management studies

There are a number of studies in the literature describing the development of asset management approaches and supporting tools, at various levels of management (see Section 2.4.2) for a variety of railway asset types. For example Burrow et al. (2009) and Dashepour (2018) developed a track maintenance management system to inform M&R budget allocations at a network level. The tool entails observation of a variety of measures of track condition, evaluation of condition-based M&R needs based on pre-established maintenance standards, determining feasible maintenance within budget constraints and evaluation of the impact of M&R on overall track network condition. Sasidharan et al. (2020) proposed a whole life cycle costing approach under uncertainty to inform strategic track maintenance planning at route-level. Their approach considers the costs associated with track system construction, maintenance, use and end-of-life, and compares multiple intervention strategies to advise on the most suitable strategy. At the section-level, Sharma et al.

(2018) leverage data-driven tools to enable geo-defect forecasting and probabilistic transition matrices for defect progression, thus providing a tool for the optimisation of proactive track maintenance (Sharma et al., 2018). At the component level, Le et al. (2017) apply Petri-net modelling for the optimisation of railway bridge maintenance strategies with consideration of degradation, inspection and maintenance of individual asset components.

### 2.4.4 Need for risk-informed asset management in railway drainage systems

Since the drainage infrastructure of many railways is old and often buried, there is a paucity of detailed inspection and maintenance history data. The available data collected from walking inspections suffers from being subjective, inconsistent and incomplete (Xie et al., 2020). Such data introduces uncertainty into the decision-making process, which is exacerbated by the uncertain future impacts of land-use and climate change. Therefore, there is a need for approaches that can deal with these uncertainties, such as risk management, to support established asset management decision-making at the various hierarchy levels (section 2.4.2). Chapter 3 describes the process of risk assessment in detail.

## 2.5 Summary

This chapter provided a description of the railway drainage system components, condition degradation of drainage assets, potential problems and appropriate interventions. Currently, drainage interventions are either reactive or trigger-based, where the choice between reactive versus proactive approaches solely depends on the strategic importance of the route. The chapter introduced the applications of condition-based maintenance for cost-effective intervention planning. CBM entails development of tools for regular performance monitoring as well as the use of reliable condition prediction models. Therefore, the chapter reviewed drainage assets' condition modelling applications in rail and urban systems. Machine learning algorithms were found suitable to be applied for condition modelling of railway drainage infrastructure. Thereafter, the chapter reviewed the principles of asset management and the studies thereof in railway systems to establish the need

for risk-informed asset management in railway drainage systems to deal with uncertainty in decision-making. This will be investigated in the next chapter along with the need for risk assessment.

# Chapter 3: Risk and flood modelling

## 3.1 Introduction

This chapter addresses risk-informed asset management in railway drainage infrastructure through first reviewing the importance/use of and information required for risk-informed asset management. Then, it reviews risk assessment standards to understand components, procedures and potential techniques for use in this research. Thereafter, it reviews flood risk modelling applications to identify the gaps in the current body of knowledge and to identify suitable methods for use in this research. This chapter addresses objectives three, four and five of the research (see section 1.3).

## 3.2 Risk-informed asset management

IAM (2015) identifies risk-informed asset management as a main requirement for developing an effective asset management strategy. A risk-informed approach defines risk tolerability criteria and prioritises activities according to the criticality of the asset and the level of risk associated with it (IAM, 2015, ISO, 2014).

### 3.2.1 Benefit of risk-informed asset management

Figure 3. 1 shows how quantifying risk associated with drainage assets can theoretically enable the optimal frequency of planned maintenance. As can be seen from Figure 3.1, a higher frequency of planned maintenance increases an organisation's direct costs but reduces the cost risk of asset failure. The optimal frequency of maintenance is achieved is where the sum of the direct costs and risk costs are minimised (i.e. the economic optimum where the total business impact is lowest).

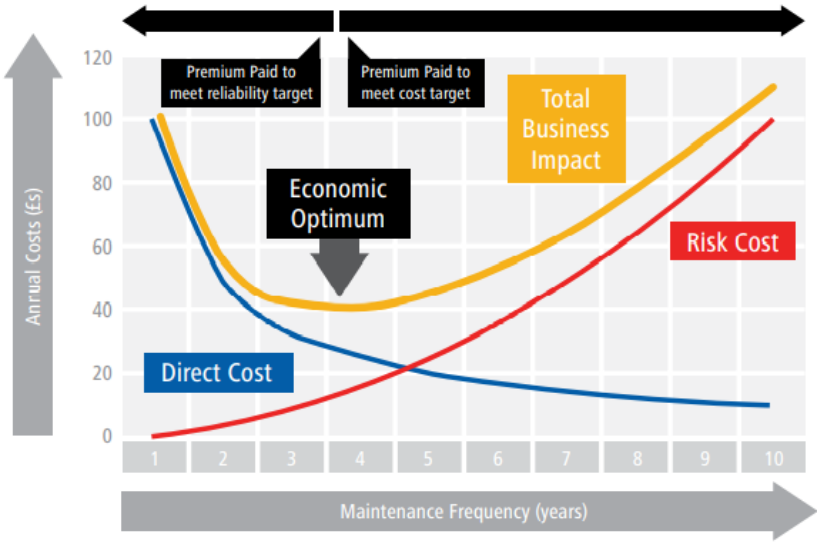



*Figure 3.1. Optimising frequency of planned maintenance (IAM, 2015). From the chart, the optimal maintenance frequency occurs at 4.5 years where the total business impact is minimum, at annual cost of £40.*

Figure 3.2 illustrates the scope of risk-informed asset management in a railway system at the various levels of asset management described in Section 2.4.2.

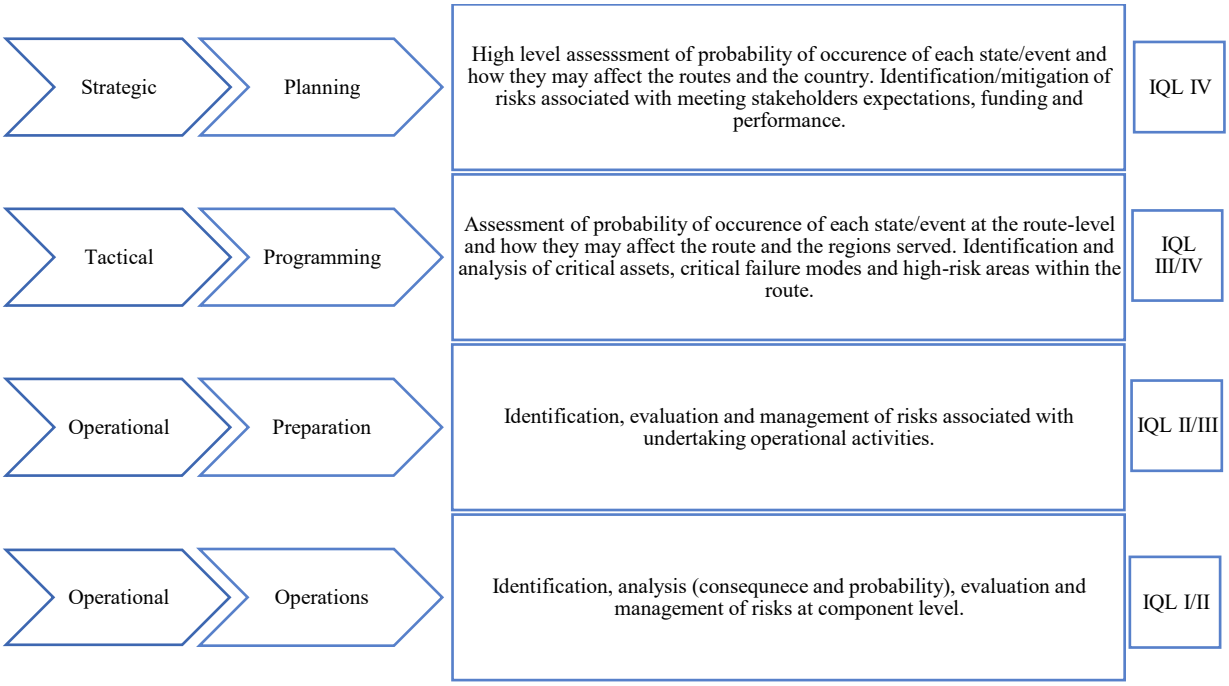



*Figure 3.2. Scope of risk-informed asset management at various levels of railway drainage asset management (adapted from (Sasidharan et al., 2022)*

### 3.2.2 Asset information required for risk-informed asset management

Asset information is an essential building block for risk-informed asset management (IAM, 2015). Figure 3. 2 shows that for operational level of risk-informed asset management, IQL I/II is required. As described in Section 2.4.2, this level of information consists of asset inventory and condition data. Asset inventory contains the as-built asset characteristics like what it is, where it is, the types of components and their dimensions which define the 'as-built' capacity of the asset (Spink et al., 2014). It is obtained from historical records and drainage surveys (Spink et al., 2014). Asset condition is the previously described structural and service condition of the asset. The two components define asset performance.

### 3.2.3 Studies on risk informed asset management in railway systems

To address the need for risk-informed asset management, multiple studies have incorporated risk assessments into asset management strategies at section- or component-level. For example, Consilvio et al. (2016) developed a risk-based network-level predictive maintenance scheduling framework for rail assets. The study uses petri nets, condition degradation models and considers direct and indirect costs. Work carried by Sasidharan et al. (2022) assessed risk of track-quality-related derailments in a track section using a fuzzy-Monte Carlo approach to evaluate linguistic uncertainties associated with expert opinion as inputs. Work by Dinmohammadi (2019) developed a risk-informed modelling approach to maintenance optimisation of rolling stock components like pantographs. The study used expert opinion and historic data in a Fault Tree Analysis (FTA) to assess pantograph failure risk in terms of safety, M&R and service interruption costs. This is employed in a time-varying risk-cost function to determine the optimal frequency of proactive inspection and maintenance of rolling stock components (Dinmohammadi, 2019). Power et al. (2016) used risk matrices to inform prioritisation of earthwork assets for maintenance interventions as part of a proposed strategic/tactical level whole life cost decision support tool to optimise the earthworks policy in the mid- and long-term planning frames. Dindar and Kaewunruen (2022), (Dindar et al., 2018) established a risk-based maintenance approach for rail turnout systems. The

framework assesses weather-related derailment risk at turnouts component level using Bayesian networks. This is to inform planning of proactive maintenance in the interest of minimising derailment risk as well as reducing expenditures over the asset's lifecycle. An et al. (2011) developed a risk management system for railway risk analysis using fuzzy reasoning and analytic hierarchy approaches to analyse level of risk associated with various hazards at a railway depot (e.g. derailment, collision, fire). He et al. (2015) developed an optimization tool for planning interventions for rectification of railway track geometric defects based on a derailment risk-assessment. The tool comprises data-driven models to capture degradation of track geo-defects, assess derailment risk, and optimise rectification activities to balance costs and risks (He et al., 2015). Papathanasiou and Adey (2021) proposed the use of scenario analysis event trees for component-level risk assessment of switches, track sections, and bridges. Furthermore, the study stresses the importance of making comparable risk estimates for the various railway asset types in order to evaluate any risk-reducing intervention measure, in monetary terms.

However, despite its importance in ensuring the efficient functioning of the railway system, there is a relative paucity of studies on asset management tools and techniques specifically for drainage. To support planning and programming levels of railway drainage asset management, Rezaei (2020) developed a risk-informed drainage asset management tool that can be used to support the planning of railway investment, the identification of multi-year expenditure requirements and for arguing for funding for drainage maintenance and renewal. At the preparation level of management, Usman (2020), and Usman et al. (2021) devised a risk informed approach that can be used to identify railway track sections at greatest flood risk as a function of drainage condition, track usage and the surrounding land use. The research used expert opinion and historic data in a Fault Tree Analysis (FTA) to determine failure modes and associated probabilities and applies MCs to consider probabilistic uncertainties in the data. The data used was identified as of IQL II/III (Usman et al., 2021).

Despite the above research, in order to inform proactive maintenance strategies at preparations/operations level of management, i.e., to be able to prioritise maintenance interventions

in the short-term, as well as to assess risk-mitigation measures, a comprehensive flood risk assessment of the railway drainage system at component level is required.

## 3.3 Risk Assessment concepts

### 3.3.1 Definition

Risk is defined in ISO31000 and ISO55001 as the 'effect of uncertainty on objectives' (ISO, 2014, ISO, 2018, BSI, 2019b). In the context of railway drainage assets, risk has been defined as the probability of loss of performance due to an event (Spink et al., 2014). The event may be excessive rainfall or a blockage and the loss of performance could manifest in safety risks like a derailment, operational disruptions like line closure or risk of flooding in adjacent property (Spink et al., 2014). However, the definition of risk extends beyond just the probability of an event occurring. It also entails the assessment of the severity of consequence of that event as discussed in section 3.3.2. Risk management is the set of coordinated activities to direct and control an organization with regard to risk (BSI, 2021). Figure 3.3 illustrates the stages for a risk management framework as described in ISO (2018). The process of managing risk requires establishing processes for the identification of risks, assessment of risks, determining the significance of assets in achieving asset management objectives, implementation of appropriate treatments and monitoring of risks (ISO, 2014).

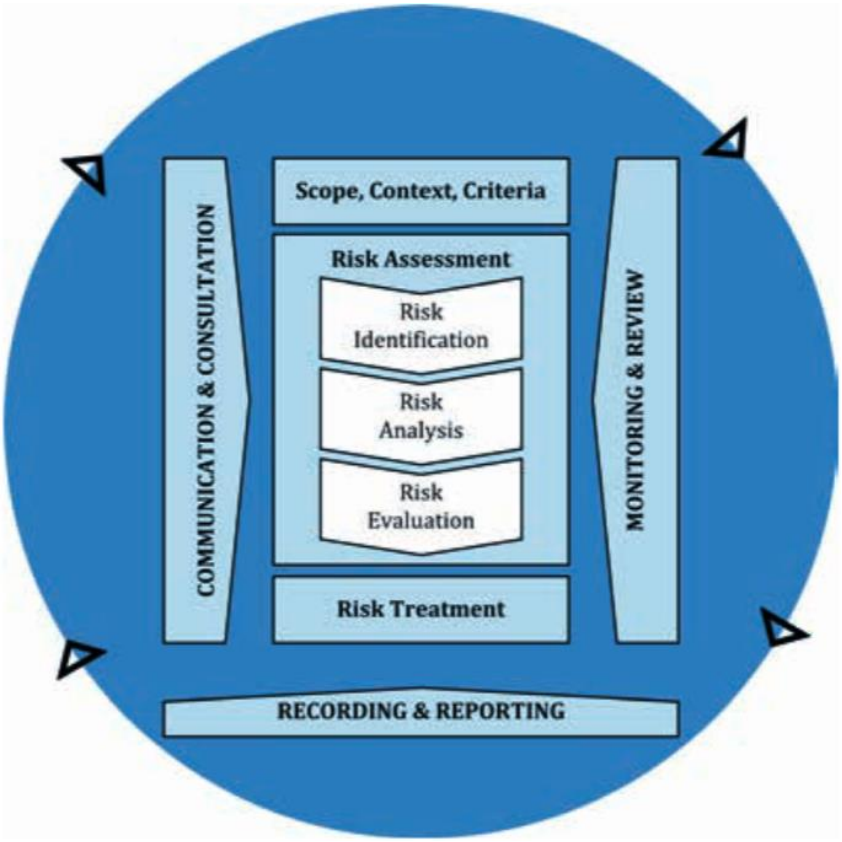



*Figure 3.3. Risk management process (ISO, 2018)*

### 3.3.2 Risk assessment terminology

The following are the definition of terms relevant to risk assessment according to (ISO, 2018, BSI, 2019b)

- Risk: effect of uncertainty on objectives and is measured in terms of the likelihood of an event occurring and its consequence.
- Likelihood: chance of something happening and is measured quantitatively in terms of probability or frequency of occurrence within a time period.
- Probability: measure of the chance of occurrence expressed as a number between 0 and 1, where 0 is impossibility and 1 is absolute certainty.
- Consequence: outcome of an event affecting objectives.
- Risk source: an element which alone, or in combination, has the potential to give rise to risk. It is uncertain and therefore is specified in terms of a likelihood.

- Risk driver: a factor that has an influence on risk and exposure to risk.

### 3.3.3 Risk assessment process

Figures 3.3 illustrates that the risk assessment process comprises of three main stages: Risk Identification, Risk Analysis and Risk Evaluation. The following subsections describe each stage in the context of a railway drainage system.

a. Risk identification

Risk identification is the process of finding, recognising and describing sources and drivers of risks (BSI, 2021). PAS 55 standards categorise the types of identified risk sources into (IAM, 2008a):

i. Physical failures such as functional failure or incidental damage. E.g. inadequate capacity of the drainage asset due to deteriorating service/structural condition, or outdated/inadequate design capacity.
ii. Operational sources, including control of asset, human factors and other activities which may affect performance, condition or safety of asset.
iii. Natural environment events, such as extreme rainfall events.
iv. Factors outside the organisation's control, such as failures in externally supplied material and services.
v. Stakeholder factors, such as failure to meet regulatory performance requirements or risks to reputation of the organization.

b. Risk analysis

It is the process of comprehending the nature of the risk and to determine the level of risk (BSI, 2021). The level of risk is defined as the magnitude of a risk or combination of risks, expressed in terms of the combination of consequences and their likelihood (BSI, 2021). The mathematical formulation is shown in equation 3.1.

*Equation 3.1*

$$\text{Risk} = \text{Likelihood of a risk occurring (L)} \times \text{Consequence of risk (C)}$$

Where likelihood refers to the likelihood of an event or the likelihood of a specified consequence (BSI, 2019b). It can be quantitatively described in terms of probability or frequency of an event occurrence or using descriptive terms (e.g. 'highly likely') (BSI, 2019b). The likelihood of a drainage failure can rely on historic failure frequencies combined with performance degradation modelling (Spink et al., 2014). If no such data is available then expert judgment may be used (Spink et al., 2014). Observed drainage asset condition (both structural and service condition) is normally used as a proxy for likelihood of a failure (Spink et al., 2014). The observed condition provides an indication for proactive intervention planning, however this may be unreliable in preventing failures especially when looking at longer-term planning.

Consequence analysis can vary from a description of outcomes to detailed quantitative modelling (BSI, 2019b). Risk can be associated with a number of different types of consequences affecting different objectives (BSI, 2019b). The assessor should decide the type of consequences analysed beforehand (BSI, 2019b). For drainage assets, both direct and indirect consequences should be considered including operational delays and impacts on other assets like earthworks and the track (Spink et al., 2014).

Figure 3.4 shows the identified impacts of a drainage failure as: direct flooding impacts, impacts on other assets and pollution impact (Spink et al., 2014). However, the direct impacts of flooding on other assets (earthworks, structures and track) are not reflected in the diagram. These consequences will depend on various parameters including the proximity of an asset to the flood location and the inherent vulnerability/fragility of that asset (e.g. asset condition). For example, a failure in a collector drain adjacent to track bed has a more significant impact on track performance compared to a failure in a carrier drain at the toe of an embankment (Spink et al., 2014). The following analyses could be performed using detailed asset information to enable identification of performance gaps and assessment of flood risk at component level. (Spink et al., 2014):

a. Carry out catchment and surface water flood modelling to identify locations where specific storm events would exceed capacity of the drainage assets. Section 3.4 reviews flood modelling applications in literature.

b. Identify hazards to other assets. For example, where earthworks are susceptible to flood risk or potential track wet beds.

c. Assess third party risk like nearby critical infrastructure that is in potential flooding zones.

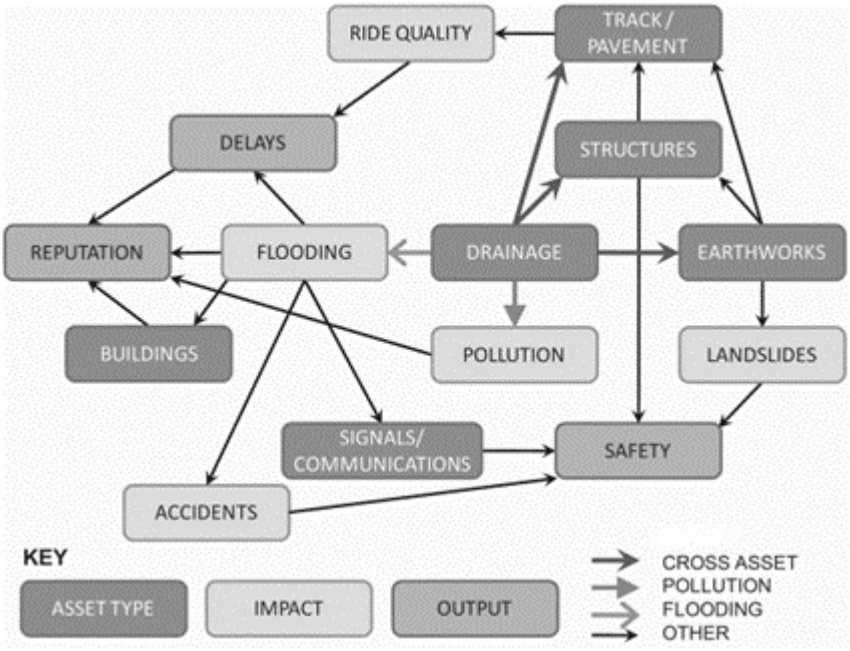



*Figure 3.4. Drainage system failure consequences (Spink et al., 2014)*

The two components of risk may be defined in qualitative, semi quantitative or quantitative terms, depending on the type of data available to determine the two components (ISO, 2018). Qualitative approaches are based on nominal or ordinal scales for quantifying consequences and likelihood (BSI, 2019b). Quantitative approaches express consequences and likelihoods using numerical scales. In this case, the assessor needs to ensure units are consistent throughout the quantitative analysis (BSI, 2019b). Semi-quantitative approach express one parameter quantitatively and the other qualitatively (BSI, 2019b).

Ideally however consequence should be, where possible, quantified in monetary terms to enable like-for-like comparisons when conducting cost-benefit analyses or comparative analysis of interventions for the purpose of prioritisation at an operational level of planning (IAM, 2008b, Spink et al., 2014).

In a quantitative risk analysis, the single value estimation of the likelihood of consequence provided by the simple mathematical product (Equation 3. 1) may not be an accurate description of risk (BSI, 2019b). It eliminates the distinction between. scenarios with low likelihood but high consequence and the high-frequency low consequence scenarios (BSI, 2019b). To address this, BSI (2019b) recommends the expression of risk as a probability distribution of consequences. A measure of risk can then be obtained as the 'expected value', that is the weighted average of consequence, i.e. mean of distribution. Percentile statistics can also be used to quantitatively represent risk uncertainty (BSI, 2019b).

c. Risk evaluation

Risk evaluation is the process of comparing the results of risks analysis with risk criteria to determine whether the risk and/or its magnitude is acceptable or tolerable (BSI, 2021, BSI, 2019b). Risk criteria are directly related to organisational objectives which specify the required level of service and tolerability of risk (BSI, 2019b). Traditionally, risk matrices are developed to inform the intervention decisions (Spink et al., 2014). These risk matrices are qualitative in nature and are developed considering the expected risk impact such as damage to other assets. Tolerability of risk in the railway industry normally depends on the strategic importance of the route, line speed, traffic volumes and income/penalty levels (Spink et al., 2014). Figure 3.5 shows an example of a drainage intervention policy given condition of other assets.

| Drainage performance | Track, earthworks or other asset condition (related to drainage) | | |
|---|---|---|---|
| | *Serviceable* | *Marginal* | *Poor* |
| *Serviceable* | Inspect<br>Survey<br>**Maintain** | Inspect<br>Survey<br>**Maintain** | Inspect<br>Survey<br>**New build**<br>Maintain |
| *Marginal* | Inspect<br>Survey<br>**Maintain** | Inspect<br>Survey<br>**Refurbish**<br>Maintain | Inspect<br>Survey<br>**Refurbish**<br>Maintain |
| *Poor* | Inspect<br>Survey<br>**Renew**<br>Maintain | Inspect<br>Survey<br>**Renew**<br>Maintain | Inspect<br>Survey<br>**Renew**<br>Maintain |
| *Absent* | **Inspect** | **Inspect** | **New build**<br>Inspect<br>Survey<br>Maintain |

*Figure 3.5. Example asset interaction risk matrix (Spink et al., 2014)*

### 3.3.4 Risk assessment techniques

Table 3.1 lists the techniques that can be used at different stages of the risk assessment process (see Figure 3.3) according to BSI (2019b). Table 3.2 summarises the potentially applicable tools for risk identification and quantitative risk analysis; namely, Event Tree Analysis, Cause-Consequence Analysis, Scenario Analysis and Monte Carlo Simulations. It provides a description of their use and identifies the main strengths and limitations of each.

*Table 3.1. Applicability of various techniques for the different stages of the risk assessment process (BSI, 2019b)*

| Use | Technique | Risk assessment process | | | | | Qual./Quant./Semi-quant |
|---|---|---|---|---|---|---|---|
| | | Risk Identification | Risk analysis | | | Risk evaluation | |
| | | | Consequence | likelihood | level of risk | | |
| Techniques for eliciting views | Brainstorming | SA | NA | NA | NA | NA | Qual |
| | Nominal group | SA | A | A | NA | NA | Qual |
| | Delphi technique | SA | NA | NA | NA | NA | Qual |
| | Interviews | SA | NA | NA | NA | NA | Qual |
| | Surveys | SA | NA | NA | NA | NA | Qual |
| Risk Identification | Techniques for identifying risk | | | | | | |
| | Check lists | SA | NA | NA | NA | NA | Qual |
| | Failure Mode and Effect Analysis (FMEA) | SA | SA | NA | NA | NA | Qual/semi-quant/quant |
| | Failure Mode and Effect and Criticality Analysis (FMECA) | SA | SA | SA | SA | SA | Qual/semi-quant/quant |
| | Hazard and Operability studies (HAZOP) | SA | A | NA | NA | NA | Qual |
| | Scenario analysis | SA | SA | A | A | A | Qual |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | Structured What-If (SWIFT) | SA | SA | A | A | A | Qual |
| | Determining sources, causes and drivers of risk | | | | | | |
| | Cindynic approach | SA | NA | NA | NA | NA | Qual |
| | Ishikawa method | SA | A | NA | NA | NA | Qual |
| Risk Analysis | Techniques for analysing controls | | | | | | |
| | Hazard analysis and critical control points (HACCP) | SA | SA | NA | NA | NA | Qual |
| | Layers protection analysis (LOPA) | A | SA | A | A | NA | Qual/quant |
| | Bow tie analysis | A | SA | A | A | A | Qual/semi-quant/quant |
| | Techniques for understanding consequence and likelihood | | | | | | |
| | Event tree analysis (ETA) | NA | SA | A | A | A | Qual/quant |
| | Fault tree analysis (FTA) | A | NA | SA | A | A | Qual/quant |
| | Cause-consequence analysis | A | SA | SA | A | A | Quant |
| | Business impact analysis | A | SA | NA | NA | NA | Quant/qual |
| | Monte Carlo simulation | NA | A | A | A | SA | Quant |
| | Bayesian analysis | NA | NA | SA | NA | NA | Quant |
| | Bayesian network | NA | NA | SA | NA | SA | Quant |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | Markov analysis | A | A | SA | NA | NA | Quant |
| | Techniques for analysing dependencies and interactions | | | | | | |
| | Causal mapping | A | A | NA | NA | NA | Qual |
| | Cross impact analysis | NA | NA | SA | NA | NA | Quant |
| | Techniques that provide a measure of risk | | | | | | |
| | Toxicological risk assessment | SA | SA | SA | SA | SA | Quant |
| | Value at risk (VaR) | NA | A | A | SA | SA | Quant |
| Risk Evaluation | Techniques for Evaluating significance of risk | | | | | | |
| | ALAARP/SFAIRP | NA | NA | NA | NA | SA | Qual/quant |
| | Frequency-Number (F-N) diagram | A | SA | NA | NA | SA | Quant |
| | Pareto chart | NA | A | A | A | SA | Semi-quant/quant |
| | Reliability-centred maintenance | A | A | A | A | SA | Qual/semi-quant/quant |
| | Risk indices | NA | SA | SA | A | SA | Semi-quant |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | Techniques for selecting between options | | | | | | |
| | Cost/benefit analysis | NA | SA | NA | NA | SA | Quant |
| | Decision tree analysis | NA | SA | SA | A | A | Quant |
| | Game theory | A | SA | NA | NA | SA | Quant |
| | Multi-criteria analysis (MCA) | A | NA | NA | NA | SA | Qual |

*Table 3.2. Risk techniques and indicative characteristics according to BSI (2019b)*

| Method | Description | Application | Qual/Quant/Semi-quant | Strength | Limitation |
|---|---|---|---|---|---|
| Event Tree Analysis | Models the possible outcomes from a given initiating event and the status of controls thus analysing the frequency or probability of the various possible outcomes | Analyse Consequence and controls | Qual./Quant. | • Potential scenarios following an initiating event are analysed and the influence of the success or failure of controls shown in a clear diagrammatic way that can, if required, be quantified.<br>• It identifies potential single point failures. | • For a comprehensive analysis, all potential initiating events need to be identified. There is always potential for missing some important initiating events.<br>• Only success/failure states of the system are dealt with and it is difficult to incorporate partially operating controls.<br>• For complex systems the event tree can be difficult to build from scratch |
| Cause-consequence analysis | A combination of fault and event trees analysis that allows the inclusion of time delays | Analyse causes and consequences | Quant. | • In addition to the strengths of event tree, CCA is better able to simultaneously represent the causes and consequences of a focus event and time dependencies. | • CCA is more complex than event trees, both to construct and in the manner in which dependencies are dealt with during quantification. |

| | | | | | |
|---|---|---|---|---|---|
| Scenario Analysis | Identifies possible future scenarios through imagination, extrapolation from the present or modelling. Risk is then considered for each of these scenarios. | Identify risk, Consequence analysis | Qual. | • Takes account of a range of possible futures.<br>• It supports diversity of thinking.<br>• It encourages monitoring of lead indicators of change.<br>• Decisions made for the risks identified can help build resilience for whatever does occur. | • The scenarios used might not have an adequate foundation, for example might be speculative.<br>• There is little evidence that scenarios explored for the long-term future are those that actually occur. |
| Monte Carlo simulation | Calculates the probability of outcomes by running multiple simulations using random variables | Analyse likelihood | Quant. | • The method can, in principle, accommodate any distributions in input variable, including empirical data derived from observations of related systems.<br>• Models are relatively simple to develop and can be extended as the need arises.<br>• Any influences or relationships can be represented, including conditional dependencies.<br>• Sensitivity analysis can be applied to identify strong and weak influences of input parameters.<br>• Models can be easily understood as the relationship between inputs and outputs is transparent.<br>• It provides a measure of accuracy of a result.<br>• Software is readily available. | • The accuracy of solutions depends upon the number of simulations which can be performed.<br>• It can be difficult to set up a model that adequately represents the situation.<br>• Large and complex models can be challenging to the modeller and make it difficult for stakeholders to engage with the process.<br>• The technique tends to underemphasise high consequence/low probability risks. |

## 3.4 Flood risk modelling applications

Flood risk assessments conducted on railway system have mainly addressed fluvial flooding (Murphy et al., 2016, Bubeck et al., 2019, Wang et al., 2021, Zhu et al., 2021). The studies which addressed pluvial flooding, did not consider the role of the railway drainage system in processing water and have mainly relied on historic flood hazard maps (Koks et al., 2019, Oslakovic et al., 2013, Cheetham et al., 2016). The one study identified in this research, by Forero-Ortiz et al. (2020), which addressed pluvial flooding and represented the capacity of the drainage systems was conducted on the underground railway system. Forero-Ortiz et al. (2020) study simulated flooding caused by Urban Drainage System (UDS) in underground metro stations. However, the environment and drainage of an underground railway system is different from a traditional ballasted overground railway drainage system that can be situated within a cutting or on an embankment and hence, has very different rainfall-runoff -drainage system interactions. Furthermore, flooding in the two types of railways is likely to exhibit different flow behaviour and different impact patterns on surrounding assets. Therefore, as far the literature review has been able to show currently, there are no flood risk analysis models which analyse pluvial flood risk associated with railway systems at a component level which include all potential flood risk sources. The scope of this work falls between fluvial flooding considerations (i.e., open flooding layout) and urban drainage system considerations (e.g., buried drainage assets). To address this, this section considers both fluvial flood modelling applications in rail systems and pluvial flood modelling applications in UDS to draw on approaches which might be suitable for this research. Table 3.3 summarises the reviewed studies in terms of the tools used for flood modelling, the considered flood sources and drivers, the obtained flood exposure measures, and the approach to damage quantification, if any was performed. The following sections describes aspects and requirements for flood risk modelling in light of these studies.

*Table 3.3. Reviewed flood modelling studies*

| Application | Authors | Location | Flood Modelling tool | Type of flooding | Flood sources/drivers | Flood exposure measures | Damage receptor assets | Damage quantification method | Outputs |
|---|---|---|---|---|---|---|---|---|---|
| UDS | Ellis and Viavattene (2014) | UK | STORM model for 1D hydrological rainfall-runoff and 2D Flood Area model for extent and depth | Pluvial flood | Rainfall event<br>Asset capacity (pipe size)<br>Land use, soil type, infiltration rate<br>Topography | Flow depth<br>Flood spatial distribution | Roads network | Water depth-traffic disruption chart | Not considered |
| | Zhou et al. (2013) | Denmark | MIKE FLOOD for 1D&2D flood modelling | Pluvial flood | Rainfall event intensity and frequency<br>Imperviousness of catchments (land use)<br>Topography<br>Drainage system design capacity | Water depth<br>Spatial distribution of flooding (flood maps) | Houses, basements and roads | depth-damage functions using binary (flooded/not flooded threshold) | Quantitative Expected Annual Damage (EAD) |
| | Zhu et al. (2016) | China | Storm Water Management Model (SWMM) for rainfall-runoff simulation modelling | Pluvial flood | Rainfall return period<br>Catchment Land use<br>Catchment area<br>Drainage system | Inundation duration<br>total flood volume<br>largest flow | Not considered | no damage quantification | Spatial distribution maps of flood risk at individual manholes |
| | Phillips et al. (2005) | Australia | XP SWMM2D & TUFLOW 2D for flood mapping | Pluvial flooding | Rainfall event<br>Drainage system design | Node flood level<br>inundation depth on flood plain<br>flow velocity | Not considered | No damage quantification | No risk evaluation just flood mapping |
| | Salinas-Rodriguez et al. (2018) | Netherlands | PCSWMM | Pluvial flood | Rainfall event intensity and probability<br>Drainage system design<br>Catchment land use | Flood extent inundation depth | Roads, buildings and power supply | Qualitative Expert judgment of level of damage depending on inundation depth | Semi-quantitative risk matrix and accordingly, risk maps |
| | Yazdi et al. (2022) | Iran | SWMM for1D hydrologic/hydraulic modelling HECRAS 2D for 2D hydraulic modelling | Pluvial Flood | Rainfall event return period<br>Land use<br>Topography | Flood depth<br>Flood volume<br>Flood maps | Different use buildings | Water depth-Damage % curves for individual buildings | Damage EAD-Flood volume graphs |
| | Blanc et al. (2012) | UK | Infoworks CS for simulation of runoff, sewer flow and surface flood modelling | Pluvial flood | Rainfall event (intensity and duration)<br>Topography<br>Sewer design capacity (size)<br>Blockages/collapses | Flood depth<br>Flood volume | Buildings | Water depth-damage curves | Response surfaces for monetary damage-rainfall event |
| Railway | Forero-Ortiz et al. (2020) | Spain | Infoworks ICM 1D/2D rainfall-runoff and flood modelling | Pluvial flooding | Rainfall intensity-duration<br>Drainage system capacity<br>Catchment Topography<br>Catchment area | Water depth | Metro stations | Qualitative level of damage depending on metro station ridership | Qualitative risk matrix and accordingly, color- coded risk maps reflecting |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | | | Catchment surface roughness | | | | risk level at various section lengths of the metro line and stations |
| Kellermann et al. (2015) | Austria | Historic fluvial flood hazard maps | Fluvial flooding | Event return period | Flood Spatial extension<br>Water level<br>Flow velocity<br>energy head intensity indicator of flow force | Railway substructure cross section | Water level-monetary damage class<br>Flow velocity-monetary damage class<br>energy head-monetary damage class<br>intensity-monetary damage class<br>indicator of flow force- monetary damage class | Distribution maps for Damage class over the length of track line<br>Total Monetary EAD |
| Murphy et al. (2016) | UK | Infoworks ICM 1D representation of river channel level and 2D representation of floodplain | Fluvial flooding | Rainfall event into river level<br>Terrain topography<br>Land-cover | Spatial Extent and depth of flood | Not considered | Not considered | Visual flood maps |
| Bubeck et al. (2019) | Europe | LISFLOOD hydrologic model for flood mapping<br>OpenRailwayMap for rail data | Fluvial flooding | Climatic conditions affecting river flow (temperature, precipitation, evaporation, wind speed and solar radiation)<br>Landcover | Flood depth | Railway substructure | Kellermann et al. (2015) three-tier categorisation of rail section monetary damage classes depending on water level | Regional EAD maps |
| Koks et al. (2019) | Global | OpenStreetMap (OSM) for transport infrastructure data<br>Global Hazard maps:<br>1- Fathom Global pluvial and fluvial flood hazard dataset<br>2- coastal inundation maps generated by hydrological model LISFLOOD-FP | Fluvial flooding, pluvial flooding, coastal flooding | Return period | Water depth<br>Flood spatial extent | Rail and road infrastructure assets | Asset Fragility ratio-flood depth curves<br>Unit damage cost per asset repair activity<br>Annual infrastructure asset flood exposure (length)-water depth charts | Regional total EAD maps |
| (Oslakovic et al., 2013) | Netherlands | Historic data frequency of asset failures related to various weather phenomena | Pluvial flooding | precipitation intensity | Not considered | Railway asset failures:<br>Crossing<br>Structure<br>Track<br>Catenary<br>Signal<br>switch | Not considered | Projected number of failures for various predicted climate scenarios |
| Wang et al. (2021) | Netherlands | OpenStreetMap for railway infrastructure data | Fluvial flood | Rainfall event intensity and probability/return period) | Depth of inundation | Railway earthworks | Damage ratio-water depth | EAD |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | GLObal Flood Risk with Image Scenario (GLOFRIS) for Flood hazard maps | | | | | Asset replacement cost and probability given by return period | |
| | Zhu et al. (2021) | China | Flood hazard maps from GLOFRIS | Fluvial flood | Rainfall event return period<br>Annual Exceedance Probability (AEP)<br>Drainage capacity rate and design standard | Flood depth<br>Spatial extent of flood | Service/operational performance loss | Water Depth-AEP chart<br>Water level calculation after drainage<br>Calculation of performance loss metrics | National performance loss maps |
| | Cheetham et al. (2016) | France | Historic flood maps | Fluvial flood<br>Pluvial flood<br>Coastal flooding | Qualitative description of:<br>rainfall event intensity<br>catchment size and ground slope<br>landcover<br>topography<br>earthwork type and material | Spatial extent of flood | Earthwork structure | Not considered | Qualitative risk matrix |
| River basin | Jung and Merwade (2012) | US | Hydrologic Engineering Center–River Analysis System (HEC-RAS) 1D hydraulic model | Fluvial flood | Streamflow<br>Roughness<br>topography | Inundation width<br>Inundation area | Not considered | Not considered | Not considered |
| | ten Veldhuis and Clemens (2010) | Netherlands | Historic databases of flood incidents and reported damage calls | Fluvial flood | Rainfall intensity | Resident calls about damage | Traffic disturbance<br>Private property<br>Human health | Number of calls-rainfall volume chart | Probability-damage curves |
| | Lekuthai and Vongvisessomjai (2001) | Thailand | MIKE-1 hydrodynamic model | Fluvial flood | Not specified | Flood depth<br>Flood duration | Exposed establishments | Stage-damage | Probability - damage curve |
| | Garrote et al. (2016) | Spain | IBER 2D hydraulic model | Fluvial flood | Rainfall return period<br>Terrain topography (DEM)<br>Land uses and Surface roughness | Flood depth<br>Flow velocity | Exposed buildings | Damage-depth curve | Spatial distribution of economic damage to buildings |
| | Apel et al. (2008) | Germany | MCs | Fluvial flood | Rainfall event<br>river hydrographs | Inundation depth<br>Inundation area | Exposed residential buildings | Damage-depth curve | Damage cost-return period charts |
| | Arrighi et al. (2018) | Italy | Rapid Analysis and Spatialization of Risk (RASOR) platform for risk analysis | Fluvial flood | Rainfall | Flood depth | Exposed buildings | Depth-damage model | Damage-frequency curves |
| | Mushar et al. (2019) | Not specified | Fuzzy modelling | Fluvial flood | Not specified | Flood depth<br>Flood duration<br>Type of debris | Exposed buildings | Fuzzy logic membership functions of damage given impact measures | Qualitative damage factor |
| | Van Dau et al. (2017) | Vietnam | HEC-MAS and HEC-RAS MCs | Fluvial flood | Rainfall event | Flood depth | Damage to areas based on their land use | Damage-depth curve | Exceedance probability-damage chart |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Nofal and van de Lindt (2021) | US | HEC-HMS and HEC-RAS | Fluvial flood | Rainfall event<br>Land use<br>Terrain topography | Flood depth | Exposed buildings | Depth-damage function | spatial distribution f damage in terms of EAD |
| Gouldby et al. (2008) | England | MCs and hydraulic flood spreading model | Fluvial flood | River flow rate and level | Flood depth | Exposed buildings | Depth-damage curves | Damage-frequency curves |
| Tsakiris (2014) | Greece | FLOW-RD2 hydraulic model<br>Flood hazard maps | Fluvial flood | Return period river flow hydrograph<br>Land use<br>Terrain | Depth<br>velocity | Exposed buildings | Vulnerability functions given by the magnitude of event | Flood risk map in terms of monetary damage |
| Foudi et al. (2015) | Spain | Historic hydrological databases of flood areas and depths<br>Grid GIS assessment of exposure | Fluvial flood | Rainfall return period<br>DTM | Depth<br>Area<br>velocity | Damage to residential/agricultural areas and human damage | Stage-damage functions | Damage-probability curves in terms of EAD |

### 3.4.1 Flood risk sources and drivers

Pluvial flooding occurs when there is a difference between the capacity of the railway drainage system and the volume of water received by the railway. Following a Fault Tree Analysis of drainage failure causal factors in Usman et al. (2021), a Monte Carlo simulation (MCs) sensitivity analysis found that the main cause for a drainage asset failure is blockage (related to service condition of asset) and the main driver of surface flooding is heavy rainfall (defined by duration and intensity).Therefore, the main sources and drivers of flood risk are rainfall event, catchment characteristics, and as-built asset capacity, in addition to condition of the drainage assets.

A rainfall event was used in almost all the reviewed studies as a main source of flood risk (Table 3. 3). It is mainly characterised by intensity and duration of the event using Intensity-Duration-Frequency (IDF) curves (Yazdi et al., 2022). To simulate a rainfall event, the specification of a return period and duration is required. Cheetham et al. (2016), Zhou et al. (2013), and Wang et al. (2021) used the rainfall event return period as a direct representation of the probability of flood occurrence in their risk assessments. Blanc et al. (2012) used rainfall frequency as one of the uncertain probabilistic inputs for the rainfall characteristics, in addition to rainfall duration and spatial distribution. Similarly, Yazdi et al. (2022) considered rainfall intensity and duration as stochastic uncertain variables as part of the risk analysis.

Runoff volume received by a drainage system is largely affected by the following characteristics of the catchment, namely the size of catchment, land use, soil type, and topography of the surrounding area (Ellis and Viavattene, 2014). A number of UDS studies considered some of these characteristics (see Table 3. 3), Zhu et al. (2016) considered catchment area, Zhu et al. (2016), Ellis and Viavattene (2014), Zhou et al. (2013), Salinas-Rodriguez et al. (2018), and Yazdi et al. (2022) considered land use, Ellis and Viavattene (2014), Zhou et al. (2013), Yazdi et al. (2022), and Blanc et al. (2012) considered topography. In railway flooding studies, Murphy et al. (2016), Bubeck et al. (2019), and Cheetham et al. (2016) considered land use and topography in their flood mapping applications.

The size of catchment is a major driver of runoff volume, and hence flood risk because a larger volume of runoff received by the railway drainage system increases the likelihood that assets will experience a performance gap due to limited design capacity and possibly condition. This is especially evident at locations where the drainage system was designed to cater for a smaller assumed catchment than what is actually catered for by the system. For example, surrounding roads may have their own drainage system, however it was reported by railway drainage engineers that often runoff from roads is processed by the railway drainage system. Furthermore, consideration of the variability in catchment topography is important for accurate representation of flow routes to/ from manhole/ flood point (Gouldby et al., 2008). Blanc et al. (2012), Zhou et al. (2013), Ellis and Viavattene (2014), Cheetham et al. (2016), and Forero-Ortiz et al. (2020) used Digital Elevation Models (DEM) to represent the surface topography. It is important to note that adequate representation of the surface topography requires a high-resolution digital elevation model (Blanc et al., 2012, and Ellis and Viavattene, 2014). Such models are also important in railway drainage modelling applications in order to accurately reflect the high level of topographic detail in a track section and surrounding area. For example, a track layout may change along its section from being nested in a steep cutting, to approaching ground level, and then to gradually build up to an embankment, this variability in Earthwork slopes along a given section significantly influences the flow patterns into/ and away from the drainage system. Therefore, the topography model must enable elevation changes to a be quantified to a fine scale.

For an accurate modelling of runoff, land surface cover and associated infiltration and roughness properties is required to be represented in the surface maps. In their studies of pluvial flooding in UDS and underground metro, respectively, Zhu et al. (2016), and Forero-Ortiz et al. (2020) reflected impact of surface permeability on runoff by calculating impermeable and permeable surface areas in the catchment. In an urban pluvial flood inundation modelling application, Zhou et al. (2013) made a conservative, although unrealistic, assumption that the full 2D terrain is an impervious surface. In a study of the regional-level European railway flood risk, Bubeck et al. (2019) considered the variation in land use using landcover datasets (Coordinated Information on the European

Environment (CORINE)). Furthermore, the infiltration rate varies with season and soil moisture content which is difficult to predict at a local scale.

In addition the above characteristics of the catchment, representation of the condition of the as-built asset is crucial for accurate modelling of the true behaviour of the drainage system. The condition of the railway drainage assets impacts their ability to process flow and thus can significantly contribute to surface flooding in railway systems. Kellagher et al. (2009) developed a risk-based approach for sewage system performance, and showed the importance of moving away from approaches that do not account for potential system failures like collapses, blockages or deteriorating hydraulic condition. Blanc et al. (2012) also referred to, but deemed negligible, the random effect of uncertain blockages and collapses in drainage pipes on pluvial flooding. However, none of the other UDS or railway focused studies reviewed in this research considered asset condition as a flood risk source. Therefore, the output from condition modelling should be used as an onward input into flood modelling.

### 3.4.2 Flood risk scenario analysis

The risk analysis of urban drainage systems (and hence, railway drainage system) can be enhanced by analysing different scenarios associated with risk sources and drivers which have a large effect on drainage flood risk and the quantitative evaluation of resulting damage. These include different rainfall events, asset condition, and changes in land use. Such analyses better equip infrastructure managers to make comparative risk-informed analysis of mitigation measures.

Rainfall scenario analysis enables predictive decision making to be risk-informed under prespecified risk tolerance criteria. Furthermore, in order predict the impacts of climate change on the railway systems and enable mitigation strategies to be put in place well-ahead, there is a need to consider flood risk for various climate change rainfall scenarios (Palin et al., 2021). For example, in the study by Bubeck et al. (2019), it was shown that the current flood risk to railway networks is projected to increase by 255%, 281% and 320% under a 1.5 °C, 2 °C, and 3 °C warming scenarios respectively.

These projections translate to widely ranging economic damages and hence, mitigation strategies need to be decided according to risk tolerance.

Moreover, scenario analysis can be used to consider the effects on the drainage system of potential future changes in land use and associated runoff characteristics. Scenario analysis can also be used to assess the viability of potential maintenance strategies and mitigation plans on perceived threats, such the impact of ageing drainage assets on drainage capacity.

For scenario analysis of flood risk, integrated hydraulic models offer the agility for adaption of the system to various changes in the risk sources and drivers through standard user-friendly interface with animated visual output display which supports stakeholder understanding and decision making (Ellis and Viavattene, 2014). Published flood mapping studies have relied on fluvial flood hazard maps to inform flood risk analysis through depiction of the spatial distribution of flood and the intensity at various locations such as those by Wang et al. (2021), Zhu et al. (2021), and Koks et al. (2019). However, the applications described lack the agility to reflect changes in risk drivers, the representation of drainage system interaction with the catchment, and the integrated impact of topography and geology catchment on flood routing. Catchment modelling for railway drainage assets is best reflected, to a high level of detail, through the use of flood modelling software. To this end, 2D hydraulic models have the advantage that they do not require pre-specification of all flow paths, rather, they use existing terrain models, although computationally expensive, to direct flow (Blanc et al., 2012). Moreover, 2D hydraulic models enable the representation of flood exposure parameters within a floodplain (e.g. spatial extent of flooding, depth, duration and velocity) which enables identification of flood receptor assets and the subsequent damage quantification in a flood risk assessment (Murphy et al., 2016).

Various computer models of drainage systems have been used to model interactions between rainfall and flooding (Blanc et al., 2012). The models used in the studies reviewed in this research include SWMM (Zhu et al., 2016, Phillips et al., 2005, and Yazdi et al., 2022), MIKE FLOOD and InfoWorks (Blanc et al., 2012, Forero-Ortiz et al., 2020, and Murphy et al., 2016), and HECRAS

(Jung and Merwade, 2012, Van Dau et al., 2017, and Nofal and van de Lindt, 2021). Section 5.4.1 describes the criteria adopted to choose the most appropriate of these models for this research.

### 3.4.3 Flood damage quantification

For railway systems in order to quantify damage, all track assets which are at some level of exposure to inundation should be considered, including earthworks, track and track bed, point assets like signalling, switches and crossings. Previous railway flood modelling studies have mainly focused on damage to one individual asset like earthworks in Wang et al. (2021), and Cheetham et al. (2016), or aggregated track asset sections as in Kellermann et al. (2015), Bubeck et al. (2019), and Koks et al. (2019). In a route-level study of railway drainage system failure, Usman (2020) quantified the impact of a drainage failure on track substructure, drainage and signalling. To consider flood damage to all individual asset components in a section of track it is necessary to have a detailed layout of the track section under investigation and the different types of assets present (Koks et al., 2019, Bubeck et al., 2019, and Wang et al., 2021). As mentioned in Section 2.2.6, flooding of the track can have a variety of impacts including damage to drainage and other assets or indirect impacts associated with delays, environmental impact, and third party assets. Merz et al., 2010 quantifies these in terms of, direct, indirect, tangible and intangible damages (Merz et al., 2010). Direct damages are those which occur due to the physical contact of flood water with humans, property or any other objects. Indirect damages are induced by the direct impacts and occur – in space or time – outside the flood event. Both types of damages are further classified into tangible and intangible damages, depending on whether or not they can be assessed in monetary values (Merz et al., 2010). Tangible damages are damage to manmade capital or resource flows which can be easily specified in monetary terms, whereas intangible damage is damage to assets which are not traded in a market and are difficult to transfer to monetary values (Merz et al., 2010). Table 3.4 shows examples of the damage classifications which may result from a railway flood incident.

*Table 3.4. Example damage classifications resulting from a flood incident*

| | **Tangible damage** | **Intangible damage** |
|---|---|---|
| **Direct damage** | Earthwork Washout | Environmental damage |
| | Derailment | M&R GHG emissions |
| **Indirect damage** | Knock-on operational delays | Reputation damage |
| | Third party land flood | Surrounding road floods |

Such quantification of various types of damage will require reliance on exposure parameters other than only inundation depth or spatial extent of damage like duration and velocity (Zhu et al., 2016). For example, operational disruptions will require an understanding of the duration of an inundation and its impact on train delays and speeds. Previous studies which have looked at quantification of railway flood damage have mainly considered one type of rail flood damage like direct structural damage to track subsection as in Kellermann et al. (2015), and Bubeck et al. (2019), the cost of earthwork damage as in Wang et al. (2021) and indirect service performance loss in terms of affected passengers and trains due to cancellation and increased travel time as in Zhu et al. (2021). Usman (2020) did consider in addition to unplanned maintenance costs, the delay costs, third party damage and passenger travel costs.

Furthermore, when looking at component-level damage quantification it is important to consider the various levels of experienced damage. Flood risk literature normally defines fragility functions, such as stage-damage curves to estimate the damage level; given flood exposure, and asset vulnerability; characterised by a set of asset properties (Van Dau et al., 2017, and Foudi et al., 2015). Stage-damage functions are widely used in urban flooding studies to translate flood exposure parameters into monetary terms through establishing damage level thresholds (Van Dau et al., 2017, and Foudi et al., 2015). Table 3. 3 shows that depth was the main threshold criterion considered for damage quantification at component-level, for both urban drainage systems and rail systems. In railway assets, the level of damage determines the required type of intervention and what follows from cost elements to obtain monetised damage. Kellermann et al. (2015) developed RAIL (Rail Infrastructure

Loss) model which relates the depth of flood on a railway section to the level of observed damage and the associated overall M&R costs. The three levels defined by Kellermann et al. (2015)were:

Class 1: Track substructure partly inundated

Class 2: Substructure and superstructure fully inundated

Class 3: further damage to superstructure, damage to catenary and/or signals

However, for a disaggregate approach to damage costing, it is required to use degradation models or fragility curves which study the influence of water exposure on the asset under the specific relevant asset properties. For example, Kaewunruen and Tang (2019) studied the dynamic behaviour of ballast under flooding conditions by relating the depth of water as a percentage of the ballast thickness to the damping and stiffness coefficients of ballast. Furthermore, Hamarat et al. (2021) studied the impact of flooding on the dynamic behaviour of turnouts and track performance using Finite Element modelling. Their study considered the impact of flood water level on ballast stiffness combined with the properties of the materials used in the track. Hamarat et al. (2021) reported the observed twist value in the turnouts which reflected on criticality of overall track performance. Rushton and Ghataora (2014) developed a numerical model to describe the impact of rainfall on the stiffness of subgrade based on water level, duration of inundation, slope of subgrade and presence of a sand blanket.

Tsubaki et al. (2016) developed fragility curves for railway embankment scour due to overtopping flood flow. The considered earthwork properties were shape and height of embankment (Tsubaki et al., 2016). Johnston et al. (2021) specifies that earthwork type, soil type and live loading also affect stability of Earthwork asset. Cheetham et al. (2016) evaluated the level of damage to railway earthworks, albeit qualitatively, according to their type, geometric structure and soil type. Cheetham et al. (2016) adds that presence of flood protection on earthwork contributes to the level of damage experienced. the exposure parameters considered were depth of water and duration of inundation (Tsubaki et al., 2016, Johnston et al., 2021, DeVinne et al., 2022). Such relationships between exposure parameters, asset-specific vulnerabilities and level of damage enable prediction of specific intervention needs by understanding the severity of damage to track elements, e.g. whether ballast

requires cleaning, tamping or renewal and whether switches and crossing are safe to operate or require urgent intervention.

Describing flood risk in terms of economic damage is useful for infrastructure managers as it provides guidance for optimisation of strategies as was utilised in a subsequent cost/benefit assessment of interventions by Zhou et al. (2013), and Yazdi et al. (2022). Moreover, in a risk analysis, damage quantification should be structured across a range of rainfall events in order to illustrate a comprehensive view of flood risk to the stakeholders. ten Veldhuis and Clemens (2010) proposed the use of risk curves for estimation of level of risk, which are a representation of flood damage and the associated exceedance probability. Many of the studies reviewed herein looking at component-level quantitative flood risk assessment quantified risk in terms of monetary Expected Annual Damage (EAD). These include those by Phillips et al. (2005), Gouldby et al. (2008), Forero-Ortiz et al. (2020), Kellermann et al. (2015), Salinas-Rodriguez et al. (2018), Yazdi et al. (2022), Zhou et al. (2013), Koks et al. (2019), Bubeck et al. (2019), and Wang et al. (2021). EAD corresponds to the average annual economic damage expressed in monetary terms. It is given by the area under the damage-exceedance probability curve (risk curve) (Apel et al., 2008). When assessing railway risk, presenting the total economic damage as a probability distribution curve is preferable over a point-value of damage in order to reflect uncertainty in the quantified risk to stakeholders.

### 3.4.4 Flood modelling

Figure 3.6 shows a UDS flood risk analysis approach used by Blanc et al. (2012). The study proposed that a complete pluvial flood risk analysis requires reflection of rainfall characteristics in the area, modelling water pathways from the point where rainfall hits the ground to the location where flooding occurs, estimation of consequential damage and a mechanism for integrating uncertainties in exposure and damage economic functions (Blanc et al., 2012). Integration of uncertainty over the various scenarios will be performed using MCs to consider uncertainties. However, this is outside the scope of this section and is further described in Chapter 5.

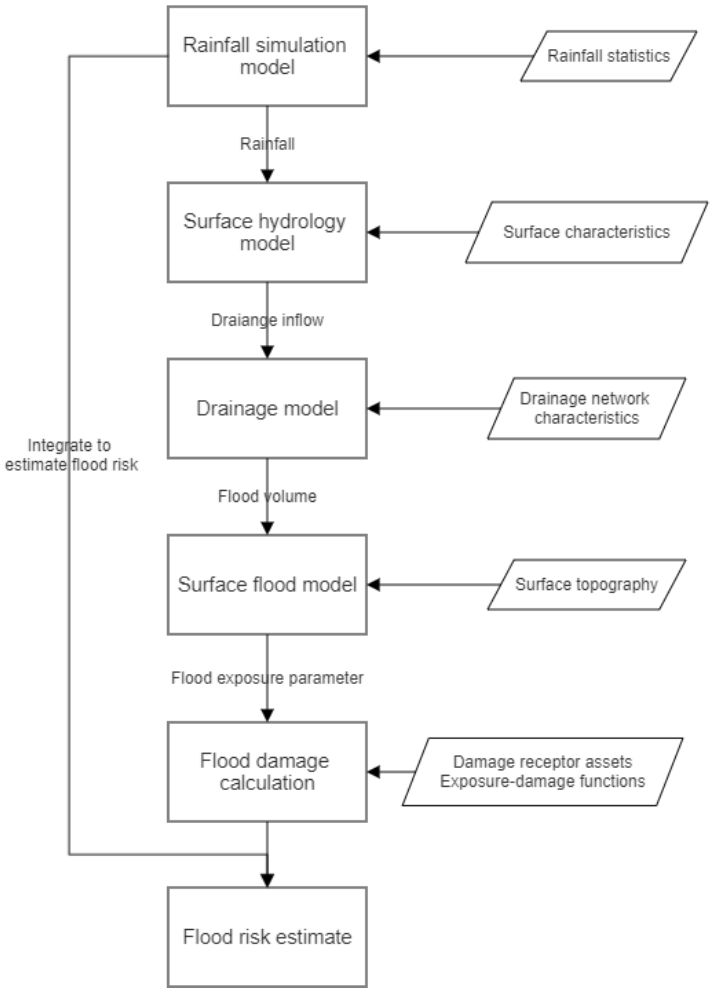



*Figure 3.6. Flood risk analysis methodology (adapted from Blanc et al. (2012))*

## 3.5 Summary

At first instance the chapter looked at the importance of a risk-informed approach to infrastructure management and the studies conducted thereof in the context of railway infrastructure. It then reviewed the principles of risk assessment, consisting of risk identification, analysis, and evaluation. The main identified techniques for a risk assessment included scenario analysis, Monte Carlo simulations. Thereafter, the chapter provided a review of flood modelling studies (section 3.4). It identified flood sources and drivers, including Storm event, asset condition and catchment properties. It also identified the benefit of integrated catchment modelling for flood scenario analysis using available software packages as agile tools for reflecting possible scenarios of flood risk sources and drivers. Section 3.4.3 looked at consequence analysis, i.e. damage quantification in the form of

damage charts, to quantify direct, indirect, tangible and intangible costs. This informs the development of a comprehensive economic flood cost model. To quantify these costs there is a need to obtain the appropriate exposure parameters such as depth, flood time and spatial extent of flooding.

# Chapter 4: Methodology

## 4.1 Introduction

There is, as outlined in Chapter 3, a paucity of research conducted to address flood risk in railway drainage systems at component level. This chapter describes the research methodology followed in this research to develop a framework for flood risk assessment of railway drainage assets at an asset component level.

## 4.2 Research Methodology

Figure 4.1 shows a flowchart of the stages entailed in this research. Each of these stages is described in the following subsections.

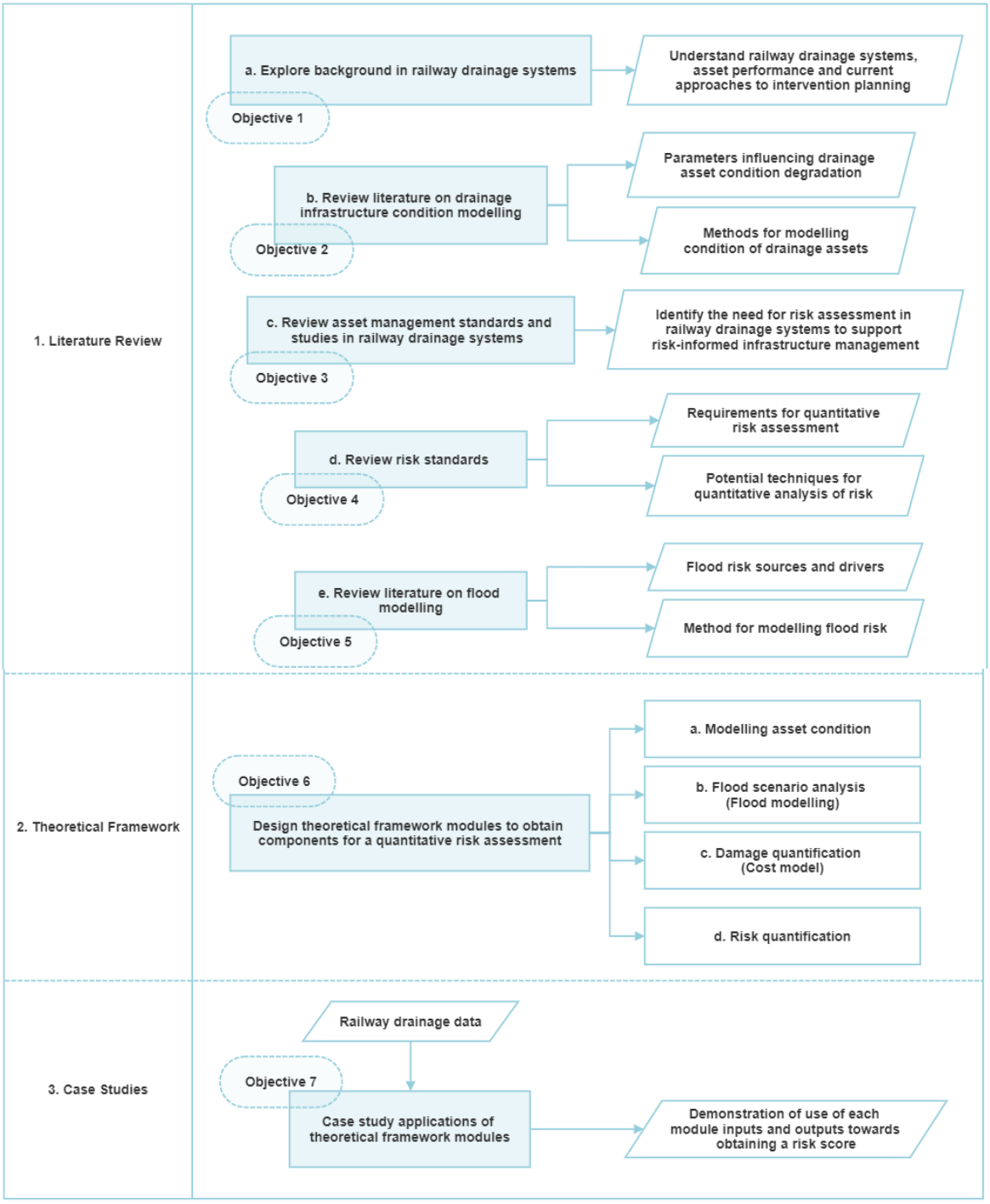



*Figure 4.1. Research Methodology*

1. Literature review

a. Explore background in railway drainage systems

This section fulfils the first objective of the research. It develops an understanding of the railway drainage system components, effects of poor drainage, characterisation of asset

performance and current approaches to intervention planning. Thereby, it identifies the need for predictive condition models.

b. Review literature on drainage infrastructure assets condition modelling

This stage reviews condition modelling applications to identify candidate methods used for infrastructure assets that are similar to railway drainage assets. Models are classified based on the type of method used, i.e., deterministic, statistical or Machine Learning (ML). Comparisons are drawn between the different genres based on input requirements, output type, level of analysis and success rate. The review also identifies the factors influencing drainage asset condition degradation which were considered in the previous studies. This section of the review forms the steppingstone for the development of a condition prediction/classification model at a component level. Thereby, achieving the second objective of the research.

c. Review asset management standards and studies in railway drainage systems

This stage fulfils the third objective of research. Through review of asset management concepts and principles and asset management studies in railway systems, it identifies the lack of a risk-informed decision support tools for infrastructure management of drainage systems at component level. It also reviews benefits, requirements and studies on railway risk-informed infrastructure management. Thereby, it establishes the need for a risk assessment framework to support railway drainage asset management decision making.

d. Review risk assessment standards

This stage fulfils the fourth objective of the research. It reviews risk assessment standards and provides a guide for developing a risk assessment framework through:

1. Understanding the risk assessment procedures and components.
2. Identifying potentially useful techniques for the purpose of this research.

e. Review of flood risk modelling applications

Although there is currently a lack of hydraulic flood modelling studies for railway drainage infrastructure, there is wealth of research on fluvial flood risk modelling and flood damage

quantification in urban areas. These applications are reviewed to identify potential methods to be used for railway drainage hydraulic modelling and the appropriate representation of modelled results. This section achieves the fifth objective of the research.

2. Theoretical framework

This stage fulfils Objective six of the research through designing a risk assessment framework, consisting of several modules, to obtain components for risk quantification following the broad definition of risk: Risk = Probability× Consequence. The development of each module involves the proposal of methods based on the reviewed literature. The following defines the four main modules:

a. Condition modelling: A drainage asset undergoes natural degradation throughout its lifecycle. Asset condition directly influences the asset's capacity to process runoff. Therefore, as discussed in section 3.4.1, asset condition is regarded as a source of risk wherein, its potential scenarios should be identified. This module, hence, provides a tool for prediction of individual asset condition. In choosing an appropriate method of modelling asset condition it is felt that the method should enable data-driven predictive individual asset condition modelling. Following the reviewed infrastructure condition modelling methods (see Section 2.3.5), it is proposed to investigate the use of Machine Learning (ML) algorithms. To this end. ML algorithms are chosen since they have been shown to achieve a high performance in identifying complex relationships between inputs and outputs for drainage assets condition prediction, even when collected data is incomplete, inconsistent or inaccurate, such as the case of railway drainage assets. Chapter 6 describes the selection of an appropriate machine learning algorithm and its use for the task at hand.
b. Scenario analysis: This module utilises scenario analysis techniques to identify possible flood source combinations and evaluate their impact on flood risk occurrence. For this task, hydraulic flood modelling is chosen since it provides a user-friendly and agile interface for scenario analysis of uncertain risk sources and changing risk drivers (e.g., asset condition, rainfall events and changes in land use). It enables visual representation of the two-way

interaction between the catchment and the linear drainage system based on mathematical hydraulic equations. Thereby, enabling robust evaluation of flood exposure on surrounding railway assets.

c. Damage quantification: The objective of this module is to obtain a quantifiable damage value associated with the consequences of possible sources of flood risk. This entails the development of a comprehensive parametric cost model in stage 1 (Section 5.5.1). Following the identification of flooding assets and flood exposure from hydraulic modelling, the developed cost model monetises damage that would be incurred by the infrastructure manager due to: reactive M&R, operational disruptions, surrounding land damage and reputational damage. Thereon, for a risk-informed approach, stage 2 of the module requires to carry out an uncertainty analysis (see section 5.5.2). Since uncertainties in cost parameters, and flood exposure parameters would influence the calculated damage value, the module proposes the use of Monte Carlo simulations to represent epistemic uncertainties when quantifying damage consequence (i.e., using the cost model). MCs is chosen because it is a powerful statistical tool which utilises simple iterative process to represent any probability distribution of the uncertain inputs, thereon produces a quantitative output distribution of the defined model.

d. Risk Quantification: The objective of this module is to bring together the likelihood of an asset flood occurring (given probabilities of flood risk sources) and the consequence of the flood (as quantified in the damage quantification module) to obtain a quantitative risk score, where Risk = Probability× Consequence. This module is described in Section 5.6.

3. Case study applications

To demonstrate the applicability of each module in the developed theoretical framework, case studies are performed using data provided by the railway drainage and lineside team at Network Rail in the UK. These case studies enable demonstrations of the inputs, procedures and output of each module and show how the modules work together to obtain a risk score for an asset associated with a certain asset annual flooding likelihood in economic terms). The first case study is a comparative demonstration of ML algorithms as methods for condition modelling of pipe railway drainage assets

(Chapter 6). The second case study is a flood modelling application over a railway section. It demonstrates the use of scenario analysis for understanding flood risk impact at multiple locations over the studied track section (Chapter 7). The third case study utilises scenario analysis output to demonstrate scenario damage quantification using the cost model (Chapter 8). It also entails a demonstration of risk quantification. A risk score is obtained for two different asset locations over the studied track section. This application highlighted the value of the framework for comparative risk assessment of various sites, thus informing maintenance prioritisation strategies.

# Chapter 5: Theoretical framework

## 5.1 Introduction

This chapter describes the development of the risk-based theoretical framework for the assessment of flood risk in the railway drainage system at a component level. The framework is developed in light of the reviewed risk standards, literature on condition modelling and flood risk assessments (Chapters 2 and 3) and using the research methodology presented in Chapter 4. The framework consists of four modules designed to obtain components required to determine a quantitative flood risk score for a given asset. The methods used and the steps entailed in each module are described in detail below.

## 5.2 Overview of the framework

The framework is based around obtaining the elements of risk i.e. the probability of a risk scenario and the consequences if the risk scenario occurs, following the BSI definition of risk i.e. Risk= Probability × Consequence. The probability component is given by the probability of the various sources contributing to occurrence of flooding. The consequence component monetises flood damage in the vicinity of the drainage asset. For the flood risk assessment in this study, the identified sources contributing to a flood are the combination of asset condition and rainfall. The framework is designed to:

1. Address the lack of degradation models for railway drainage assets.
2. Utilise scenario analysis of various combinations of the identified risk sources.
3. Rely on robust quantitative methods for scenario analysis of exposure and consequent damage.
4. Describe risk in terms of a monetary value to enable comparative risk assessment.
5. Consider uncertainties within damage quantification.
6. Enable what-if analyses for whole life cycle cost assessments.
7. Enable comparative risk assessment of railway sites to inform maintenance strategies.

Figure 5.1 provides an overview of the framework's modules. The output of each module provides the input for the next module. Each module provides certain elements for risk quantification. Module 1 'Condition Modelling' provides a Machine Learning approach for drainage asset condition prediction to identify asset condition as a source of flood risk. Module 2 'Flood Modelling' uses engineering flood modelling software as a mean to employ Scenario Analysis techniques to understand the drivers of flood risk and the resulting levels of asset exposure to flooding. Module 3 'Damage Quantification' provides the understanding of the consequences of rail asset flood exposure in monetary terms under the performed Scenario Analysis. The final Module 'Risk Quantification' brings together risk scenario probabilities with the scenario consequences to determine a quantitative risk score or a particular asset within a site. The modules are described further below.

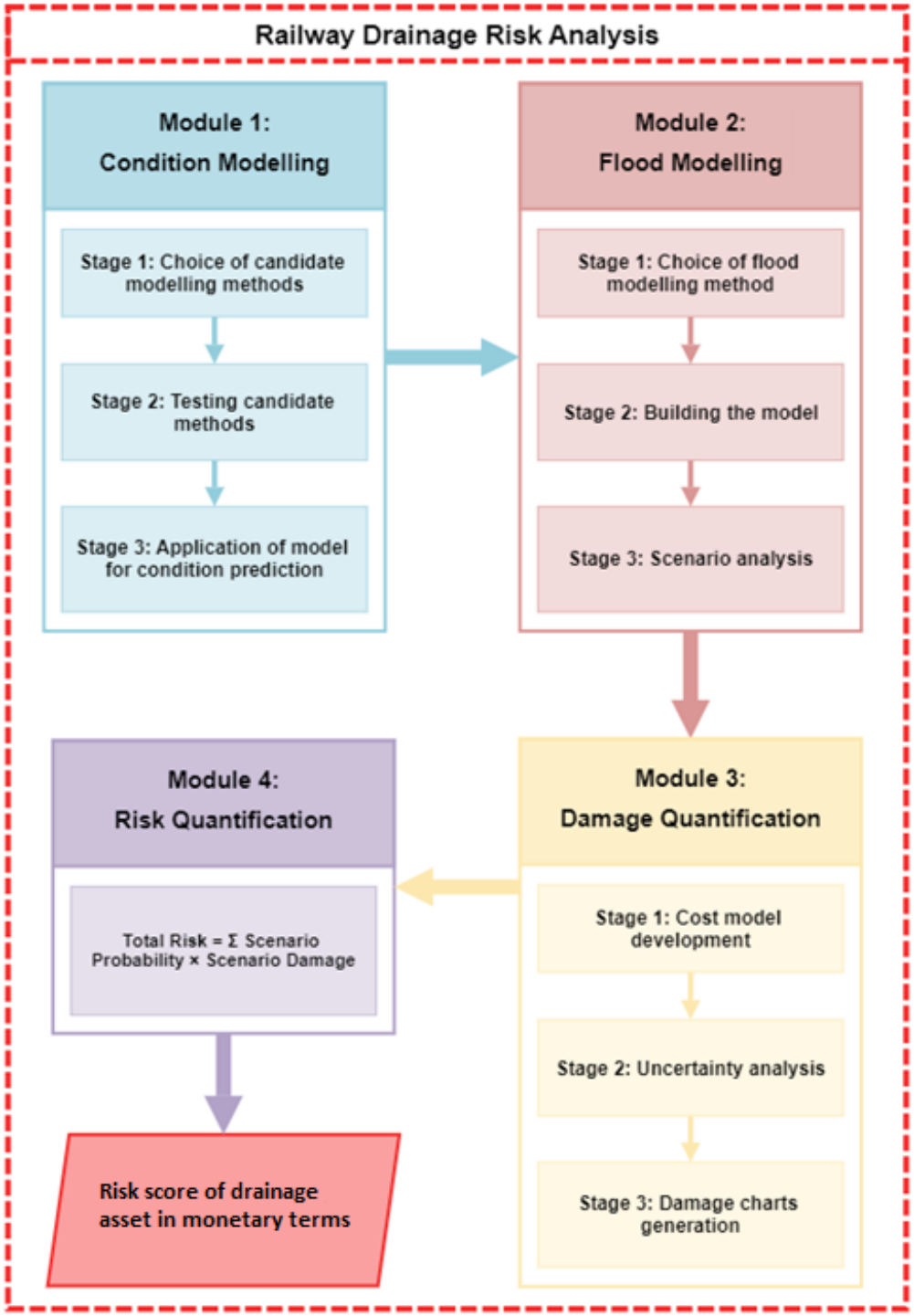



*Figure 5.1. Risk-based framework for railway drainage risk assessment*

## 5.3 Module 1: Condition modelling

This module provides data-driven modelling of asset condition degradation. Asset condition affects the ability of the asset to accommodate flow which is the first identified source of flooding. This enables infrastructure managers to predict asset condition and identify intervention needs. Thereby, providing a tool to facilitate the development of proactive M&R strategies. Figure 5.2 shows the methodology for developing the condition prediction model. The following subsections describe the methodology in detail.

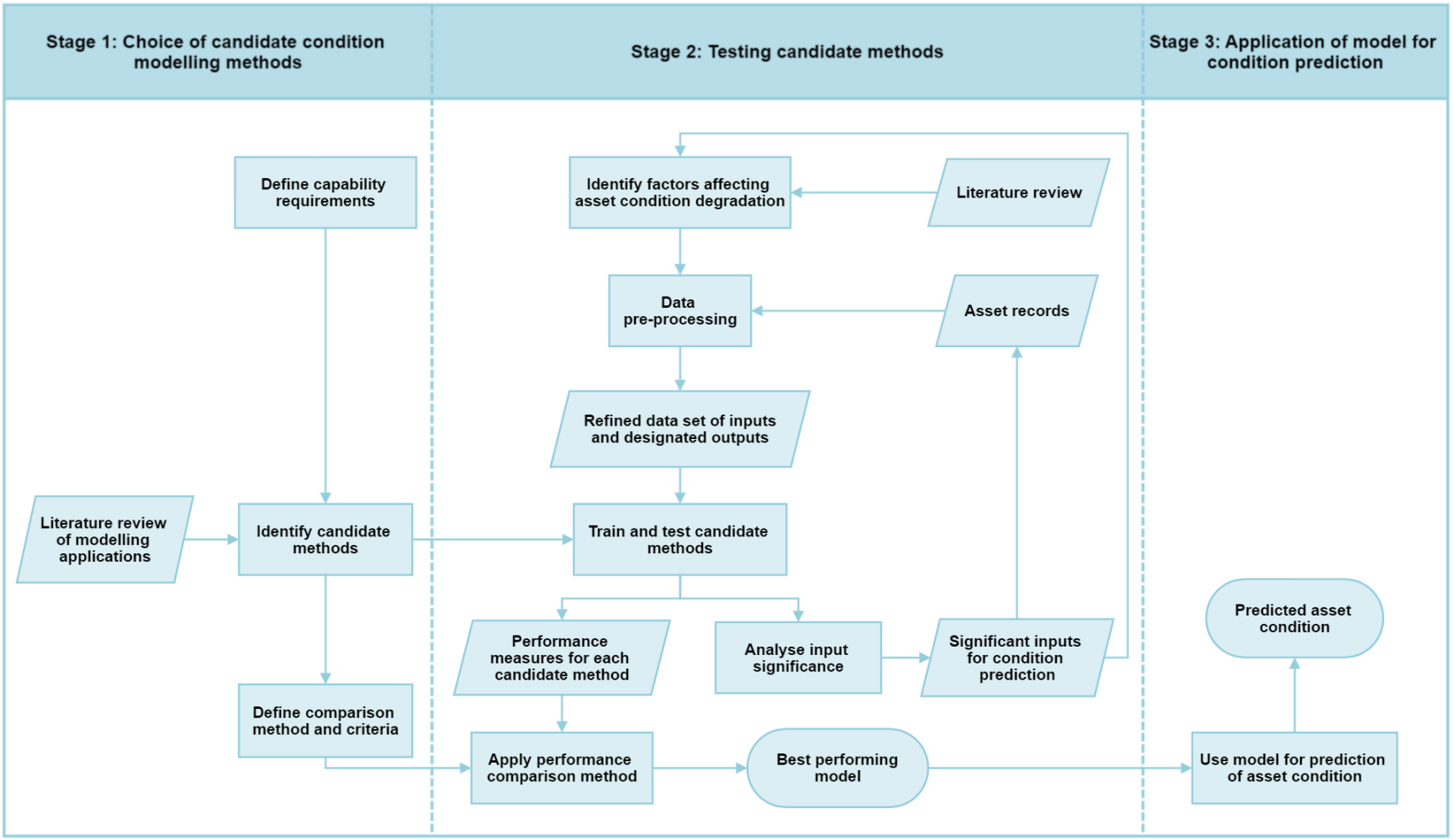



*Figure 5.2. Module 1: Condition model*

### 5.3.1 Stage 1: Choice of candidate condition modelling methods

1. Define requirements

To inform the choice of the candidate algorithms, the requirements of the condition modelling method are identified. These are decided based on the level of assessment, and availability and abundance of asset records. The following are the proposed considerations for choice of a condition modelling application for a railway drainage asset.

- Allow assessment of condition for individual assets.
- Incorporate input from asset inspection databases.
- Capable of handling both ordinal and numerical variables.
- Capable of handling noisy imprecise data.
- Data-driven with minimal assumptions and external input.
- Cater for probabilistic quantitative output.
- User-friendly application on a software platform.
- Allow significance analysis of the different input factors.

2. Identify candidate condition modelling methods

Based on the previous considerations, and in light of the conducted literature review on condition modelling methods (Chapter 2), data-driven Machine Learning (ML) algorithms are proposed for condition modelling of railway drainage assets. They offer a user-friendly platform to enable condition predictions for individual assets using various input formats from asset databases. The following are the ML algorithms identified from condition modelling applications in literature.

- Neural Networks (NN)

  A basic neural network consists of an input layer, a hidden layer and an output layer (Svozil et al., 1997). A Feed Forward Back Propagation technique is used to train the Network. It entails an iterative training process to allow for 'Back-Propagation' calibration of assigned weights based on

the performance error observed during the iteration (Svozil et al., 1997). During the iterations, the training data is fed into the network at various shuffled orders of training data points. Studies show that one hidden layer is good enough for approximating most non-linear functions like pipe condition (Tran, 2007, Asnaashari et al., 2013, Svozil et al., 1997, Xu and Sinha, 2021). The number of hidden neurons in the hidden layer requires parameter tuning through trial. Figure 5.3 shows the structure of a typical NN.

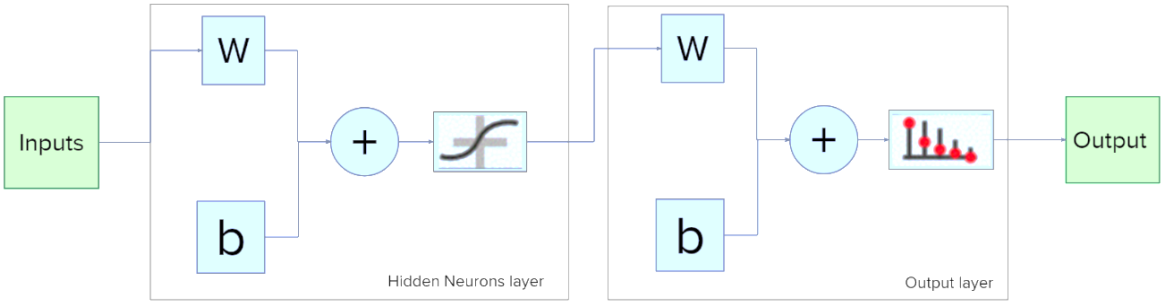



*Figure 5.3. Structure of a Typical Neural Network*

- Decision Trees (DT)

  Decision trees are classification algorithms graphically structured in the form of a tree with a root node, decision nodes and terminal nodes known as leaf nodes (Quinlan, 1990). The classification decision is governed by 'if-then' rules which are learned through the training process. Training involves recursive partitioning of the data based on the input variables until the leaf node (class) is reached (Quinlan, 1990). Figure 5.4 shows the typical structure of a DT.

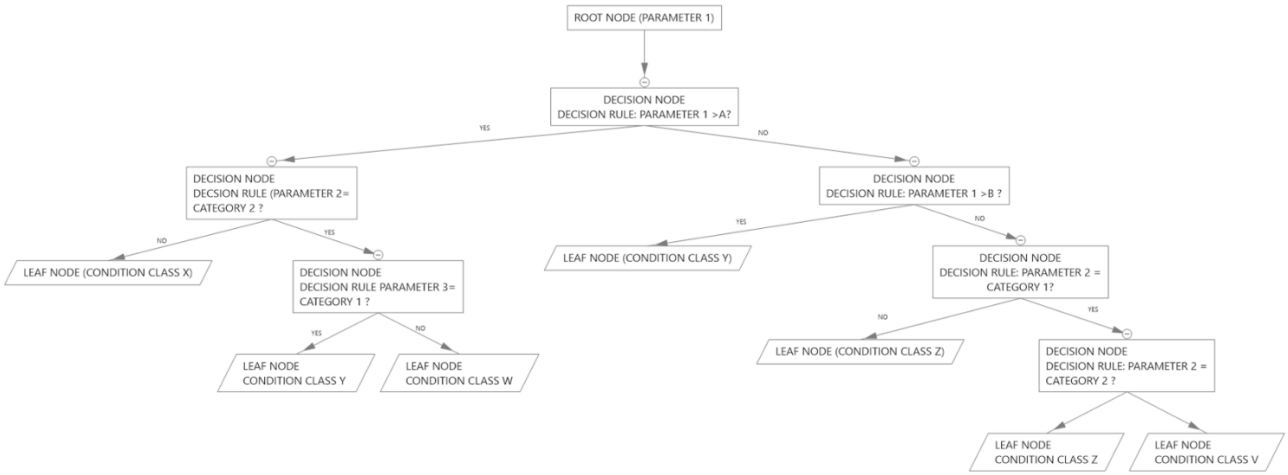



*Figure 5.4. Structure of Decision Trees*

- K-Nearest Neighbours (KNN)

  This is a type of classifier where the algorithm stores all available data as feature vectors and measures how far off the test vector is from each of the stored vectors using Euclidean distance (Zhang, 2016). The test vector is then classified based on the most voted classification of 'K' of its nearest neighbours (Zhang, 2016, Ahmed et al., 2021). Figure 5.5 shows a representation of a KNN.

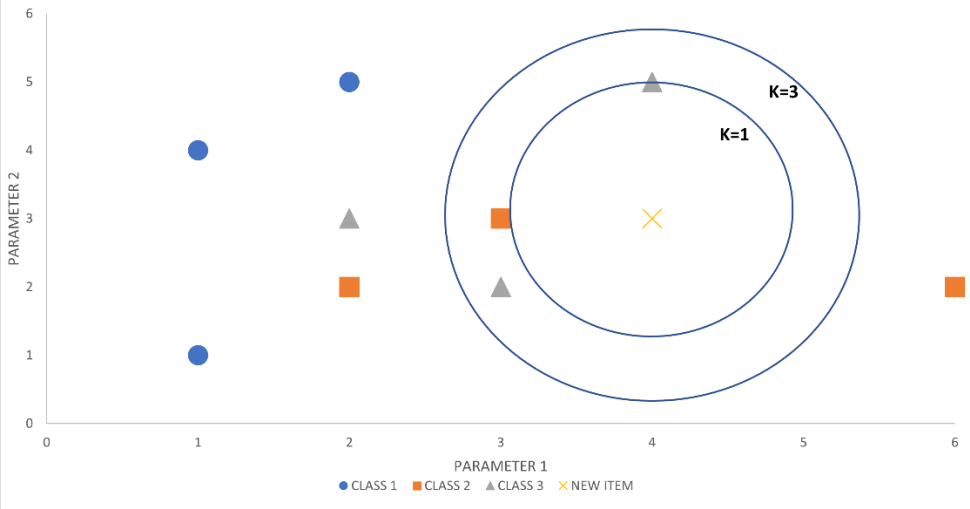



*Figure 5.5. Structure of K-Nearest Neighbours*

- Bagged Trees (BT)

Bagged trees or bootstrap aggregated trees are ensembles of multiple decision trees. The method aims to improve the performance of decision trees by reducing the variance observed in an individual decision tree through bagging the training data into 'N' samples which are then used to train 'N' Trees/Learners (Hastie et al., 2009, Miller et al., 2016). After training, the classification prediction is the averaged class of the 'N' decision trees (Miller et al., 2016). Figure 5.6 shows the structure of a typical BT.

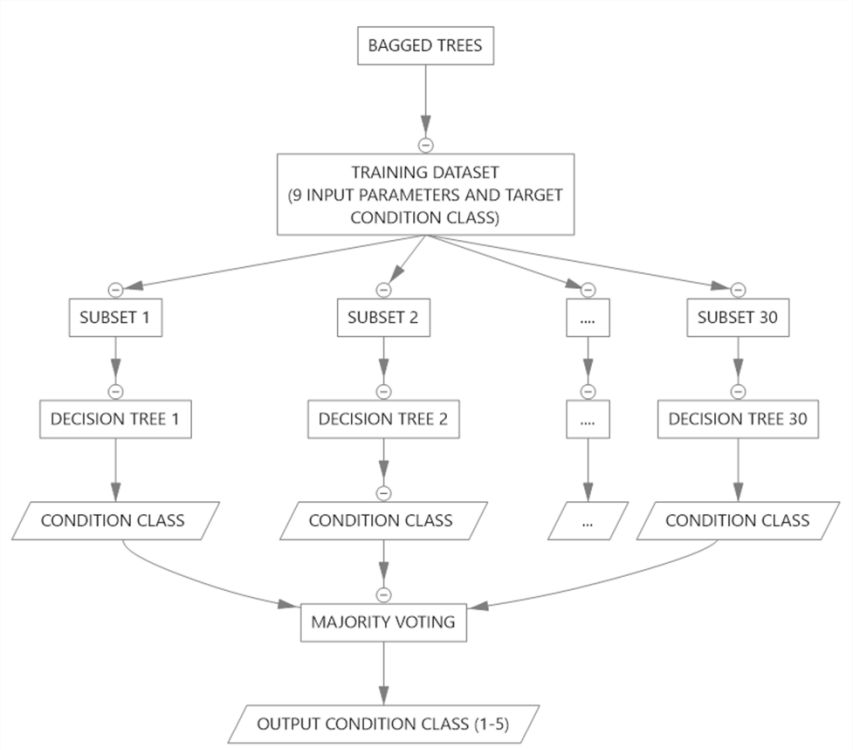



*Figure 5.6. Structure of Bagged Trees*

- Adaptive Boosted Trees (BsT)

  Adaptive boosted trees are a form of ensemble classifier which rely on sequential learning of multiple weak learners, i.e. decision trees to create a strong learner. It is suggested as an alternative to bagged trees which may be prone to mistakes because of parallel testing of the decision trees. Instead, BsT uses an iterative approach in which it "adapts" the previously trained tree and allocates

higher weights to the wrongly classified instances. In the final step all trees are amalgamated into a single strong classifier. Figure 5.7 shows the structure of an BsT.

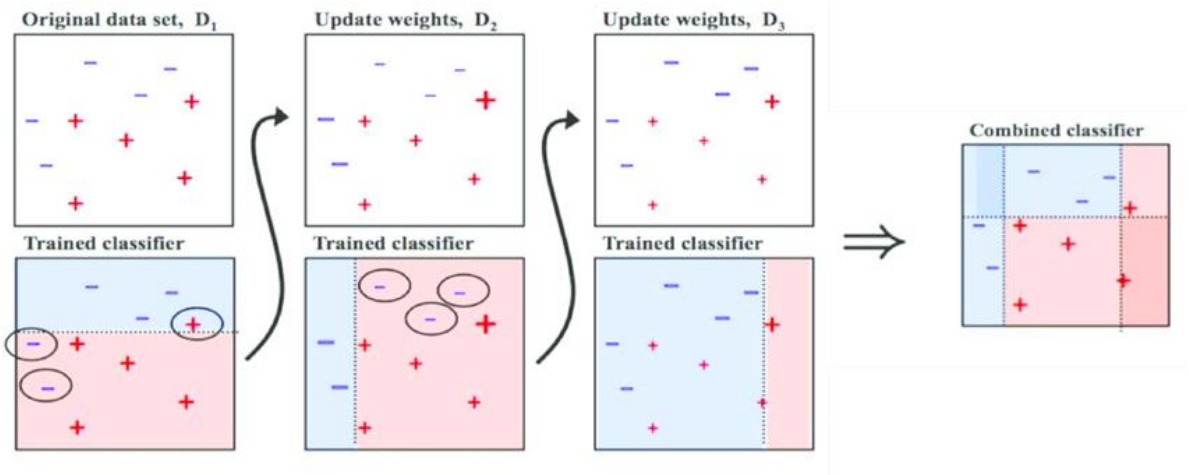



*Figure 5.7. Structure of Adaptive Boosted Trees (Marsh, 2016)*

3. Define comparison method and criteria

Following the nomination of candidate methods based on initial capability requirements, further criteria are used to assess the performance of the above shortlisted methods. The proposed criteria in order of importance are as follows:

a. Prediction performance: It is the main consideration for accepting any model for asset condition prediction. It is evaluated through several measures, described in section 5.3.1.
b. Speed: The model must be time efficient to be useful for incorporation into asset management decision making processes.
c. Ability to cope with large datasets: When working with large networks of drainage systems, the model must deal with a large amount of data from asset databases.
d. Probabilistic output: Since the output from the condition model is part of a risk assessment, accounting for uncertainty in condition is crucial. Therefore, the model must be capable of giving a probability associated with each condition prediction.

e. Ability to avoid overfitting: The training process should achieve a generalised model applicable for any data set. It should not be prone to overfitting to the training dataset, especially for complex multi-dimensional problems.

f. Interpretability of model: The model output should enable understanding the cause-effect relationships between inputs and outputs as well as the significance of input factors towards prediction performance. This is relevant to consistency of the model in making predictions and it helps asset managers gain trust in the model (Linardatos et al., 2020). Interpretability could be an issue when the problem is multi-dimensional and stochastic, such as condition degradation. There are techniques for improving interpretability of the model as described in section 5.3.2

Prediction performance measures

There are two main outputs which can be used to assess the prediction performance of ML classification algorithms, namely a confusion matrix and a Receiver Operator Characteristic curve (ROC) (Ferrer, 2022, and Grandini et al., 2020). Derived from these are five measures to be used as bases for performance comparison of individual classes, namely: Overall Accuracy, Recall, Precision, F-score and Area Under the Curve (AUC). In the reviewed literature on ML classification problems (Chapter 2), overall accuracy is predominantly used for performance evaluation (Table 2. 5), as in Wu et al. (2015), Mohammadi et al. (2020), Liu et al. (2018), Asadi et al. (2019), and Alawad et al. (2020). However, in multi-class ranking problems in which some classes are of greater performance criticality, it is important to examine a model's performance in each individual class (Grandini et al., 2020). It is especially important for a model to prove reliable in predicting critical condition for it to be accepted as a means of informing asset management decisions. From the literature review, the following studies were identified which addressed individual-class prediction reliability using the reported parameters:

- Allah Bukhsh et al. (2019); where the F-score was used in addition to overall accuracy,
- Caradot et al. (2018), and Harvey and McBean (2014); where Recall was used,

- Xu and Sinha (2021), and Rokstad and Ugarelli (2015); where AUC was used.
- Kalathas and Papoutsidakis (2021), and Mittal and Rao (2017); where recall and precision were used.

The following subsections describe the five adopted measures of prediction performance and their derivations.

a. Confusion Matrix

A confusion matrix is a visual summary of the trained model's performance. Table 5.1 shows the configuration of the confusion matrix customised for five possible outcomes of asset condition prediction. Overall Accuracy, Precision and Recall are calculated from the confusion matrix, using Equations 5.1, 5.2, and 5.3, respectively.

*Table 5.1. Configuration of confusion matrix*

| | | Target class | | | | |
|---|---|---|---|---|---|---|
| | P \ t | 1 | 2 | 3 | 4 | 5 |
| Predicted class | 1 | $TP_1$ | $FP_{1,2}$ ($FN_{1,2}$) | $FP_{1,3}$ ($FN_{1,3}$) | $FP_{1,4}$ ($FN_{1,4}$) | $FP_{1,5}$ ($FN_{1,5}$) |
| | 2 | $FP_{2,1}$ ($FN_{2,1}$) | $TP_2$ | $FP_{2,3}$ ($FN_{2,3}$) | $FP_{2,4}$ ($FN_{2,4}$) | $FP_{2,5}$ ($FN_{2,5}$) |
| | 3 | $FP_{3,1}$ ($FN_{3,1}$) | $FP_{3,2}$ ($FN_{3,2}$) | $TP_3$ | $FP_{3,4}$ ($FN_{3,4}$) | $FP_{3,5}$ ($FN_{3,5}$) |
| | 4 | $FP_{4,1}$ ($FN_{4,1}$) | $FP_{4,2}$ ($FN_{4,2}$) | $FP_{4,3}$ ($FN_{4,3}$) | $TP_4$ | $FP_{4,5}$ ($FN_{4,5}$) |
| | 5 | $FP_{5,1}$ ($FN_{5,1}$) | $FP_{5,2}$ ($FN_{5,2}$) | $FP_{5,3}$ ($FN_{5,3}$) | $FP_{5,4}$ ($FN_{5,4}$) | $TP_5$ |

Note: $FP_{p,t}$: False Positive (e.g. $FP_{1,2}$ means false positive with respect to predicted class 1, actual class is 2)
$FN_{p,t}$: False Negative (e.g. $FN_{1,2}$ means false negative with respect to target class 2, misclassified as 1)
TP: True Positive

Overall accuracy provides a broad overview of the model performance (Equation 5.1). Precision and recall provide insight into individual class performance by dissecting the confusion matrix into prediction rows and target columns (Davis and Goadrich, 2006). Precision is concerned with the exactness, or relevance, of predictions (Equation 5.2) (Raghavan et al., 1989). Meanwhile, recall is concerned with the class retrieval ability of the model (Equation 5.3) (Raghavan et al., 1989). In condition prediction

problems, there is usually a trade-off between precision and recall (Buckland and Gey, 1994). F-score is useful to reflect the average of both parameters (Equation 5.4).

$$\boldsymbol{Accuracy} = \frac{\sum_{p=1}^{n} \boldsymbol{TP_p}}{\sum_{p=1}^{n} \boldsymbol{TP_p} + \sum_{t=1}^{n} \sum_{p=1}^{n} \boldsymbol{FP_{p,t}}} \qquad \textit{Equation 5.1}$$

$$\boldsymbol{Precision_{class=c}} = \frac{\boldsymbol{TP_c}}{\boldsymbol{TP_c} + \sum_{t=1}^{5} \boldsymbol{FP_{c,t}}} \qquad \textit{Equation 5 2}$$

$$\boldsymbol{Recall_{class=c}} = \frac{\boldsymbol{TP_c}}{\boldsymbol{TP_c} + \sum_{p=1}^{5} \boldsymbol{FN_{p,c}}} \qquad \textit{Equation 5 3}$$

$$\boldsymbol{F-score_{class=c}} = \mathbf{2} \times \frac{\boldsymbol{Recall \times Precision}}{\boldsymbol{Recall + Precision}} \qquad \textit{Equation 5.4}$$

*Where,*

| | |
|---|---|
| $TP_p$ | *number of True Positives correctly predicted as class p* |
| $FP_{p,t}$ | *number of False Positives incorrectly predicted as class p when target class was t* |
| $TP_c$ | *number of True Positives with respect to class c* |
| $FP_{c,t}$ | *number of False Positives with respect to class c, where predicted class was c but actual class was t* |
| $FN_{p,c}$ | *number of False negatives with respect to class c, where predicted class was p and actual class was c* |
| $n$ | *number of possible classes* |

b. ROC Curve

ROC shows the True Positive Rate (i.e., Recall) against the False Positive Rate (FPR, i.e., false alarms). FPR for a specific class is the ratio between the number of false positives with respect to the specific class and the total number of instances that are not relevant to the specific class. The calculation of FPR from a confusion matrix is given by Equation 5.5. Figure 5.8 shows an example ROC curve from one of the NN simulations in the case study (Chapter 6). As a rule of thumb, the highest point above the diagonal ROC, would be expected to have the least randomness in the classifications (Harvey and McBean, 2014). A larger AUC indicates higher performance (low randomness). Therefore, AUC is proposed as a measure for prediction performance comparisons within individual classes.

$$\boldsymbol{FPR_{class=c}} = \frac{\sum_{t=1}^{n} \boldsymbol{FP_{c,t}}}{\sum_{p \neq c} \boldsymbol{TP_p} + \sum_{t \neq c} \sum_{p=1}^{n} \boldsymbol{FP_{p,t}}} \qquad \textit{Equation 5.5}$$

*Where,*

| | |
|---|---|
| $FP_{c,t}$ | *number of False Positives with respect to class c, where predicted class was c but actual class was t* |
| $TP_p$ | *number of True Positives correctly predicted as class p* |
| $FP_{p,t}$ | *number of False Positives incorrectly predicted as class p when target class was t* |
| $n$ | *number of possible classes* |

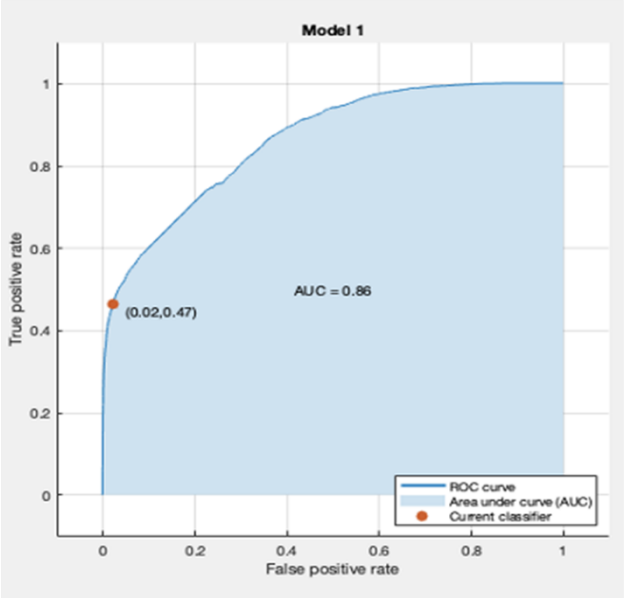



*Figure 5.8. ROC curve*

Performance comparison method

Choice of an algorithm for the condition prediction task as part of a risk assessment requires comparison of the candidate algorithms based on their performance in the various predefined categories of performance comparison. For this purpose, Analytic Hierarchy Process (AHP) is used as a performance comparison method to consider the various comparison criteria (i.e. prediction performance, speed, etc.) in the evaluation of the candidate algorithms. AHP is a multi-criteria decision-making tool developed by Saaty in the 1970s (Saaty, 1977). It is widely used by researchers for various applications of Multi-Criteria Decision Making (MCDM) problems (Vaidya and Kumar, 2006, Waris et al., 2019). It is particularly useful because it is based on mathematics and enables the consideration of tangible and intangible criteria (Vargas, 1990). The following describes the process for AHP (Ishizaka and Labib, 2011):

1. Define problem and criteria for performance judgment.
2. Define alternatives (Candidate algorithms).
3. Establish priority among criteria using pairwise comparison. This will create a pairwise comparison matrix.

Table 5.2 shows the scale used for pairwise comparison as developed by Saaty (1987).

*Table 5.2. Fundamental 1–9 point scale for pairwise comparison*

| Intensity of importance | Definition |
|---|---|
| 1 | Equal importance |
| 3 | Moderate importance of one over another |
| 5 | Essential or strong importance |
| 7 | Very strong importance |
| 9 | Extreme importance |
| 2,4,6,8 | Intermediate values between two adjacent judgements |

4. Synthesise criteria to achieve a relative weight for each criterion:
    a. Sum values in each column of the pairwise comparison matrix,
    b. Divide each cell value in the pairwise comparison matrix by its respective column total. This will achieve a normalized pairwise comparison matrix,
    c. Average values in each row of the normalised comparison matrix. This achieves a relative priority weight for each criterion.
5. Check for consistency:
    a. Multiply pairwise comparison matrix criterion column elements by the respective relative priority weight for the criterion,
    b. Sum values across each row,
    c. Divide each weighted sum by the associated relative weight for the criterion,
    d. Average the values ($\lambda_{max}$),
    e. Calculate Consistency Index (CI) using Equation 5.6,

$$\boldsymbol{CI} = \frac{\boldsymbol{\lambda_{max} - n}}{\boldsymbol{n-1}} \qquad \textit{Equation 5.6}$$

*Where, n is the number of performance criteria considered*

    f. Obtain Random Index (RI) value. See Table 5.3.

*Table 5.3. Random Index number values (Saaty, 1987)*

| n | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---|---|---|---|---|---|
| RI | 0.58 | 0.9 | 1.12 | 1.24 | 1.32 | 1.41 |

g. Calculate Consistency Ratio (CR) as shown in Equation 5.7. If CR ≤ 0.1, then consistency is acceptable. If consistency is not acceptable, then the allocated weights need to be revised to improve consistency (Kułakowski, 2015). A series of methods have been proposed for AHP consistency improvement, including the works of Saaty (2013), Ergu et al. (2011), and Koczkodaj and Szarek (2010). General rules are to ensure: no contradictions exist in the allocated relative scores for the criteria, avoid overuse of the large comparative scores, avoid more than nine elements to compare.

$$\boldsymbol{CR} = \frac{\boldsymbol{CI}}{\boldsymbol{RI}} \qquad \textit{Equation 5.7}$$

6. Allocate scores for each alternative method under each criteria category
7. Calculate the performance score for each candidate algorithm using Equation 5.8

$$\boldsymbol{P_k} = \sum_{\boldsymbol{i=1}}^{\boldsymbol{n}} \boldsymbol{W_i} \times \boldsymbol{S_{ik}} \qquad \textit{Equation 5.8}$$

*Where, $P_K$ is the performance score of algorithm K*

*$W_i$ is the relative weight of criterion i*

*$S_{ik}$ is the allocated score for criterion i for the $k^{th}$ algorithm*

### 5.3.2 Stage 2: Test candidate methods

Training and testing candidate algorithms concerns tailoring the algorithm for the required asset application and the data records held by the infrastructure manager. Thereafter, the most appropriate algorithm for a predictive model is selected by comparing the performance of various tested models.

1. Identifying factors affecting asset degradation

At the start of a condition modelling study, it is important to understand the different factors which contribute to asset natural condition degradation. Initially, these factors are identified through a literature review, where significance analysis of inputs from previous condition modelling applications are compared. The identified parameters which are available in the asset inspection records are used as inputs to the condition model. At a later stage, significance analysis is performed using the output from the condition modelling application to inform future condition modelling inputs.

2. Data pre-processing

Based on the identified significant inputs from the literature review and the availability of input parameters in asset records, the database records are filtered to obtain a refined dataset. The refined dataset contains inputs and designated outputs used for training the algorithms. To obtain the refined dataset, the raw data records held in infrastructure managers' databases undergo the following pre-processing steps:

a. Extract input parameters and designated outputs

   The process of extracting parameters involves "as-is" parameters which are readily recorded in the asset database and are left intact, or "derived" parameters which are extracted from other readily recorded data with some manipulation and assumptions.

b. Sort duplicate records

Asset inspections take place periodically, therefore, within a timespan multiple records can be found for the same asset. Duplicate condition scores for the same asset on the same dates should be eliminated as subjective anomalies.

c. Normalise continuous inputs

Normalising inputs improves convergence and performance during training (Singh and Singh, 2020). Feature clipping is a normalising technique for continuous data which discards unrealistic outliers by capping the variable within a min/max range.

d. Transforming categorical inputs

Asset properties are mostly categorical inputs, and therefore they need to be converted to numerical data. There are two main ways for converting categorical input: 'ordinal encoding' in which each nominal category is assigned an integer, and 'one-hot encoding' in which a feature vector is created indicating the presence of each possible category using binary integers. The choice of method depends on the algorithm application. For instance, Neural Networks require 'one-hot encoding' format whereas other ML algorithms can work with 'ordinal encoding'.

e. Integrating inputs and outputs

This step is used to sort inputs and designated outputs in a training dataset format which is compatible with different tested ML algorithms.

f. Fix class imbalance

Often in multi-class real training datasets, one or more output classes are represented with more samples than the other classes, creating data imbalance (Guo and Viktor, 2004). The imbalance can have detrimental impact on performance of model (Buda et al., 2018); it causes the trained model to favour the over-represented classes in predictions, while, the minority class may be the critical class in asset condition datasets. In such case, the overall accuracy measure ceases to be a suitable indicator

of performance. Imbalance creates the illusion of high performance when in reality the model fails to retrieve the critical-condition observations (Guo and Viktor, 2004).

From a performance analysis point of view, Recall, precision, and AUC (Section 5.3.1) are reflective measures of individual class performance and are therefore considered in addition to overall accuracy. However, from a performance enhancement point of view, class imbalance requires attention. There are two data-level methods suggested to fix class imbalance, namely: under sampling and over-sampling (Buda et al., 2018). Under-sampling reduces the size of majority-class data to match the size of the minority class data (Buda et al., 2018). This is an unreasonable option when the difference in representation is substantial which leaves very little data for training the models. Two common over-sampling methods are replication and Synthetic Minority Over-sampling Technique (SMOTe) (Buda et al., 2018). Using replication, as the name implies, the underrepresented classes' samples are replicated repeatedly to reach the size of the over-represented class. Replication can make the model prone to overfitting as it reduces the decision region (Chawla et al., 2002). Whereas SMOTe is an advanced method that avoids over-fitting (Buda et al., 2018, Chawla et al., 2002). SMOTe augments the dataset by creating a statistical space between a pre-specified number of neighbouring feature points of the minority class and interpolates new synthetic data points. Both methods are explained and demonstrated in the condition modelling application (Chapter 6)

3. Train and test candidate methods

The refined input-output datasets are used to train the models. The datasets should be split into training and testing subsets. Training is a requirement for 'eager' classifiers while 'lazy' classifiers require no prior training, wherein training data is stored to retrieve for predictions on blind data (Perrizo et al., 2002b). Testing is essential for both model types before they can be used to make predictions. Any programming language which can deal with large datasets can be used for the training and testing stage. In Chapter 6 MATLAB 2020a (MathWorks, 2022) is used for demonstration because it offers toolboxes and applications for various ML algorithms.

4. Performance comparisons

After training candidate models, Accuracy, Recall, Precision, F-score, AUC metrics are extracted to evaluate the prediction performance. Thereafter the models are scored for each of the performance judgment criteria specified in section 5.3.1. AHP is performed to obtain the model's performance scores. The highest scoring algorithm is the one to be used for future condition predictions. Every time new data records are collected; training should be reiterated to update the model and improve prediction performance.

5. Analysis of input significance

Significance analysis is important to tackle the issue of the 'Black-Box' associated with ML, i.e. lack of interpretability of internal work mechanism and identification of causal relationships (Adadi and Berrada, 2018, Ana and Bauwens, 2010, Allah Bukhsh et al., 2019). Olden et al. (2004) developed a method called Connection Weight Analysis (CWA). This approach achieves Interpretable ML (IML) by analysing individual model components (Molnar et al., 2020). It uses the generated weight to compare the relative significance of the input parameters (Olden et al., 2004). Tran et al. (2009) further developed CWA to make it applicable to multiclass output prediction. Table 5.4 lists the steps of CWA for an example network of 3 Hidden Neurons (HN) as described by Tran et al. (2009). Application of CWA is demonstrated in Chapter 6 to compare the significance of the input parameters towards the prediction. The results are then compared to the findings from the literature.

*Table 5.4. Steps for Connection Weight Analysis for input significance from NN*

| Step | Factor $X_j$ | $HN_1$ | $HN_2$ | $HN_3$ |
|---|---|---|---|---|
| 1 | Connection weights between the input factor $X_j$ and HN from NN code | $A_1$ | $A_2$ | $A_3$ |
| 2 | Connection weights between HN and the output neuron C from NN code | $B_1$ | $B_2$ | $B_3$ |
| 3 | Local Significance measure $Z_{j,c}$ of input factor $X_j$ to output neuron C | $Z_{j,c} = \sum_{i=1}^{3} A_i * B_i$ | | |

| | | |
|---|---|---|
| 4 | Overall significance measure $OZ_j$ of input factor $X_j$ to NN model | $OZ_j = \frac{1}{3}\sum_{c=1}^{3} abs(Z_{j,c})$ |
| Source: Reprinted with permission from Tran et al. (2009). | | |

The benefits of analysing significance of input variables are two-fold. From a decision maker point of view, interpretability and transparency of the model are crucial in order to invest trust in the output of any decision-aid tool (Allah Bukhsh et al., 2019). Furthermore, financial decisions related to asset inspection data collection can be informed by the identification of the prime input parameters with the greatest impact on model performance. It is therefore important to perform a significance analysis after training to enhance and tailor the model for future use. This back-feed is reflected in the proposed module flow chart (Figure 5.2)

### 5.3.3 Stage 3: Apply the chosen model for condition prediction

After training, testing and comparing the candidate algorithms, the best-performing algorithm is chosen for use in asset condition prediction. Records from regular inspection surveys of the drainage system are incorporated into the training dataset and the model is retrained to improve its prediction. Hence, ML for condition modelling is an iterative process in which the model performance continues to improve as more data is obtained from inspections.

## 5.4 Module 2: Flood modelling

This module enables scenario analysis of flood risk through the proposed use of 2D hydraulic simulations. Scenario analysis defines in detail the scenarios of risk sources and drivers to be considered and explores the implications of each scenario and associated risk (BSI, 2019b). The output is a reflection of how each scenario may turn out in terms of flood exposure (BSI, 2019b). The components of this module and the process used are shown in Figure 5.9. The 2D hydraulic simulation software provides a user-friendly, robust flood analysis through mathematically driven visual representation of flooding. This enables the understanding of the contribution of flood sources and drivers to likelihood of flood occurrence and to quantitatively assess a sites' level of flood exposure to various risk sources. The simulated flood risk is specified by risk sources and drivers. Risk sources are characterised by the storm event return period and duration, and the asset condition. Furthermore, detailed catchment representation and as-built asset properties are reflected in the developed model as drivers of risk. Further details of the approach are provided in the following subsections.

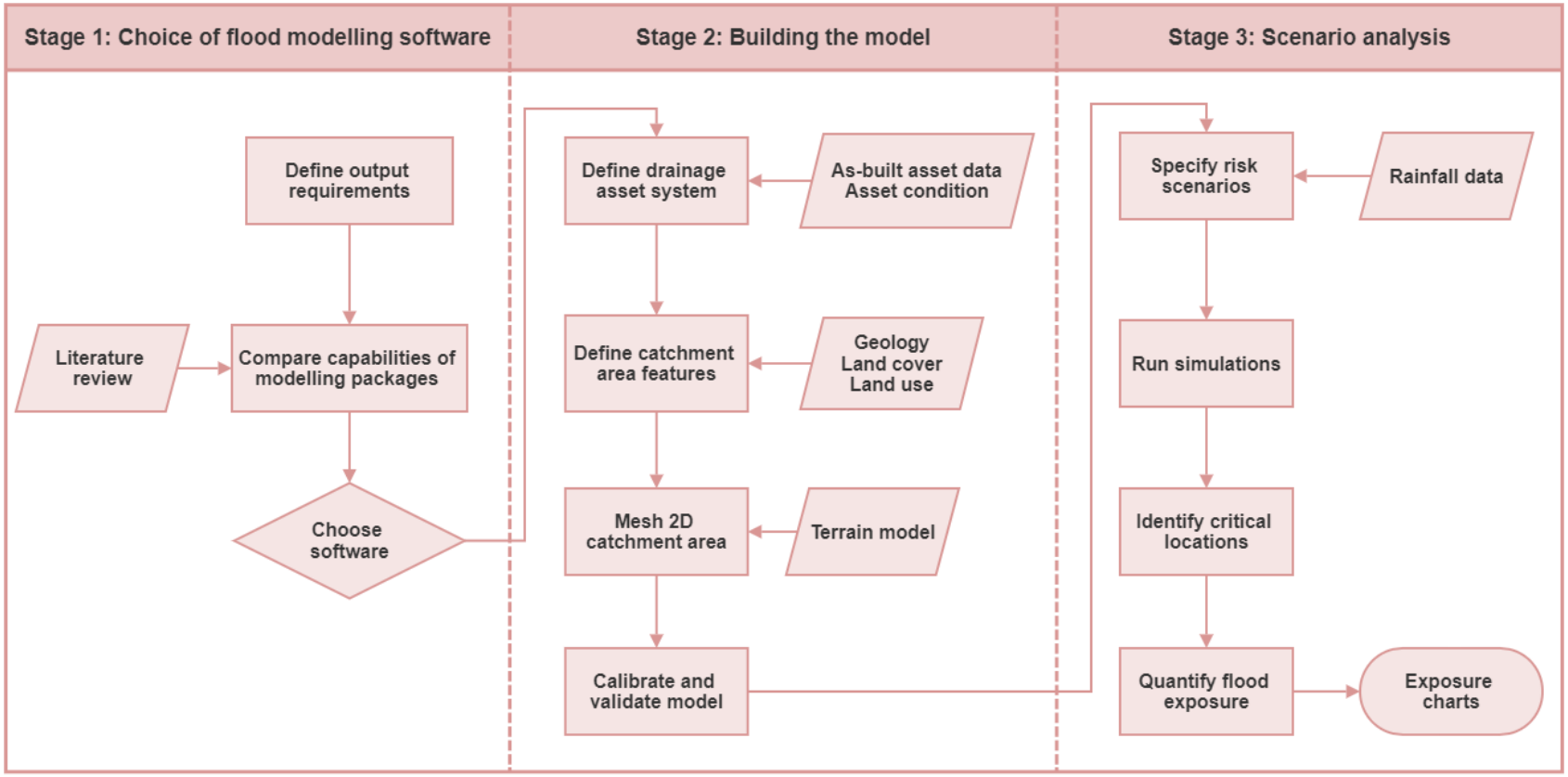



*Figure 5.9. Module 2: Flood modelling*

### 5.4.1 Stage 1: Choice of flood modelling software

1. Define requirements

The first step in choosing the modelling software is to define the required capabilities of the software, taking into account the objectives of the application. The railway drainage system is a complex system which consists of many types of drainage asset, are laid out in topographically diverse locations, and entails potential flood exposure of both track and off-track assets in addition to surrounding urban/rural areas. With this in mind, the following criteria are proposed as the main considerations for the accurate representation of the railway drainage system (Halff (2021)):

a. Dual drainage modelling: i.e. that which is capable of modelling both underground and surface drainage systems.
b. Coupled 1D and 2D modelling: able to combine the drainage of 1D flows with the 2D impact on surrounding floodplains.
c. Hydrograph routing: able to reflect how unsteady flow changes with time through the drainage and surface networks to simulate flood volume.
d. Geographic information system (GIS) integration: capable of using GIS data for meshing 2D terrain.

2. Compare capabilities of software packages

Halff (2021) conducted a software evaluation for a city-wide hydraulic modelling project. It included the following software packages:

- Innovyze Infoworks ICM (Innovyze, 2021a),
- Innovyze XPSWMM,
- CHI PCSWMM (CHI, 2021),
- DHI MIKE FLOOD (DHI, 2021),
- Bentley OpenFlows/Civil Storm (Bentley, 2021),
- Streamline Technologies ICPR-4 (Streamline Technologies, 2021),

- FLO-2D (FLO-2D, 2021).

Among these, the top performing packages according to a secondary screening were ICM Infoworks ICM, XPSWMM, and MIKE FLOOD which offer similar capabilities and cost while FLO-2D has less capabilities, but it costs significantly less than the other three. Infoworks ICM, and MIKE FLOOD offer flexible meshing which allows shorter simulation times compared to the rigid grid used in XPSWMM. While infoworks ICM offers higher GIS integration compared to MIKE FLOOD. A previous comparative study was performed in the UK by the University of Waterloo (Néelz and Pender, 2010) and suggested that Infoworks ICM stood out in terms of simulation run time. DEFRA (2021) also recommends Infoworks ICM as a widely-used software for modelling integrated urban drainage networks. Table 5.5 shows examples of studies using InfoWorks for various applications.

*Table 5.5. InfoWorks ICM applications*

| Publication | System | Application of InfoWorks ICM | Location |
|---|---|---|---|
| Wu et al. (2021a) | UDS | Hydraulic simulation of rainfall runoff and pollutants simulation using hydraulic and water quality models | China |
| Ferguson and Fenner (2020) | Rural and Urban drainage interface | Coupled hydraulic modelling using Dynamic TOPMODEL, HEC-RAS, and InfoWorks ICM models were used to simulate the response of surface watercourses to Natural Flood Management interventions. | UK |
| Bailey et al. (2020) | Sewer System | Evaluated the impact of reducing the amount of water used in households on sewer network water quality. | Netherlands |
| Russo et al. (2014) | UDS | InfoWorks ICM used to build a 1D/2D coupled model, simulating surface and sewer flows to investigate impact of climate change on flood risk assessment | Spain |
| Archetti et al. (2011) | Coastal storm sewer network | InfoWorks CS (now InfoWorks ICM) used to study the behavior of seaside sewer network, estimating the threshold condition for flooding and severity of flooding in order to generate flood probability charts. | Italy |
| Mahmoodian et al. (2018) | Wastewater Sewer system | InfoWorks ICM simulations used to build training and validation datasets to train and validate a data-driven emulator for a computationally expensive simulator. | Luxembourg |
| Ben et al. (2019) | UDS | InfoWorks used for simulations to develop an optimization model for Real Time Control of Urban Drainage System | Spain |
| Yang et al. (2021) | River basin | InfoWorks ICM is used to establish a 2D hydraulic model in a river basin to evaluate the waterlogging effect of the dispatching strategies of a deep tunnel construction project in the basin. | China |
| Cheng et al. (2017b) | UDS | InfoWorks ICM 2D used to investigate rainstorm flooding and carry flood risk zoning due to climate change | China |

In addition to satisfying the initial criteria, the following are the features which make Infoworks ICM an appealing choice for flood modelling in this research:

a. High GIS integration. It allows the import of GIS Shapefiles to create Digital Elevation Models (DEM).
b. Flexible meshing. It allows to vary the size of grid with the level of detail of the area which enables shorter and more efficient simulation runs.
c. Simulation interface. Hydrographs showing the combined inflow and outflow and flow elevations for every time step. It also shows the limiting 2D components and any nodes/links that are failing.
d. The SQL queries feature. Queries can be developed to select and modify individual network objects according to user-defined criteria. They can also be used to identify results that meet user-defined thresholds.
e. Applications. It provides the ability to model the complete natural and engineered above- and below-ground drainage system including sewers, surface water, rivers and floodplains (Innovyze, 2021b). Examples of this are summarised in Table 5. 5.

Based on the above Infoworks ICM is chosen as the most suitable software for 2D hydraulic modelling of the railway drainage system. The mathematical representation of two-dimensional (2D) flow is given by the depth-average Navier-Stokes equation, known as the Shallow Water Equations (SWE) (Innovyze, 2021b). SWE assume flow is predominantly horizontal and that the variation of the velocity over the vertical coordinate is neglected. The conservative (conservation of mass and linear momentum) formulation of the SWE used in Infoworks ICM is described by the continuity equation (Equation 5.9) and momentum equations (Equations 5.10 and 5.11). Further information on the 2D hydraulic theory used for Infoworks simulation engine can be found in Innovyze (2021b).

$$\frac{\partial h}{\partial t} + \frac{\partial (hu)}{\partial x} + \frac{\partial (hv)}{\partial y} = \sum_{i=1}^{n} q_i$$ *Equation 5.9*

$$\frac{\partial (hu)}{\partial t} + \frac{\partial}{\partial x}\left(hu^2 + \frac{gh^2}{2}\right) + \frac{\partial (huv)}{\partial y} - \frac{\partial}{\partial x}\left(\varepsilon h \frac{\partial u}{\partial x}\right) - \frac{\partial}{\partial y}\left(\varepsilon h \frac{\partial u}{\partial y}\right) = gh(S_{0x} - S_{fx}) + \sum_{i=1}^{n} q_i u_i$$ *Equation 5 10*

$$\frac{\partial (hv)}{\partial t} + \frac{\partial}{\partial y}\left(hv^2 + \frac{gh^2}{2}\right) + \frac{\partial (huv)}{\partial x} - \frac{\partial}{\partial x}\left(\varepsilon h \frac{\partial v}{\partial x}\right) - \frac{\partial}{\partial y}\left(\varepsilon h \frac{\partial v}{\partial y}\right) = gh(S_{0y} - S_{fy}) + \sum_{i=1}^{n} q_i v_i$$ *Equation 5 11*

*Where:*

*h is water depth (m),*

*u and v are the velocities (m/s) in the x and y directions, respectively,*

*$q_i$ is the ith net source discharge per area (m/s),*

*$u_i$ and $v_i$ are the velocities (m/s) in the x and y directions of the ith net source discharge, respectively,*

*g is gravity acceleration ($m^2/s$),*

*ε is eddy viscosity ($m^2/s$),*

*$S_{0x}$ and $S_{0y}$ are the bed (geometric) slopes in the x and y directions, respectively,*

*$S_{fx}$ and $S_{fy}$ are the friction (energy grade line) slopes in the x and y directions, respectively,*

*n is the number of source discharges.*

### 5.4.2 Stage 2: Building the model

After choosing a suitable software package, the 1D/2D hydraulic-hydrologic model shall be built using drainage asset data, catchment/floodplain characteristics data and rainfall data. The following describes each step undertaken to build the model.

1. Define drainage asset system

For accurate representation of the drainage system capacity, as-built properties and condition of individual assets shall be used to build the hydraulic model. As-built properties include asset length, material, shape, size, geographic location and gradient. These could either be imported directly from asset database in CSV format or manually created in the software interface.

Asset condition can be obtained from either the latest asset inspection records or from the condition modelling predictions obtained from module 1. The impact of asset condition shall be represented in the model in terms of changes to capacity, for example the degree of sedimentation or blockage in the asset. This can be informed by the standards or by expert opinion.

2. Define catchment area surface features

For a conservative representation of catchment runoff into the drainage system, flow shall be considered as coming from both the track as well as surrounding off-track areas. The surrounding areas can vastly vary in terms of land use, land cover and geologic features like soil and rock types as well as slope. All these properties affect the amount of runoff flowing into the railway drainage system (Goel, 2011). Therefore, it is important to reflect the variation in these properties within the study area. Ordnance Survey and Environment maps are to be imported to create zones within the study area based on land use. For a detailed depiction of the above-mentioned land characteristics and their impact on runoff and flood action, each zone is to be represented with an infiltration value and a roughness value which reflects land cover and land use. These values can be obtained from literature.

3. Mesh the 2D catchment area

The first step is to set the size of the catchment area. It can be arbitrarily set for a more conservative approach. However, the larger mesh will require longer simulation time. Expert judgment can help deciding which areas contribute to runoff into the system. Afterwards, ground elevation data is used to generate the 2D mesh for the catchment/flood zone. LiDAR is used to obtain the Digital terrain Model (DTM). DTM approximates the ground heights at specific unique 2D points in reference to geodetic surface. Higher resolution of DTM ensures higher accuracy of the output. Infoworks ICM meshes the 2D zones using flexible triangular mesh elements. The elevation of each mesh element is the average of the elevation points of the area it covers. If the mesh element is smaller than the resolution of the DTM then the elevation is determined based on the centroid location of the element (Innovyze, 2021b). For more efficient simulations, terrain sensitive meshing should be used. It adapts the size of the mesh elements to the level of detail or elevation variation of the location. this ensures the mesh picks up the smallest elevation variations for higher resolution while not increasing the number of elements in flat areas. The elevations combined with the infiltration and roughness features will significantly affect the behaviour of flow.

4. Calibration and validation of model

According to advice by DEFRA (2021) on 2D hydraulic modelling, calibration of the model requires previous recorded flood events against which the results of the model should be compared. The data should be obtained from existing records of flood extents, flood properties and aerial photography.

If calibration is not possible, due to lack of data, then the model performance should be validated using anecdotal data collected during past flood events or data collected from water-level gauges.

Infoworks ICM has a built-in engineering validation tool which enables to check network data consistency against expected engineering values. More on these rules are specified in Innovyze (2021b).

### 5.4.3 Stage 3: Scenario analysis

To harness the benefits of 2D hydraulic modelling for risk assessment, flood scenario analysis shall be conducted. A scenario is a combination of the possible values of the identified risk sources. The associated exposure is modelled using the 2D hydraulic model. In practice, the infrastructure manager should decide the scenarios to be tested for a comparative risk assessment or a What-If analysis of intervention schemes.

1. Specify risk scenarios

For flood simulation, the identified risk sources leading to a flood are the asset condition (C), the storm event duration (D) and storm event return period (S). The asset condition can either be informed by the asset database or by the condition modelling output from Module 1. Rainfall data is obtained from the meteorological databases in the country. Rainfall data can either be for a specific rainfall event or assigned using the design rainfall feature on Infoworks ICM. The design rainfall feature in Infoworks ICM offers statistical representation of characteristics of rainfall derived from analysis of actual rainfall records over many years (Innovyze, 2021b). The design rainfall generator feature requires the 5 year-1hour rainfall event and the rainfall ratio. Thereon, rainfall durations and return periods are specified. For the purposes of this research these were obtained from the maps provided in Wallingford (1981) for

the UK. The Wallingford procedure was developed in the 1970s and 1980s and relies on rainfall intensity studies published in the 1975. This included a national scale study of data from hundreds of rain gauges to create a map of rainfall intensities and characteristics for the whole of the UK. The use of the Wallingford Intensity-Frequency-Duration curves are recommended in BS EN 16933-2 for site-specific synthetic rainfall generation in the U.K. for flow simulation purposes. In fact, the Wallingford Rainfall profiles are built into many standard flow simulation packages in the UK, one of these is Inforworks ICM. In order to consider Climate change uplift, a Climate Change Allowance (CCA) is recommended to be applied according to BS EN 752.

2. Run simulations

A range of scenarios are created for different possible combinations of the sources. Simulations are run for multiple scenarios, changing one factor at a time. Each scenario is characterised by a storm intensity (S), duration (D) and asset condition (C). In practice, the scenarios should be decided by the infrastructure manager informed by the goal of the study.

The duration of a simulation is another important consideration to ensure time efficiency. To obtain a complete image of the flood exposure at a location, the duration of simulation depends on the time of concentration for an area, i.e., time required for the runoff to flow from the furthest point in the catchment to the drainage inlet. This can be investigated by simulation trials at a critical location and observing the duration it requires for the flood water to dissipate.

3. Identify critical locations

For a specific asset condition, the output of the software reflects the return period at which an asset fails to sustain the flow. The output also reflects the exposure to flooding at different return periods and durations. Based on the simulation output parameters, criteria should be defined against which a railway section can be established as ‘critical’. For example, these criteria can be the return period at which the asset floods, the volume of the flood or a combination of the two. The criteria should be customised based on the infrastructure manager’s standards, level of service and nature of application. The use of

2D hydraulic modelling enables the identification of multiple critical locations which can be followed by a comparative risk assessment of the damage consequence to inform infrastructure manager's intervention decisions as will be shown in the next modules.

4. Quantify flood exposure

Results from Infoworks ICM can be extracted from the simulation outputs in tabular format, reflecting the change in depth, speed, and volumes with each simulation time-step. Additionally, the results can be manually extracted from the visual interface replay of the simulation; this enables measurements of track flood lengths and areas of flood plains.

Each of these parameters are useful in monetary damage quantification as will be shown in module 3. However, for the purpose of exposure quantification, exposure parameters can be reflected using exposure charts. Exposure charts are visual summaries of the flood exposure parameters at each location versus associated storm event. At one site, multiple exposure charts are generated over the varied flood risk scenarios of asset condition and storm duration. They allow comparison of flood exposure between multiple locations. Exposure charts can be used to develop monetary damage charts as described in Module 3.

## 5.5 Module 3: Damage quantification

This module aims to translate the outputs from flood modelling into a structured, quantitative and easy-to-interpret graphical representation of monetary damage caused by the various tested scenarios. That is the consequence component of risk analysis. Exposure is the various types of measurable parameters obtained from the flood simulations (module 2). Whereas consequence is the economic damage incurred from flood exposure at the section. The translation of exposure into consequence is achieved through a cost model. Figure 5.10 provides an overview of the module. The steps entailed are described in detail in the following subsections.

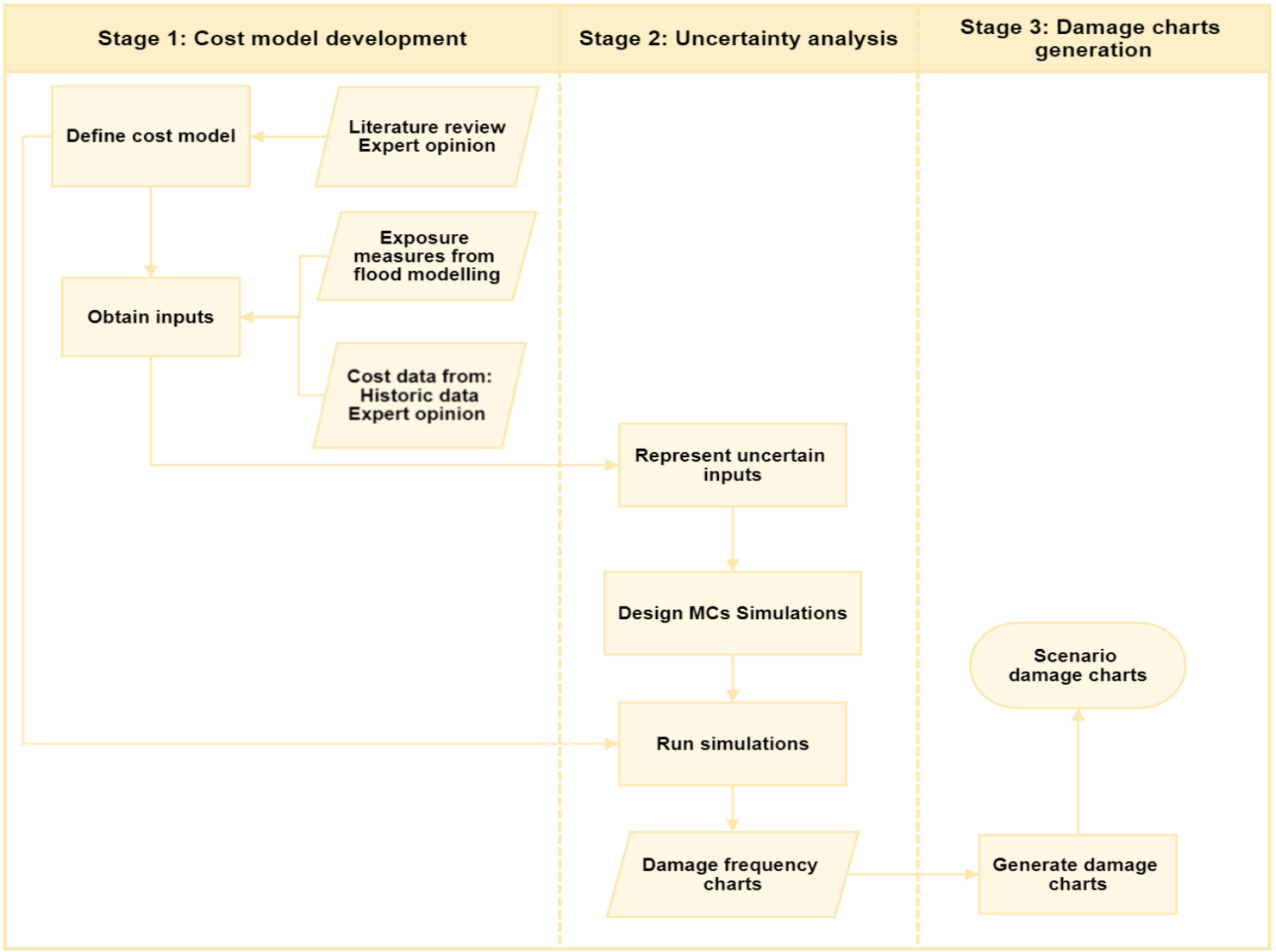



*Figure 5.10. Module 3: Damage quantification*

### 5.5.1 Stage 1: Cost model development

1. Define cost model

This work aims to provide a tool for infrastructure managers to inform their maintenance prioritisations in monetary terms. The cost model is the parametric relationship which translates the flood exposure from flood simulations into monetary damage consequences. The first step is to identify the party(ies) subject to the damage cost. This ensures consistency in perspective to ensure no costs are double counted. In this research, the theoretical cost model is developed to consider direct and indirect costs experienced by the infrastructure managers, third parties and the impact on environment.

Depending on space and time scales of flood exposure, damage can be either direct or indirect (Merz et al., 2010). According to a report published by CIRIA on asset management of railway drainage systems, flooding in the railway drainage system directly affects the performance and lifespan of other rail assets including: track structure, earthworks, signalling and communications (Spink et al., 2014). This incurs direct tangible M&R costs and indirect tangible damage to long-term deterioration of an asset over its lifecycle. Furthermore, drainage flooding can have direct tangible impacts on adjacent property like roads or other private property (Spink et al., 2014). From an operational perspective, a flooding incident can cause operational delays which have both tangible compensation costs and intangible reputational costs incurred by the infrastructure manager (Spink et al., 2014). Additionally, train derailment is a potential direct impact of flood associated with infrastructure rehabilitation costs and potential loss of lives. Lastly, indirect environmental pollution due to M&R activity and operational modal changes are additional impacts of inadequate drainage (Spink et al., 2014, Sasidharan et al., 2020). These costs are considered in the development of the costs model in this study. The most relevant and major proportion of costs from the viewpoint of the infrastructure manager would be M&R and operational disruption. Environmental and reputation costs are intangible, and their importance and quantification will therefore vary depending on priorities of stakeholders. Derailment costs could be orders of magnitude larger than the rest of the

costs. Therefore, if they were to be considered, they would need to be accurately estimated. where there is a substantial variation in size of costs it may be appropriate to separate the analysis of these costs. Equation 5.12 describes the general theoretical cost model proposed to study the damage caused by flooding in the drainage system in a certain section of the railway. This includes costs of incident inspections, M&R, operational disruptions, damage to off-track property, environmental and reputational impact.

$$\boldsymbol{Flood\ damage} = \boldsymbol{C_I} + \boldsymbol{C_{MR}} + \boldsymbol{C_{Op}} + \boldsymbol{C_{OT}} + \boldsymbol{C_R} \qquad \textit{Equation 5.12}$$

*Where,*
*$C_I$ is Cost of incident inspections*
*$C_{MR}$ is Cost of maintenance and repair*
*$C_{Op}$ is Cost of track operational disruption*
*$C_{OT}$ is Cost of off-track damage*
*$C_R$ is Cost of impact on reputation*

In the following subsections, each component of the general cost model is described in detail in terms of subcategories, cost elements and exposure parameters required for calculation.

a. Inspections

Inspection costs are the costs of deployment of inspection teams to the location of flood to investigate and assess the level of damage and required maintenance and renewal works on the flooded section. Costs of inspection consists of cost of equipment operation and cost of employees deployed (Sasidharan et al., 2020). Both are measured in units of length of flooded track. Equation 5.13 shows the inspections cost model.

$$\boldsymbol{C_I} = \boldsymbol{C_{I-E}} \times \frac{\boldsymbol{L_{FT}}}{\boldsymbol{L_{I-E}}} \times \boldsymbol{N_{I-E}} + \boldsymbol{C_{I-Eqp}} \times \frac{\boldsymbol{L_{FT}}}{\boldsymbol{L_{I-E}}} \qquad \textit{Equation 5.13}$$

*Where,*
*$C_{I\text{-}E}$ is cost of inspection employee per shift,*
*$L_{FT}$ is length of flooded track,*
*$N_{I\text{-}E}$ is number of inspection employees required,*
*$L_{I\text{-}E}$ is length covered by employees per shift,*
*$C_{I\text{-}Eqp}$ is cost of inspection equipment per shift*

b. Maintenance and repair

The costs of M&R interventions are split into cost of labour, materials and equipment, following the approach suggested by Rama and Andrews (2016). M&R interventions are associated with repairing flood damage to drainage systems , the track superstructure including dislodging and fouling of ballast, geometry degradation of track , softening of the track substructure, in addition to causing landslips and failures in points, signalling, electric and telecommunications (Cheetham et al., 2016, Johnston et al., 2021, Anbazhagan et al., 2012, Kaewunruen and Chiengson, 2018). Equations 5.14 to 5.20 provide the cost components for potential M&R activities triggered by a flood incident. The cost of M&R is given in terms of quantity of work required based on the spatial spread of flooding on track.

*Equation 5.14*

$$\boldsymbol{C_{MR} = C_{TSup} + C_{TSub} + C_{EW} + C_{SEC} + C_{D} + C_{MR-Env}}$$

*Equation 5.15*

$$\boldsymbol{C_{TSup} = C_{TSup-E} \times \frac{L_{FT}}{L_{TSup-E}} \times N_{TSup-E} + C_{TSup-Eqp} \times L_{FT} + C_{TSup-Mat} \times L_{FT} \times N_{TSup-Mat}}$$

*Equation 5.16*

$$C_{TSub} = C_{TSub-E} \times \frac{L_{FT}}{L_{TSub-E}} \times N_{TSub-E} + C_{TSub-Eqp} \times L_{FT} + C_{TSub-Mat} \times L_{FT} \times N_{TSub-Mat}$$

*Equation 5.17*

$$C_{EW} = C_{EW-E} \times \frac{L_{FEW}}{L_{EW-E}} \times N_{EW-E} + C_{EW-Eqp} \times L_{FEW} + C_{EW-Mat} \times L_{FEW} \times N_{EW-Mat}$$

*Equation 5.18*

$$C_D = \sum_{i=type\ of\ linear\ drainage\ asset}^{number\ of\ linear\ drainage\ assets\ affected\ by\ flood} C_{D-E} \times \frac{L_{FDi}}{L_{D-E}} \times N_{D-E} + C_{D-Eqpi} \times L_{FDi} + C_{D-Mati} \times L_{FDi} \times N_{D-Mati}$$

*Equation 5.19*

$$C_{SEC} = \sum_{i=type\ of\ SEC\ equipment}^{number\ of\ SEC\ equipment\ affected\ by\ flood} C_{SECi} \times N_{SECi}$$

*Equation 5.20*

$$C_{MR-Env} = \sum_{P=type\ of\ pollutant}^{number\ of\ pollutants} C_{Env-MRP} \times (V_{Env-TSupP} \times L_{FT} + V_{Env-TSubP} \times L_{FT} + V_{Env-EWP} \times L_{FEW} + V_{Env-DP} \times L_{FD})$$

*Where,*

$C_{TSup}$ *is cost of M&R for track super structure*
$C_{TSub}$ *is cost of M&R for track sub structure*
$C_{EW}$ *is cost of M&R for Earthwork assets*
$C_{D}$ *is cost of M&R for drainage assets*
$C_{SEC}$ *is cost of M&R for signaling, electric and communication assets*
$C_{MR\text{-}Env}$ *is the Environmental cost incurred due to the various M&R interventions*
$L_{FT}$ *is length of flooded track,*
$L_{FEW}$ *is length of flooded Earthworks,*
$L_{FDi}$ *is length of flooded drainage asset i*
$L_{TSup\text{-}E}$ *is length of superstructure M&R covered per shift*
$L_{TSub\text{-}E}$ *is length of superstructure M&R covered per shift*
$L_{EW\text{-}E}$ *is length of Earthwork M&R covered per shift*
$L_{D\text{-}E}$ *is length of Drainage M&R covered per shift*
$C_{TSup\text{-}E}$ *is employee cost of track superstructure M&R per shift*
$C_{TSub\text{-}E}$ *is employee cost of track Substructure M&R per shift*
$C_{EW\text{-}E}$ *is employee cost of Earthwork M&R per shift*
$C_{D\text{-}E}$ *is employee cost of drainage M&R per shift*
$C_{SECi}$ *is unit cost of SEC M&R for asset i*
$C_{TSup\text{-}Eqp}$ *is unit cost of track superstructure M&R equipment per unit length of flooded track*
$C_{TSub\text{-}Eqp}$ *is unit cost of track Substructure M&R equipment per unit length of flooded track*
$C_{EW\text{-}Eqp}$ *is unit cost of Earthwork M&R equipment per unit length of flooded EW*
$C_{D\text{-}Eqpi}$ *is unit cost of M&R equipment for drainage asset i per unit length of flooded drainage*
$C_{TSup\text{-}Mat}$ *is unit cost of track superstructure M&R Material per quantity*
$C_{TSub\text{-}Mat}$ *is unit cost of track Substructure M&R Material per quantity*
$C_{EW\text{-}Mat}$ *is unit cost of Earthwork M&R Material per quantity*
$C_{D\text{-}Mati}$ *is unit cost of M&R Material for drainage asset i per quantity*
$C_{Env\ MRP}$ *is unit volume cost of environmental pollutant P produced by M&R activity*
$V_{Env\ TsupP}$ *is volume of emission of pollutant P produced by Track Superstructure M&R activity per unit length of flooded track*
$V_{Env\ TsubP}$ *is volume of emission of pollutant P produced by Track Substructure M&R activity per unit length of flooded track*
$V_{Env\ EWP}$ *is volume of emission of pollutant P produced by Earthwork M&R activity per unit length of flooded earthwork*
$V_{Env\ DP}$ *is volume of emission of pollutant P produced by Drainage M&R activity per unit length of flooded drainage*
$N_{TSup\text{-}E}$ *is number of employees required for a Track Superstructure M&R intervention*
$N_{TSub\text{-}E}$ *is number of employees required for a Track Substructure M&R intervention*
$N_{EW\text{-}E}$ *is number of employees required for an Earthwork M&R intervention*
$N_{D\text{-}E}$ *is number of employees required for a Drainage M&R intervention*
$N_{TSup\text{-}Mat}$ *is quantity of material required for Track super structure M&R intervention per unit length of flooded track*
$N_{TSub\text{-}Mat}$ *is quantity of material required for Track sub structure M&R intervention per unit length of flooded track*
$N_{EW\text{-}Mat}$ *is quantity of material required for Earthwork M&R intervention per unit length of flooded earthwork*
$N_{D\text{-}Mati}$ *is quantity of material required for M&R intervention for drainage asset i per unit length of flooded drainage*
$N_{SECi}$ *is number of SEC asset i units requiring intervention*

It is important to note that when quantifying the M&R work required, it is necessary to consider the degree of damage to track. The unit cost components in the M&R cost equations are specific to the type

of intervention warranted. As multiple types of intervention are possible when costing M&R activities, the associated equipment intervention durations, materials, etc will depend on the level/degree of damage. For robust and accurate predictive estimation of damage cost, it is important to understand the degradation behaviour of various assets under flood exposure. Section 3.4.3 described this in more detail. However, development of degradation models is out of the scope of this research.

c. Track operations

A flood event obstructs the regular operations of trains on the railway track. The considered track operation cost refers to the costs associated with unplanned operational delays and cancellations due to the presence of water on track, planned closure cancellations for remediation interventions, environmental pollution resulting from potential change in transport mode when closures are warranted, and potential derailments. Equation 5.21 reflects these components. Equations 5.22-5.26 describe the calculations of each of these costs as may be incurred by the infrastructure manager. The probability of derailment can be determined from historical records based on the likelihood of a flood event to cause a derailment (Sasidharan et al., 2020). Cost of derailment should consider the damage to third party property and carried goods, loss of life and passenger injuries in addition to cost of rescue, delays, investigation and repair and renewal of track and rolling stock (Sasidharan et al., 2020).

*Equation 5.21*

$$C_{Op} = C_{UPD} + C_{UPC} + C_{PC} + C_{Op-Env} + C_{Der}$$

*Equation 5.22*

$$C_{UPD} = C_{Op-D} \times T_{Op-SR} \times N_T \times \left(\frac{L_{FT}}{S_R} - \frac{L_{FT}}{S_L}\right)$$

*Equation 5.23*

$$C_{UPC} = C_{Op-C} \times T_{Op-C} \times N_T$$

*Equation 5.24*

$$C_{PC} = \sum_{i=types\ of\ maintenance\ works} C_{Op-C} \times T_{MR} \times L_{Fi} \times N_T$$

*Equation 5.25*

$$C_{Op-Env} = \sum_{P=types\ of\ pollutant\ emissions} C_{Env-OpP} \times V_{Op-P} \times L_{Alt} \times N_T \times (T_{MR} + T_{Op-C}) \times \frac{N_{Pass}}{N_{Alt}}$$

*Equation 5.26*

$$C_{Der} = P_{Der} \times C_{Op-Der}$$

*Where,*

| | |
|---|---|
| $C_{UPD}$ | *is cost of unplanned operational delays due to presence of flood water on track* |
| $C_{UPC}$ | *is cost of unplanned operational cancellations due to presence of flood water on track* |
| $C_{PC}$ | *is cost of planned operational cancellations due to maintenance activity on track* |
| $C_{Op-Env}$ | *is cost of environmental pollution due to change of transport mode during track closures* |
| $C_{Der}$ | *is cost of derailment resulting from a flooding incident* |
| $C_{Op-C}$ | *is unit cost of compensation per cancelled train* |
| $C_{Op-D}$ | *is unit cost of compensation per unit time delay per train* |
| $C_{Op-Der}$ | *is cost of a train derailment incident* |
| $T_{Op-SR}$ | *is duration of track inundation where depth of water is above level warranting a speed restriction.* |
| $T_{Op-C}$ | *is duration of track inundation where depth of water is above level warranting a track closure* |
| $T_{MR}$ | *is track possession time for maintenance per unit length* |
| $N_T$ | *is number of trains passing the site per unit time* |
| $L_F$ | *is flooded length of asset i* |
| $S_R$ | *is restricted speed on track* |
| $S_L$ | *is regular track line speed* |
| $C_{Env-OpP}$ | *is unit cost of pollutant P per unit volume of emission* |
| $V_{Op-P}$ | *is volume of emission per unit length of alternative route per unit of alternative mode* |
| $L_{Alt}$ | *is length of alternative route* |
| $N_{Pass}$ | *is unit capacity of passenger train* |
| $N_{Alt}$ | *is unit capacity of alternative mode* |

d. Off-track damage

Off-track damage can be quantified using hydraulic simulations to determine the geospatial magnitude of the flood. Vinet (2008) categorised four types of off-track flood damage, namely damage to private property, damage to agriculture, damage to roads and damage to industries. These four categories are used to characterise the off-track damage in the proposed cost model, as shown in Equation 5.27. In addition the model also considers the environmental damage inflicted on surrounding waterbodies, e.g. pollution to a nearby local river due to a flood incident. The type of surrounding environment is used to decide the cost of damage incurred. Flooding onto a private property may result in compensation claims by the owners depending on the area flooded, type of property and its market value with consideration of depth and velocity of water covering the property (Vinet, 2008, Arrighi et al., 2020). Damage to crops on

farm land may incur compensation claims based on the area affected and level of damage experienced which depends on crop value, crop type, time of the year, inundation duration and flow velocity (Tapia-Silva et al., 2011, Merz et al., 2010). Damage to road networks entails damage which may be directly inflicted on the road pavement condition, electric, communication and water processing networks due to flood water presence (Vinet, 2008, Arrighi et al., 2021, Liang et al., 2022). Furthermore, flood water on the road networks result in costs incurred by the road users, which entail vehicle-related costs of detours, reduced speeds, poorer road condition, queuing at work zones, damage and accidents, in addition to travel time-related costs associated with detours, waiting at work zones and reduced speeds (Liang et al., 2022). Pregnolato et al. (2017) investigated the operational disruption caused by the presence of flood water on a road network through studying the relationship between flood depth, car speeds and flows. These traffic disruption may lead to road diversions and extended travel times (Arrighi et al., 2021). Therefore, given the spatial magnitude, duration and depth of flood water presence on the road network, the damage to road networks can then be estimated. Lastly, the quantification of direct impact to industrial facilities depends on the type of industry and is highly plant-specific with no standard function for damages (Merz et al., 2010). The inclusion of any of these off-track costs into the consequence analysis will depend on whether the asset owner incurs any tangible compensation costs for off-track flooding. Alternatively, if no tangible cost is incurred, the asset manager may choose to own and quantify these costs as part of a comprehensive impact analysis.

Equation 5.27

$$C_{OT} = C_{PP} + C_{Ag} + C_{RN} + C_{Ind} + C_{OT-Env}$$

*Where,*

| | |
|---|---|
| $C_{PP}$ | *is cost of damage to off-track private property* |
| $C_{Ag}$ | *is cost of damage to off-track agricultural land* |
| $C_{PN}$ | *is cost of damage to off-track road networks* |
| $C_{Ind}$ | *is cost of damage to off-track industrial property* |
| $C_{OT-Env}$ | *is cost of pollution damage to surrounding natural environment* |

e. Reputation

The reputational impact of flood events is an indirect and intangible impact. Loss of operational resilience affects people's as well as industries' willingness to use trains as a mode of transport and hence inhibits the sustainability goal for shift from car to train (Golightly and Dadashi, 2017). Loss of passengers and freight use directly impacts the amount of revenue and potentially loss of future funding by infrastructure managers' (Golightly and Dadashi, 2017). This is a highly intangible impact and quantification of this varies between infrastructure managers.

2. Cost model inputs

The developed theoretical cost model should be adapted and tailored according to the infrastructure manager's standards, costing units and predefined performance thresholds. For example, the threshold at which operational disruptions, i.e., closures or speed restrictions, are imposed. Availability of tangible costing data may be a limiting consideration when adapting the cost model. After customisation, exposure parameters are obtained for the various scenarios from the exposure charts generated in module 2. The unit costs of damage and relevant quantification parameters like M&R efficiencies can be obtained from historic records such as work orders, and expert elicitation.

### 5.5.2 Stage 2: Uncertainty Analysis

As part of risk assessment, uncertainties reflect the impact of potential variations in inputs parameters and model assumptions on the reliability of model output (BSI, 2019a). When it comes to describing uncertainty in risk, Vose (2008), and BSI (2019a) differentiate between the terms: uncertainty and variability. Uncertainty, or epistemic uncertainty, is described as the assessor's lack of knowledge which is reducible through further studies, measurements or consultation. Whereas variability, or stochastic uncertainty, is an inherent property of a system which occurs due to randomness and is not reducible (Vose, 2008). The associated likelihood of the stochastic property is referred to as probability. whereas the epistemic uncertainty is associated with subjective likelihood or, confidence. The uncertainties involved in total monetary risk quantification are the combined effect of uncertainties associated with the

cost parameters, the exposure measurements and the risk sources. In this research, the identified sources (condition, storm return period and event duration) are considered stochastic variabilities associated with random occurrence probabilities. Whereas uncertainties in costing parameters (due to lack of data) and those stemming from measurement errors, are considered epistemic uncertainties associated with likelihoods.

1. Uncertain inputs

All types of uncertainties can be represented with probability distributions (Vose, 2008). The type of probability distribution used depends on the type of uncertainty and availability of data. The following describes the main types of distributions that might be useful for the damage costing parameters considered in this study:

1. Normal distribution

This is a symmetric bell-shaped distribution centred around the mean where most values are located and distributed symmetrically according to a standard deviation. A normal distribution is commonly used to represent stochastically variable data. Measurement errors in engineering have been observed to closely follow a normal distribution (Vose, 2008).

2. Triangular distribution

The triangular distribution is a continuous probability distribution shaped like a triangle and defined by the minimum, most likely and maximum values a parameter can take. It is commonly used where data is scarce. According to Vose (2008), it is useful to model expert opinion and is commonly used to represent uncertainties in cost items. The PERT distribution is another three-point estimate distribution commonly used to model expert opinion (Elcheikh and Burrow, 2017).

3. Discrete distribution

It is a general type of function which describes a variable that can only take a specific discrete value with a specific probability. The sum of probabilities for all possible values should equal unity.

2. Tools for damage quantification

Monte Carlo simulations (MCs) is one of the methods proposed by BSI (2019a) for understanding the consequences and likelihood quantitatively. The MCs process entails iterative random sampling of each input distribution and performing calculations using a prespecified model to obtain a distribution of the model's output (BSI, 2019b). This process enables likelihood analysis of a failure event using historical data and the likelihood analysis of the consequences (BSI, 2019b). It is applicable where a set of input parameters interact to define an output and where the relationship between inputs and output can be expressed as a set of dependencies (BSI, 2019b). Furthermore, it enables the representation of uncertainty in input parameters and their propagation through the model (BSI, 2019b). The output can be a single value, or a probability or frequency distribution (BSI, 2019b). MCs also enables the identification of the main parameters within the model that have the greatest impact on the output (BSI, 2019b). Figure 5.11 shows a simplified overall reflection of MCs. The following are the advantages of MCs found relevant to the study's application (BSI, 2019a):

a. Employs a user-predefined mathematical model

b. Models input uncertainty and accommodates any (probability) distribution of input variation

c. Applied on readily available software like @RISK™ (Palisade, 2022).

d. Provides a statistically reliable quantitative output in the form of frequency charts

e. Provides statistical measures of output uncertainty, like standard deviation and confidence ranges

f. Allows sensitivity analysis to evaluate the impact of various input uncertainties on the output values

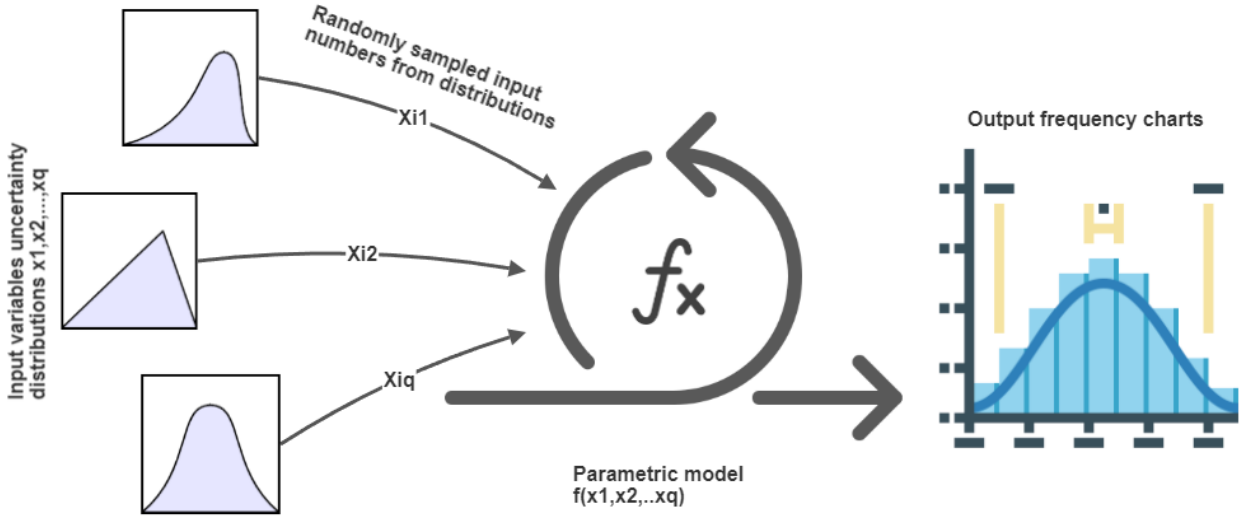



*Figure 5.11.* Schematic reflecting MCs

Tornado charts:

As part of uncertainty analysis it is important to observe the impact of variability in the inputs on the total output from the cost equation. For this purpose, tornado charts are a form of sensitivity analysis to deterministically observe the impact of input variability on the output (Dionisio, 2018). The following are the generic steps to develop tornado charts (Dionisio, 2018):

1. Define the nominal state of the output. That is the overall simulated average of the output.
2. Determine the high and low values for each input in the model. Each is represented with a double-edged horizontal bar.
3. Determine the likely outcome of the output based on the variation of one selected input, holding all other variables constant.
4. Rank the output averages on a horizontal bar from left to right. The lowest average value of output is on the left edge of the bar (input low) and the highest average output value is on the right edge of the bar (input high).
5. Return the first input to its nominal state, select the next variable, and repeat the process until all variables have been evaluated.

6. Display the results using the horizontal bars. The bars of the largest width, i.e., showing variables that have the greatest degree of variation from the nominal value on the output, at the top of the chart, and those with the smallest width, showing lowest impact, on the bottom of the chart. The outcome is shaped like a tornado, hence the name tornado diagram.

3. Design and run simulations

Figure 5.12 shows the generic procedure for an MCs application (O'Connor and Kleyner, 2012). The customised cost model developed in stage 1 is the used parametric model for running the simulations. For the damage quantification task, epistemic uncertainties are the relevant uncertainties to be considered, wherein the impacts of uncertain estimates of exposure and cost parameters on the estimated damage output for each risk scenario are evaluated. Therefore, each risk scenario of asset Condition (C), storm Duration (D) and Storm return period (S) is treated as a stand-alone MCs run. With the above in mind, individual simulations are designed to calculate damage associated with each scenario according to the following steps:

1. Define a suitable mathematical distribution of input uncertainty for both exposure and costing parameters. Exposure parameters from flood modelling simulations are scenario-specific; therefore, create a table/matrix to represent the exposure parameters for 'C×D×S' number of scenarios with their uncertainty distributions defined.

2. For the purpose of quantifying estimated damage for each risk scenario ($D_{C\text{-}D\text{-}S}$), create a matrix of cells for each individual C-D-S scenario. Each cell should contain the tailored cost model equations, with reference to the appropriate distribution of exposure and cost components relevant to the C-D-S scenario.

3. Determine a suitable number of simulation iterations. The number of simulations determines convergence and hence, the accuracy of the model; where more iterations achieves higher accuracy (O'Connor and Kleyner, 2012). Equation 5.28 gives an approximate calculation of the number of iterations required to achieve a certain error within a confidence interval.

*Equation 5.28*

$$Er(\mu) = \frac{Z_{\alpha/2}\,\sigma}{\sqrt{m}}$$

*Where,*

*Er(μ) = standard error of the mean. α = 1 − C, where C is the confidence level.*

*zα /2 = is the standard normal statistic.*

*σ = standard deviation of the output.*

*m = number of Monte Carlo runs.*

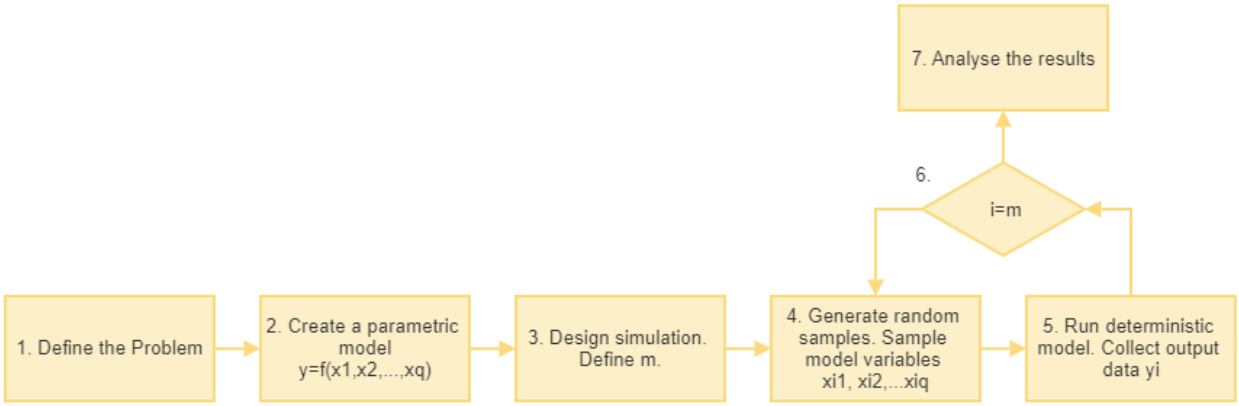



*Figure 5.12.* Monte Carlo simulation process (O'Connor and Kleyner, 2012)

The result from MCs runs in each C-D-S scenario cell represent the calculated damage for the scenario in the format of monetary damage frequency charts and associated output statistics. The latter include the mean, standard deviation, 5$^{th}$ and 95$^{th}$ percentiles and cumulative distribution function statistics. These can be used in stage 3 to generate damage charts as illustrated in Section 8.7.**5.5.3 Stage 3: Damage charts generation**

The damage output for each scenario produced from the MCs shall be used in the research to create damage charts of monetised flood damage ($D_{C\text{-}D\text{-}S}$) versus storm event Annual Exceedance Probability (AEP). Each chart is specific to a condition and storm duration, therefore C×D number of charts is generated. For each C-D damage chart, uncertainty envelopes are used to reflect uncertainty or confidence in the estimated damage to infrastructure managers. Using the output statistics from the MCS

damage frequency charts in stage 2, uncertainty envelopes are created around the mean value of damage, based on the standard deviation, $5^{th}$ and $95^{th}$ percentiles.

## 5.6 Module 4: Risk quantification

The damage quantification output from MCS runs is used to quantify risk at a certain location using the standard definition of risk (i.e. Risk = Probability × Consequence) mentioned previously. The probability is defined as the probability of the C-D-S scenario ($P_{C\text{-}D\text{-}S}$) given by the product of probabilities of each identified risk source, that is: asset condition (C), Duration of storm (D), Storm return period (S). Consequence is the quantified damage associated with the C-D-S scenario ($D_{C\text{-}D\text{-}S}$). In the damage quantification stage, damage of each C-D-S scenario is depicted in the damage charts with the mean value and associated uncertainty envelopes to reflect uncertainties. However, for risk quantification, a single-point value of damage is used. The following steps describe the calculation of risk:

1. Calculate the probability of each risk scenario, using Equation 5.29

*Equation 5.29*

$$P_{C-D-S} = P_C \times P_D \times P_S$$

*Where,*
$P_{C\text{-}D\text{-}S}$ *Probability of risk scenario C-D-S*
$P_C$ *Probability asset being in condition C*
$P_D$ *Probability of storm duration D*
$P_S$ *Probability of storm event of return period S*

2. Obtain Cumulative Density Function (CDF) 1st -99th percentile statistics from MCs output for each scenario's damage frequency charts.
3. Calculate the area under the frequency chart using CDF 1st -99th percentile statistics to obtain a single-point value of damage in which epistemic uncertainties are reflected, as shown in Equation 5.30.

*Equation 5.30*

$$D_{C-D-S} = \sum_{p=1\%}^{99\%} \left[P(D \leq d_P) - P(D \leq d_{p-1})\right] \times d_p$$

*Where,*
*P ($D \leq d_p$) is probability of damage is less than or equal to damage value at the $p^{th}$ percentile ($d_p$)*

*P ($D \leq d_{p-1}$) is probability of damage is less than or equal to damage value at the percentile preceding the $p^{th}$ percentile*

4. Multiply each calculated damage value ($D_{C\text{-}D\text{-}S}$) by the respective $P_{C\text{-}D\text{-}S}$ of the scenario.
5. To obtain total risk at a location in terms of economic damage, sum the products of individual scenario damage and its respective scenario probability across all C-D-S scenarios (Equation 5.31).

*Equation 5.31*

$$Flood\ Damage = \sum_{C-D-S} P_{C-D-S} \times D_{C-D-S}$$

The above method of risk quantification involves a large number of calculations to obtain the probability and the damage value for each individual C-D-S scenario. This task could be tedious when dealing with many flooding scenarios. To address this, an alternative design setup for MCs runs is suggested. The equations are setup to consider/incorporate the risk scenarios and their probabilities (stochastic variabilities) within the MCs simulations. The output of this approach is a total monetary risk frequency chart. This approach is suitable when running comparative risk assessment between multiple locations where only a total flood risk score is required and not flood damage charts. This method skips the damage quantification stage and carries on directly from the exposure quantification (Module 2). Both approaches are demonstrated in Chapter 8. The steps entailed in the proposed method are described below:

1. Define probability distributions for the risk sources C-D-S
2. Define a suitable mathematical distribution of input uncertainty for both exposure and costing parameters. Exposure parameters are scenario-specific; therefore, a table/matrix should be created to represent the exposure parameters for C×D×S number of scenarios with their uncertainty distributions defined.
3. Create a table of "If-Then" cost rules. The stochastic variabilities in the three risk sources constituting a scenario (C-D-S) and their respective probabilities are represented in the "If" term.

The epistemic uncertainties in exposure parameters and cost parameters are represented in the "Then" term, through definition of the parametric cost model. This ensures that during the MCs random generation of risk scenarios, the appropriate relevant exposure parameters are utilised for damage cost calculation, while also accounting for their epistemic uncertainties.

4. Specify number of iterations and run simulations.
5. Obtain the output cost distributions chart and the associated output statistics: Mean, Std. Dev., 5$^{th}$ and 95$^{th}$ percentiles.
6. Represent total risk in terms of economic damage (mean) and associated uncertainty envelope.

## 5.7 Summary

This chapter has described the developed risk-based framework for monetary risk analysis of railway drainage system at a component level. It describes in detail four modules that obtain the components required for the calculation of quantitative risk. Module 1 entails condition modelling for predictive modelling of drainage assets. Module 2 utilises flood modelling for robust engineering representation of flood exposure consequences and likelihood under the prespecified risk scenarios of asset condition, duration of event and storm intensity. Module 3 specifies damage quantification methods to understand the consequences in monetary terms and associated uncertainties through a comprehensive cost model. Module 4 describes the risk quantification method where the quantitative scores for consequences and risk scenario occurrence probabilities are combined to obtain a monetary risk score.

# Chapter 6: Condition modelling of railway drainage assets: A case study of pipe assets

## 6.1 Introduction

The devised risk assessment framework proposes the use of ML learning algorithms for data-driven condition modelling of drainage assets. This chapter investigates the suitability of multiple ML algorithms for condition modelling of railway drainage assets on a component level, through a demonstration of their use for condition modelling of railway drainage pipes in UK. The choice of only pipe assets is to provide focus for an extensive analysis within the time limitation of the project. The case study uses condition data provided by NR historic asset records as datasets for training and testing the algorithms. The study provides insight on the overall prediction performance as well as the performance in each individual condition class using a set of appropriate measures (Chapter 5). The tested algorithms are compared using AHP method (described in Chapter 5) to recommend an optimal ML algorithm for the condition modelling task. Furthermore, it tackles the issue of class-imbalance often observed in multi-class real asset networks. The study also addresses the issue of black-box or lack of interpretability associated with ML through a significance analysis of input parameters to inform data collection for future drainage asset records.

## 6.2 Methodology

To this end, the following describes the suggested steps for condition modelling of railway drainage assets.

1. Identify potential ML algorithms for condition prediction of rail drainage assets (Section 6.3).
2. Define measures for performance comparisons of algorithms (Chapter 5).
3. Construct case study data from rail asset database (Section 6.4).
4. Perform case study runs to test the proposed algorithms (Section 6.5).

5. Perform comparisons using predefined performance measures (Section 6.6 and Section 6.7).
6. Perform significance analysis of input factors (Section 6.8).

## 6.3 Description of tested classifiers

Following the literature review of condition modelling methods in Chapter 2, the theoretical framework (Chapter 5) nominates ML algorithms for condition modelling of railway drainage assets. Each of the following ML algorithms are tested and compared. Detailed descriptions of these classifiers are provided in Section 5.3.1.

- Neural Networks (NN) as a popular form of deep learning in recognising patterns between input and outputs (Dawood et al., 2018). In this study, 20 hidden neurons are found optimal.
- Decision Trees (DT) as a basic form of Tree-like models. The maximum number of decision splits for the decision tree training is set at 100.
- K-Nearest Neighbors (KNN) as a simple and powerful form of non-parametric model for large datasets (Parvin et al., 2008). After trials of different 'K' values, K value of three nearest neighbours is found to achieve acceptable results.
- Bagged Trees (BgT) as an ensemble classifier which uses bootstrapping and parallel learning. Multiple 'N' values are trialled, N=30 Learners is found enough to achieve an acceptable outcome.
- Adaptive Boosted Trees (BsT) as an ensemble classifier using sequential learning. In the case study, N=30 is found to achieve good results.

## 6.4 Case study data

The data used for case study is obtained from the UK Network Rail's (NR) drainage asset database 'DAMBUSTER'. The database records 88% of the rail drainage assets that NR manages in the UK (Wu et al., 2021b). The retrieved records are structured into 11 individual datasets, covering 11 routes from the main geographical regions in the UK, namely: Wales, Scotland, Wessex, Sussex, Western, Anglia,

Kent, East Midlands (EM), London North Eastern (LNE) and London North Western South coast (LNWS), London North Western North coast (LNWN).

The parameters recorded during routine inspections describe the physical structure of the assets, surrounding area, flow, and the condition score. Both service and structural conditions are assessed on a scale of '1' to '5'. Table 6.1 lists the description of the condition scores according to drainage asset inspection standards by NR. In this case study, conditions '3' and '4' are viewed as critical and condition '5' shows failure.

*Table 6.1. Structural and Service condition scores descriptions*

| Condition score | Structural description | Service description |
|---|---|---|
| 0 | Not inspected | Not inspected |
| 1 | No defects | Clear |
| 2 | Superficial defects | Superficial deposits |
| 3 | Minor defects | Performance slightly reduced |
| 4 | Major defects | Performance severely reduced |
| 5 | Not fit for purpose/unsafe | Blocked |
| Source: Adapted from NR (2018**).** | | |

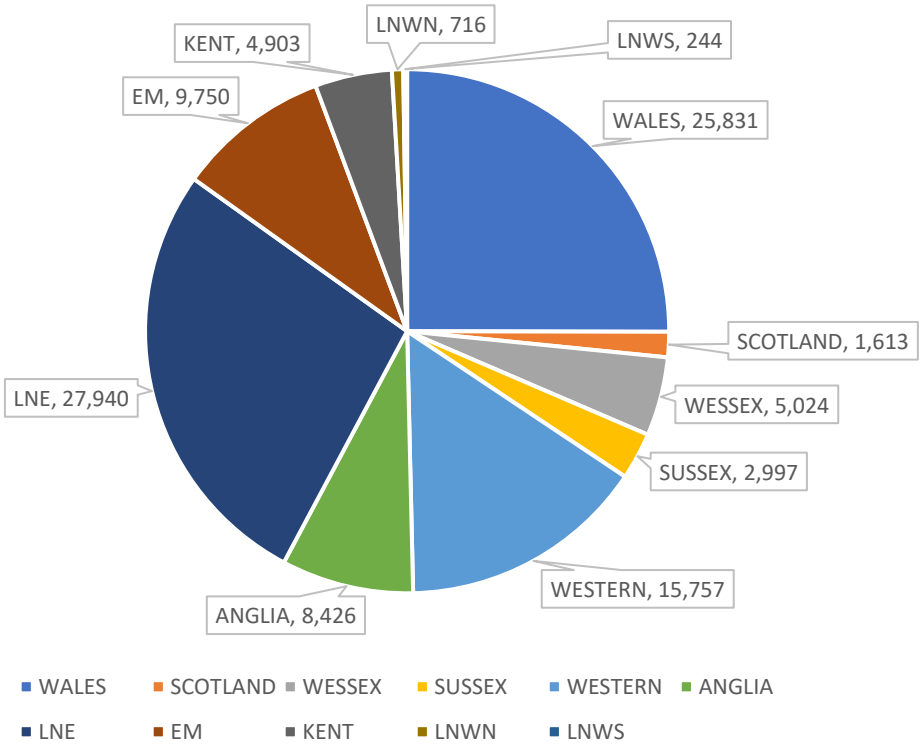
Since the focus of the case study is on prediction of pipe condition, only asset records identified as pipes are extracted to form the models' training datasets. The records examined span the period from 2010 to 2020, during which many assets have had multiple inspection entries with a range of conditions. Thus, a temporal dimension to the model inputs is provided. The parameters extracted from the records are length, type of effluent, topography, material, size, shape, service condition, structural condition, and date of inspection.

### 6.4.1 Data sets

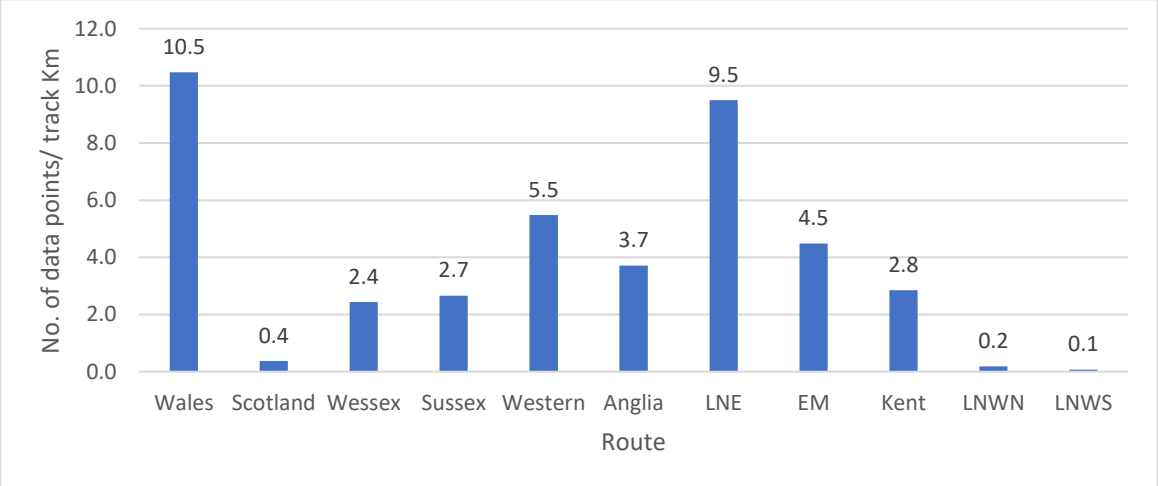
The total number of data points from the raw datasets for all the routes combined without filtering was 261,852 datapoints. In order to construct the datasets for analysis, the records obtained are filtered based on:

- Length: only use records of pipes that are equal or under 100m long. Due to the subjective nature of survey inspections, the inspector would survey consecutive pipes of the same observed condition as one continuous length. Therefore, the 100m cap is introduced on recommendation by NR expert on the common pipe lengths.
- Condition state: discard records with condition class '0', indicating the pipes were inaccessible for survey.

After filtering, two datasets are extracted from each route database: one is used for service condition prediction (SRVC) and the other for structural condition prediction (STRC). The datasets from the individual routes are combined into one large dataset of all routes. For STRC, the dataset consisted of 103,201 datapoints, that is 39% of the raw dataset. For SRVC, the dataset consisted of 123,799 data points, that is 47% of the raw dataset. This loss of data was due to elimination of duplicate records to get rid of subjective anomalies (as described in section 5.3.1), and the above rules for pre-processing. This reduced the number of data points for training the model. Figure 6.1 (a) and Figure 6.2 (a) show the sample size contribution of each route towards the collective dataset for STRC and SRVC, respectively. Figure 6.1 (b) and Figure 6.1 (b) show each route sample size divided by the total length of the route to reflect maturity of data collection on each route. Evidently, Wales is collecting the most mature at drainage pipes data collection. It is also evident that more service condition surveys take place than structural condition surveys, particularly on Sussex and Anglia.

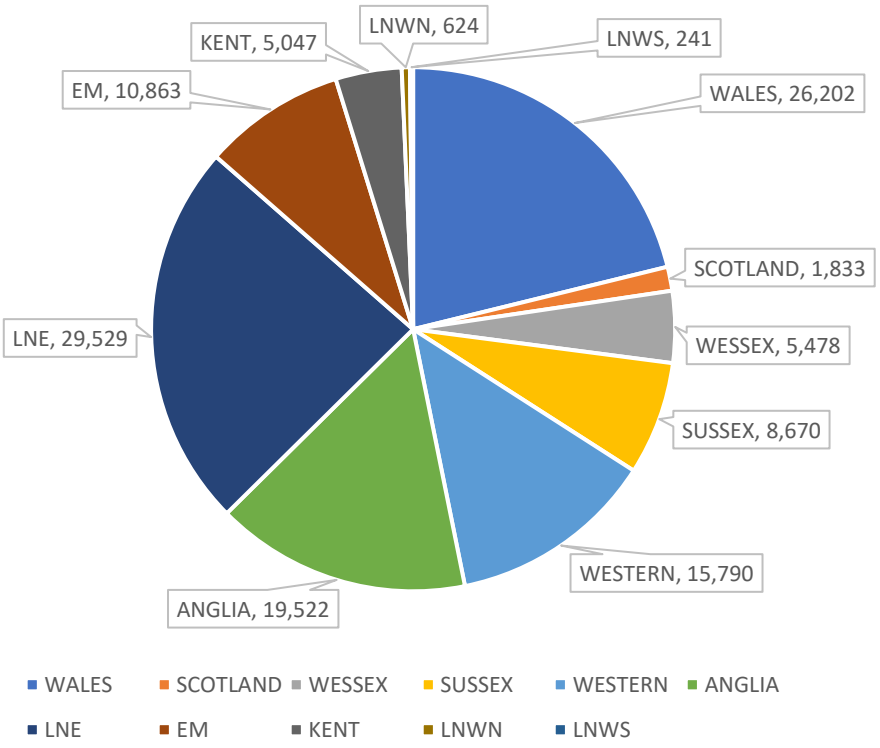



(a)

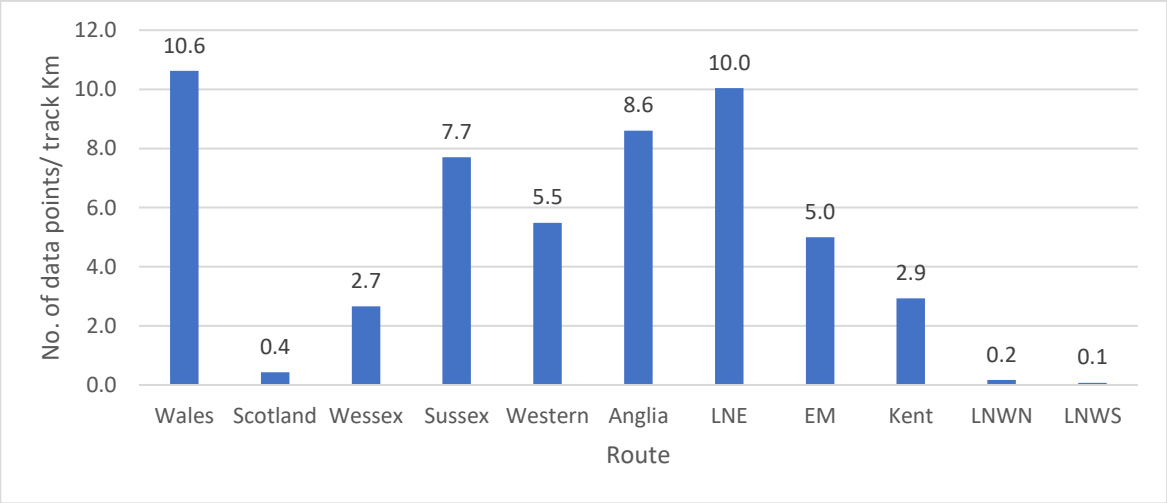



(b)

*Figure 6.1. (a) STRC Condition dataset sizes from 11 routes in U.K. (b) STRC No. of data samples per track Km for each route*




(a)




(b)

*Figure 6.2. (a) SRVC condition dataset sizes from 11 routes in U.K. (b) SRVC No. of data samples per track Km for each route*

### 6.4.2 Issue of class imbalance

As described in section 5.3.2, data imbalance has a major bias influence on the training process of ML algorithms. Previous pipe condition modelling studies have not yet addressed this problem in the datasets. Therefore, the imbalance issue is addressed in this study. Figure 6.3 and Figure 6.4 show the distribution of samples across the five condition classes for STRC and SRVC, respectively. The data imbalance is reflected in the distinct unequal split of samples across the five classes. Conditions 1 and 2 are over-represented while critical conditions 3, 4 and 5 are significantly under-represented in both service and structural datasets. The imbalance is fixed using the two proposed methods: Replication and SMOTe. Both methods can be applied using MATLAB R2020a (Michio, 2020). The impacts of both aforementioned over-sampling methods on prediction performance are compared to that of the unbalanced dataset.

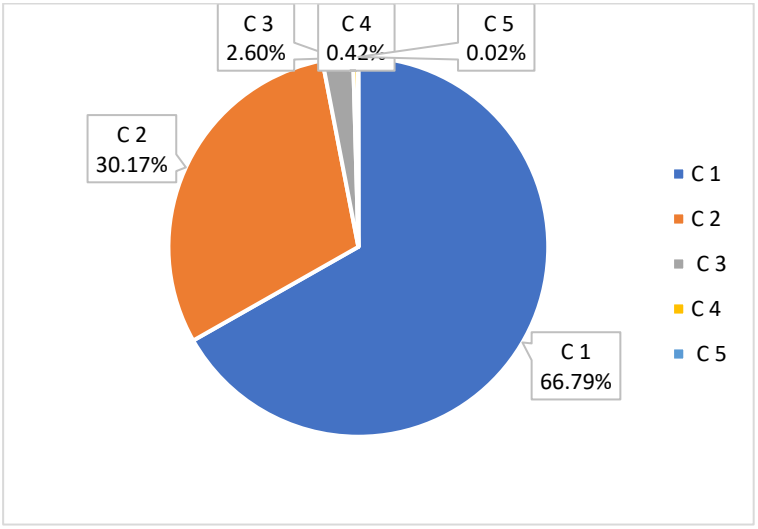



*Figure 6.3. STRC condition data distribution, where C1= no defects, C2= superficial defects, C3=minor defects, C4= major defects and C5= not fit for purpose/unsafe*

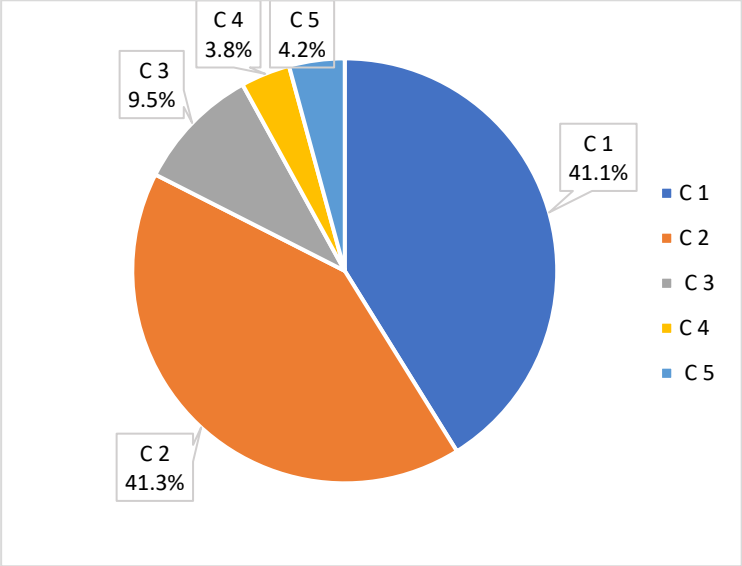



*Figure 6.4. SRVC condition data distribution, where C1= clear, C2= superficial deposits, C3= performance slightly reduced, C4= performance severely reduced and C5= blocked*

### 6.4.3 Inputs

After filtering, the following six basic inputs are directly extracted from database: 'Effluent', 'Topography', 'size', 'material' and 'shape'. These are all categorical variables except for length being a scale parameter, as shown in Table 6.2. Slope, tree count and soil type were considered as significant factors in previous literature (Tran et al., 2006, Tran et al., 2009, Baik et al., 2006, Wirahadikusumah et al., 2001, Davies et al., 2001a, Angarita et al., 2017, Micevski et al., 2002, Rokstad and Ugarelli, 2015). Including soil type as a prediction parameter would require either the collection of this data at the time of asset survey inspections or retrospectively identifying the parameter at the time of cleaning the data. The latter would require obtaining the soil maps and matching the location of the individual assets to the maps to identify soil types surrounding each asset. The same process would be required for tree count. Slope would require installation drawings of assets to be obtained and matched to the assets for the parameter to be specified retrospectively in the asset records. Due to the extensive effort that would be required to source these factors, these tasks were not pursued. Two additional parameters, 'Previous Condition' and 'Years since previous recorded condition' are derived from the data by matching asset ID and are used as inputs.

The temporal inspection data is used as proxy for age of an asset, if age is unknown, through treating the previous condition as an age reference point. Thus, the two factors 'previous condition' and 'years since previous condition' intrinsically account for the change in deterioration rate with age and initial condition. Finally, 'Maintenance' parameter is derived by comparing the derived 'Previous Condition' with the current condition for each record. The observed inconsistency is that for some records, the previous condition is worse than the current condition. In these cases, it is assumed that a 'significant' maintenance intervention took place between the two inspections which led to improvement in condition. Another explanation for such observation is the subjectivity in inspector's judgment. Furthermore, this assumption is not to eliminate the possibility that maintenance had taken place previously, in fact it could have taken place while maintaining the same condition. However, this cannot be confirmed due to the lack of relevant maintenance data in the UK. Therefore, for the purpose of this work the assumption is only made to explain discrepancies. 'Maintenance' is added as a dichotomous variable indicating whether maintenance is assumed to have taken place. A total of nine inputs are extracted, which are described in Table 6.2.

*Table 6.2. Input parameters used in case study*

| **Input** | **Description** | **Possible values** |
|---|---|---|
| Length | Scale | (0 m-100 m) |
| Effluent | Categorical (1-3) | 1; Surface water<br>2; Combined<br>3; Foul water |
| Topography | Categorical (1-3) | 1; At Grade<br>2; Cutting<br>3; Embankment |
| Size | Categorical (1-4) | Ranges between (<150 mm->451 mm) |
| Material | Categorical (1-11) | Steel, uPVC, Concrete, Cast Iron, Vitrified Clay, Pitch Fibre, Spun Iron, Asbestos Cement, lined Brick, Unlined Brick, other. |
| Shape | Categorical (1-4) | 1; Circle<br>2; Rectangle<br>3; Square<br>4; egg |
| Previous recorded condition | Ordinal (1-5) | 1, 2, 3, 4, 5 |
| Years since previous recorded condition | Scale | Number of years since the previous recorded condition<br>(0 if not matched) |

| | | |
|---|---|---|
| Maintenance | Dichotomous | 1; If condition improved since previous recorded condition |
| | | 0; If else |

## 6.5 Description of runs

A total of 30 training runs are performed, one for each combination of: classifier (out of five), type of prediction (service or structural) and data balance (unbalanced, balanced with replication, balanced with SMOTe). A comparison of the prediction performance results is discussed in Section 6.6. The datasets for NN are split into 60% training, 15% validation and 25% testing following the methodology adopted by Tran (2007), Liu et al. (2018), and Caradot et al. (2018), Moghtadernejad et al. (2021). The validation dataset is required as part of NN for 'Early-Stopping' of training to avoid over-fitting the model while updating the neural weights (Svozil et al., 1997). In DT, BgT, BsT and KNN, the validation dataset is the same one used for testing; therefore, datasets are split into 75% training and 25% hold-out as a test dataset, similar to the split used by Fathi et al. (2019), Asnaashari et al. (2013), Assaad and El-adaway (2020), Harvey and McBean (2014), and Xu and Sinha (2021). All the runs are performed using the Neural Net Pattern Recognition and Classification Learner toolboxes on MATLAB R2020a.

## 6.6 Prediction performance results and comparisons

Comparisons between the algorithms are based on prediction performance in each individual class. For each run, the overall accuracy, precision, recall and AUC for each class are obtained from the confusion matrix and ROC (Chapter 5). This section describes prediction performance comparisons between the classifiers and the data-balancing techniques based on the five measures.

### 6.6.1 Overall accuracy

Figure 6.5 and Figure 6.6 show the comparison of accuracy across the runs for STRC and SRVC, respectively. Structural prediction models generally perform better than service prediction models. This

indicates that the input parameters are more pertinent for structural condition prediction. More on this is discussed in Section 6.8. The highest accuracy for structural condition is attained by BsT, using the balanced dataset, which is 88% while for service condition it is 72%.

Before balancing, all classifiers perform within +/- 10% of the same accuracy. After balancing, NN seems to be the most affected by balancing techniques where the overall accuracy reduces significantly. As the data becomes evenly distributed among classes, each class has an equal contribution towards the calculation of overall accuracy. Therefore, post-balancing accuracy is considered a better representative of the actual prediction ability of the model. The reduced accuracy show the masked underperformance of NN pre-balancing. Alternatively, DT, BgT and BsT maintain the same accuracy performance when using the balanced by replication dataset. When using SMOTe balancing, all classifiers except KNN exhibit a slight reduction in accuracy. KNN however experiences a slight increase in overall accuracy when using replication and maintains around same accuracy when using SMOTe. BsT shows highest performance both before and after balancing. This reflects the sophistication of ensemble classifiers as a result of collective learning and reduced variance. Wu et al. (2015) also observed superior performance of ensemble classifiers for pipe classifications over single models for pipe defect classification. Perhaps the insignificance of the observed change in accuracy of DT, BgT and BsT after balancing implies high resilience of Tree-based classifiers when subjected to unbalanced datasets. The inconsistency in post-balancing behaviour between NN and the other classifiers indicates that NN is more sensitive to class imbalance in the training dataset

The consistent performance and resilience of KNN may be explained with it being a ‘lazy classifier’ (Perrizo et al., 2002a). While ‘Lazy’ classifiers do not entail a training process, they use a richer hypothesis space compared to ‘eager classifiers’ which make predictions using the trained generalised single-hypothesis model (Shreemali et al., 2021).

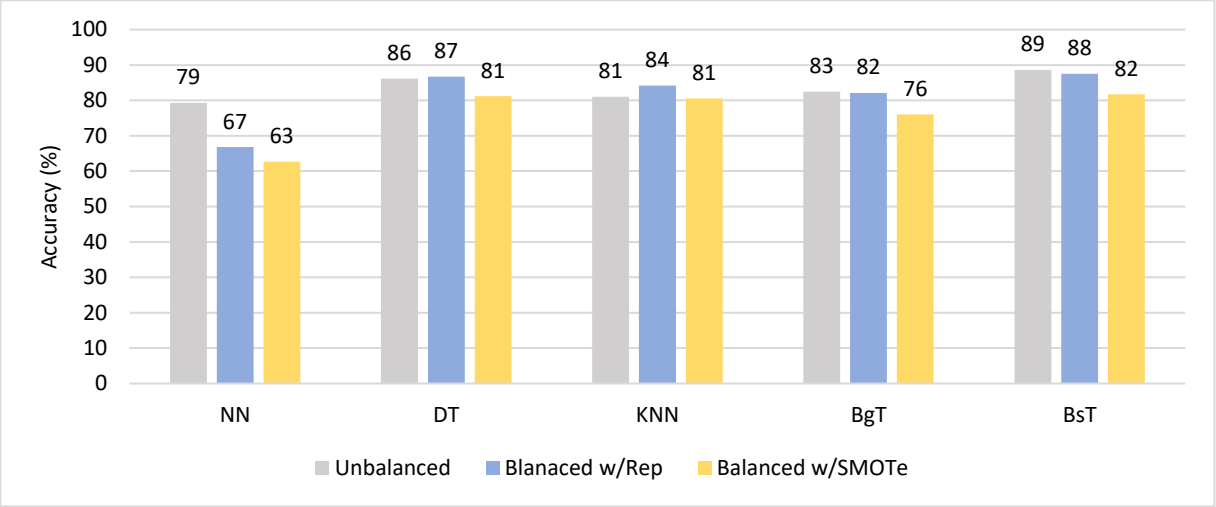



*Figure 6.5. STRC Overall Accuracy comparison between unbalanced, balanced with replication (w/Rep) and balanced with SMOTe (w/SMOTe) datasets among five ML algorithms: NN, DT, KNN, BgT, BsT*

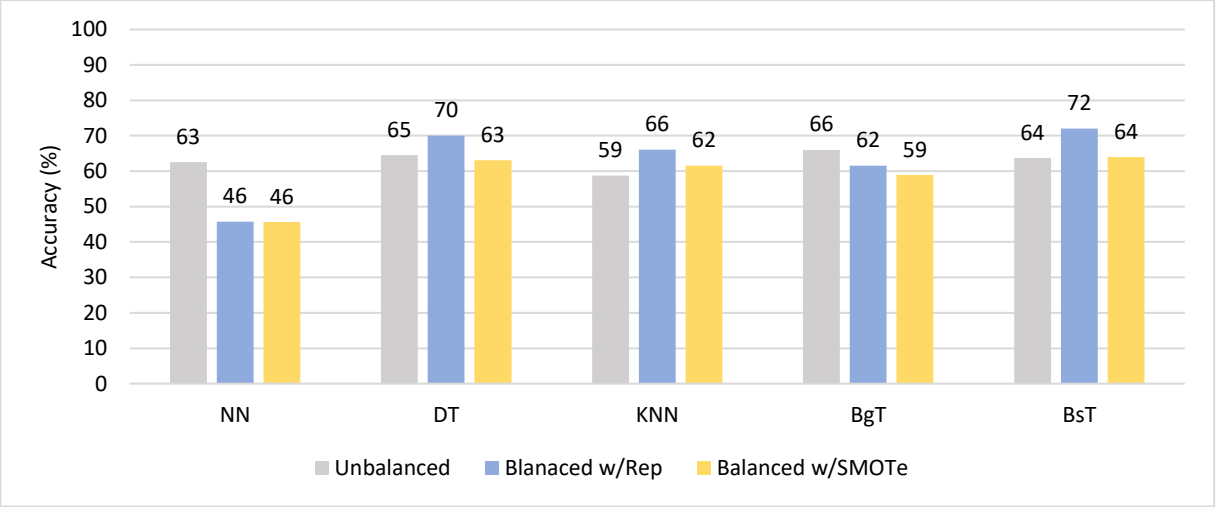



*Figure 6.6. SRVC Overall Accuracy comparison between unbalanced, balanced with replication (w/Rep) and balanced with SMOTe (w/SMOTe) datasets among five ML algorithms: NN, DT, KNN, BgT, BsT*

### 6.6.2 Recall

Recall gives insight into the performance at an individual-class level. Figure 6.7 and Figure 6.8 demonstrate the change in Recall rates at a class-level for STRC and SRVC, respectively. Results show that for unbalanced runs, Recall rates of classes 3, 4 and 5 are significantly lower than the rates for classes 1 and 2. Thus, highlighting the unreliability of overall accuracy as a performance measure when class imbalance is present. From an asset management point of view, high Recall of pipes in critical

condition is crucial. Since the critical classes are the minority group 3, 4 and 5, the imbalance-induced low Recall is emphasised as a deficiency in the model. The highest Recall for STRC, prior to balancing, is in class 1, which makes up to 67% of the data distribution (Figure 6. 7). Similarly, for SRVC, the highest Recall is in classes 1 and 2, with a smaller gap between the two because the class distribution is more even (Figure 6. 8).

After balancing, the recall rates for classes 3, 4 and 5 increase drastically. The increase is larger when using replication. However, bearing in mind the identical nature of generated samples using replication compared to the synthetic new data generated with SMOTe, the model is therefore less likely to over-fit with SMOTe. Chawla et al. (2002) demonstrated this conclusion through a DT application by visually comparing the decision regions created with both replication and SMOTe. The synthetic examples cause the classifier to create larger and less specific decision regions, allowing better generalisation of model (Chawla et al., 2002). Hence, SMOTe is likely to produce a more realistic and reliable model than replication.

Conversely, Recall for class 1 reduces after balancing. Although, KNN displays a smaller reduction in post-balancing Recall for condition 1 than BsT and DT, all four classifiers demonstrate the same net level of post-balancing Recall for classes 1 and 2. KNN, BsT and DT's consistently high Recall rates across the classes suggest they are the best performing classifiers.

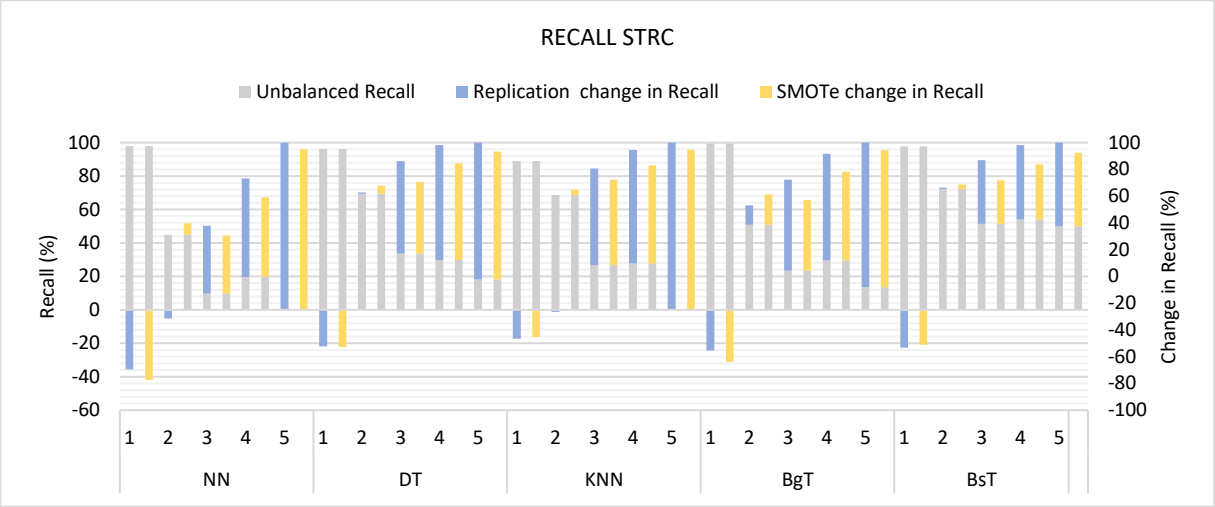



*Figure 6.7. STRC Recall comparison for five class (1-5) among five ML algorithms: NN, DT, KNN, BgT, BsT*

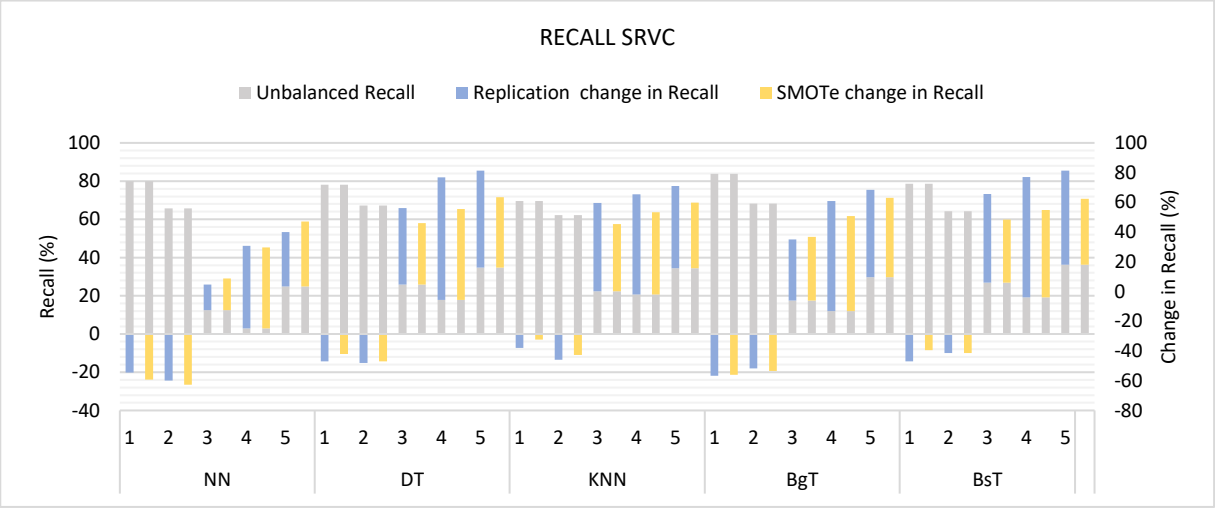



*Figure 6.8. SRVC Recall comparison for five class (1-5) among five ML algorithms: NN, DT, KNN, BgT, BsT*

### 6.6.3 Precision

Comparison of precision for STRC shown in Figure 6.9, indicate that post-balancing precision reduces significantly across the five classes for NN, DT, BgT and BsT. KNN experience minor drops in class 1 and improvement in classes 3, 4 and 5. The drastic precision improvement in condition 5 for STRC may be caused by the lack of test samples in STRC 5 pre-balancing. Consequently, no frame of reference existed for the change in precision of STRC 5 post-balancing. On the contrary, SRVC predictions (Figure 6.10) using DT, KNN, BgT and BsT experience different patterns from STRC, more like those observed

in recall comparisons. SRVC precision reduces for classes 1 and 2 (the overrepresented) and improves for critical classes 3,4 and 5. Looking at the pre-balancing precision rates, STRC predictions observe exceptionally high precision rates compared to SRVC predictions. This could be a misleading precision rate possibly caused by the larger class imbalance in the STRC dataset (Figure 6.9) compared to SRVC dataset (Figure 6.10). Looking at the post balancing precision for STRC and SRVC, balancing closes the large gap between the pre-balanced precision rates between STRC and SRVC predictions, i.e. the achieved precision by each algorithm is equal between the two types of prediction. Therefore, balancing helped deliver a more credible and representative precision rate.

The observed reduction in precision and improvement in Recall (Section 6.6.2) for critical classes 3 and 4, reflects a trade-off dilemma between the two measures. From a risk point of view, the ability of the model to identify more of the critical pipes (high risk of failure) bears more advantage than the disadvantage of false alarms. Whereas, from a financial viewpoint, false alarms incur higher costs associated with unnecessary inspections. Therefore, the models should be enhanced to achieve a balance of high precision and high Recall. To further analyse this, F-score is used as a representation of the two.

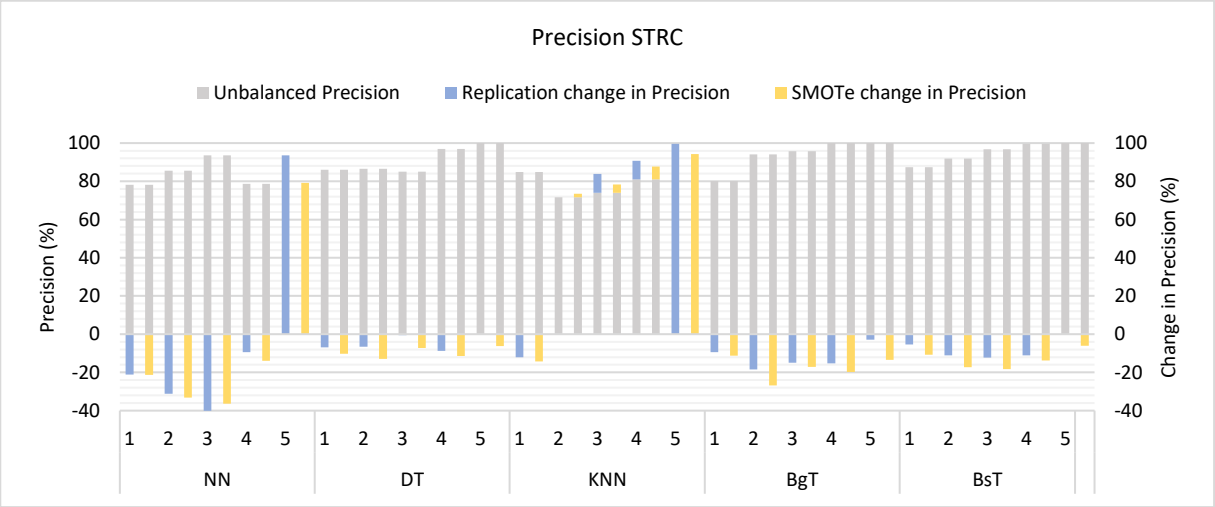



*Figure 6.9. STRC Precision comparison for five class (1-5) among five ML algorithms: NN, DT, KNN, BgT, BsT*

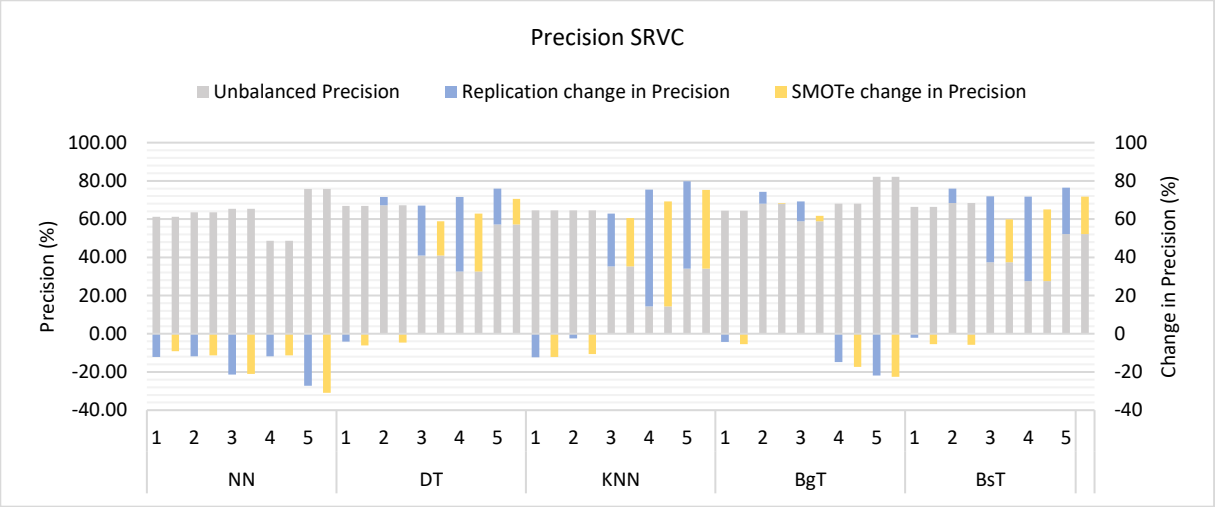



*Figure 6.10. SRVC Precision comparison for five class (1-5) among five ML algorithms: NN, DT, KNN, BgT, BsT*

### 6.6.4 F-Score

F-score provides a good representation of the model performance by combining both precision and Recall (Sokolova and Lapalme, 2009). Figure 6.11 and Figure 6.12 show F-score for STRC and SRVC conditions, respectively. Across all classifiers, balancing results in a slight reduction in F-score for classes 1 and 2. Whereas it has increased the F-score for classes 3, 4 and 5. It can be therefore concluded that balancing increases individual class predictive performance. The highest performance is observed by BsT. For STRC, F-scores are 87%, 93% and 99% for classes 3, 4 and 5, respectively. For SRVC, F-scores for the three critical classes are 72%, 77% and 81%, respectively.

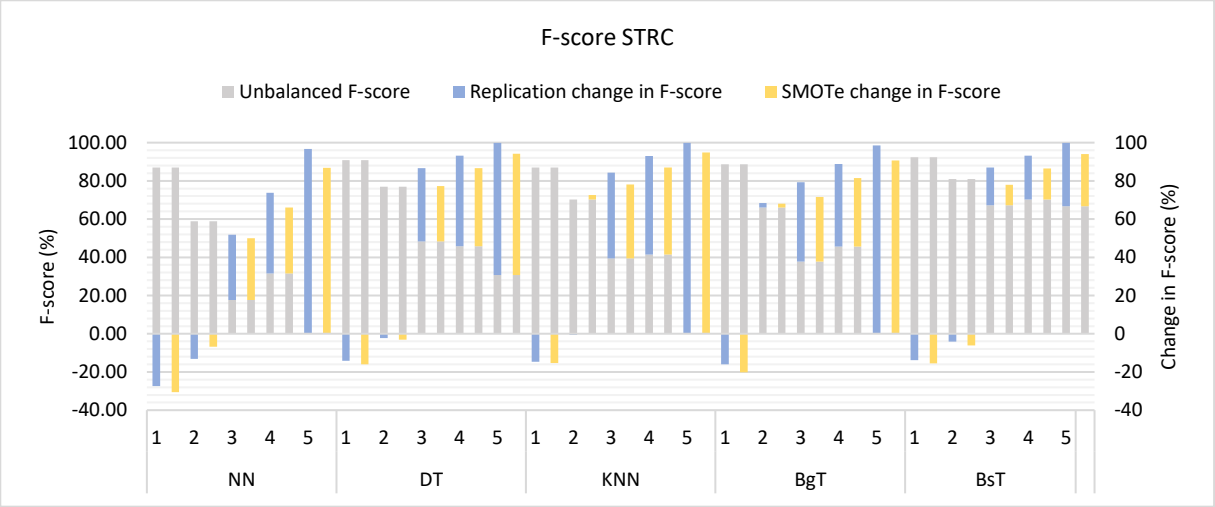



*Figure 6.11. STRC F-score comparison for five class (1-5) among five ML algorithms: NN, DT, KNN, BgT, BsT*

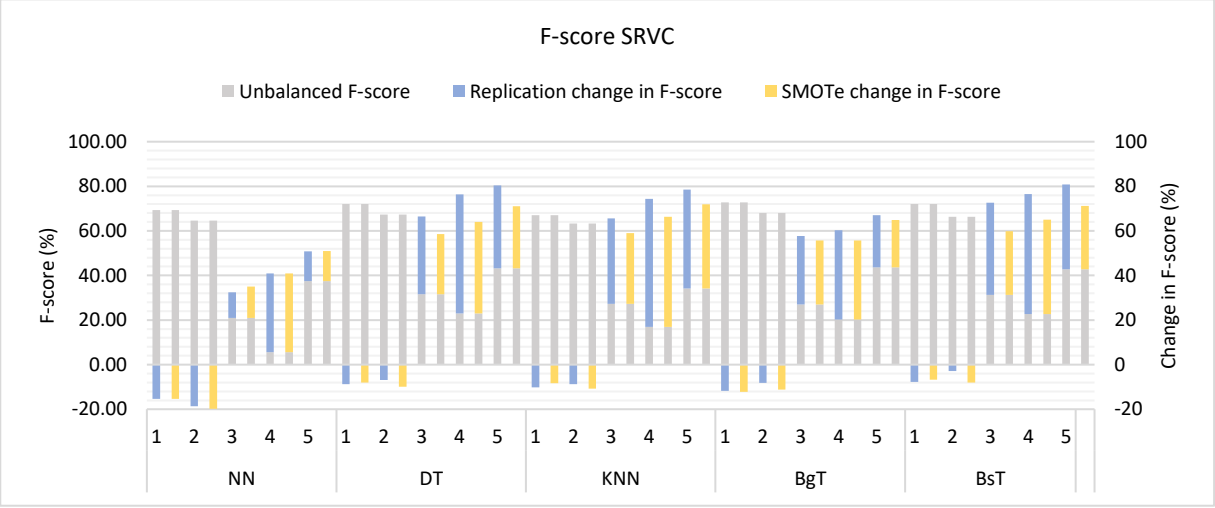



*Figure 6.12. SRVC F-score comparison for five class (1-5) among five ML algorithms: NN, DT, KNN, BgT, BsT*

### 6.6.5 AUC

AUC for each class for STRC is shown in Figure 5.18 while for SRVC, it is shown in Figure 5.19. In STRC models, AUC improves across all classes after balancing. The improvement indicates that balancing reduces the randomness in classification for all classes. This is especially interesting for classes 1 and 2 where the Recall rates reduce after balancing (Section 6.6.2) while AUC improves. This could possibly indicate that there is some level of randomness in classification with the unbalanced set. Rokstad and Ugarelli (2015) specifies that AUC less and equal to 0.5 characterises a random

classification. Harvey and McBean (2014) proposes 0.8 as threshold for an 'excellent classifier'. In light of this, comparing AUC for the different classifiers after balancing shows BsT to exhibit the highest performance, especially for critical classes 3, 4 and 5.

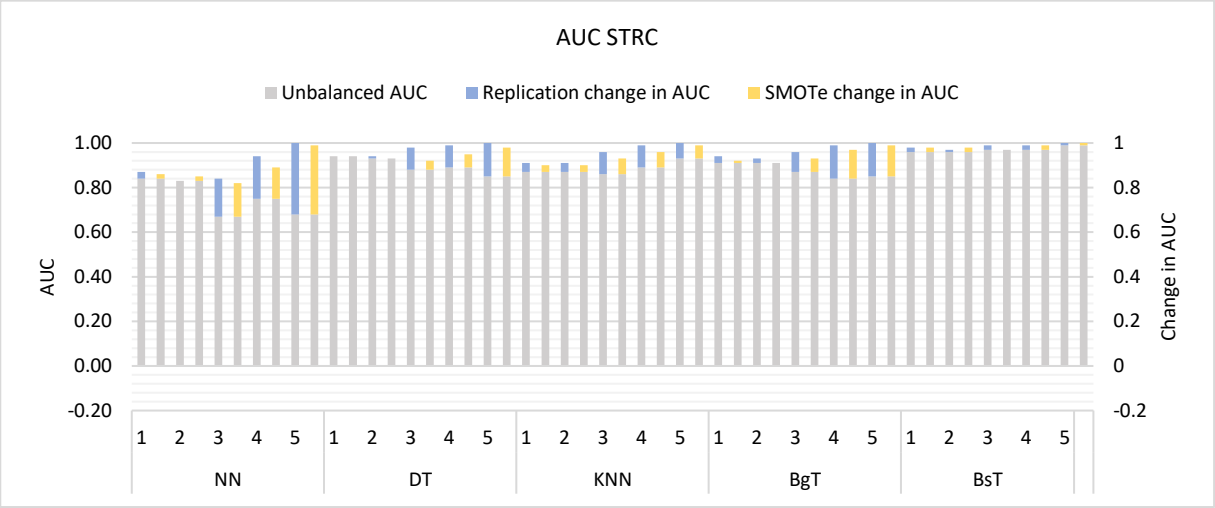



*Figure 6.13. STRC AUC comparison for five class (1-5) among five ML algorithms: NN, DT, KNN, BgT, BsT*

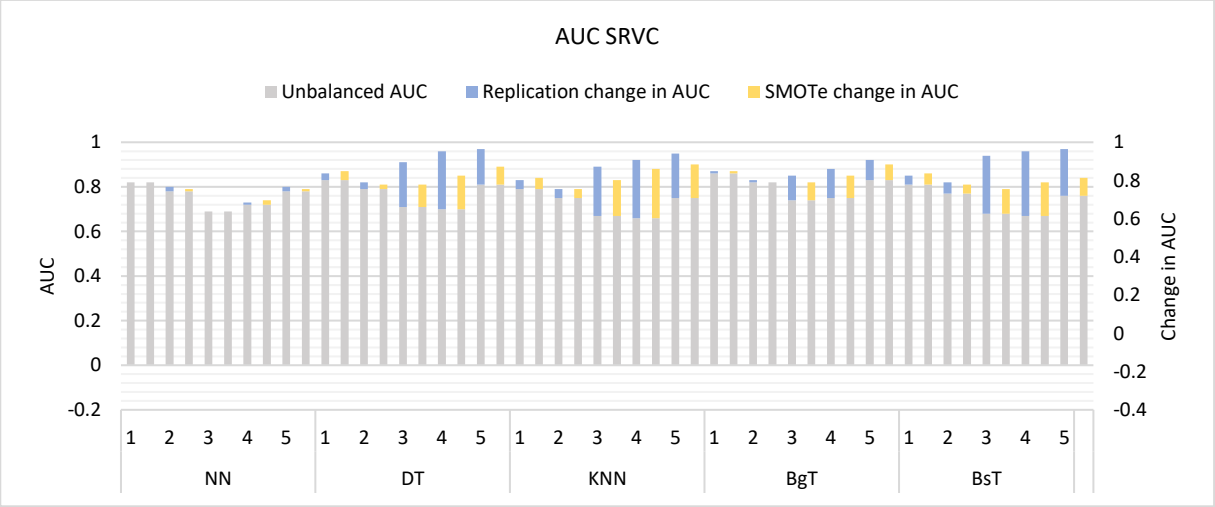



*Figure 6.14. SRVC AUC comparison for five class (1-5) among five ML algorithms: NN, DT, KNN, BgT, BsT*

## 6.7 AHP Performance evaluation

Prediction performance measures (Accuracy, Recall, precision, F-score, AUC) provide an insight into prediction performance at individual class level. In order to compare algorithm performance, multiple criteria is considered using Analytic Hierarchy Process (AHP) proposed in Chapter 5. This section is

an application of the AHP process for performance evaluation among the classifiers. The performance evaluation metrics chosen to compare the candidate algorithms are:

- Prediction performance
- Training speed
- Handling large datasets
- Ability to produce probabilistic output
- Interpretability
- Avoiding overfitting

As part of AHP, the above-mentioned metrics are used in a pairwise comparison to evaluate the relative importance of each parameter, as shown in Table 6.3. The normalised scores are shown in Table 6.4. 'Prediction performance' is considered the main judgment criteria for adoption of the algorithm, therefore it is allocated the highest importance. The 'ability to model large dataset' is an important consideration when dealing with thousands of drainage asset conditions and over-the-years records. 'Speed' is also an important consideration for efficiency of asset management decision processes. Since this work is aimed to be incorporated as part of a risk assessment framework, uncertainty in the algorithm output should be factored. Therefore, the 'ability of the algorithm to produce a probabilistic output' is introduced as a judgment criterion. 'Interpretability' and 'avoiding overfitting' are given equal importance because there usually is a trade-off between the two; complex model structures which avoid overfitting normally have poor interpretability (Wang, 2019). Table 6.5 illustrates the consistency check for the pairwise comparison. Since consistency ratio (CR) <0.1, consistency is acceptable.

Each algorithm is allocated a score for each performance metric on a scale of 1-4, as done by (Wang, 2019). The scores for prediction performance and training speed are allocated based on the overall accuracy and training times output from the training and testing runs of the SMOTe-balanced dataset. The achieved accuracies and training speeds are converted to the 4-level scale, shown in Table 6.6. The

scores for modeling large datasets, probabilistic output, interpretability and avoiding overfitting are allocated based on review of each algorithm's structure and modelling approach.

*Table 6.3. Pairwise comparison of performance metrics*

| A \ B | Prediction performance | Training speed | Model large dataset | Probabilistic output | Interpretability | Avoid overfitting |
|---|---|---|---|---|---|---|
| **Prediction performance** | 1 | 3 | 3 | 5 | 7 | 7 |
| **Training speed** | 0.33 | 1 | 3 | 5 | 5 | 5 |
| **Model large dataset** | 0.33 | 0.33 | 1 | 3 | 3 | 3 |
| **Probabilistic output** | 0.2 | 0.2 | 0.33 | 1 | 3 | 3 |
| **Interpretability** | 0.14 | 0.2 | 0.33 | 0.33 | 1 | 1 |
| **Avoid overfitting** | 0.14 | 0.2 | 0.33 | 0.33 | 1 | 1 |

*Table 6.4. Normalised scores from pairwise comparison of performance metrics*

| A \ B | Prediction performance | Training speed | Model large dataset | Probabilistic output | Interpretability | Avoid overfitting | Criteria Weight | metric |
|---|---|---|---|---|---|---|---|---|
| **Prediction performance** | 0.46 | 0.61 | 0.38 | 0.34 | 0.35 | 0.35 | 0.41 | $W_{Perf.}$ |
| **Training speed** | 0.15 | 0.2 | 0.38 | 0.34 | 0.25 | 0.25 | 0.26 | $W_{Speed}$ |
| **Model large dataset** | 0.15 | 0.07 | 0.13 | 0.2 | 0.15 | 0.15 | 0.14 | $W_{Large}$ |
| **Probabilistic output** | 0.09 | 0.04 | 0.04 | 0.07 | 0.15 | 0.15 | 0.09 | $W_{Prob.}$ |
| **Interpretability** | 0.07 | 0.04 | 0.04 | 0.02 | 0.05 | 0.05 | 0.05 | $W_{Intp.}$ |
| **Avoid overfitting** | 0.07 | 0.04 | 0.04 | 0.02 | 0.05 | 0.05 | 0.05 | $W_{Overfit.}$ |

*Table 6.5. Pairwise comparison Consistency check*

| Step a | | | | | | Step b | Step c |
|---|---|---|---|---|---|---|---|
| **Performance** | **Training speed** | **Model large dataset** | **Probabilistic output** | **Interpretability** | **Avoid overfitting** | | |
| 0.41 | 0.78 | 0.42 | 0.45 | 0.35 | 0.35 | 2.76 | 6.731707 |
| 0.1353 | 0.26 | 0.42 | 0.45 | 0.25 | 0.25 | 1.7653 | 6.789615 |
| 0.1353 | 0.0858 | 0.14 | 0.27 | 0.15 | 0.15 | 0.9311 | 6.650714 |
| 0.082 | 0.052 | 0.0462 | 0.09 | 0.15 | 0.15 | 0.5702 | 6.335556 |
| 0.0574 | 0.052 | 0.0462 | 0.0297 | 0.05 | 0.05 | 0.2853 | 5.706 |
| 0.0574 | 0.052 | 0.0462 | 0.0297 | 0.05 | 0.05 | 0.2853 | 5.706 |
| | | | | | Step d: $\lambda_{max}$ | | 6.319932 |
| | | | | | Step e: CI | | 0.063986 |
| | | | | | Steps f & g: CR | | 0.051602 |

*Table 6.6. Rescaled accuracy and training speed categories*

| Level | Classification threshold | |
|---|---|---|
| | **Performance thresholds** | **Training speed thresholds** |
| 1 (score 4) | >80% | < 1 min |
| 2 (score 3) | >70% | < 5 min |
| 3 (score 2) | >60% | <10 min |
| 4 (score 1) | <60% | >10 min |

In terms of speed, BsT is a sequential learner where individual decision trees are trained in sequence, hence the longer time they require. Whereas BgT train individual learners in parallel, thus, outperforming BsT. Another issue associated with sequential learning is the lower generalisability compared to BgT and DT. As the trees adapt to every error, they can therefore be sensitive to noise in data especially when working with large datasets and they become prone to overfitting. In contrast, BgT do not learn from errors and are based on majority voting, hence they are less prone to overfitting. Decision trees are likely to overfit when the structure is very complex. Interpretability is an issue when dealing with all complex structures of tree-based algorithms especially for large-datasets. However, DT are potentially more interpretable since they are traceable and no random bootstrapping takes place. However, when dealing with large dataset they still experience interpretability issues due to complex structures.

KNN as a lazy classifier is associated with slower speed for training because the data is kept in memory and retrieved for distance-based comparison. When dealing with large and noisy datasets, KNN are very prone to overfitting, especially when using a low K value. KNN are less interpretable than Decision trees because they do not employ feature selection or choose inputs that seem most valuable, the manner in which decision trees are carried out.

NN are less likely to overfit data as they are tolerant of noise in large datasets. However, they are viewed as black boxes with low interpretability. NN can potentially be adjusted to obtain probabilistic output of classification, that is what is called Probabilistic Neural Networks. KNN are not designed to output

probabilities of class membership. Due to majority voting of bootstrapped trees, BgT can be adjusted to return a probability of classification. BsT and DT and uncapable of giving a probabilistic output, the first because of sequential learning, the latter due to the inherent leaf-split structure.

Table 6.7 and Table 6.8 show the weighted scorings of all tested algorithms for both structural and service condition runs. It is evident that BgT perform best for modelling both structural and service condition of drainage pipes. Looking at the rankings, Tree-based structures outperform lazy classifiers and Neural Networks for modelling condition of drainage assets and are therefore, the recommended approaches.

*Table 6.7. Weighted scoring comparisons for STRC condition modelling*

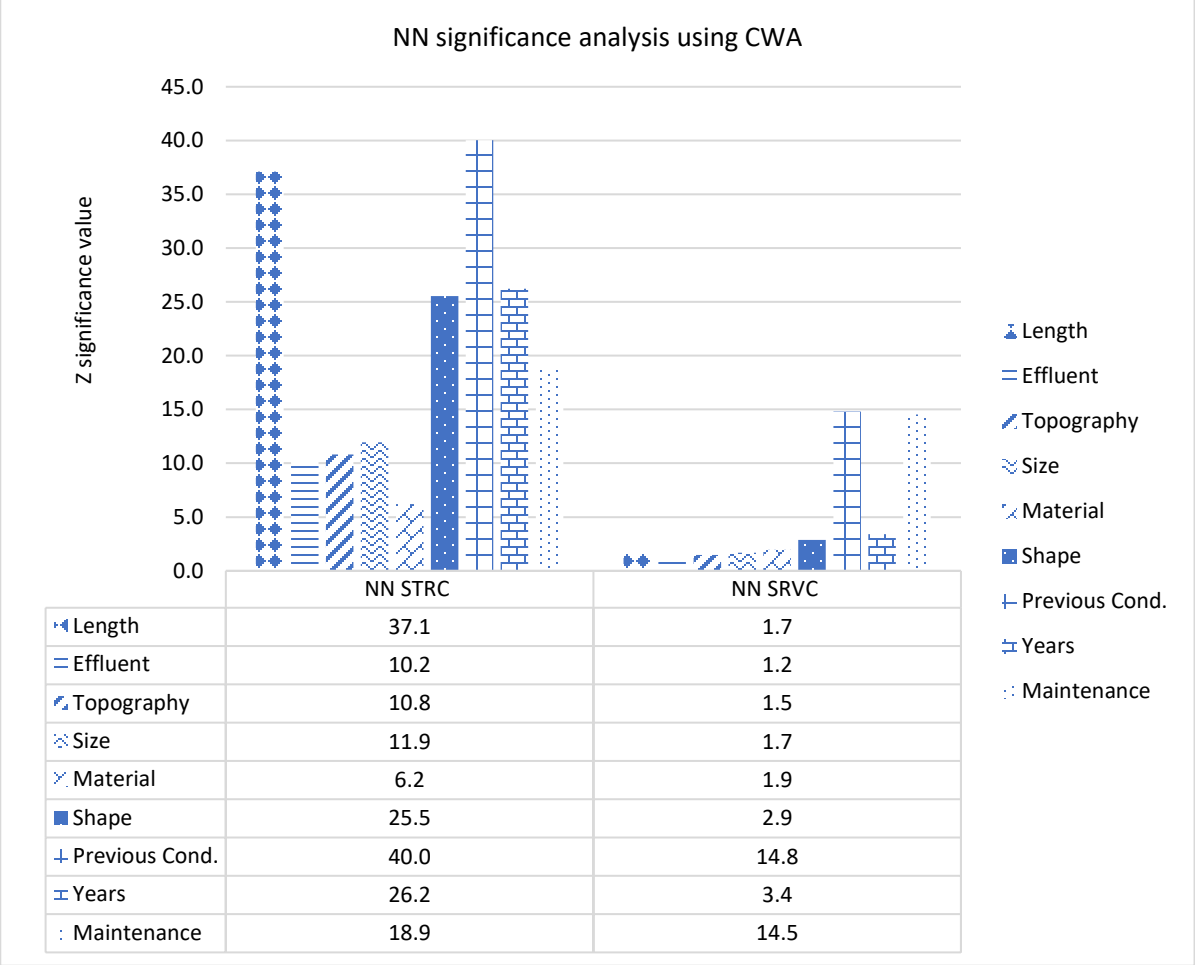
| **Algorithm** | $W_{Perf.}$ | $W_{Speed}$ | $W_{large}$* | $W_{Prob.}$* | $W_{Intp.}$* | $W_{Overfit.}$* | **Weighted score** | **Ranking** |
|---|---|---|---|---|---|---|---|---|
| | **0.41** | **0.26** | **0.14** | **0.09** | **0.05** | **0.05** | | |
| NN | 2 | 2 | 3 | 3 | 1 | 3 | 2.23 | 5 |
| DT | 4 | 4 | 2 | 1 | 3 | 2 | 3.3 | 3 |
| KNN | 4 | 3 | 2 | 1 | 2 | 2 | 2.99 | 4 |
| BgT | 3 | 4 | 4 | 4 | 1 | 4 | 3.44 | 1 |
| BsT | 4 | 3 | 4 | 1 | 1 | 4 | 3.32 | 2 |

*Table 6.8. Weighted scoring comparisons for SRVC condition modelling*

| **Algorithm** | $W_{Perf.}$ | $W_{Speed}$ | $W_{large}$* | $W_{Prob.}$* | $W_{Intp.}$* | $W_{Overfit.}$* | **Weighted score** | **Ranking** |
|---|---|---|---|---|---|---|---|---|
| | **0.41** | **0.26** | **0.14** | **0.09** | **0.05** | **0.05** | | |
| NN | 1 | 2 | 3 | 3 | 1 | 3 | 1.82 | 5 |
| DT | 2 | 4 | 2 | 1 | 3 | 2 | 2.48 | 3 |
| KNN | 2 | 4 | 2 | 1 | 2 | 2 | 2.43 | 4 |
| BgT | 1 | 4 | 4 | 4 | 1 | 4 | 2.62 | 1 |
| BsT | 2 | 3 | 4 | 1 | 1 | 4 | 2.5 | 2 |

## 6.8 Discussion of input significance

CWA (Section 5.3.2) is applied on the NN training weights in order to analyse the significance of each of the nine input factors towards the prediction ability. Although NN does not show the highest performance, the model still shows an AUC greater than 0.75 which indicate the predictions by NN are not arbitrary. Therefore a significance analysis of input parameters based on NN Connection weights is valid. Olden et al. (2004) performed a comparison between multiple methods to quantify input significance of NN. These methods included CWA, Garson's Algorithm, Partial Derivatives, Input perturbation, Sensitivity Analysis, Stepwise Addition and Elimination (Olden et al., 2004). It was found that CWA was the only method that consistently identified the correct ranked importance of all predictor variables (Olden et al., 2004). Figure 6.15 shows a comparison between the significance of the inputs for both service and structural models. The following six basic inputs; length, effluent type, topography, pipe size, material and shape are evidently more pertinent to structural condition prediction than service condition prediction. This indicates that for service condition, other factors need to be considered like soil type, pipe slope and tree count (Tran et al., 2008). Table 6.9 summarises the observed order of significance using CWA. The rest of the section discusses the findings in light of the literature.




| | NN STRC | NN SRVC |
|---|---|---|
| Length | 37.1 | 1.7 |
| Effluent | 10.2 | 1.2 |
| Topography | 10.8 | 1.5 |
| Size | 11.9 | 1.7 |
| Material | 6.2 | 1.9 |
| Shape | 25.5 | 2.9 |
| Previous Cond. | 40.0 | 14.8 |
| Years | 26.2 | 3.4 |
| Maintenance | 18.9 | 14.5 |

*Figure 6.15. NN input significance analysis using CWA*

*Table 6.9. Order of inputs significance for structural and service condition prediction of pipe drainage assets*

| Order of significance | STRC | SRVC |
|---|---|---|
| 1 | Previous condition | Previous condition |
| 2 | Length | Maintenance |
| 3 | Years since previous condition | Years since previous condition |
| 4 | Shape | Shape |
| 5 | Maintenance | Material |
| 6 | Size | Length |
| 7 | Topography | Size |
| 8 | Effluent | Effluent |
| 9 | Material | Topography |

### 6.8.1 Significance of input factors for service condition prediction

Tran et al. (2008) used the Wald test Z-statistic to evaluate the significance of input factors towards service condition prediction using an ordinal regression model. Age, slope, location, climatic condition, Thornthwaite Moisture Index (TMI), and structural condition were found to be significant for serviceability prediction while pipe size, depth, soil type and tree count were found insignificant. Tran et al. (2008) explained that tree count and soil type are inherently reflected through Location and TMI. Similarly, depth and size are correlated factors and are reflected through structural condition, when used as an input. Contrary to Tran et al. (2008) and current study, Wu et al. (2021b) found that size of pipe is a significant factor for service condition modelling where smaller pipes are more likely to get blocked. The current study shows low significance of location, presented as topography in case of railway, towards service condition. However, Wu et al. (2021b) found that location, presented as rail route where the asset lies, is a significant factor because of what it inherently implies in terms of varied hydrological conditions. This indicates that a simple cutting/embankment description is not enough. More nuance is required regarding degree of slope and type of cover. There is a link between topography and slope of earthwork as well as type of cover. Higher slope increases intensity of surface erosion due to surface runoff (Cheng et al., 2017a). Eco-hydrologic simulations by Bieger et al. (2015) showed that increase in forested area, reduces surface runoff and erosion. Whereas, deforested hillslopes are more susceptible to erosion (Alavez-Vargas et al., 2021). Moreover, Wu et al. (2021b) found that material is a significant factor. Material impacts pipe rate of siltation due to material roughness, thus affecting service condition. None of the other significant factors for service prediction used in this study are identified in the literature. Effluent type and shape of pipe is expected to affect degree of sedimentation for service condition. Moreover, Effluent type is likely to be more relevant to urban drainage systems compared to railway drainage systems. Length could be significant for service condition when considering flow velocity, which in turn affects level of sedimentation. Equation 6.1 shows the directly proportional

relationship between frictional head loss and pipe length. It also shows the inversely proportional relationship between length of pipe and flow velocity; where a longer pipe would induce lower flow velocity. A lower flow velocity reduces the pipe's self-cleaning property, thus, increasing level of sedimentation in a pipe.

$$H_f = f\frac{L}{D}\frac{v^2}{2g} \qquad \textit{Equation 6.1}$$

*Where:*
*f= friction factor*
*L= length of pipe*
*D= diameter of pipe*
*v= fluid velocity*
*g= gravitational acceleration*

### 6.8.2 Significance of input factors for structural condition prediction

For structural predictions, comparisons were drawn with Baik et al. (2006), Davies et al. (2001a), Tran et al. (2006), Tran et al. (2009). Tran et al. (2009) applies CWA on the NN model for structural condition of storm water pipes. Tran et al. (2006) used univariate analysis for significance analysis with probabilistic NN while it used stepwise method with the discriminant model. (Davies et al., 2001b) studied significance of the factors for sewer pipe condition through a stepwise multivariate logistic regression. Baik et al. (2006) identified significance of variables based on the parameters' estimates of the ordered probit model for sewer pipe condition prediction. Table 6.10 shows a summary of the significance analysis for the factors used in the literature.

*Table 6.10. Comparison of input significance from this study in light of literature*

| Literature | Pipe Size | Pipe Length | Pipe Material | Effluent type | Location | Pipe Shape | Slope | Soil type | Tree count | Age | Depth | Groundwater table | Climatic condition | Road traffic | Hydraulic condition |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| (Baik et al., 2006) | S | S | NS | - | - | - | S | - | - | S | - | - | - | - | - |
| (Davies et al., 2001a) | S | S | - | S | S | - | - | - | - | - | - | - | - | - | S |

| | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| (Tran et al., 2006) | NS | - | - | - | NS | - | S | NS | NS | NS | S | - | NS | - | S |
| (Tran et al., 2009) | S | NS | - | - | S | - | NS | S | S | NS | - | - | - | - | - |
| (Micevski et al., 2002) | S | - | S | - | - | - | - | S | - | - | - | - | S | - | NS |
| (Wirahadikusumah et al., 2001) | - | - | S | - | - | - | - | S | - | - | S | S | - | - | - |
| (Angarita et al., 2017) | S | - | S | S | S | - | - | - | - | - | - | - | - | - | - |
| (Ugarelli et al., 2013) | S | - | - | S | - | - | - | S | S | S | - | | - | S | - |
| Mohammadi et al. (2020) | S | S | S | - | - | - | S | NS | - | S | S | S | - | | - |
| Current study from CWA | S | S | NS | S | S | S | - | - | - | - | - | - | - | - | - |

Note: S indicates the factor was considered and found significant
NS indicates the factor was considered and found not significant
- indicates the factor was not considered

Pipe size, length and material are the factors that were used both in the literature and in this study as shown in Table 6.10. Size of a pipe seems to be significant across all the previous studies (Micevski et al., 2002, Baik et al., 2006, Davies et al., 2001a). Despite the consensus around the significance, there are contradicting views around the nature of impact the pipe size has on pipe condition. Micevski et al. (2002) found that smaller pipes experience greater deterioration due to underestimation of design requirements in terms of loadings and cover. Angarita et al. (2017) made a similar observation, particularly for pipes smaller than 500 mm. Baik et al. (2006) however, explained that larger pipes are more likely to have higher rates of deterioration. Davies et al. (2001a) provided two contradicting views: one stated that larger sewers were more structurally sound, the other provided evidence that risk of structural failure is higher for larger pipes due to installation difficulties.

Pipe length, which was considered by Baik et al. (2006) and Davies et al. (2001a) showed high significance for condition prediction, similar to the current analysis. With regards to the nature of impact of pipe length on pipe condition, Baik et al. (2006) suggests that shorter pipe section runs induce faster condition deterioration due to increased number of connections. Similarly, Davies et al. (2001b) claimed that sewage pipes with length more than 1.5 m are less likely to be in failing condition, as shorter

individual sewer pipe runs indicate greater number of joints per unit length of sewer. This was linked with infiltration of soils and sedimentation being more likely through joints/connections. On the other hand, Davies et al. (2001a) described that the higher length to diameter ration causes increased structural bending stress and hence, worse structural condition. The two opposite views on nature of impact on hydraulic and structural conditions make it difficult to make a recommendation on the optimal pipe length. However, they indicate that there is trade-off between the two during design process.

Conversely, pipe material was found insignificant by both Baik et al. (2006) and Davies et al. (2001a). However, Micevski et al. (2002) and Wirahadikusumah et al. (2001) both used material as a grouping criteria when applying the Markov chains for storm water-pipe prediction and showed that it was a statistically significant factor in pipe condition. Angarita et al. (2017) also showed that material is a significant factor as the type of material affects the rate of corrosion experienced by the asset. The findings of this study, however, show the insignificance of material as an input factor.

Effluent type is found to be significant in this study. Davies et al. (2001a)' includes it as 'sewer purpose/use', with the following three categories: foul water, surface water and combined. It was shown to be among the top 10 significant factors, from the 18 tested factors. Angarita et al. (2017) also confirmed its significance through a linear regression study of explanatory variables.

Topography was not used in any other studies, except for Davies et al. (2001a) and Tran et al. (2009). Both showed location to be a significant factor. These studies considered storm water and wastewater systems in urban and suburban areas, in which location depended on the use of the area, mainly reflecting the impact of traffic load and type of cover on structural condition of pipes. In the scope of railway drainage, 'topography' is viewed as a derivative of 'location'. Pipes in a cutting are more likely to experience tree-root penetration compared to embankments. Thus, explaining the observed significance of the parameter towards structural condition in this study.

Shape is found to be of high significance in this study, possibly because it influences the load distribution or because it is indicative of other significant factors that are unaccounted for, like installation and connection workmanship.

Factors that were found significant in other studies but are not included in the current study are slope, soil type and tree count. Slope was found to be significant in Probabilistic Neural Networks (PNN) (Tran et al., 2006) and ordered probit model used with Markov chains (Baik et al., 2006). Baik et al. (2006) explained that steeper slopes are associated with higher flows and lower stability, leading to increased rate of deterioration and consequently condition reduction.

Soil type has conflicting views around it. Tran et al. (2009) identified soil type as significant towards NN but insignificant towards the ordered probit model. Tran et al. (2006) also identified soil type as insignificant towards both PNN and discriminant model. Whereas, Davies et al. (2001a) listed two soil-related factors in the top ten most significant factors in pipe deterioration; soil fracture potential and soil corrosivity. Micevski et al. (2002) also confirmed the significance of soil type. Similarly, Wirahadikusumah et al. (2001) stressed the importance of using soil type in grouping cohorts when using the Markov chains for pipe condition modelling.

Tree count only showed significance towards NN model in Tran et al. (2009) but not towards the ordered probit model, discriminant model or PNN (Tran et al., 2006, Tran et al., 2009). It is an interesting finding since tree root interference is a major cause of structural damage in pipes (Davies et al., 2001a, Rokstad and Ugarelli, 2015). Angarita et al. (2017) also reflected the high impact of tree roots through the use of 'cover type' as a significant explanatory factor in pipe condition models. The issue is even more prevalent in railway drainage, considering the substantial portion of earthworks using green cover for stabilisation. Tree count is therefore a parameter worth sourcing.

Age is a matter of controversy, although it is a central factor in any Markov chain model (Baik et al., 2006, Micevski et al., 2002, Wirahadikusumah et al., 2001, Tran et al., 2010, Le Gat, 2008, Kannapiran et al., 2008), it was determined insignificant in Tran et al. (2006), Tran et al. (2009) and Davies et al.

(2001a). Baik et al. (2006) also noted that age parameter becomes less significant when pipe is in worse condition. Tran (2007) suggested that age is more a reference point for monitoring and that pipe condition is affected by a combination of many factors and damaging events which are independent of pipe age.

Based on the literature review, it seems that tree count, pipe slope, and soil type as well as age, despite the contradicting views, are parameters which should be investigated for future development of the model.

Hydraulic or serviceability condition as an input parameter for structural condition prediction was found significant by Tran et al. (2006) and Tran et al. (2009). Davies et al. (2001a) also reflected on the significance of hydraulic condition, although indirectly, through the use of 'debris presence' which observed to be a significant factor (Table 6. 10). Micevski et al. (2002) on the other hand found hydraulic condition to have insignificant influence on structural condition. However, they still explain a need to consider both structural and service condition for maintenance strategies.

The importance of hydraulic condition and structural condition as inputs for structural prediction and service prediction, respectively, can be explained with the bidirectional correlation between the two factors. On the one hand, more structural damage (cracks) allows for more intrusion of material that hinders the flow of water in the pipe. Furthermore, deteriorating hydraulic condition may cause frequent surcharges due to blockages and intrusion which, in turn, cause a need for rehabilitation or replacement (Micevski et al., 2002). Despite their importance, the reason for not including these factors as inputs is that the primary objective of the study is to predict the structural and service condition of drainage, therefore the developed model treats them as output rather than input parameters.

Finally, with respect to the derived parameters, Previous condition shows highest significance towards both the structural and service model. 'Years since previous condition' is the third-highest significant factor for STRC and SRVC. Considering that previous condition and years since previous condition are significant prediction factors, it can be inferred that shorter term condition prediction will be more

reliable than longer-term predictions. Maintenance shows high significance towards both models. It shows higher significance towards service prediction which is a rational result since regular maintenance mainly entails serviceability-related works, like rodding and jetting to improve hydraulic behaviour of pipes.

### 6.8.3 Expert opinion on input significance

An Expert from the TfL drainage department was consulted to obtain their opinion on the significance of the various factors considered and additional factors to be considered.

In terms of order of significance, they believe size is more important than shape of the pipe as it affects the stresses that the pipe structure undergoes, hence, its structural condition. Length should have lower significance as its effect on structural integrity is dependent on the flexibility of the pipe, where the structural integrity of a flexible pipe is more likely to be affected by stresses over longer length compared to more rigid pipes where length isn't a very significant factor as they are less affected by stress variation. Therefore, pipe material should have a higher significance. Topography is also a significant factor as it affects the loading condition of pipes.

In terms of additional factors that should be considered, they mentioned geology of track bed, tree count, age and third-party interface. Type of track bed affects the structural condition by influencing the amount of loading the pipe undergoes. It also affects the service condition by influencing the amount of silt going into the pipes. For example, a gravel bed causes heavier loading than a sand bed and an ash bed may cause more contamination than a limestone bed. Tree count affects structural integrity of pipes due to root penetration and increased siltation in pipes. The effect of third-party interface manifests in loading and unloading of material over the pipes which affects their plastic deformation and hence, their structural integrity. Type of material is a confounding factor in this situation as loading/unloading criteria is particularly an issue with flexible and semi-rigid pipes.

## 6.9 Limitations and further work

The following are some points of consideration for future extension of this study:

1) In this study the only maintenance record involved is the assumption that maintenance took place when condition improved. However, maintenance could have taken place at other points in time where condition did not necessarily improve, or improvement was not reported. Therefore, investigating the significance of maintenance intervention on pipe's condition remains a prospect for further research. This requires accurate historical data regarding maintenance intervention.
2) A step-wise elimination analysis could be applied particularly on the factors which were found to be insignificant. This exercise would reflect the impact of each individual factor on prediction performance and training time. It identifies the factors that should be cut off from the analysis as having marginal impact on performance improvement. Thus, improving the efficiency of the model.
3) Handling dataset imbalance is normally concerned with the target output parameters which is the scope of this work. Further extension of the work could be on investigating the imbalance in individual input parameters. It could enhance prediction performance by expanding the dataset and exposing the classifier to more variations in input vectors. Higher variation and representation of different input parameters could result in a better analysis of significance of the input parameters.
4) CWA is the chosen method to investigate input significance based on NN connection weights as an attempt to tackle the black-box issue associated with NN. Other methods like stepwise elimination/ addition analysis or sensitivity analysis could be applied to other models to investigate parameter significance.

5) As part of a risk assessment into the future, it is more appropriate to obtain probabilistic output of an asset's condition rather than a deterministic output. This encourages infrastructure managers to adopt ML methods for condition prediction for 'What-If' analyses and management strategies. It is therefore important to pursue an algorithm structure which returns a range for probable condition of an asset and associated probabilities. This then provides the probability components for risk calculation. This is not pursued in this study because of time limitation.
6) To understand the bidirectional influence between service condition and structural condition, it would be pertinent to use each of the two as input parameter for the prediction of the other condition. This would enable observing whether performance of the predictive model for either conditions would improve where the other condition is available.
7) The investigated techniques used for demonstration of the condition modelling application are limited to the models applied in literature. Future research should consider adoption of emergent methods in Machine learning such as: Convolutional Neural Networks, Probabilistic Neural Networks and Autoencoders (Surucu et al., 2023).

## 6.10 Summary

This case study is a demonstration of the use of ML algorithms as a data-driven tool for condition prediction of condition of railway drainage asset relying on extensive historic survey records. The study focuses son railway drainage assets for demonstration but can be extended to other drainage assets. A comparison between the performance of NN, DT, KNN, BgT and BsT for condition prediction of railway drainage pipes is conducted using nine input factors. Data is obtained from the UK NR drainage and lineside asset database. The results show that for structural condition prediction BsT performs best on balanced dataset with 88% overall accuracy. Similarly, for service condition, BsT performs the best with 72% accuracy on balanced dataset.

The input factors (Shape, Material, Length, Size, Effluent and Topography, Previous condition, Years since previous condition and Maintenance) are found to be more relevant to structural condition prediction. This is confirmed with the CWA which also showed that length, effluent type, topography, pipe size, and shape are not significant in predicting service condition. The derived parameters 'previous condition', 'maintenance' and 'years since previous condition' show the highest significance towards prediction of both service and structural conditions.

The impact of data balancing is analysed by investigating Recall and Precision of individual condition classes. Balancing improves the Recall as well as precision rates for condition classes 3, 4 and 5 while reducing these rates for classes 1 and 2. The F-score is used as a mean measure of Recall and Precision. When balancing, F-score improves significantly for critical classes, but it reduces slightly for classes 1 and 2. When improving the model, high F-score and high AUC should be aimed for the critical class as they characterise a reliable classifier performance.

Finally, the case study conducts an AHP performance comparison using the performance metrics: Prediction performance, speed, dealing with large datasets, overfitting, interpretability and potential for probabilistic output. Bagged Trees ranked first in AHP, achieving comparative scores of 3.44 for structural condition prediction and 2.62 for service condition prediction. Although the achieved overall prediction accuracy with Bagged Trees (BgT) was not the highest (at 82% for STRC and 62% for SRVC), the final recommendation is that BgTs are the suitable algorithm for a risk assessment condition prediction of railway drainage assets. Their point of strength is their potential for probabilistic output and the shorter time they take for training. This overweighed the higher prediction accuracy achieved by Boosted Trees.

These prediction models can be used to predict future conditions of drainage assets for operational decision making through understanding the needs for preventative maintenance in the short and medium term. They can also be used to complete the gaps in the database where assets are identified in the database but no asset condition is recorded. As will be seen in chapter 7, understanding current likely

condition as well as projecting future condition will enable to assess flood risk at different location through modelling condition and rainfall scenarios to study where flooding occurs and the consequences of a flood.

# Chapter 7: Flood simulation for quantitative assessment of flood impact: A case study

## 7.1 Introduction

This chapter is a demonstration of the second module of the developed risk assessment framework. The aim is a quantitative assessment of occurrence of and exposure to railway system flooding at a section-level. The proposed method for a quantitative assessment is the use of 2D hydraulic modelling, demonstrated through a case study on a railway site in the UK. The case study reports on component-level exposure to floods in railway drainage systems caused by the combined influence of asset condition and volume of flow entering the system. To this end, scenario analysis is conducted for combinations of probable asset condition, storm duration and storm event return period. The outputs from simulation scenarios are used to develop exposure charts to reflect flood exposure characteristics in the subsection surrounding the flooded drainage component. The evaluation entails identification of three flood-susceptible locations at component level as well as the accurate quantification of exposure using four main exposure parameters.

## 7.2 Methodology

For the case study, a 2D hydraulic modelling software is utilised to allow simulation of flood occurrence within the railway section. The flood risk occurrence and resulting exposure is influenced by topography, land use, land cover and hydrology. They are included in this case study through an integrated GIS model. The consequent flood exposure of track system is then quantified. The following are the steps followed in the case study.

1. Select appropriate software for 2D hydraulic modelling (Section 5.4.1)
2. Build the model using asset data and site data (section 7.4)
3. Define simulation scenarios (section 7.5)

4. Identify critical locations (section 7.6)
5. Quantify exposure by generating exposure charts (section 7.6.5)

## 7.3 Case study location

The case study site is a NR railway line that connects Patchway and Pilning train stations located 3 km North of Bristol city, UK , shown in Figure 7. 1. The site is classified as urban/suburban area. It consists of two rail tracks separated by a vegetated island. The Upside (US) track line runs towards Patchway station while the Downside (DS) line runs towards Pilning station. Figure 7. 1 demonstrates the track elevations along the case study sections. The two points at which only DS elevation is shown are locations where DS line enters/exists the tunnel later than/prior to the US line. Starting from the up-side -closer to Patchway station-, both track lines are at ground level of 56 m and elevation difference increases between the two tracks until both become laid in a cutting with elevation difference of 7 m. Both track lines pass through a tunnel. On the down-side end of tunnel, the tracks come out in a cutting and elevation difference reduces until both lines continue at ground level at 23 m at the end of the case study section (See Figure 7. 1). At this point the drainage goes into an outlet that diverts water away from track. The total length of case study line is around 3 km. The broken-down section lengths are shown in Figure 7.1. The case study region is split into two sections, referred to as ‘pre-tunnel’ describing the up-side section closer to Patchway station and ‘post-tunnel’ describing the down-side section closer to Pilning station. The drainage system through the tunnel section is advised by NR drainage and lineside team to be represented with one carrier pipe for each side (US and DS) to carry the pre-tunnel and flow into the post-tunnel drainage system as no outlet exists for the pre-tunnel drainage system.

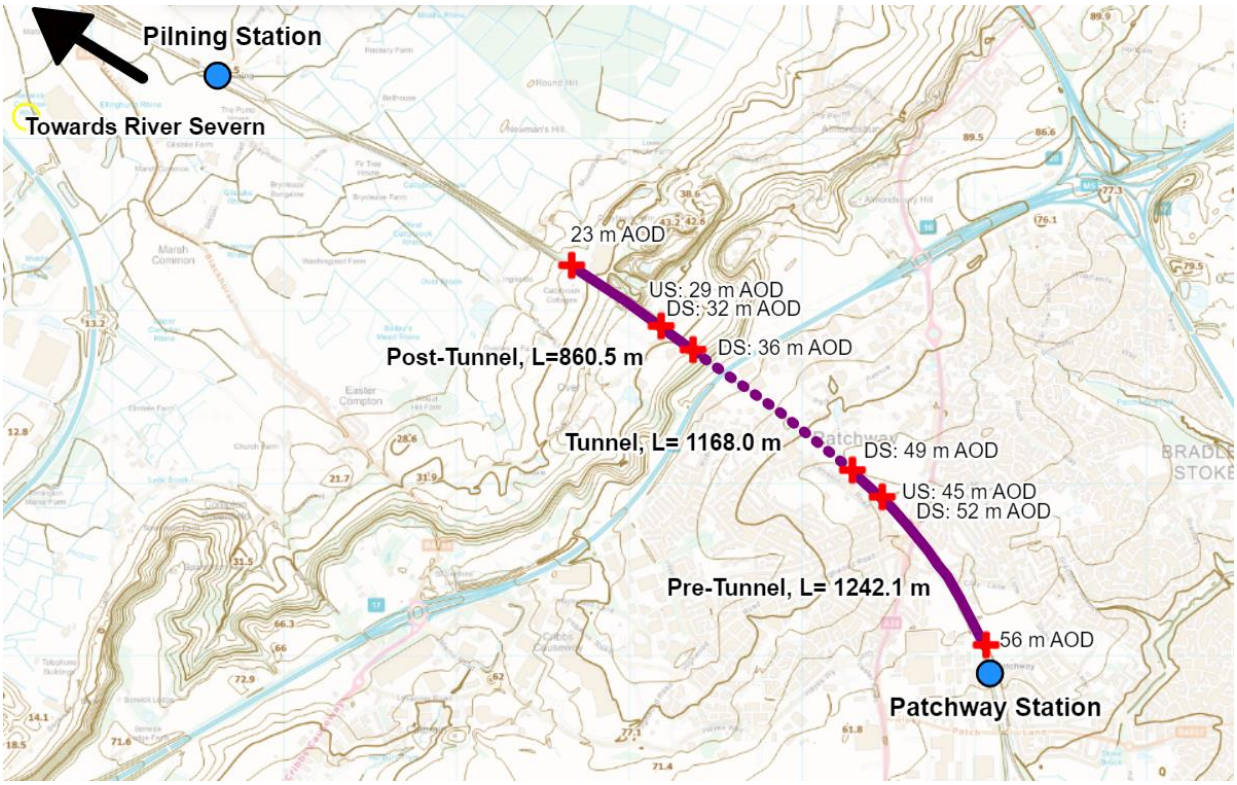



*Figure 7.1. Location of the case study section of track: between Patchway and Pilning train stations from Digimaps OS (Digimap, 2022b).*

## 7.4 Building the hydraulic model

For accurate representation of the drainage system, the study uses the as-built properties (shape, material, length, gradient, location, invert levels) and condition of individual assets to build the hydraulic model. The study assumes that the provided as-built drawings accurately reflect the geometry of the system. In order to account for off-track runoff contribution, areas surrounding the track are treated as catchments. The volume of runoff is affected by land use, ground cover and topography. Therefore, the study provides a detailed depiction of the characteristics of track and off-track features. The following subsections describe these characteristics.

### 7.4.1 Assets and catchment

The following data was obtained to build the hydraulic model:

1. Asset Data

The drainage system consists of 142 nodes (manhole chambers), 142 pipes and 2 outfalls. Properties of drainage system including invert levels, length, size and material of pipes, as well as depth and cover level of chamber nodes and gradient of drains are obtained from NR asset database. The ground level for chamber nodes is inferred from an existing Digital Terrain Model (DTM). NR maps do not specify details of the surface drainage assets, therefore, presence of surface drainage including natural ditches in the area are detected automatically from the DTM during the meshing stage to reflect the topography variation of these features. The manning's roughness value for pipes is determined by the pipe material for the inner walls of pipes. Table 7.1 shows the pipe materials for the case study and the adopted roughness coefficients. Service condition of assets is obtained from NR DAMBUSTER asset database, which reports condition on a scale of 1-5. The condition manifestation is described in Section 7.5.1

*Table 7.1. Materials of pipes in the case study*

| Inner wall Material | Roughness coefficient |
|---|---|
| Brick | 0.015 |
| High Density Polyethylene | 0.012 |
| Stainless Steel | 0.011 |
| Vitrified Clay | 0.014 |
| uPVC | 0.011 |

2. Topography

The topography of the catchment area is used to guide the direction and velocity of runoff flow. The DTM of the area, which approximates the ground heights at specific unique 2D points in reference to geodetic surface, is used. DTM is imported from EDINA national data centre for UK academia, Digimap Lidar imagery maps (Digimap, 2022a). The imported DTM has a spatial resolution of 1 m and a vertical resolution of +/- 15 cm. The catchment area boundaries are set during the meshing stage, described in Section 7.4.2

3. Catchment Area Features

As DTM only represents the bare ground of terrain, it is important to reflect the impact of ground cover and land use on runoff volume and velocity for both track and off-track catchments. Ordnance Survey (OS) maps are imported for the site from EDINA Digimaps (Digimap, 2022b) to represent the mosaic of area in terms of land use and cover. Thereof, infiltration and roughness zones are introduced to reflect the runoff coefficient and manning's roughness, respectively. Each infiltration zone is assigned an infiltration surface. The study area includes many different types of land use. Consequently, a thorough amount of manual inspection of the maps is performed to judge the appropriate infiltration coefficients and roughness values. Figure 7.2 shows an example portrayal of the area mosaic. Table 7.2 summarises the runoff coefficients for the various surfaces in the catchment area. The runoff coefficient depends mainly on land use, soil type, slope and rainfall intensity (Goel, 2011). Soil type in this area is mainly loam clay according to the Land Information System (LandIS) maps (LandIS, 2022). Table 7.3 summarises the roughness values associated with different surface types. The roads are only represented with manning's roughness as they are assumed to be paved with asphalt, and are ,therefore, considered to be 100% impervious (Shaw, 1993, Molinas and Mommandi, 2012). The buildings are represented as voids in the mesh, i.e., flow is diverted away from them during simulations and no representation of them is shown in the results.

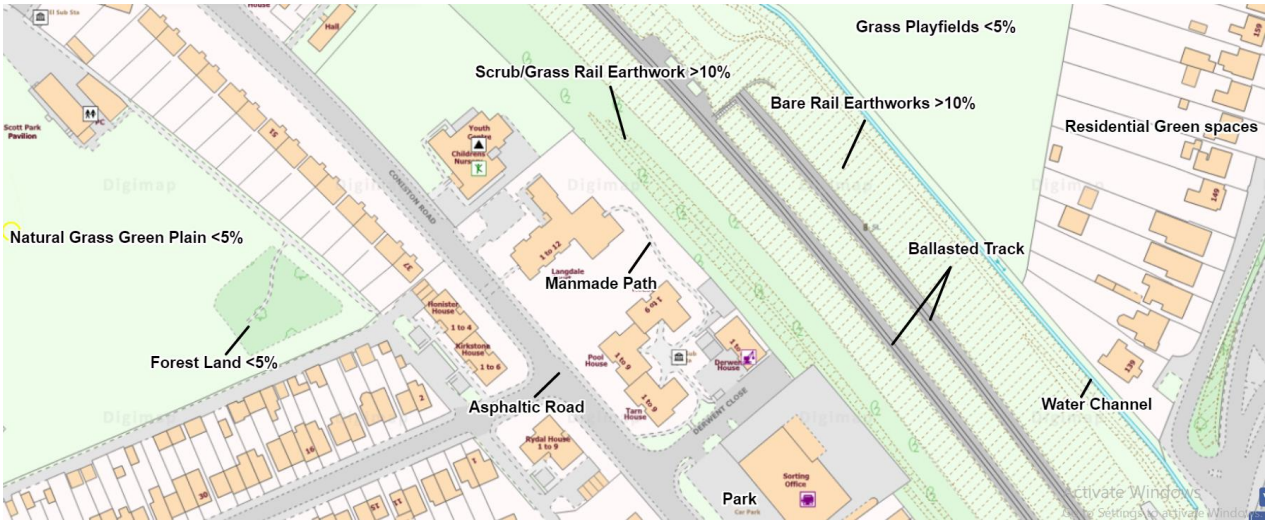



*Figure 7.2. Reflection of the various features of case study area*

*Table 7.2. Infiltration surfaces and associated runoff coefficients*

| Land use/soil type/slope | Runoff coefficient | Source |
|---|---|---|
| Residential green spaces | 0.6 | (Molinas and Mommandi, 2012) |
| Ballasted rail (2.5%) | 0.84 | |
| Parks | 0.6 | |
| Grass on loam clay (0.5-5%) | 0.41 | (Mahmoud and Alazba, 2015) |
| Grass on loam clay (>10%) | 0.59 | |
| Bare loam clay (>10%) | 0.79 | |
| Vegetated forest loam clay (>10%) | 0.49 | |
| Crop on loam clay (0.5-5%) | 0.43 | |
| Forest on loam clay (0.5-5%) | 0.31 | |

*Table 7.3. Manning's Roughness Values*

| Surface type | Manning's roughness | Source |
|---|---|---|
| Ballasted rail track (gravel) | 0.023 | (Chow, 1959) |
| Asphaltic roads | 0.016 | |
| Green plains (institutional grounds, residential lawns, golf courses, playfields) | 0.035 | |
| Manmade paths | 0.012 | |
| Heavily vegetated land (roadside or rail earthwork slope) | 0.15 | |

### 7.4.2 Meshing

A 2D mesh is generated for the catchment covering track and off-track area. The size of the mesh is set manually to cover a substantial size of the area surrounding the track, shown in black shade in Figure 7.3. This is the conservative approach which covers a significantly larger proportion than what the system would receive as it covers far-off urban areas where there would be existing urban drainage systems. Depending on terrain sloping direction, not all rainfall from meshed area would go into the railway drainage system. Further, terrain gradient majorly affects the amount and speed of flow runoff into individual assets. It is therefore important for the mesh to be sensitive to terrain. Since this study is carried at component level, terrain-sensitive meshing is important to capture slight changes in elevation in the track cuttings/embankments. The sensitivity is set to pick up changes in ground level elevation

from DTM with a 10 cm resolution. The tunnel section of the study area is missing from the DTM as shown in Figure 7.3. No analysis of this section is required, as NR confirmed no flooding occurs within the tunnel. NR team confirmed the drainage system through the tunnel consisted of carrier pipes for each pipeline.

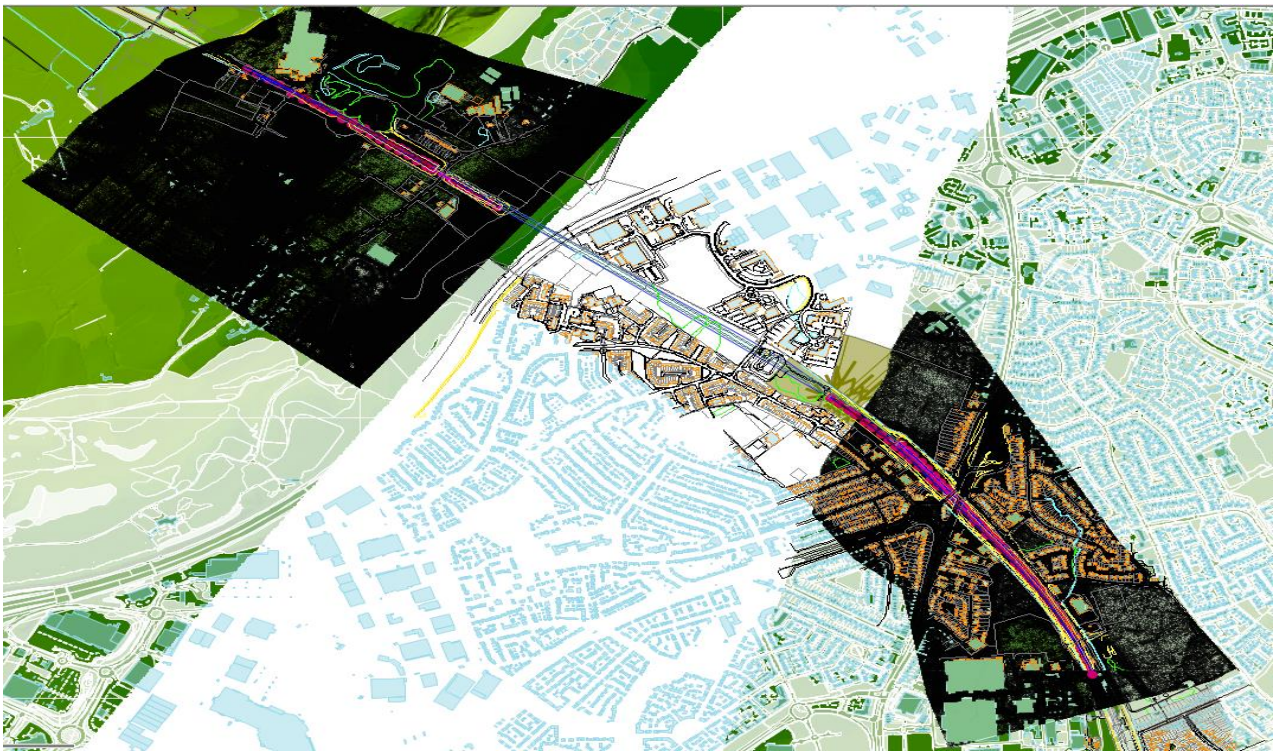


*Figure 7.3. Case study area depiction of meshed catchment zones (black shaded area)*

## 7.5 Simulation scenarios

As per literature review (Chapter 3), the main sources of flood risk are condition of the drainage asset and rainfall event. The rainfall event is characterised by Intensity-Duration-Frequency charts (Yazdi et al., 2022). Thereon, to define a storm event specification of return period and duration is required. Scenario analysis is conducted to investigate the impact of asset condition, rainfall duration and storm event return period. Simulation scenarios are constructed using combinations of these three factors. The following subsections describe the potential values for each flood source and their reflection in the

model. The outputs of simulations are used to evaluate flood occurrence and scale of flood exposure caused by the different scenarios.

### 7.5.1 Asset Condition

In order to reflect the impact of asset condition on the behaviour of the simulated drainage system, the recorded condition score for each pipe asset is translated into a physical input property for the modelled conduit. According to NR DAMBUSTER databases, asset condition is scored on a scale of 1-5 based on expert judgment, where condition 1 is good and condition 5 is completely blocked. The scoring system is based on subjective visual inspection. Therefore, it is decided to relate service condition to level of sedimentation in conduit. Table 7.4 summarises the condition and associated level of sedimentation based on expert opinion from NR drainage engineer.

*Table 7.4. Sediment levels associated with different condition scores*

| Condition description | Condition score | Sediment level (% of pipe dia.) |
|---|---|---|
| Clear | 1 | 5 |
| Superficial deposits | 2 | 25 |
| Performance slightly reduced | 3 | 50 |
| Performance severely reduced | 4 | 75 |
| Blocked | 5 | 100 |

### 7.5.2 Storm event intensity

A storm event is defined by its return period (RP). The minimum applied rainfall event is 1 in 1, it is chosen to observe the impact of a yearly occurring event on the system. The maximum applied event is a 1 in 200 event as it is the maximum design event according to NR design standards. This is also the maximum allowable rainfall event on Infoworks software. Table 7.5 summarises the rainfall events and the associated Annual Exceedance Probability (AEP) used in this study.

*Table 7.5. Simulated Rainfall events*

| Return Period | AEP |
|---|---|
| 1 in 1 | 100% |
| 1 in 2 | 50% |
| 1 in 5 | 20% |
| 1 in 10 | 10% |
| 1 in 30 | 3.3% |
| 1 in 50 | 2% |
| 1 in 100 | 1% |
| 1 in 200 | 0.5% |

### 7.5.3 Rainfall duration

According to Chartered Institution of Water and Environmental Management (CIWEM) Rainfall Modelling Guide, multiple rainfall durations should be assessed, including 15, 30, 60, 120, 180, 240, 360, 480, 720, 900 and 1440 minute events (CIWEM, 2016). Within this research time limitation, this study tests rainfall durations of 30 mins, 60 mins and 180 mins. The duration of rainfall plays a major role in susceptibility of system to flooding. To demonstrate, Figure 7.4 shows the 1 in 10 rainfall event intensities for a 30 min and a 60 min duration. For the same return period, the volume of rainfall is fixed, hence, a 30 min event would have a higher peak intensity compared to the longer 60 min event. Similar pattern applies for the 180 min event. According to CIWEM (2016), the critical duration is proportional to the size of the catchment, where critical duration typically increases with size of catchment. This relates to the time of concentration, i.e., time for runoff from the furthest catchment point. In a smaller catchment, a shorter duration of flow may be the critical one as the system would fail to accommodate the volume of rainfall as runoff wouldn't travel long. Whereas, in a larger catchment, the same runoff volume will take longer to travel, hence allowing more time for the system to cope. Therefore, in such an instance the longer duration may be the critical one for the same intensity.

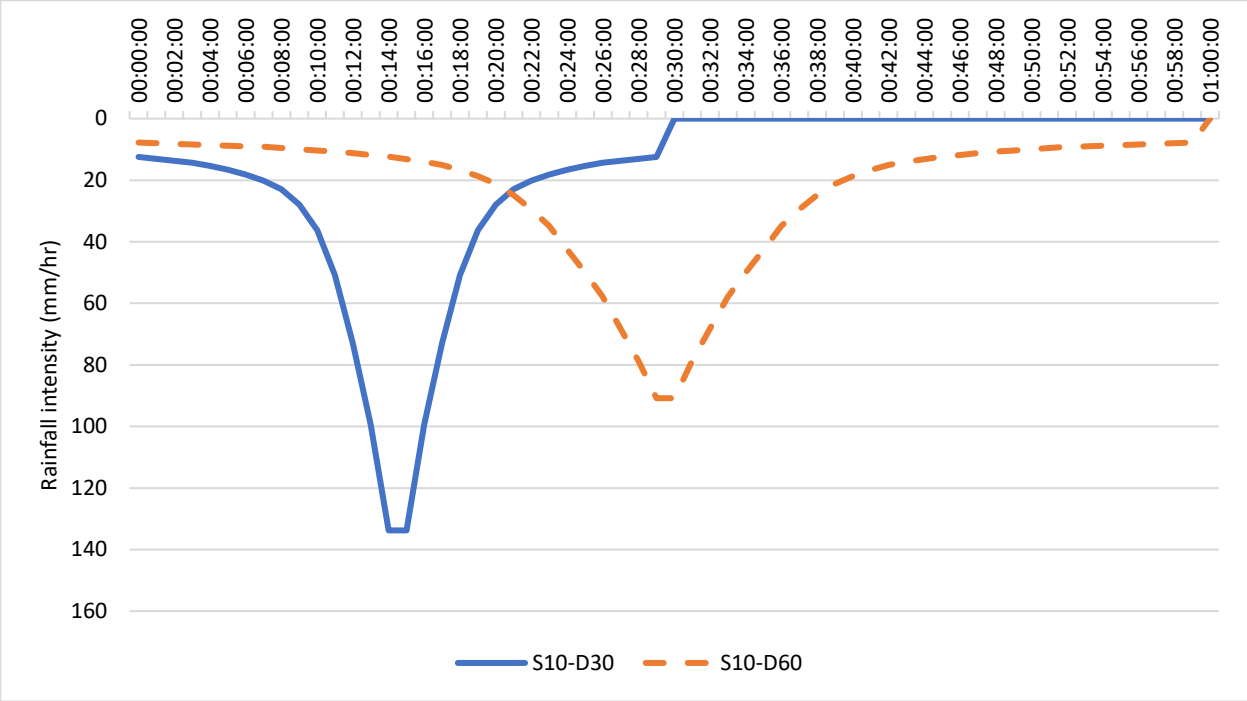



*Figure 7.4. Comparison of rainfall events M10-30 mins and M10-60 mins*

### 7.5.4 Descriptions of runs

Simulations are initially run for one condition scenario (reported in the as-built site asset data records) and one duration scenario (30 mins) while varying the storm event intensity over the eight rainfall events (characterised by annual return period). This is done to identify the critical locations. Following that, two critical locations are chosen for impact and, subsequent, risk comparisons. Scenario analysis is then expanded to consider the impact of uncertain asset condition and rainfall duration on flood occurrence in the section at each critical location. Table 7.6 shows the tested risk scenarios. This is performed by running two sets of 64 additional simulation runs, a set for each critical location. Each simulation run is a combination of downstream pipe asset condition (C), rainfall duration (D), and storm event intensity (S). There is a total of 72 simulation runs at each location.

*Table 7.6. Hydraulic simulation scenarios for asset condition, rainfall duration and storm event*

| Condition (C) | Duration (D) | Storm event (S) |
|---|---|---|
| 1 | 30 | 1 in 1 |
| | | 1 in 2 |
| 2 | 60 | 1 in 5 |

| | | |
|---|---|---|
| | | 1in 10 |
| | | 1 in 30 |
| 3 | 180 | 1 in 50 |
| | | 1 in 100 |
| | | 1 in 200 |

The duration of a simulation is another important consideration when running hydraulic simulations. To obtain a complete image of the flood exposure at a location, the duration of simulation depends on the time of concentration for an area, i.e., time required for the runoff to flow from the furthest point in the catchment to the drainage inlet. To investigate the required simulation duration for the specific site, a test simulation is initially run for the duration of one day. Based on the results, one location is chosen to evaluate the time required for flow into the system to stop and for the flood water to dissipate. This is done for the 1 in 200-30 mins rainfall event. After three hours and 30 minutes no more flood water is observed on track. Following this, the simulation duration is conservatively set at ten hours. However, as shown in subsection 7.6.4, the choice of location to perform the test is important, as time taken for flood water to fully dissipate does not necessarily mean that other locations will behave in the same.

## 7.6 Results

The hydraulic simulations reflect the bidirectional exchange of flow between the linear drainage system and the 2D representation of the flood plain on both track and off-track. Software output is used to identify critical locations, i.e., locations susceptible to flooding. The first step is to identify the critical location. Thereafter, exposure charts for the above-mentioned exposure parameters are generated for the critical nodes.

### 7.6.1 Identifying critical node

The critical node is defined as the one with highest total flood volume mapped onto surrounding 2D area. Return Period Analysis (RPA) is used to identify the critical node. RPA provides an overview of the minimum return period at which each node floods, and the amount of flood associated with that

return period. Table 7.7 shows the top 10 flooding nodes from RPA, ordered based on largest initial flood volume. Some of these nodes flood at an annual return period, which flags up the inadequate performance of assets in the section and hence, raises the criticality of site. Therefore, it is important to point out that, along with flood volume, criticality of asset also depends largely on the return period at which the asset floods. Henceforth, based on these two criteria, nodes BSW 1217 U6FT, BSW 007 1234 U6FT, BSW 007 0990 DCE and BSW 007 1126 DCE are identified as the critical nodes and are investigated along with the track section surrounding them.

*Table 7.7. Top 10 nodes with maximum flood volume from RPA*

| Node ID | Minimum flood RP | Associated flood volume at min. RP ($m^3$) |
|---|---|---|
| BSW 006 1217 U6FT | 10 | 146.024 |
| BSW 007 1234 U6FT | 2 | 120.331 |
| BSW 007 0990 DCE | 1 | 97.499 |
| BSW 007 1126 DCE | 1 | 90.658 |
| BSW 006 1492 DCE | 1 | 83.575 |
| BSW 006 1129 UCE | 30 | 79.381 |
| BSW 006 1494 DCE | 1 | 36.361 |
| BSW 007 1609 U6FT | 2 | 34.07 |
| BSW 006 1184 U6FT | 10 | 16.45 |
| BSW 006 1056 U6FT | 100 | 14.909 |

### 7.6.2 Flood volume

At first instance, flood volume is examined from simulation output. There is a direct correlation between increased flood volume on track and increased deterioration impact on other track assets (Guler et al., 2011). This is because the volume of water that does not go through the linear drainage system will saturate the ballast and underneath layers of track bed, thus causing deterioration problems like reduced track bed stiffness, wet beds, ballast fouling and geometry degradation of rails (Network Rail, 2018). Estimating the flood volume caused by different storm scenarios determines the required increase in

capacity in any renewal project. Figure 7.5 shows volume of flooding against storm event AEP for each of the four critical nodes.

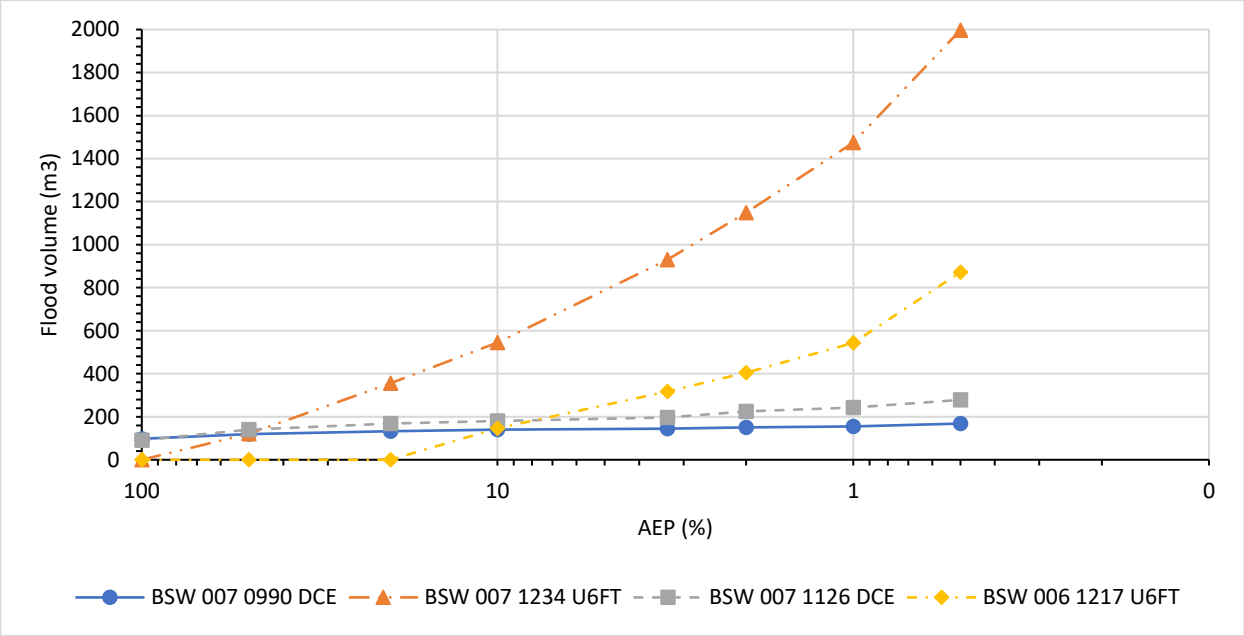
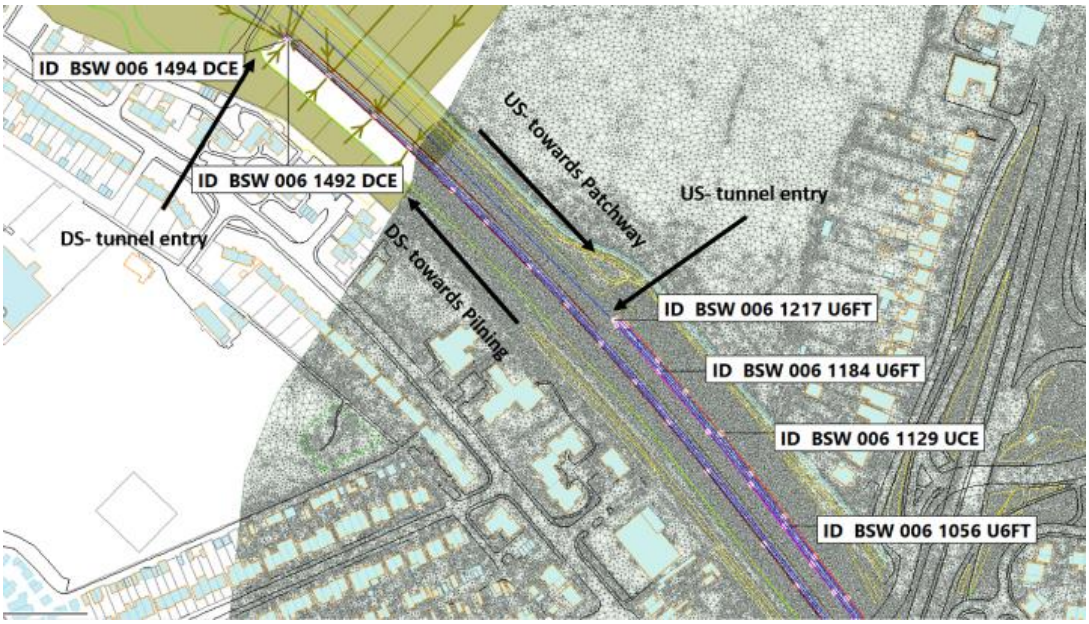


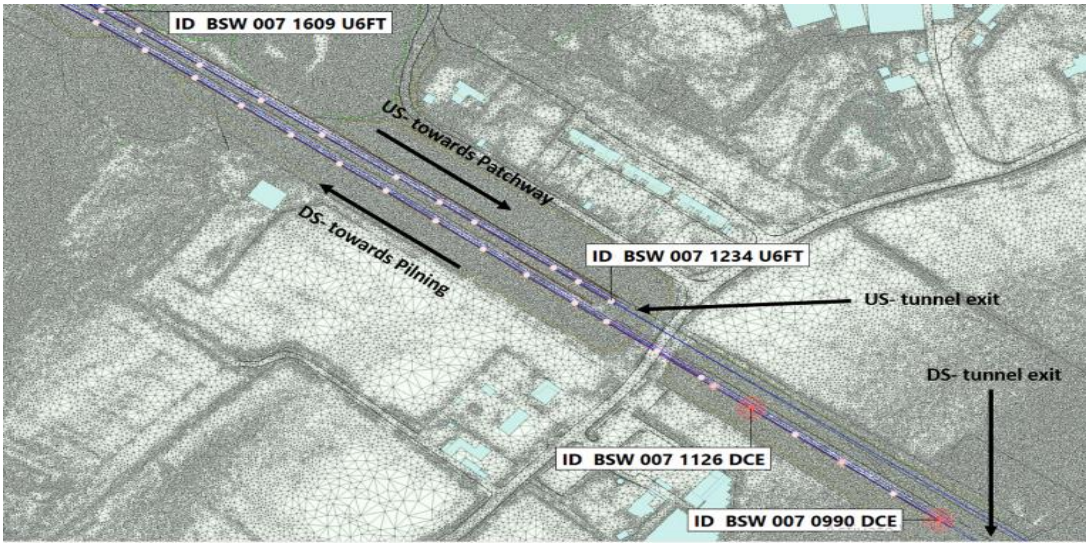

*Figure 7.5. Flood volume over various storm events for the identified critical nodes for D30*

### 7.6.3 Location of critical nodes

Figure 7.6 shows the location of the identified critical nodes on the track site both pre-tunnel (Figure 7.6a) and post-tunnel (Figure 7.6b). The nodes lie in different sections of the track; therefore, investigation of multiple critical nodes is useful to get a comprehensive view of flood situation in the different sections of the track in Patchway. Nodes BSW 007 0990 DCE and BSW 007 1126 DCE both lie in the same section and both flood at the same return period with similar initial flood volume. However, from Figure 7.5 node BSW 007 1126 DCE floods with larger volumes over the successive increasing storm events, hence having a greater contribution towards criticality of the section. To avoid unnecessary congestion of data in the investigation, node BSW 007 0990 DCE is excluded from this discussion.




(a)




(b)

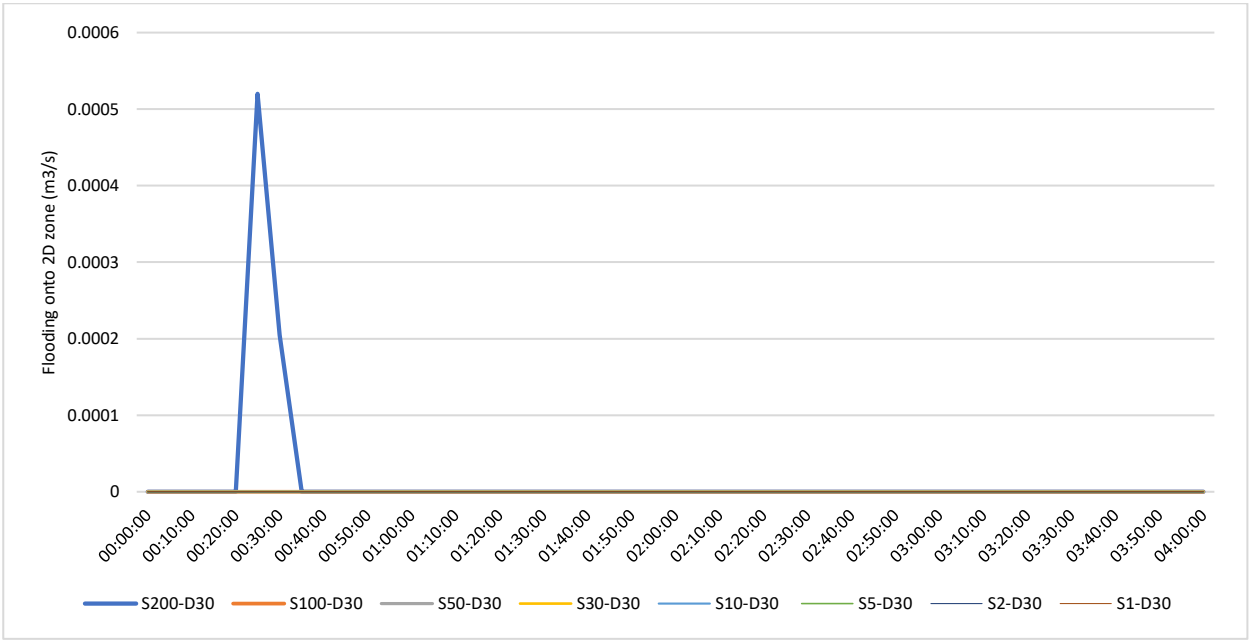
*Figure 7.6. Location of critical nodes for a) pre-tunnel and b) post-tunnel region. Radius of red circles signifies the relative magnitude of flood at S1-D30 scenario*

To demonstrate the difference in hydraulic performance between adequately performing drainage assets and critical drainage assets during storm events, Figure 7.7, and Figure 7.8 show the bidirectional flow exchange between the node and the surrounding 2D zone for non-critical node BSW 006 0315 DCE and for critical node BSW 007 1234 U6FT, respectively. Figure 7.7a shows node BSW 006 0315 DCE floods at a 200-year RP. Figure 7.7b shows flow is running into node BSW 006 0315 DCE in parallel with

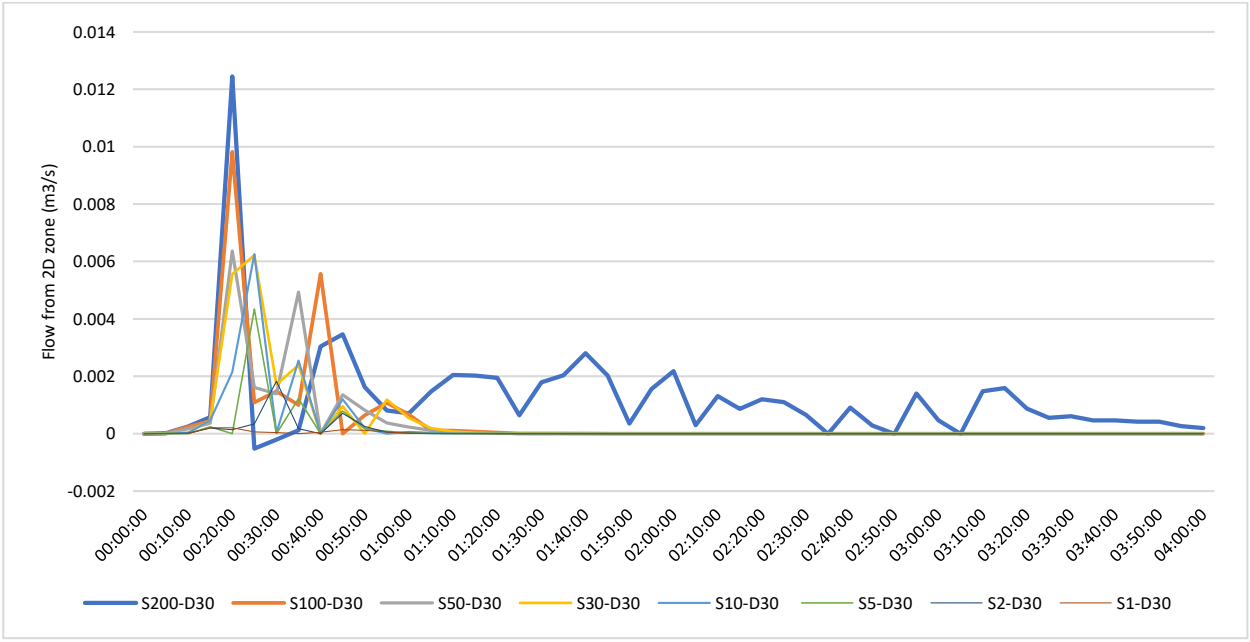
rainfall with a short lag time (10-15 mins) as time of concentration. For all rainfall events, except the 'flooding' 200-year event, flow into the node stops after 1 hour from initiation of rainfall.

On the contrary node, BSW 007 1234 U6FT is flooding at a 2-year RP, as shown in Figure 7.8b, where the system accommodates a relatively small amount of flow before flooding substantially, i.e., before the system is performing at full capacity. The zero inflow and the large flood volume indicate flow is accumulating on track bed. The flood/flow exchange behaviors for the other critical nodes are similar to that of node BSW 007 1234 U6FT.

The identified critical nodes which are flooding at low RP (BSW 007 1234 U6FT, BSW 007 0990 DCE and BSW 007 1126 DCE) all lie in the post-tunnel section. According to NR historic flood records, these nodes in the post tunnel section observe frequent flooding. Unfortunately, no records of volume, neither depth nor area, of inundation exist in the NR records for verification. It is likely that the assets do not have adequate capacity to accommodate the flow collected from the pre-tunnel section and carried through the tunnel. A possible mitigation measure is to introduce an outlet for flow in the pre-tunnel section. Alternatively, inadequate post-tunnel assets are to be regraded/ renewed to increase their capacity.

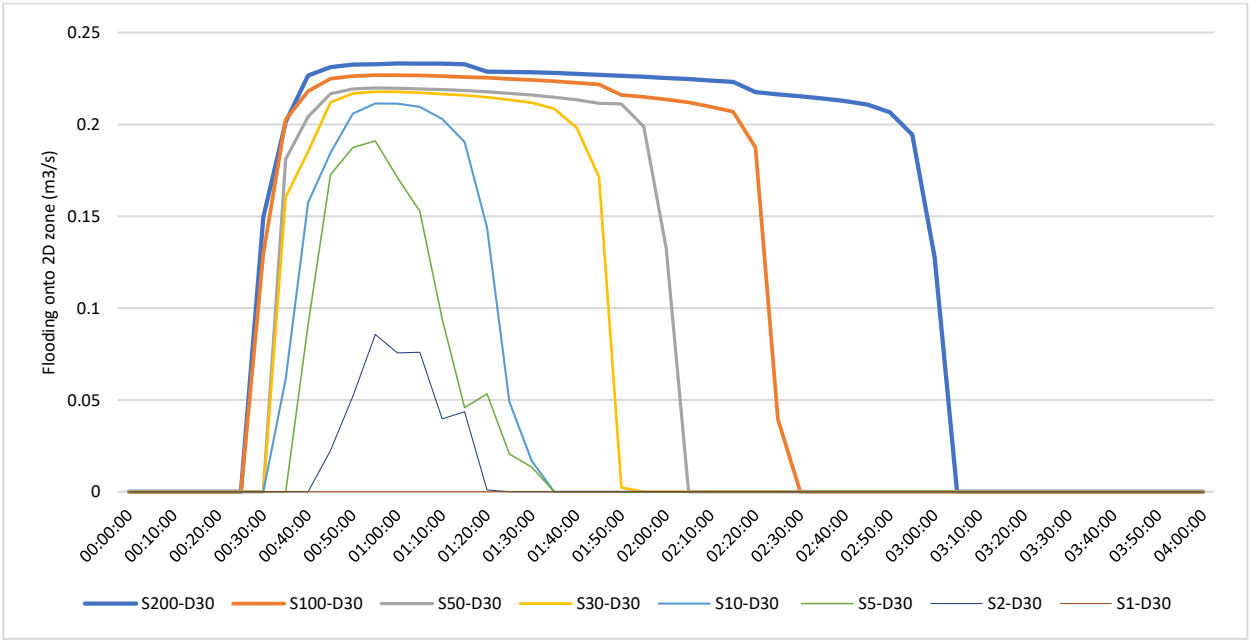



(a)

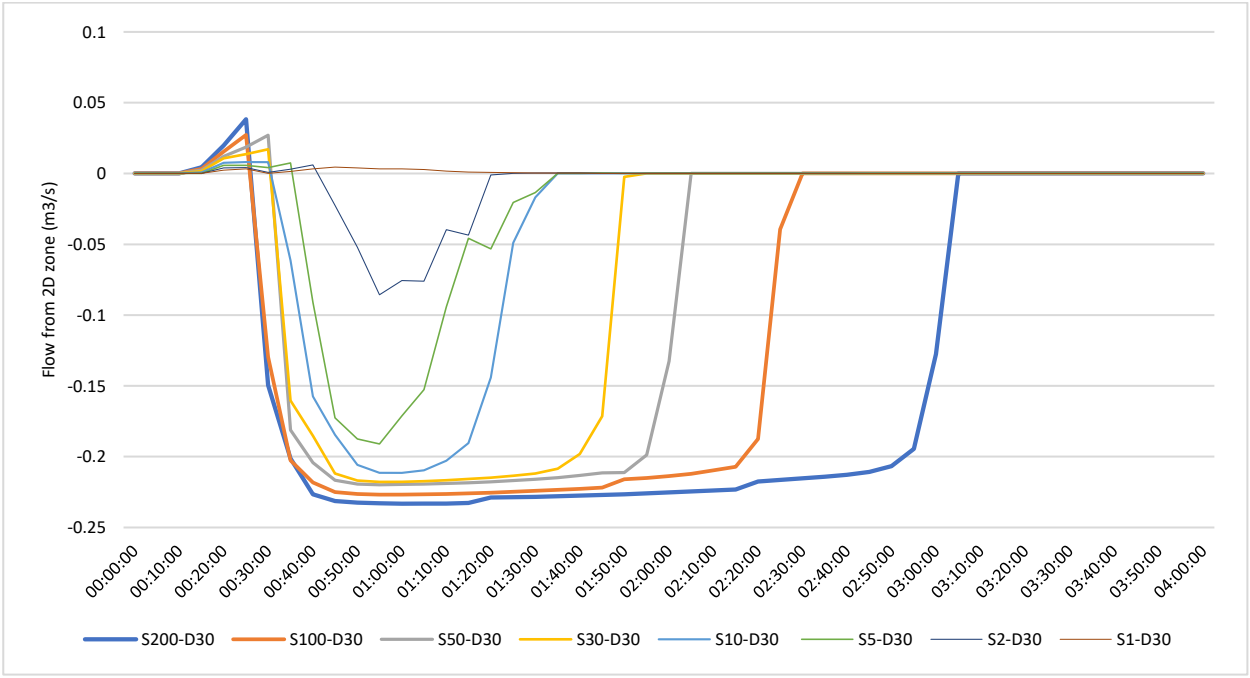



(b)

*Figure 7.7. Non-critical node example (BSW 006 0315 DCE); (a) flooding onto 2D zone and (b) flow from 2D zone over simulation duration for all storm events.*




(a)




(b)

*Figure 7.8. Critical node example (BSW 007 1234 U6FT); (a) flooding onto 2D zone and (b) flow from 2D zone over simulation duration for all storm events.*

### 7.6.4 Track inundation

The complexity of the railway flooding problem requires a detailed understanding of flood condition on the track surrounding the critical nodes. The inundation depth and speed of water on track are examined. Figure 7.9, Figure 7.10, and Figure 7.11 show the temporal change in depth of inundation and speed of flow at track elements in vicinity of nodes BSW 007 1234 U6FT, BSW 006 1217 U6FT and BSW 007 1126 DCE, respectively.

The maximum observed flood depths are 0.212 m, 2.3 m, and 0.89 m around BSW 007 1234 U6FT, BSW 006 1217 U6FT and BSW 007 1126 DCE, respectively. The significant depth of inundation at node BSW 006 1217 U6FT is explained by the topographic layout of the track within which this node lies. This location is a very restricted and deep cutting with flow from the track downside situated at a higher-level falling onto the upside track where the node lies, as shown in Figure 7.6 (a). The flood dissipates after 2 hrs 40 mins, 2 hrs 20 mins and 1 hr 25 mins after cessation of rainfall for the three nodes, respectively. This indicates that the duration set for the simulations is adequate. The longer inundation duration for node BSW 007 1234 U6FT highlights the importance of choice of location when setting duration of simulation.

Another interesting observation is that the depth of flood for node BSW 007 1234 U6FT falls sharply at around 3 hrs from the start of simulation. Fig 7.12 shows the flood pattern for the three nodes at S200-D30. It confirms that the point in time when the system stops flooding is at around the three hour mark. That is also when flow into node BSW 007 1234 U6FT picks up again (Figure 7.8b). This analysis indicates that the three-hour mark is the point in time when the system processes the flow and has the capacity to accept new flow, hence, the sharp drop in flood depth on track. Similarly for nodes BSW 006 1217 U6FT and BSW 007 1126 DCE, the points in time when flood stops (Figure 7.12) coincide with the points when inundation depth drops (Figure 7.10 and Figure 7.11), although the drop is more gradual from the peak depth compared to the sharp descend surrounding BSW 007 1234 U6FT. The

difference in behaviour is possibly due to the peak flood depth observed, wherein depth is much lower surrounding BSW 007 1234 U6FT compared to BSW 007 1126 DCE and BSW 006 1217 U6FT where the track observes higher inundation and hence more gradual descend. In addition, looking at speeds in Figure 7.9, Figure 7.10, and Figure 7.11, the flow is more stagnant surrounding nodes BSW 007 1126 DCE and BSW 006 1217 U6FT compared to BSW 007 1234 U6FT where flow is freer to move and dissipate.

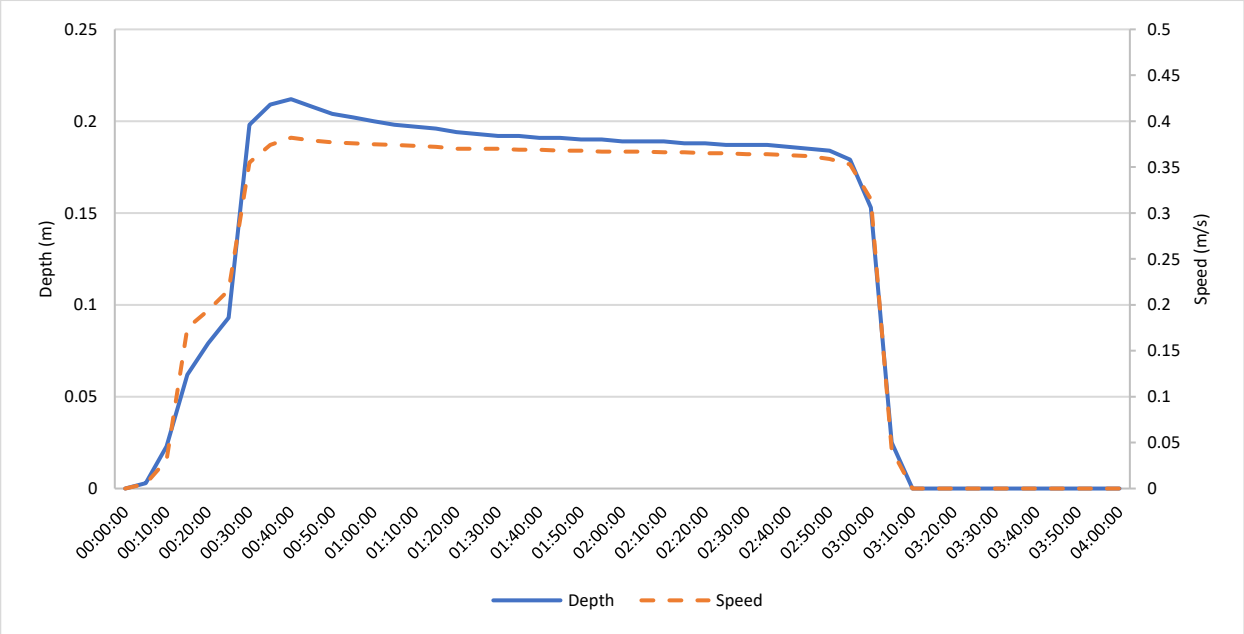



*Figure 7.9. S200-D30/ Inundation depth and speed over simulation duration for mesh element 898421 surrounding node BSW 007 1234 U6FT*




*Figure 7.10. S200-D30/ Inundation depth and speed over simulation duration for on-track mesh element 313342 surrounding node BSW 006 1217 U6FT*

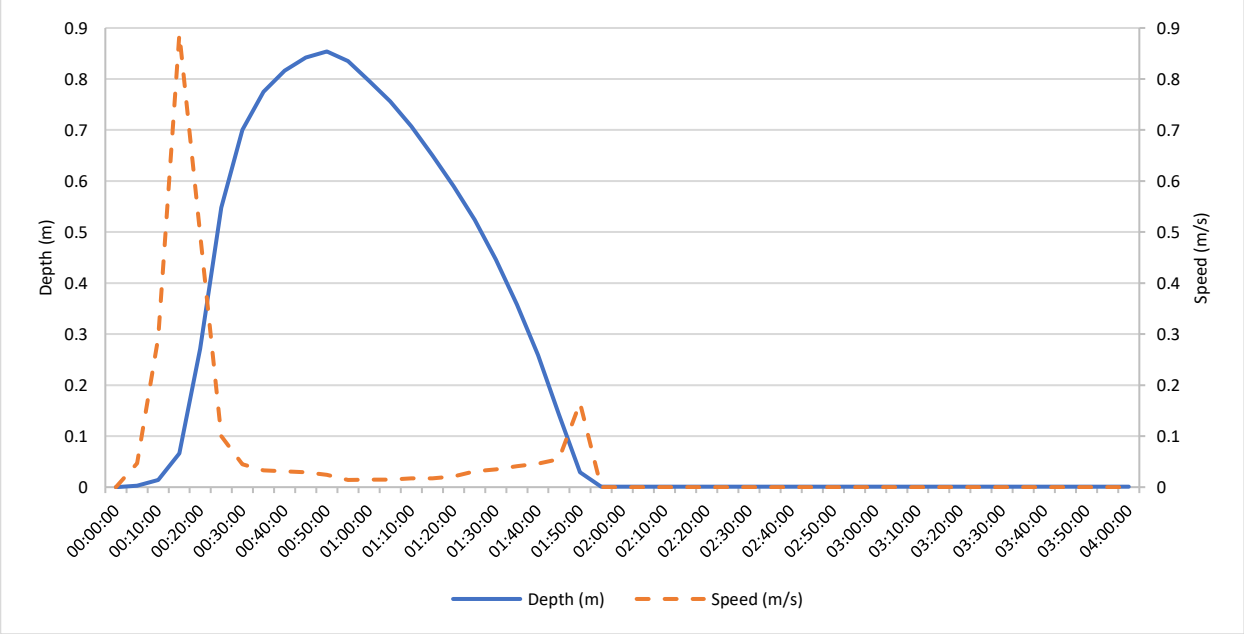



*Figure 7.11. S200-D30/ Inundation depth and speed over simulation duration for on-track mesh element 904283 surrounding node BSW 007 1126 DCE*

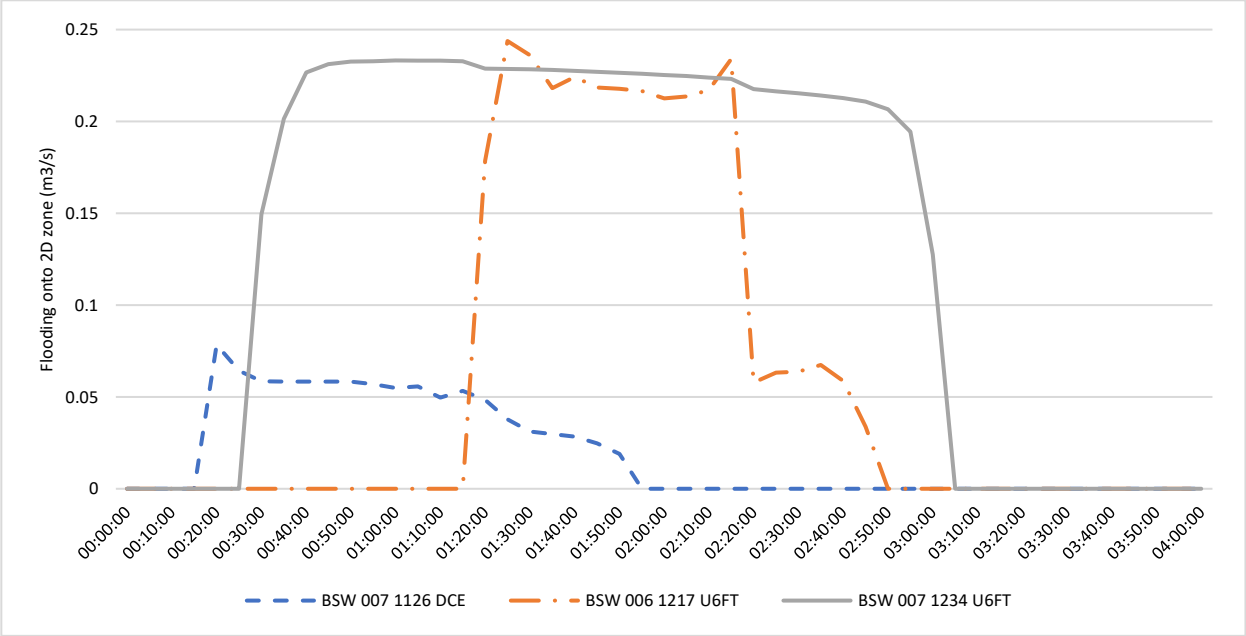



*Figure 7.12. S200-D30/ Comparison of flooding onto 2D zone between the three critical nodes.*

### 7.6.5 Exposure charts

The study uses exposure charts as a scenario analysis tool. Exposure charts show the exposure value associated with different storm return periods for a certain exposure parameter. The Flood exposure is plotted against the probability of associated storm event. Probability is provided as the annual exceedance probability of the storm event.

Due to time limitation only two critical locations are picked for demonstration of exposure charts and subsequent damage and risk quantification. The chosen locations are BSW 007 1234 U6FT and BSW 007 1126 DCE. Although location BSW 006 1217 U6FT floods at a larger volumes in RPA (Table 7.7), it floods at a larger return period and is therefore discarded as less critical.

As described in section 7.5.4, 72 simulations are run in total to obtain the scenario exposure charts. The following exposure charts (Figures 7. 13- 7.36) represent the exposure parameters over the 72 scenario simulations. Each chart represents the flood exposure resulting from storm scenarios for a specific asset condition (varying the condition of pipe downstream from the critical node). Exposure values can be

interpolated from these charts for intermediate storm events, for which simulations aren't run. The exposure charts are generated for inundation depth, duration and length as described in the following:

1. Maximum depth of inundation

Inundation depth determines the type of speed restriction imposed on the line and whether a track closure will be necessary. According to NR standards, speed restrictions are imposed when the water level reaches 0.05 m below the top of rail while a line closure is warranted when water level is at 0.1 m above rail level (Network Rail, 2018). The typical height dimension of a rail track flange is around 0.15 m (British Steel, 2017). Hence, flood level at 0.1 will warrant a speed restriction and 0.25 m flood level will warrant a closure. The exposure parameter 'maximum inundation depth on track' is filtered from 'time-depth' tables generated from simulation output results for a specific on-track mesh element. The full output depth tables are attached in Appendix C.2. The Parameter 'max depth of inundation on track' is extracted for the two sites, as shown in Figures 7.13- 7.18. It is apparent that at location BSW 007 1234 U6FT only speed restrictions are required, and no line closures are experienced. Whereas at BSW 007 1126 DCE the flood water depth on track exceeds the closure threshold.

2. Duration of inundation

Further on, duration of inundation determines the delays caused by speed restrictions/closures. This would then inform the associated direct and indirect costs of operational disruptions. Two parameters are extracted with regards to duration of inundation: duration when depth is greater than 0.09 m and duration when depth exceeds 0.25 m. These two values are chosen as the specified water level thresholds by NR for speed restriction and line closure, respectively. Similar to parameter 'maximum inundation depth', both of these parameters are filtered from the 'time-depth' tables generated from simulation output results for a specific on-track mesh element. The full output depth tables are attached in Appendix C.2. Figures 7.19- 7.27 show these parameters measured at the same element on track over the various tested scenarios. As shown in Figures 7.13- 7.15, Location BSW 007 1234 U6FT does

not experience any closures, hence no charts for duration of inundation on track when depth is greater than 0.25 are generated for the location.

3. Length of Flooded Track

Length of flooded track determines the direct M&R costs in the track section. Flood length on track is measured manually from the simulation interface output in the form of visual replays of the simulations, where depth exceeds 0.09 m 15 mins past cessation of rainfall. Screenshot images of the measurement point-in-time from the software interface simulation replays are attached in Appendix C.1. Figures 7.28- 7.33 show the length of flood on track surrounding critical nodes.

4. Length of flooded earthwork

Length of flooded earthwork informs direct maintenance cost of earthwork repair. Therefore, it is manually measured for the location where earthworks are impacted. Location surrounding node BSW 007 1126 DCE is a narrow deep cutting layout where flood water covers the parallel earthworks. Figures 7.34- 7.36 show the lengths of flooded earthworks in the section 15 minutes past cessation of rainfall, where depth of water exceeds 0.09m. The section where BSW 007 1234 U6FT lies is a shallow track section, therefore no major earthwork flooding is experienced and no charts are generated.

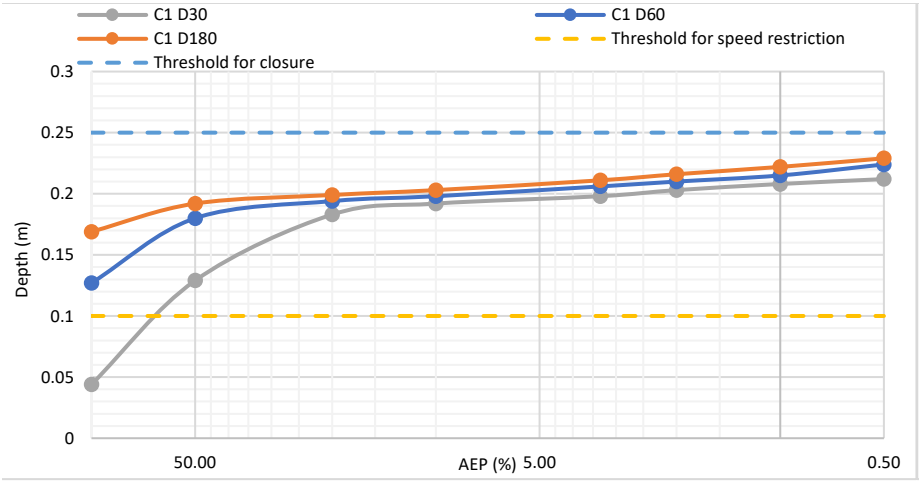



*Figure 7.13. Maximum depth of inundation on track surrounding node BSW 007 1234 U6FT when downstream pipe is in condition 1*

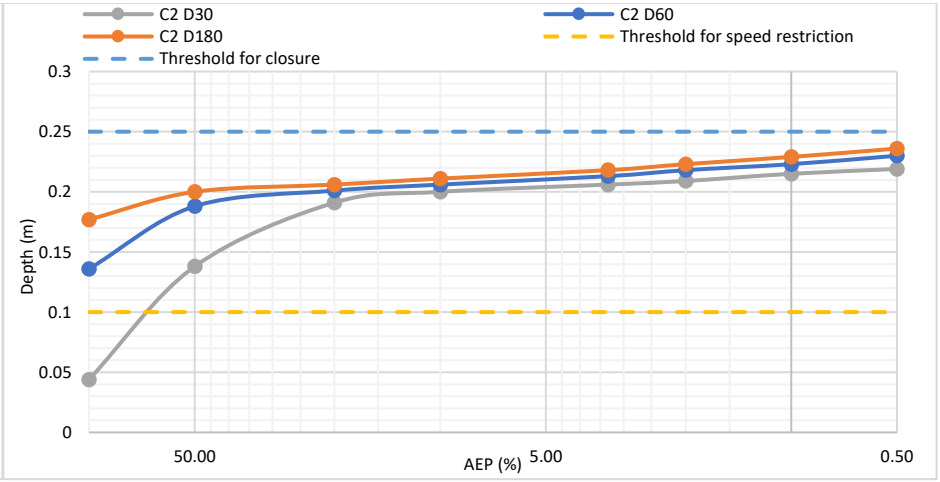



*Figure 7.14. Maximum depth of inundation on track surrounding node BSW 007 1234 U6FT when downstream pipe is in condition 2*

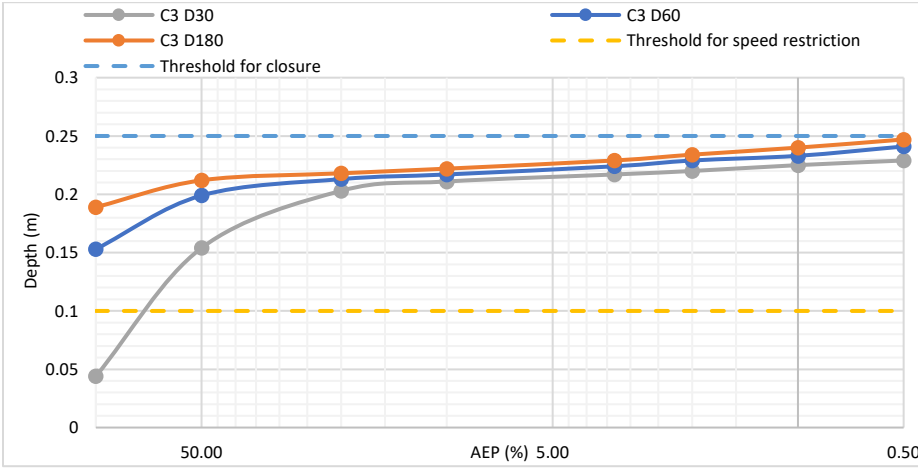



*Figure 7.15. Maximum depth of inundation on track surrounding node BSW 007 1234 U6FT when downstream pipe is in condition 3*

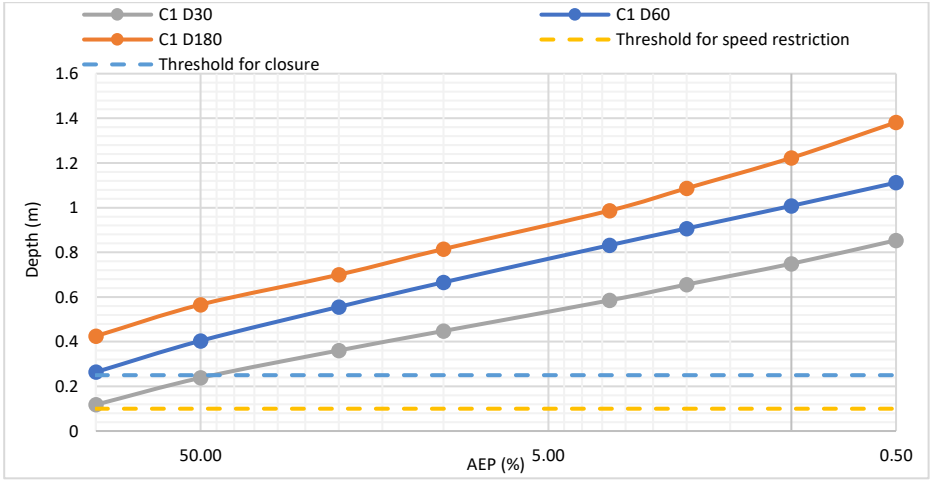



*Figure 7.16. Maximum depth of inundation on track surrounding node BSW 007 1126 DCE where downstream pipe is in condition 1*

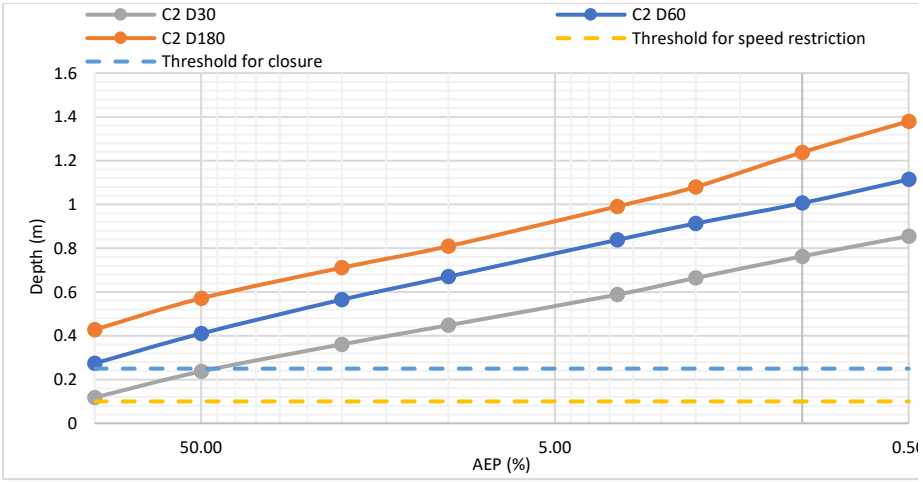



*Figure 7.17. Maximum depth of inundation on track surrounding node BSW 007 1126 DCE where downstream pipe is in condition 2*

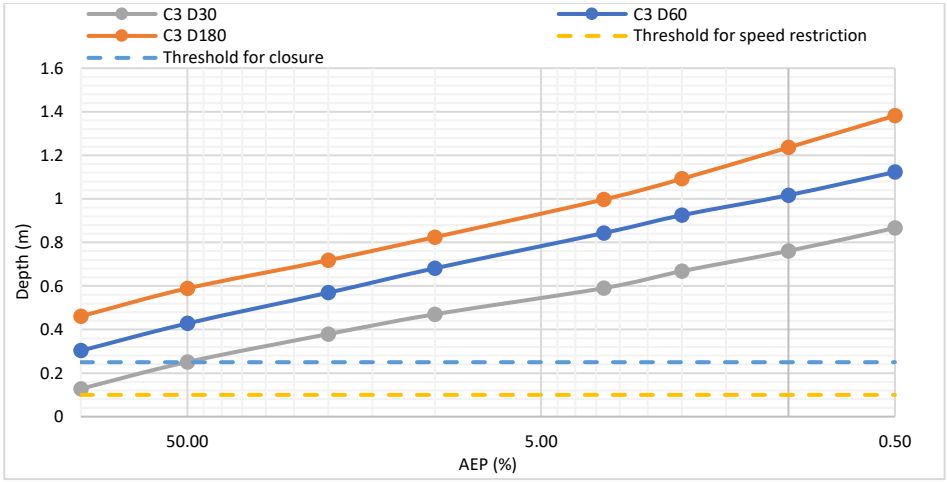



*Figure 7.18. Maximum depth of inundation on track surrounding node BSW 007 1126 DCE where downstream pipe is in condition 3*

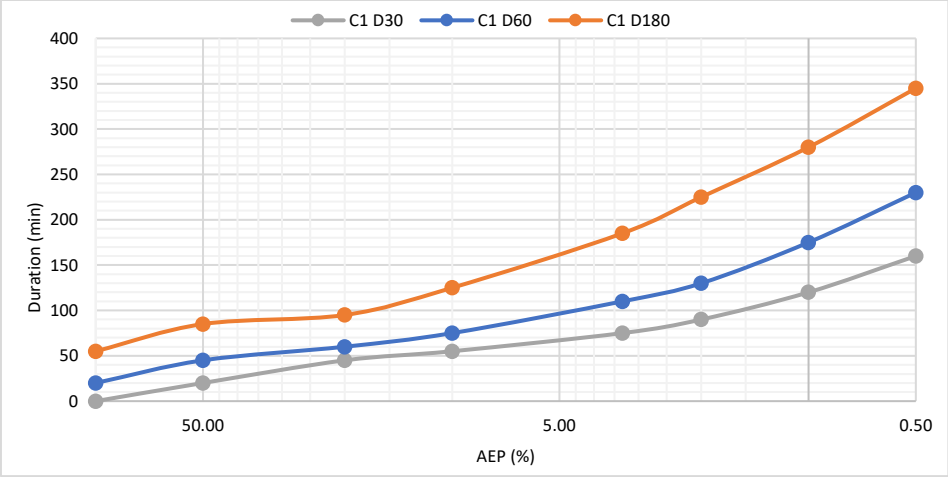



*Figure 7.19. Duration of inundation on track surrounding node BSW 007 1234 U6FT when depth of inundation is greater than 0.09; scenario when downstream pipe is in condition 1*

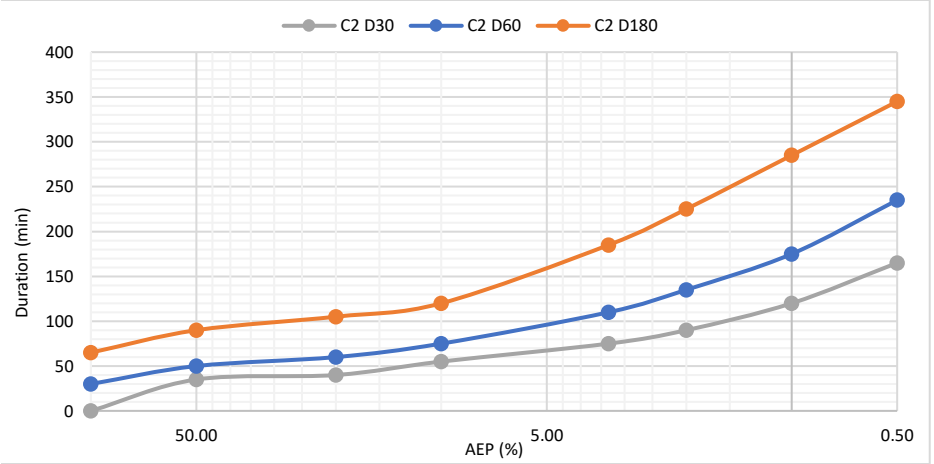



*Figure 7.20. Duration of inundation on track surrounding node BSW 007 1234 U6FT when depth of inundation is greater than 0.09; scenario when downstream pipe is in condition 2*

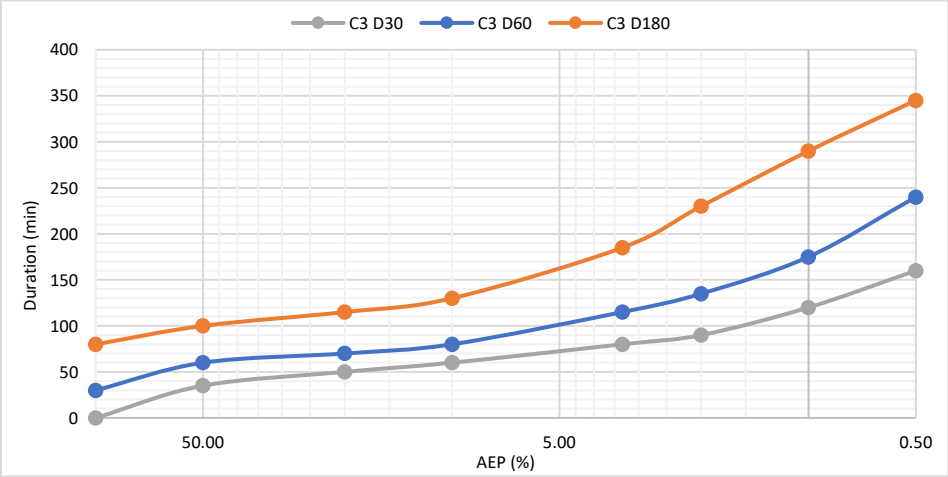



*Figure 7.21. Duration of inundation on track surrounding node BSW 007 1234 U6FT when depth of inundation is greater than 0.09; scenario when downstream pipe is in condition 3*

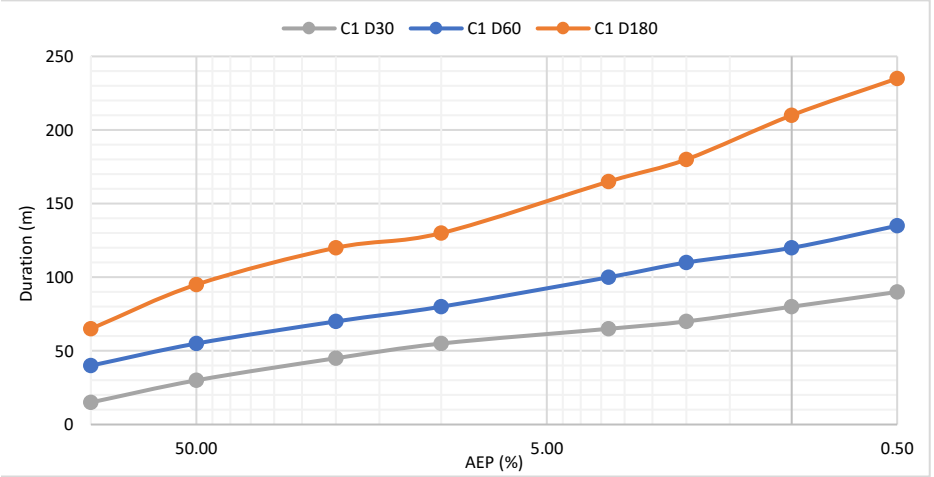



*Figure 7.22. Duration of inundation on track surrounding node BSW 007 1126 DCE when depth of inundation is greater than 0.09; scenario when downstream pipe is in condition 1*

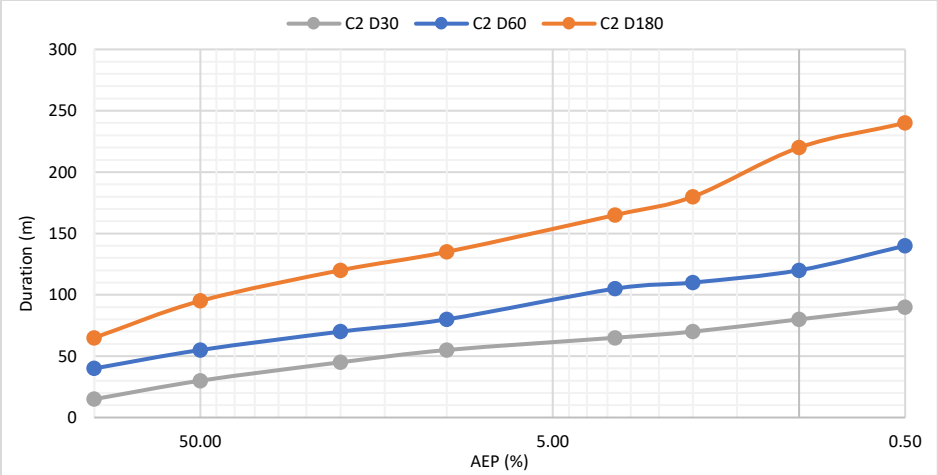



*Figure 7.23. Duration of inundation on track surrounding node BSW 007 1126 DCE when depth of inundation is greater than 0.09; scenario when downstream pipe is in condition 2*

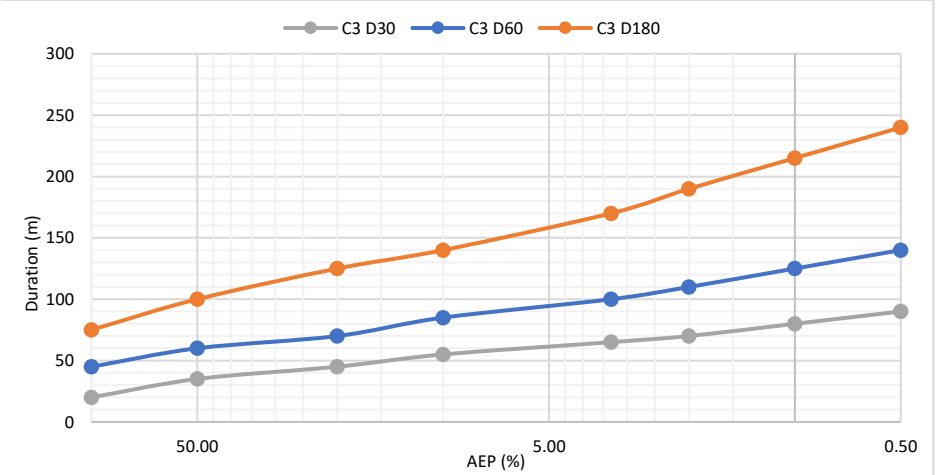



*Figure 7.24. Duration of inundation on track surrounding node BSW 007 1126 DCE when depth of inundation is greater than 0.09; scenario when downstream pipe is in condition 3*

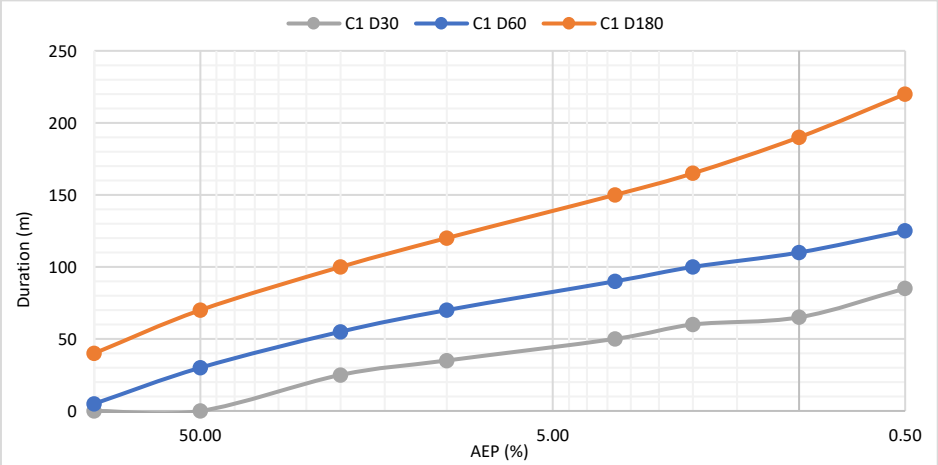



*Figure 7.25. Duration of inundation on track surrounding node BSW 007 1126 DCE when depth of inundation is greater than 0.25; scenario when downstream pipe is in condition 1*

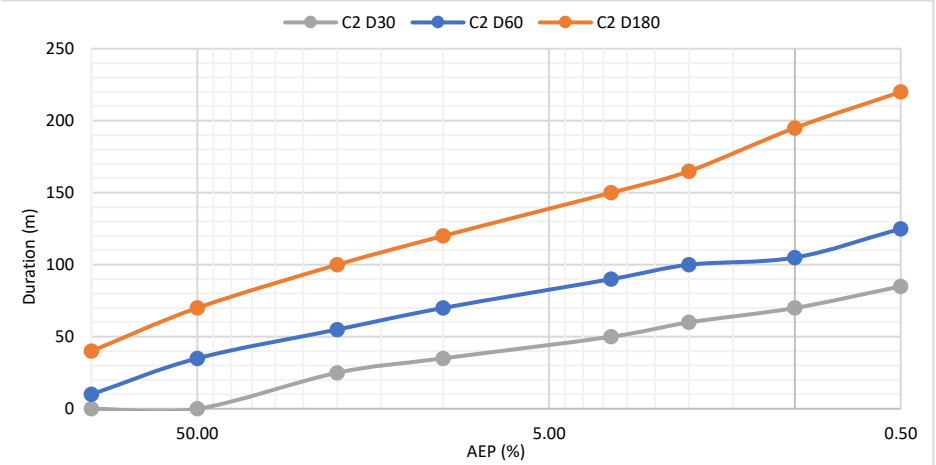



*Figure 7.26. Duration of inundation on track surrounding node BSW 007 1126 DCE when depth of inundation is greater than 0.25; scenario when downstream pipe is in condition 2*

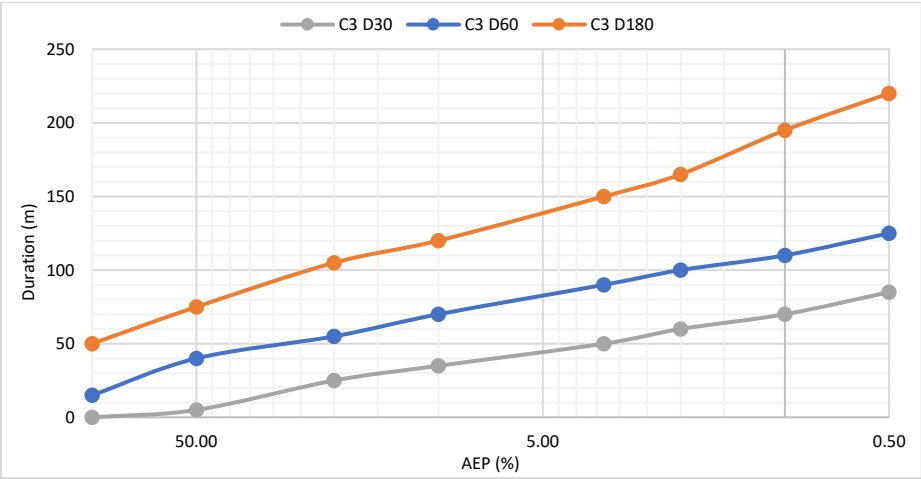



*Figure 7.27. Duration of inundation on track surrounding node BSW 007 1126 DCE when depth of inundation is greater than 0.25; scenario when downstream pipe is in condition 3*

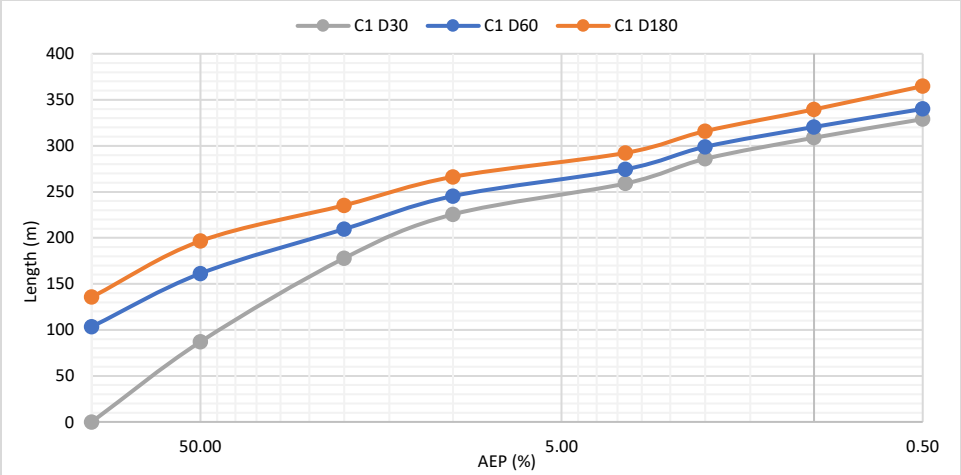



*Figure 7.28. Length of flooded track surrounding node BSW 007 1234 U6FT; scenario where downstream pipe is in condition 1*

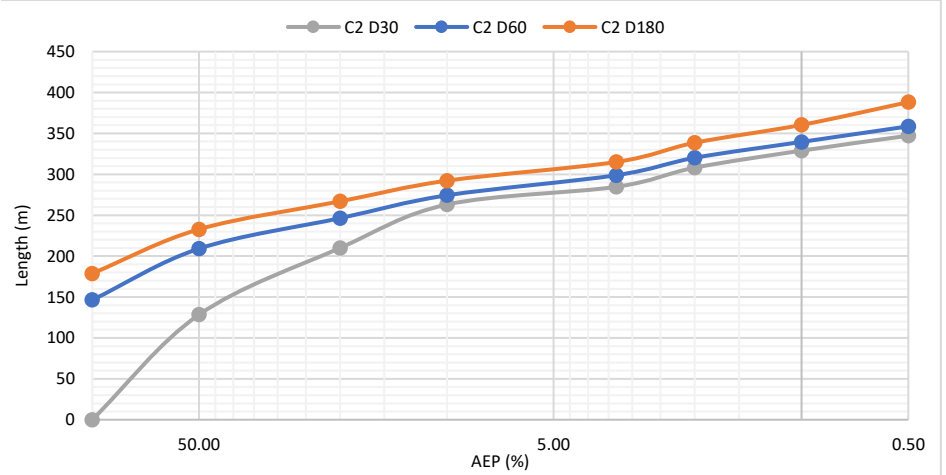



*Figure 7.29. Length of flooded track surrounding node BSW 007 1234 U6FT; scenario where downstream pipe is in condition 2*

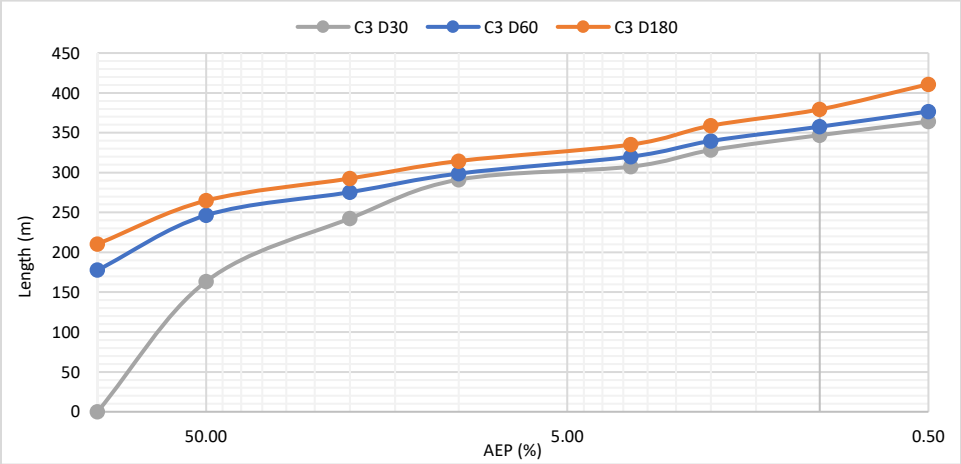



*Figure 7.30. Length of flooded track surrounding node BSW 007 1234 U6FT; scenario where downstream pipe is in condition 3*

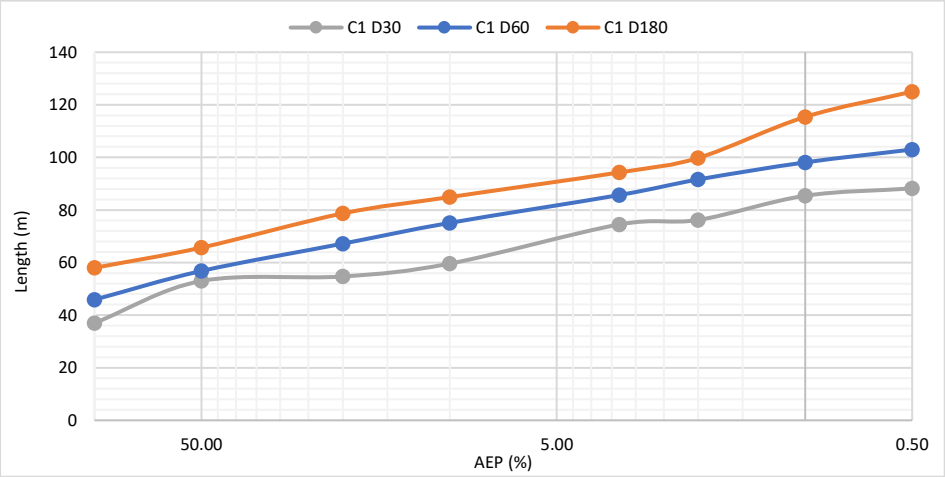



*Figure 7.31. Length of flooded track surrounding node BSW 007 1126 DCE; scenario where downstream pipe is in condition 1*

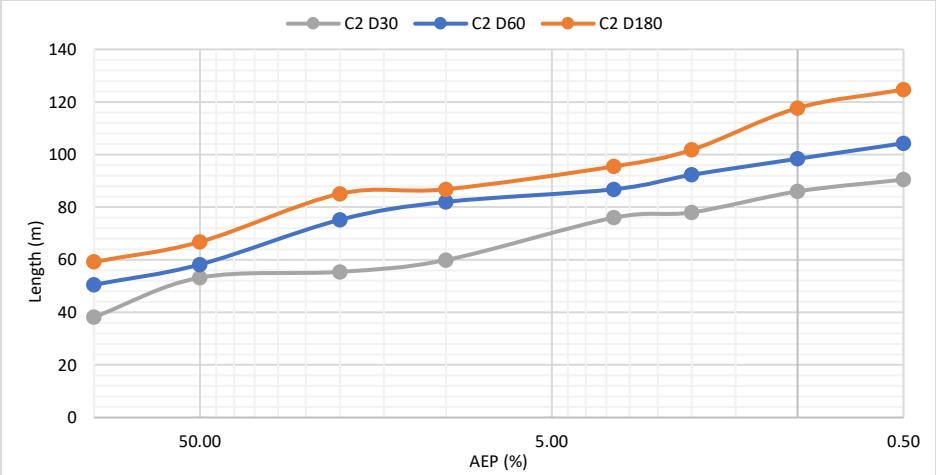



*Figure 7.32. Length of flooded track surrounding node BSW 007 1126 DCE; scenario where downstream pipe is in condition 2*

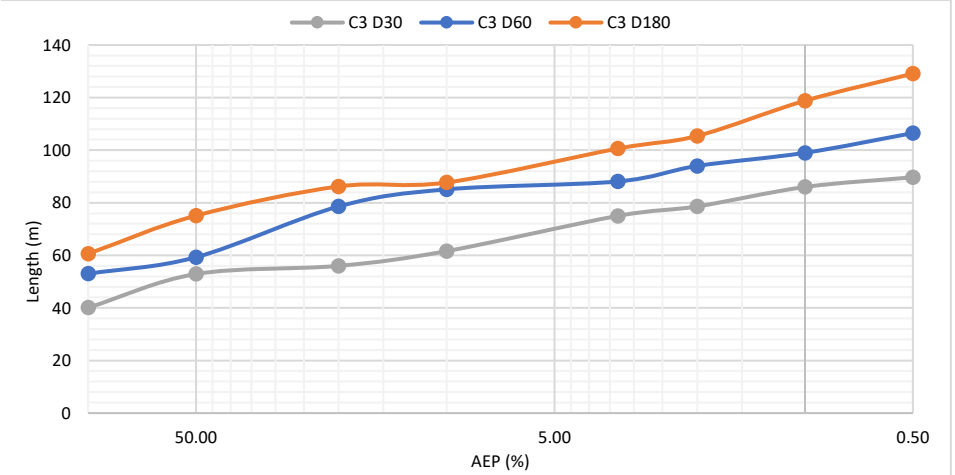



*Figure 7.33. Length of flooded track surrounding node BSW 007 1126 DCE; scenario where downstream pipe is in condition 3*

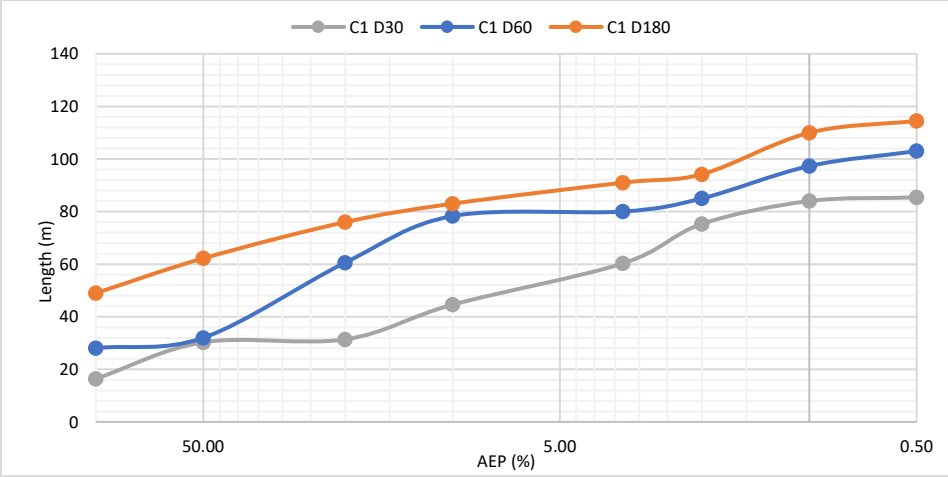



*Figure 7.34. Length of flooded earthwork surrounding node BSW 007 1126 DCE; scenario where downstream pipe is in condition 1*

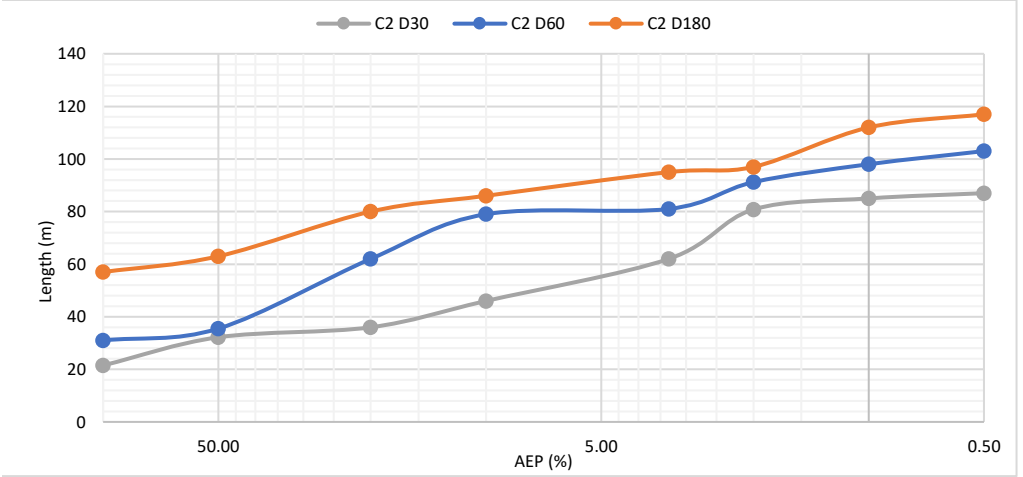



*Figure 7.35. Length of flooded earthwork surrounding node BSW 007 1126 DCE; scenario when downstream pipe is in condition 2*

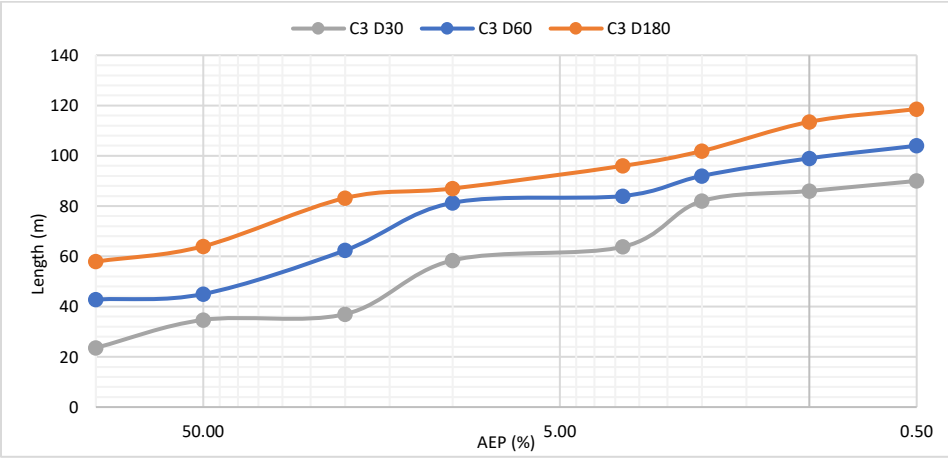



*Figure 7.36. Length of flooded earthwork surrounding node BSW 007 1126 DCE; scenario when downstream pipe is in condition 3*

## 7.7 Discussion

The demonstration of 2D hydraulic simulations makes clear their value for subsection-level criticality assessment through providing insights into the various characteristics of flood behaviour at the individual nodes in the system. In this study, RPA is used to identify critical assets for further analysis. While return period at which asset floods and volume of flood are important indications of performance inadequacy, there are more factors which contribute to criticality of locations. For instance, Node BSW 007 1234 U6FT shows higher flood volume compared to node BSW 006 1217 U6FT at all return periods, however, the maximum depth is significantly higher for the latter (see Figure 6.5 and Figure 6.10). Further on, duration of inundation is another consideration; for e.g. a larger volume which dissipates quickly would be less detrimental to the track compared to a smaller volume that is not drained away and is causing longer duration of inundation on track bed and other assets in close proximity to flooding nodes. Ghataora and Rushton (2012), and Rushton and Ghataora (2014) describe that submersion of ballast in water for extended periods of time is a major cause of railway subgrade softening which can lead to increased settlements. On a related note, when observing the change in duration of inundation over the various storm events for nodes BSW 007 1126 DCE and BSW 007 1234 U6FT (Figures 6.19-6.21 and Figures 6.22-6.24), criticality of locations changes with increasing return periods. While location BSW 007 1126 DCE is more critical for storm events S1, S2 S5 and S10, at storm event S30, location BSW 007 1234 U6FT starts observing longer durations of inundation. This stresses the importance of scenario analysis for assessment of criticality in an asset management context especially for long-term planning of strategies.

The length of inundation on track and earthwork are also used as exposure parameters, they pertain to cost quantification through determining the required amount of maintenance work. Further, they add another dimension for understanding the flood behaviour and criticality at different locations. In order

to get a full picture of flood condition, the analysis needs to consider multiple flood characteristics from simulation output, namely, depth, duration and length over a range of storm events.

As railway track system is a composite one, it varies significantly between different sites, wherein the topographic layout and interaction with surrounding areas cannot be overlooked in a flood assessment. Hence, the importance of 2D hydraulic modelling of railway drainage systems for detailed representation of flood condition. It provides a powerful tool for railway infrastructure managers to identify problem areas and help decision making when it comes to critical areas requiring immediate attention, such application can help alleviate impact of major storm events on the systems, thus reducing damages and incurred costs. The scenario analysis conducted over the various asset condition and storm events demonstrates another of the advantages of 2D hydraulic modelling; their applicability for 'what-if' analysis. This is useful to infrastructure managers to enable changing risk source values, in this case asset condition, rainfall duration and storm event return period, thus, allowing predictive risk assessment over both short- and long-term timescales. 'What-if' analysis can be conducted in combination with the previously demonstrated predictive condition models for railway drainage assets to study the exposure on the track. Such 'what-if' analysis allows investigation of outcomes of various actions in terms of allocation of time, money and manpower resources for M&R scheduling. Thus, enabling choice of a suitable action to be taken in accordance with chosen performance standards. Site criticality should be decided using a set of predefined criteria given by the infrastructure managers, based on their performance standards, accepted level of risk and the type of assets surrounding it.

Exposure charts are utilised in this study to provide a visual, comparative reflection of the flood exposure over the tested scenarios. The next stage of the of risk assessment framework uses the results from the exposure scenario analysis in a quantitative risk assessment for predictive maintenance. To integrate these exposure charts as part of a quantitative risk assessment, it is important for the predicted exposure given by the various parameters to be translated to monetary damage incurred by asset owners. Flood M&R costs are normally given by NR in units of length of flooded track. Other parameters such as

closures, delays, and associated train operator compensations, depend on depth and duration of inundation. The exposure charts can also be generated for off-track flood plains to quantify compensation damage to off-track private property in terms of affected area. This is not presented in the case study because it is a cutting layout. However, it would be highly relevant in the case of embankment layouts.

## 7.8 Limitations and recommendations

1. Limitations of the study mainly relate to the lack of calibration/ validation data from historic records. Historically, details of flooding incidents like rainfall intensity, flood volumes and dissipation data were not collected but currently NR have started recording such information. Future work could potentially use this data for calibration of hydraulic model.
2. For the purpose of demonstration of 2D hydraulic modelling, climate change is not factored to inflate rainfall intensities. However, for a prediction into the future, the climate change uplift factor should be added to the simulated rainfall events. UK Centre for Ecology and Hydrology (CEH) has maps projecting climate change allowances in the UK.
3. The hydraulic simulations and generated exposure charts enable component-level vulnerability analysis to be carried out for specific damage-receptor assets like the track, earthworks, signalling and point S&C assets. Flood characteristics like duration, depth and velocity, combined with knowledge of receptor asset condition define the exposure of the target receptor. This informs the level of damage and consequently the type of intervention required by the infrastructure manager. This type of relationship between flooding parameters and level of damage are normally called Stage-damage curves. In order to develop these stage-damage curves, further research on degradation of these assets in response to presence of water is required.
4. Furthermore, uncertainties in the imported digital terrain model could be a source of uncertainty in the flood exposure output. Arrighi and Campo (2019) carries out 2D hydraulic simulations to

evaluate the sensitivity of flood damage estimates to uncertainties in DTM. They also propose methods to improve DTM estimates through merging LiDAR-derived DTM with elevation point data. Results of the research show that an extensive amount of computational effort is required for a 5% improvement in output. The suggestion here is to validate the exposure results from the simulations using real inundation data and thereon evaluate the value of improving the DTM. This is potentially more useful in high density urban areas.

## 7.9 Summary

This case study demonstrates the use of 2D hydraulic modelling for identification of critical locations on railway section that are susceptible to flooding as well as quantitatively measure the exposure resulting from a flood occurrence. The study reflects the impact of asset condition, obtained from site survey records, on the hydraulic performance of the asset. Furthermore, the catchment area is conservatively set to account for the substantial runoff contribution by off-track areas surrounding railway. To reflect accurate runoff from both on-track and off-track, the model incorporates a detailed representation of the terrain and various land covers through the use of terrain-sensitive meshing and zoning of catchment based on roughness and infiltration coefficients. Flood volume and flooding return period are used to judge criticality of locations. Furthermore, a scenario analysis is conducted at the critical locations to demonstrate the use of 2D hydraulic modelling as part of an asset management practice. Scenario analysis entails varying the values of flooding sources, characterized by asset condition, rainfall duration and storm event return period. The study demonstrates the potential use of exposure charts as a scenario analysis tool for evaluation and comparisons of four main exposure quantification parameters. At first instance, flood volume is used to identify critical locations. On further investigation, maximum inundation depth, duration of inundation, lengths of inundation on track and surrounding earthworks, are measured from the simulation output to develop an understanding of the flood exposure caused by various scenarios of asset condition, rainfall duration and storm event.

# Chapter 8: Flood damage and flood risk quantification: Case study

## 8.1 Introduction

This chapter demonstrates the last two modules of the proposed theoretical framework. In the previous module, hydraulic flood simulations are used to identify the critical locations and obtain the flood exposure resulting from various risk scenarios in the form of exposure charts. Through damage quantification, exposure charts are converted into damage charts i.e., monetary damage charts, using the damage cost model (Chapter 5). The last stage is risk quantification which allows comparisons between the identified critical locations. To consider uncertainties in input parameters, both damage quantification and risk quantification are demonstrated in this chapter using Monte Carlo simulations (MCs). The chapter first recaps the proposed method and then describes the details of the cost model, uncertainty analysis and MCs setups for damage and risk quantification.

## 8.2 Methodology

The proposed theoretical framework separates the damage (consequence) quantification and risk quantification into two modules following the definition: Risk= Probability × Consequence. For the purpose of this demonstration, the two modules are combined into one case study. MCs output is then structured differently for either type of quantification. In light of the theoretical framework, the followed steps are described below.

1. Identify sources of risk and their probabilities (Section 8.4.1).
2. Define a parametric cost model (Section 8.4.2)
3. Identify and obtain exposure measurements for drainage and other track assets (Section 8.4.3).
4. Obtain unit costs and other cost-related parameters (Section 8.5).
5. Identify uncertainties in inputs (Section 8.5).
6. Define suitable distributions to reflect uncertainties in inputs (Section 8.5).

7. Define MCs output for damage quantification (Section 8.6).
8. Generate damage charts for the tested scenarios (Section 8.7)
9. Define MCs output for risk quantification using the parametric cost model (Section 8.6).

## 8.3 Case study site

Damage and risk quantification are carried out using the output of flood simulations for the Patchway site, shown in Figure 8.1 as the section length connecting stations Pilning and Patchway. Among the identified critical chambers, two locations are chosen for investigation in this case study, these are the locations surrounding chambers BSW 007 1234 U6FT (1234) and BSW 007 1126 DCE (1126). Chamber '1234' floods at a 1 in 2 return period (50% AEP) whereas chamber '1126' floods at a 1 in 1 return period (100% AEP). According to site specification documents provided by Network Rail (NR) drainage and lineside team, the Patchway site is considered high importance which reflects in any operational disruption costs induced by flooding. Risk is calculated and compared for the two locations as a demonstration of the proposed framework for informing asset intervention prioritisation strategies.

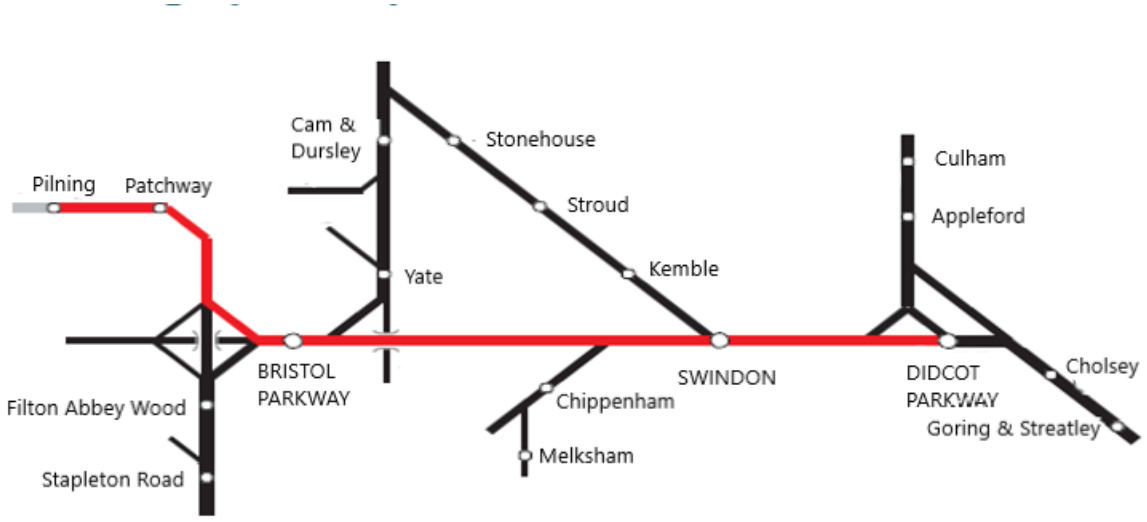



*Figure 8.1. Patchway section as part of the full local network (route specification, Network rail)*

## 8.4 Risk components

### 8.4.1 Sources of risk

As described in Chapter 3, flooding occurs as a result of excessive runoff volume met with insufficient capacity of the drainage system. Accordingly, flood risk is the result of two main sources: condition of drainage asset, and the rainfall event. Thereof, the following three factors are considered to contribute to risk scenarios: condition of drainage assets (C), storm event return period (S) and rainfall duration (D). Each of these are defined with a probability of occurrence. Table 8.1 Shows the risk sources, their likely values and the associated occurrence probabilities. The probability of storm event occurrence is the inverse of the event's return period. The shown probabilities associated with asset condition and storm duration are hypothetically set for demonstration. The asset condition reported in NR asset records is allocated the highest probability of occurrence.

The flood simulation impact scenarios are generated using various combinations of the three identified risk sources. The probability of each scenario is the product of the occurrence probabilities of each of the identified risk sources. For example, in any given year, the probability of a scenario where asset condition is 1 (C1), storm event duration is 30 mins (D30) and event of 1 in 1 (S1) is shown in Equation 8.1:

*Equation 8.1*

$$P_{C1-D30-S1} = 0.4 \times 0.3 \times 1 = 0.12\ (12\%)$$

*Table 8.1. Risk sources and associated probabilities of occurrence*

| Risk sources and probabilities | | | | | |
|---|---|---|---|---|---|
| Asset condition | Probability | Storm event duration | Probability | Storm event return period | Probability |
| 1 | 0.4 | 30 | 0.3 | 1 | 1 |
| | | | | 2 | 0.5 |
| 2 | 0.3 | 60 | 0.4 | 5 | 0.2 |
| | | | | 10 | 0.1 |
| | | | | 30 | 0.033 |
| 3 | 0.3 | 180 | 0.3 | 50 | 0.02 |
| | | | | 100 | 0.01 |
| | | | | 200 | 0.005 |

### 8.4.2 Cost model

The cost model is developed to obtain the consequence component of risk in terms of monetary damage. The cost model is the parametric relationship that translates the exposure measures from the flood simulation into consequence (damage). The theoretical cost model in Chapter 5 describes five categories of damage cost incurred by infrastructure managers (shown in Equation 8.2). The theoretical cost model is customised according to the infrastructure manager standards, data availability, costing approaches and the types of damage sustained at the site. In this case study, the cutting layout of the site eliminates off-track damage cost component where damage is limited to the track assets and neighbouring earthworks. The cost data obtained from NR is limited and aggregated in terms of inspections and track M & R. Therefore, inspection cost is not considered explicitly. Reputational and environmental damage are not considered due to difficulty in quantifying the indirect cost and scarcity of relevant data for this task. Further investigation is required beyond the time limitation of this demonstration. Thereon, the considered cost components in this case study application are the two major categories contributing to directly incurred costs: M&R and track operations. The adjusted cost model is provided in Equation 8.3. Table 8.2 provides the detailed parametric relationships used in the case study to run the MCs damage quantification simulations, along with the relevant assumptions. Within the M & R category, data obtained from NR is pertinent to track structure, earthworks and drainage. However, the obtained unit costs are associated with only one specific intervention type, namely renewal. Therefore, for the purpose of this demonstration, it is assumed that renewal is warranted by presence of flood regardless of level of flood exposure. Such scarcity of unit cost data for other types of interventions combined with the lack of degradation models which relate asset flood exposure to level; of damage (and intervention type) justify the assumption of a single type of intervention. Furthermore, as reflected in Table 8.2, the drainage cost data is more disaggregate in terms of labour and the type of drainage asset, compared to the aggregated costs for earthworks and track structure interventions. Within operational disruptions, scarcity of data also presents a challenge, where data is only obtained for

delay costs. However, for the purpose of a realistic application, distinction is made between cancellations and delays albeit by means of assumption (Table 8.2).

*Equation 8.2*

$$C_{flood\ damage} = C_{Inspections} + C_{Maintenance\ \&\ Repair} + C_{track\ operation} + C_{off-track\ damage} + C_{Reputation}$$

*Equation 8.3*

$$C_{flood\ damage} = C_{Maintenance\ \&\ Repair} + C_{operational\ disruption}$$

$$= C_{Track\ structure} + C_{Earthworks} + C_{Drainage} + C_{flood\ incident\ operational\ disruption} + C_{maintennce\ closure}$$

*Table 8.2. Case study cost equations*

| Category | Type of intervention | Equation | Relevant assumptions |
|---|---|---|---|
| Track structure | Formation renewal and re-ballasting | $C_{T-RB} \times L_{FT}$ | • Interventions for both track superstructure and track substructure are combined into one category: track structure, to adapt to the way NR reports renewal costs |
| Drainage | Catchpit renewal | $C_{D-CR} \times N_{FC}$ | NA |
| | Pipe renewal | $C_{D-PR} \times L_{FP}$ | NA |
| | labour | $C_{D-L} \times \frac{L_{FP}}{L_{D-L}}$ | NA |
| Earthworks | Earthwork renewal | $C_{EW-R} \times L_{FEW}$ | NA |
| Operational disruptions | Operational delay due to speed restrictions | $C_{OpD-D} \times T_{SR} \times N_T \times (\frac{L_{FT}}{S_R} - \frac{L_{FT}}{S_L})$ | • Route is high criticality which is reflected in choice of delay cost<br>• No freight trains passing location<br>• Based on NR drainage standards threshold for speed restrictions is set at 0.1 m (under assumption that rail flange is 0.15 m deep) |

| Category | Type of intervention | Equation | Relevant assumptions |
|---|---|---|---|
| | | | • Regular line speed =125 mph according to route speed information manual provided by drainage asset engineers<br>• Restricted speed= 20 mph according to a CCIL report provided by drainage engineer |
| | Operational cancellation due to closures | • If $T_C$<30 mins<br>$C_{OpD-D} \times T_C \times N_T \times T_C$<br>• If $T_C$> 30 mins<br>$C_{OpD-C} \times T_C \times N_T$ | • Based on NR drainage standards, threshold for closure is set at 0.25 m (under assumption that rail flange is 0.15 m deep)<br>• If duration above closure threshold is less than 30 mins, only delay due to train stoppage is assumed, where duration of delay is equal to duration of inundation above the closure threshold. Whereas if duration of closure is greater than 30 mins it is then assumed that a cancellation is warranted. |
| | Cancellation due to maintenance activity track possessions | $C_{OpD-C} \times T_{OpD-MP} \times N_T \times (L_{FT} + L_{FP} + L_{FEW})$ | • Although the three M&R intervention activities could be carried out simultaneously, they are conservatively assumed to be carried separately.<br>• The possession time per unit length is assumed the same for the three types of interventions |
| $C_{T-RB}$: Cost of track renewal and re-ballasting per unit length<br>$L_{FT}$ : Length of flooded track<br>$C_{D-CR}$ : Cost of catchpit renewal per unit<br>$N_{FC}$: Number of flooded chambers<br>$C_{D-PR}$: Drainage pipe renewal per unit length<br>$L_{FP}$: Length of flooded pipes<br>$C_{D-L}$: Cost of labor per shift<br>$L_{D-L}$: Length covered by labor per shift<br>$C_{EW-R}$: Cost of Earthwork renewal per unit length | | | $L_{FEW}$: Length of flooded earthworks<br>$C_{OpD-D}$: Compensation to operators per train per delay unit time<br>$T_{SR}$: Duration of inundation warranting speed restriction<br>$N_T$: Number of passenger trains passing site per unit time<br>$S_L$: Speed of line<br>$S_R$: Restricted speed<br>$T_C$: Duration of inundation warranting closure<br>$C_{OpD-C}$: Compensation to operators per cancelled train<br>$T_{OpD-MP}$: Maintenance possession time per unit length of work |

### 8.4.3 Flood exposure

Each scenario of flood risk sources is associated with exposure measures extracted from the flood simulations (chapter 7). These exposure parameters constitute the rail section's exposure to flooding. The extracted exposure parameters are chosen based on the required inputs for the customised cost model (section 8.4.2). These exposure parameters are represented over the scenarios with exposure charts (chapter 7). In this case study, the exposure charts are translated into monetary Damage charts for each scenario using the equations in Table 8.2. The required exposure parameters are listed below with their notation. Table 8.3 and Table 8.4 show the extracted measurements for these parameters tabulated in the format used for MCs simulations. Earthwork damage is only considered at location "1126" as it is a deep cutting layout whereas location "1234 is a shallow and earthwork damage is considered negligible.

- Length of flooded track ($L_{FT}$)
- Number of flooded chambers ($N_{FC}$)
- Length of flooded pipes ($L_{FP}$)
- Length of flooded earthworks ($L_{FEW}$)
- Duration of inundation above 0.1 m and below 0.25 m thresholds ($T_{SR}$)
- Duration of inundation above 0.25 m threshold ($T_C$)

*Table 8.3. Tabulated measurements for the exposure parameters at location "1234" for damage quantification*

| Category | Description | Storm event | C1 D30 | C1 D60 | C1 D180 | C2 D30 | C2 D60 | C2 D180 | C3 D30 | C3 D60 | C3 D180 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Track structure | $L_{FT}$ | S1 | 0.0 | 103.5 | 135.7 | 0.0 | 146.4 | 178.8 | 0.0 | 177.7 | 210.5 |
| | | S2 | 87.1 | 161.3 | 196.6 | 128.4 | 209.1 | 232.8 | 163.5 | 246.5 | 264.9 |
| | | S5 | 177.9 | 209.5 | 235.4 | 210.0 | 246.4 | 266.9 | 242.6 | 275.4 | 292.6 |
| | | S10 | 225.5 | 245.4 | 266.3 | 263 | 274.3 | 292.2 | 291.2 | 298.8 | 314.5 |
| | | S30 | 259.1 | 274.5 | 292.3 | 284.7 | 298.9 | 315.1 | 307.5 | 320.1 | 335.2 |
| | | S50 | 285.9 | 299.0 | 316.0 | 308.1 | 320.2 | 338.6 | 328.3 | 339.7 | 358.9 |
| | | S100 | 308.8 | 320.5 | 339.6 | 328.9 | 339.6 | 360.4 | 347.0 | 357.6 | 379.3 |
| | | S200 | 329.0 | 340.1 | 364.9 | 347.2 | 358.6 | 388.2 | 364.0 | 376.7 | 410.9 |
| Drainage | $N_{FC}$ | S1 | 0 | 1 | 2 | 0 | 1 | 2 | 0 | 1 | 2 |
| | | S2 | 1 | 2 | 2 | 1 | 2 | 2 | 1 | 2 | 2 |
| | | S5 | 1 | 2 | 2 | 1 | 2 | 2 | 1 | 2 | 2 |
| | | S10 | 2 | 2 | 3 | 2 | 2 | 3 | 2 | 2 | 2 |
| | | S30 | 2 | 3 | 4 | 2 | 2 | 3 | 2 | 2 | 2 |
| | | S50 | 2 | 4 | 4 | 2 | 2 | 3 | 2 | 2 | 2 |
| | | S100 | 3 | 4 | 4 | 2 | 3 | 3 | 2 | 2 | 3 |
| | | S200 | 4 | 4 | 4 | 2 | 3 | 3 | 2 | 2 | 3 |

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | $L_{FP}$ | S1 | 0.0 | 115.0 | 142.3 | 0.0 | 192.5 | 192.5 | 0.0 | 192.5 | 233.2 |
| | | S2 | 92.1 | 192.5 | 233.2 | 142.3 | 233.2 | 233.2 | 192.5 | 273.7 | 273.7 |
| | | S5 | 192.5 | 233.2 | 273.7 | 233.2 | 273.7 | 273.7 | 273.7 | 314.1 | 314.1 |
| | | S10 | 233.2 | 273.7 | 273.7 | 192.5 | 314.1 | 314.1 | 233.2 | 314.1 | 337.9 |
| | | S30 | 273.7 | 314.1 | 314.1 | 314.1 | 314.1 | 337.9 | 314.1 | 337.9 | 337.9 |
| | | S50 | 314.1 | 314.1 | 337.9 | 314.1 | 337.9 | 383.4 | 337.9 | 383.4 | 383.4 |
| | | S100 | 314.1 | 337.9 | 383.4 | 337.9 | 383.4 | 383.4 | 383.4 | 383.4 | 383.4 |
| | | S200 | 337.9 | 383.4 | 383.4 | 383.4 | 383.4 | 428.4 | 383.4 | 383.4 | 428.4 |
| Operational disruption | $T_{D>0.09}$ | S1 | 0 | 20 | 55 | 0 | 31 | 66 | 0 | 35 | 80 |
| | | S2 | 20 | 45 | 85 | 35 | 52 | 92 | 40 | 61 | 101 |
| | | S5 | 45 | 60 | 95 | 48 | 65 | 106 | 54 | 72 | 116 |
| | | S10 | 55 | 75 | 125 | 60 | 80 | 128 | 65 | 85 | 134 |
| | | S30 | 75 | 110 | 185 | 80 | 115 | 190 | 85 | 120 | 193 |
| | | S50 | 90 | 130 | 225 | 95 | 137 | 230 | 98 | 141 | 235 |
| | | S100 | 120 | 175 | 280 | 125 | 180 | 287 | 128 | 183 | 293 |
| | | S200 | 160 | 230 | 345 | 165 | 237 | 350 | 170 | 243 | 353 |
| | $T_C$ | S1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | | S2 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | | S5 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | | S10 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | | S30 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | | S50 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | | S100 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | | S200 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | $T_{SR}$ | S1 | 0 | 20 | 55 | 0 | 31 | 66 | 0 | 35 | 80 |
| | | S2 | 20 | 45 | 85 | 35 | 52 | 92 | 40 | 61 | 101 |
| | | S5 | 45 | 60 | 96 | 48 | 65 | 106 | 54 | 72 | 116 |
| | | S10 | 56 | 75 | 125 | 60 | 80 | 128 | 65 | 85 | 134 |
| | | S30 | 75 | 110 | 185 | 80 | 115 | 190 | 85 | 120 | 193 |
| | | S50 | 90 | 130 | 225 | 95 | 137 | 230 | 98 | 141 | 235 |
| | | S100 | 120 | 175 | 280 | 125 | 180 | 287 | 128 | 183 | 293 |
| | | S200 | 160 | 230 | 345 | 167 | 237 | 350 | 170 | 243 | 353 |

*Table 8.4. Tabulated measurements for the exposure parameters at location "1126" for damage quantification*

| Category | Description | Storm event | C1 D30 | C1 D60 | C1 D180 | C2 D30 | C2 D60 | C2 D180 | C3 D30 | C3 D60 | C3 D180 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Track structure | $L_{FT}$ | S1 | 37 | 45.9 | 58 | 38.2 | 50.5 | 59.2 | 40.1 | 53 | 60.6 |
| | | S2 | 53 | 56.8 | 65.7 | 53.2 | 58.2 | 66.8 | 52.9 | 59.3 | 75.1 |
| | | S5 | 54.7 | 67.2 | 78.7 | 55.4 | 75.2 | 85.1 | 56 | 78.6 | 86.2 |
| | | S10 | 59.6 | 75.1 | 84.9 | 59.9 | 82 | 86.8 | 61.6 | 85.1 | 87.7 |
| | | S30 | 74.5 | 85.7 | 94.3 | 76 | 86.8 | 95.5 | 75 | 88.1 | 100.6 |
| | | S50 | 76.2 | 91.6 | 99.8 | 78 | 92.3 | 101.8 | 78.6 | 94 | 105.4 |
| | | S100 | 85.4 | 98.1 | 115.4 | 86 | 98.4 | 117.7 | 86 | 99 | 118.8 |
| | | S200 | 88.2 | 103 | 125 | 90.5 | 104.3 | 124.7 | 89.7 | 106.5 | 129.1 |
| Drainage | $N_{FC}$ | S1 | 0 | 1 | 2 | 0 | 2 | 2 | 1 | 2 | 2 |
| | | S2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 |
| | | S5 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 |
| | | S10 | 2 | 2 | 3 | 2 | 2 | 3 | 2 | 2 | 3 |
| | | S30 | 2 | 2 | 3 | 2 | 2 | 4 | 2 | 2 | 4 |
| | | S50 | 2 | 3 | 4 | 2 | 3 | 4 | 2 | 3 | 4 |
| | | S100 | 2 | 3 | 4 | 2 | 3 | 4 | 2 | 3 | 4 |
| | | S200 | 2 | 4 | 4 | 2 | 3 | 4 | 2 | 4 | 4 |
| | $L_{FP}$ | S1 | 62.3 | 62.3 | 62.3 | 62.3 | 62.3 | 62.3 | 62.3 | 62.3 | 62.3 |
| | | S2 | 62.3 | 62.3 | 94.7 | 62.3 | 62.3 | 94.7 | 62.3 | 62.3 | 94.7 |
| | | S5 | 62.3 | 94.7 | 94.7 | 62.3 | 94.7 | 94.7 | 62.3 | 94.7 | 94.7 |
| | | S10 | 62.3 | 94.7 | 94.7 | 62.3 | 94.7 | 94.7 | 62.3 | 94.7 | 94.7 |
| | | S30 | 94.7 | 94.7 | 94.7 | 94.7 | 94.7 | 128.4 | 94.7 | 94.7 | 128.4 |
| | | S50 | 94.7 | 94.7 | 128.4 | 94.7 | 94.7 | 128.4 | 94.7 | 94.7 | 128.4 |
| | | S100 | 94.7 | 128.4 | 128.4 | 94.7 | 128.4 | 128.4 | 94.7 | 128.4 | 128.4 |

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | S200 | 94.7 | 128.4 | 128.4 | 94.7 | 128.4 | 128.4 | 94.7 | 128.4 | 159.8 |
| Earthworks | $L_{FEW}$ | S1 | 16.4 | 28.1 | 49 | 21.5 | 31 | 57 | 23.6 | 42.8 | 57.9 |
| | | S2 | 30.3 | 32 | 62.2 | 32.2 | 35.5 | 63 | 34.7 | 45 | 64 |
| | | S5 | 31.4 | 60.6 | 76 | 36 | 62 | 80 | 37 | 62.4 | 83.2 |
| | | S10 | 44.6 | 78.3 | 83 | 46 | 79 | 86 | 58.4 | 81.3 | 87 |
| | | S30 | 60.3 | 80 | 91 | 62 | 81 | 95 | 63.8 | 84 | 96 |
| | | S50 | 75.3 | 85 | 94.2 | 80.8 | 91.2 | 97 | 82 | 92 | 101.9 |
| | | S100 | 84 | 97.3 | 110 | 85 | 98 | 112 | 86 | 99 | 113.5 |
| | | S200 | 85.4 | 103 | 114.5 | 87 | 103 | 117 | 90 | 104 | 118.6 |
| Operational disruption | $T_{D>0.09}$ | S1 | 15 | 40 | 65 | 15 | 40 | 65 | 20 | 45 | 75 |
| | | S2 | 30 | 55 | 95 | 30 | 55 | 95 | 35 | 60 | 100 |
| | | S5 | 45 | 70 | 120 | 45 | 70 | 120 | 45 | 70 | 125 |
| | | S10 | 55 | 80 | 130 | 55 | 80 | 135 | 55 | 85 | 140 |
| | | S30 | 65 | 100 | 165 | 65 | 105 | 165 | 65 | 100 | 170 |
| | | S50 | 70 | 110 | 180 | 70 | 110 | 180 | 70 | 110 | 190 |
| | | S100 | 80 | 120 | 210 | 80 | 120 | 220 | 80 | 125 | 215 |
| | | S200 | 90 | 135 | 235 | 90 | 140 | 240 | 90 | 140 | 240 |
| | $T_C$ | S1 | 0 | 5 | 40 | 0 | 10 | 40 | 0 | 15 | 50 |
| | | S2 | 0 | 30 | 70 | 0 | 35 | 70 | 5 | 40 | 75 |
| | | S5 | 25 | 55 | 100 | 25 | 55 | 100 | 25 | 55 | 105 |
| | | S10 | 35 | 70 | 120 | 35 | 70 | 120 | 35 | 70 | 120 |
| | | S30 | 50 | 90 | 150 | 50 | 90 | 150 | 50 | 90 | 150 |
| | | S50 | 60 | 100 | 165 | 60 | 100 | 165 | 60 | 100 | 165 |
| | | S100 | 65 | 110 | 190 | 70 | 105 | 195 | 70 | 110 | 195 |
| | | S200 | 85 | 125 | 220 | 85 | 125 | 220 | 85 | 125 | 220 |
| | $T_{SR}$ | S1 | 15 | 35 | 25 | 15 | 30 | 25 | 20 | 30 | 25 |
| | | S2 | 30 | 25 | 25 | 30 | 20 | 25 | 30 | 20 | 25 |
| | | S5 | 20 | 15 | 20 | 20 | 15 | 20 | 20 | 15 | 20 |
| | | S10 | 20 | 10 | 10 | 20 | 10 | 15 | 20 | 15 | 20 |
| | | S30 | 15 | 10 | 15 | 15 | 15 | 15 | 15 | 10 | 20 |
| | | S50 | 10 | 10 | 15 | 10 | 10 | 15 | 10 | 10 | 25 |
| | | S100 | 15 | 10 | 20 | 10 | 15 | 25 | 10 | 15 | 20 |
| | | S200 | 5 | 10 | 15 | 5 | 15 | 20 | 5 | 15 | 20 |

## 8.5 Uncertainty analysis

Uncertainty is an essential consideration in a risk assessment as described in Section 5.5.2. Excel add-in @Risk performs Monte Carlo simulation and shows the frequency of the outcomes on the spreadsheet model. The inputs are represented with frequency distributions which @risk use to run into the mathematical model to calculate the frequency of outcome scenarios. The following describes the main types of distributions considered in this study and the input parameters represented by them. Table 8.6 then summarises the costing input parameters used in MCs, their associated uncertainties and the chosen representative distribution. Table 8.7 summarises the exposure parameters, their associated uncertainties and their representative distribution.

1. Normal distribution

   This distribution is used to reflect uncertainty involved in measurements of exposure parameters which occurs due to the following sources of error:

a. Visual inaccuracy in manual lengths measurements. This is associated with flood lengths measurements for both track and earthwork. When measuring flood length, the software interface can only be zoomed to a certain level at each location, which introduces a lack of confidence in the measurement. Therefore, for each location multiple measurements are taken for one impact scenario and the standard deviation is calculated for that scenario. Since all scenario measurements at one location are taken at the same zoom scale, the standard deviation is assumed uniform across all scenarios (time limitation preventing to take multiple measurements for each scenario). The zoom scales at each location are shown in Figure 8.2 and Figure 8.3. The smaller scale at "1234" reflects larger error and hence larger uncertainty. The standard deviations are reported in Table 8.6.
b. Randomness in choice of mesh element. This is specifically associated with the flood depth and the dependant inundation duration parameters. As depth of flood on track varies slightly across elements on track, multiple elements are randomly selected for one scenario to calculate the standard deviation in flood depth and duration measurements. The same standard deviation is assumed for all the scenarios at each location.

Theron, as shown in Table 8.7, each exposure measurement is represented with a normal distribution, the mean of which is the reported measurement in Table 8.3 and Table 8.4. Since normal distribution is continuous and unbounded, it can go to infinity on either side. This is not suitable when dealing with exposure measurements, as negative values are not logical. Therefore, all distributions are left-bounded at a value greater than zero. Figure 8.4 shows an example of the left-bounded normal input distribution of exposure parameter 'track flooded length'. The input distributions for the rest of the exposure measurements are shown in Appendix D.1.




*Figure 8.2. Screenshot of location around node 1234-scenario C1 D60 S50. Measurements were taken at 1cm:25m scale (image not to scale)*




*Figure 8.3. Screenshot of location around node 1126- scenario C1 D60 S50. Measurements were taken at 1cm:10m scale (image not to scale)*

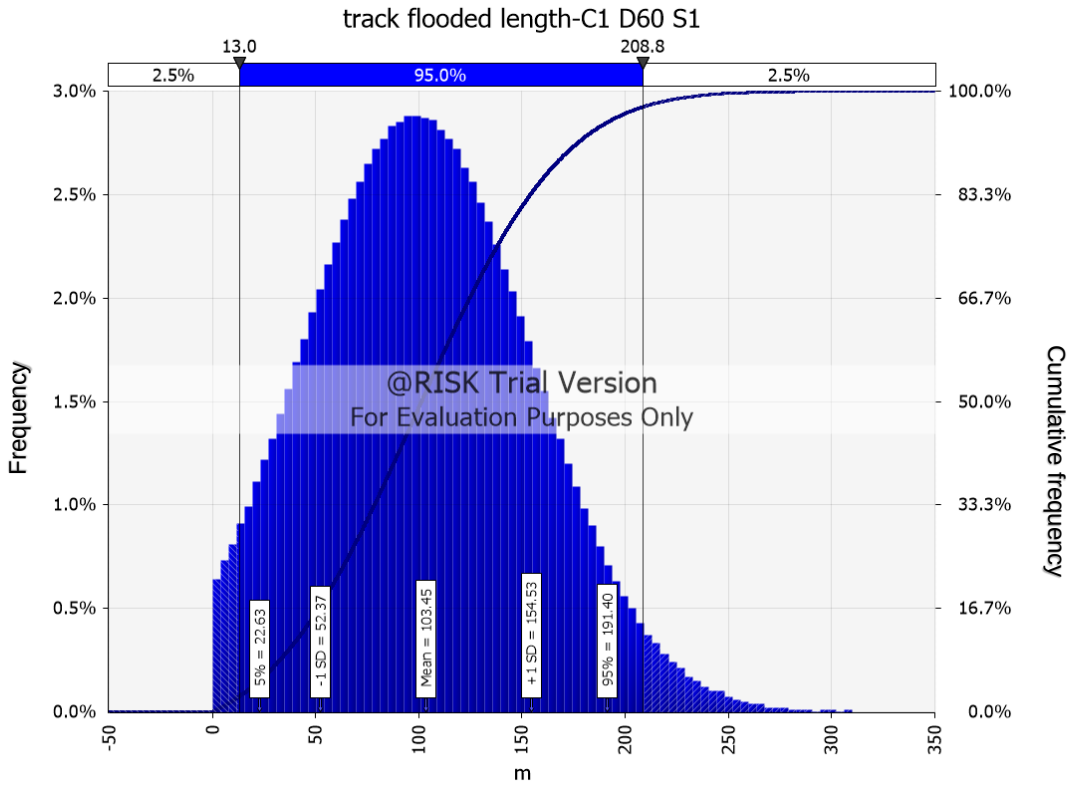



*Figure 8.4. Location "1234" track flooded length input parameter C1-D60- S1 frequency distribution*

2. Triangular distribution

Triangular and PERT distributions are used to reflect expert opinion on costing parameters. Similar MCs costing applications like Elcheikh and Burrow (2017), and Sasidharan et al. (2020) relied on three-point estimate distributions for representation of costs. In this study, PERT distribution is used where three-point estimate is available, e.g., delay cost (shown in Figure 8.5). Triangular distribution is used to represent cost data where only single-point estimate is obtained (See Figures 8.6- 8.15). Add-in @Risk allows the option to vary the triangular distribution by a percentage around the most likely value when definite minimum/maximum values are not available. It is therefore assumed the minimum and maximum values are ±30% around the NR-obtained value (assumed most likely). Figures 8.6- 8.15 show the costing triangular and PERT input distributions.

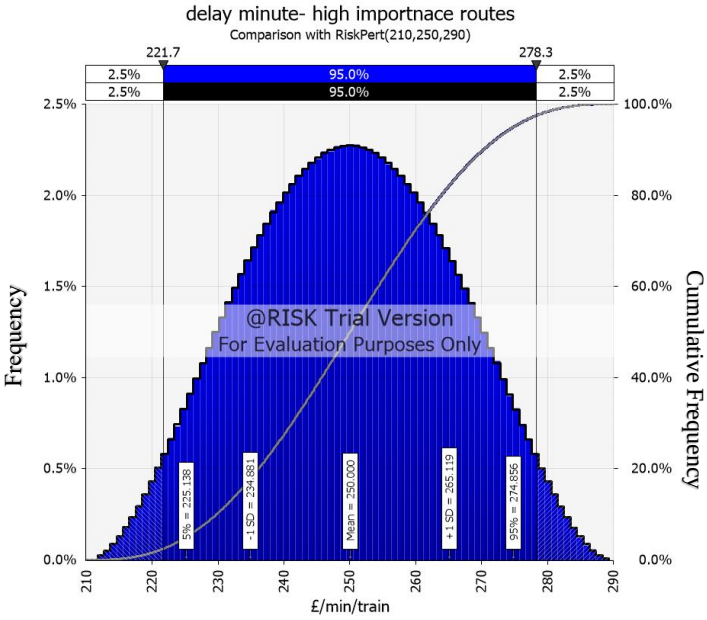



*Figure 8.5. Input Distribution for parameter Delay minute cost*

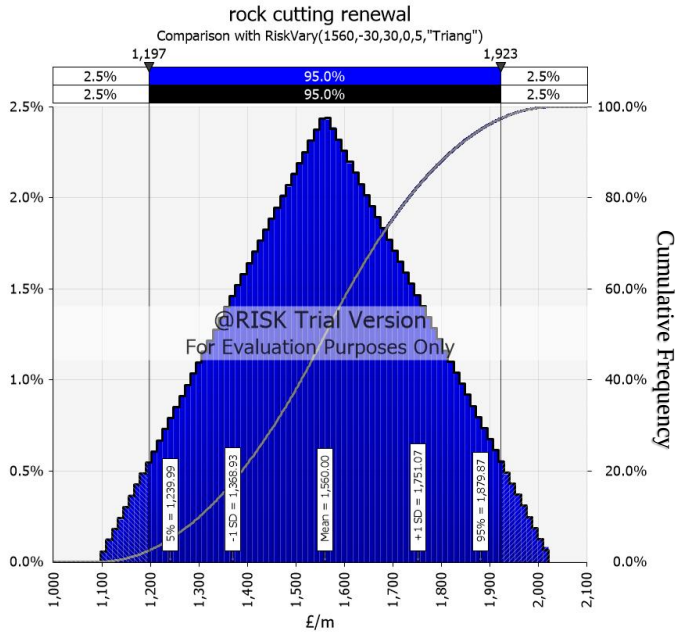



*Figure 8.6. Input distribution for parameter Rock cutting renewal cost*

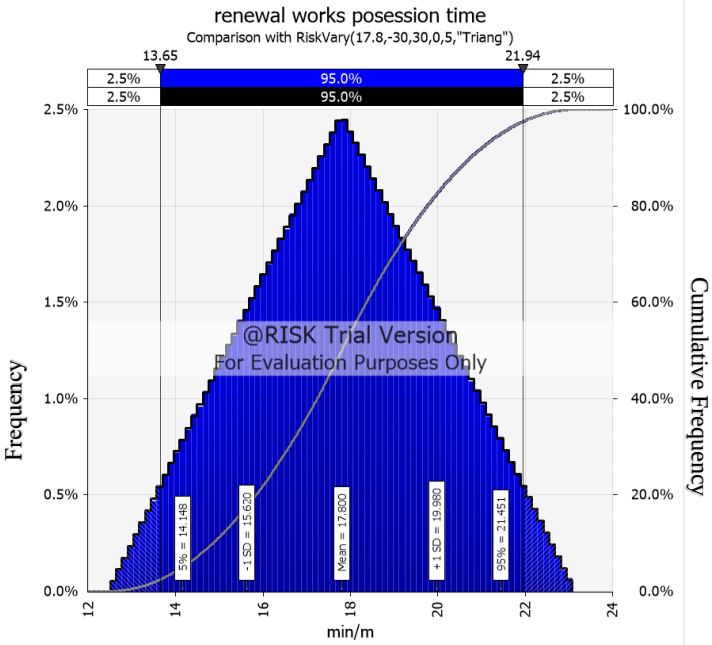



*Figure 8.7.* Input distribution for costing parameter 'renewal possession time

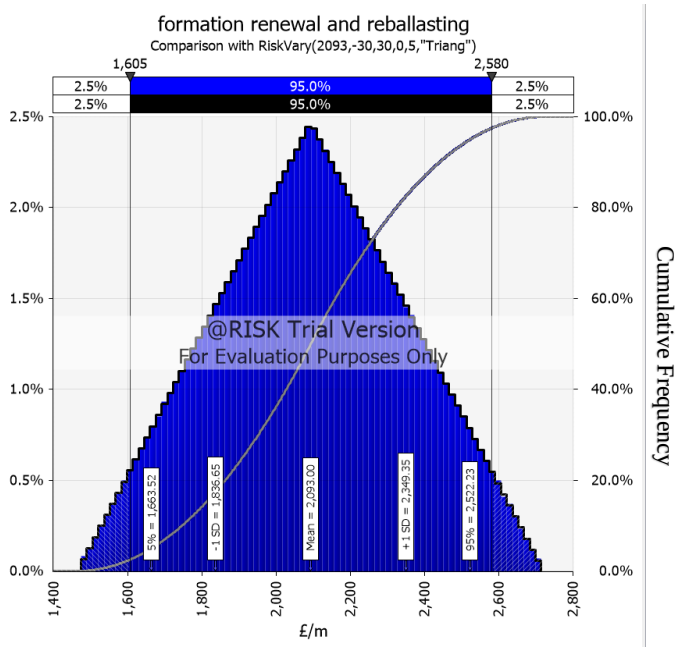



*Figure 8.8. Input distribution for parameter formation renewal and re-ballasting cost*

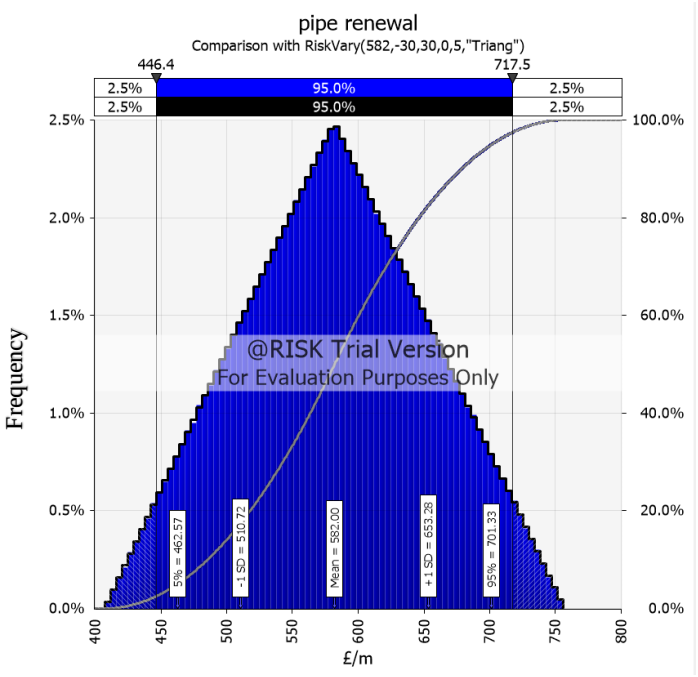



*Figure 8.9. Input distribution for parameter pipe renewal cost*

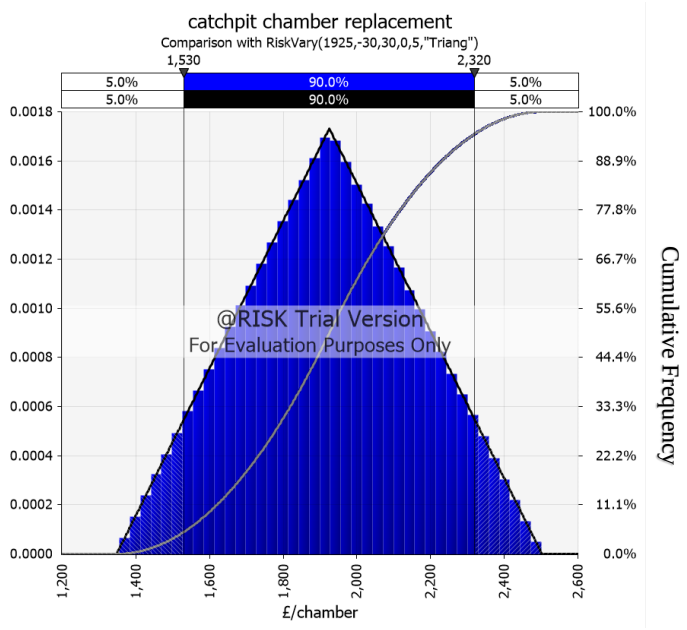



*Figure 8.10.* Input distribution for parameter catchpit chamber replacement cost

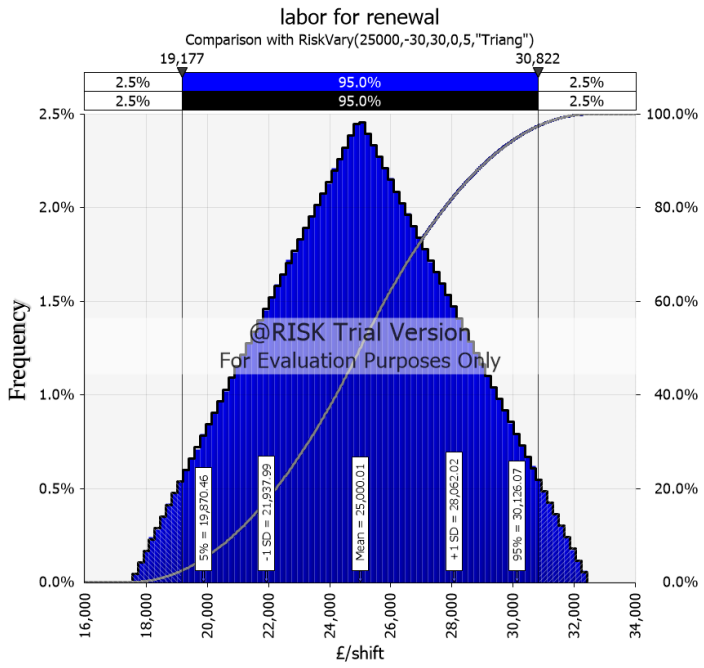



*Figure 8.11. Input distribution for parameter cost of labor for renewal activity*

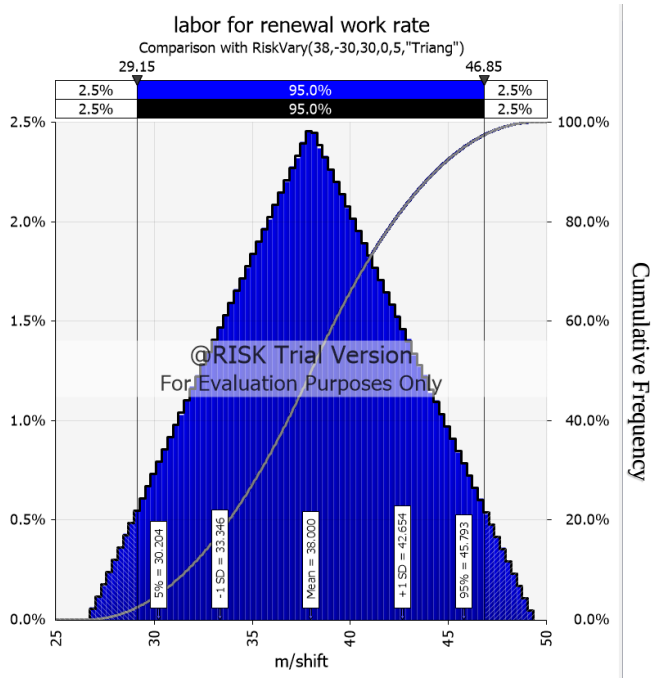



*Figure 8.12. Input distribution for parameter labor work rate*

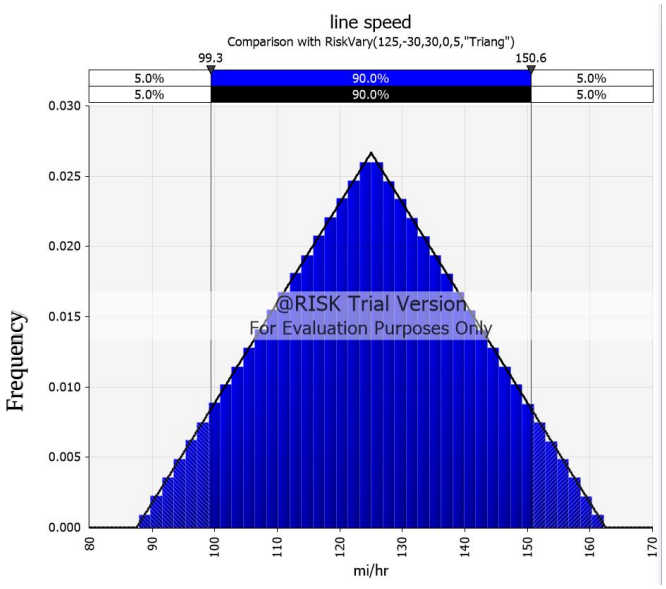



*Figure 8.13.* Input distribution for parameter line speed

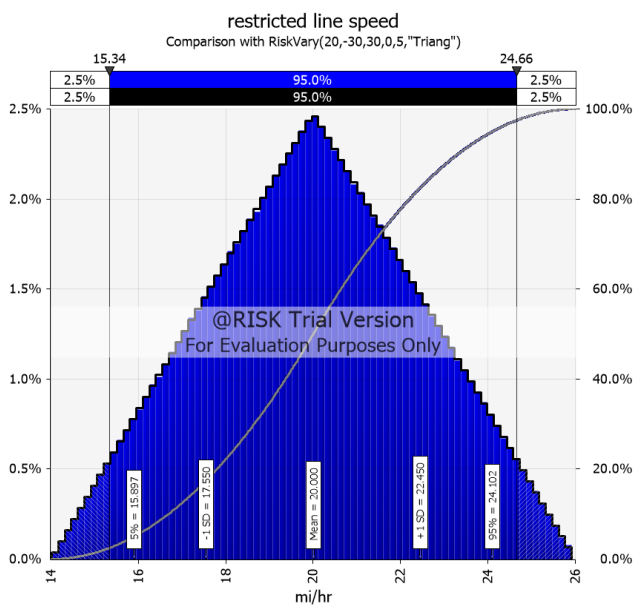



*Figure 8.14. Input distribution for parameter restricted line speed*

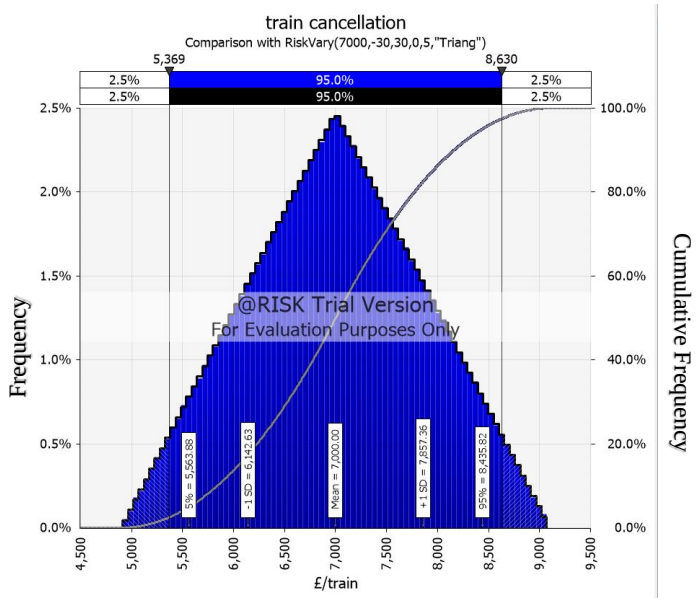



*Figure 8.15. Input distribution for parameter train cancellation cost*

3. Discrete distribution

This distribution is used for input parameters: 'Number of trains passing the site', 'condition of asset', 'rainfall duration' and 'storm event' (Figures 8.16- 8.19). In a discrete distribution, the sum of probabilities for all possible values must equal unity. This is not the case with the storm event probabilities. Therefore, the likelihoods of these events are scaled proportionately when used as a discrete distribution in @Risk. This adjustment converts the probability of a storm of a given magnitude occurring in a single year, to the probability of a given storm event having that

magnitude. The adjusted probabilities are shown in Table 8.5. The distribution is shown in Figure 8.16.

*Table 8.5. Scaled probabilities for storm event scenarios*

| Storm event return period | Original probability | Adjusted probability |
|---|---|---|
| 1 | 100% | 54% |
| 2 | 50% | 27% |
| 5 | 20% | 10.5% |
| 10 | 10% | 5.25% |
| 30 | 3.33% | 1.75% |
| 50 | 2% | 1.05% |
| 100 | 1% | 0.525% |
| 200 | 0.5% | 0.2625% |

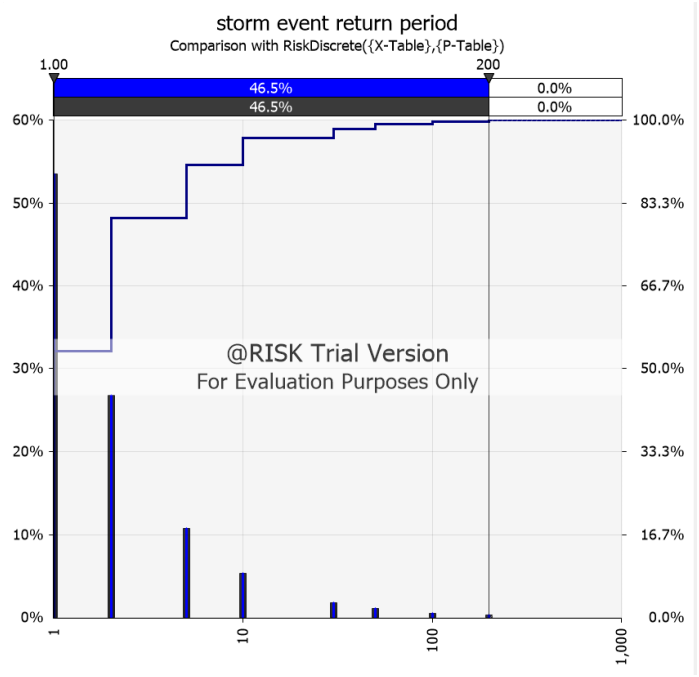



*Figure 8.16. Input distribution for parameter Storm event return period*

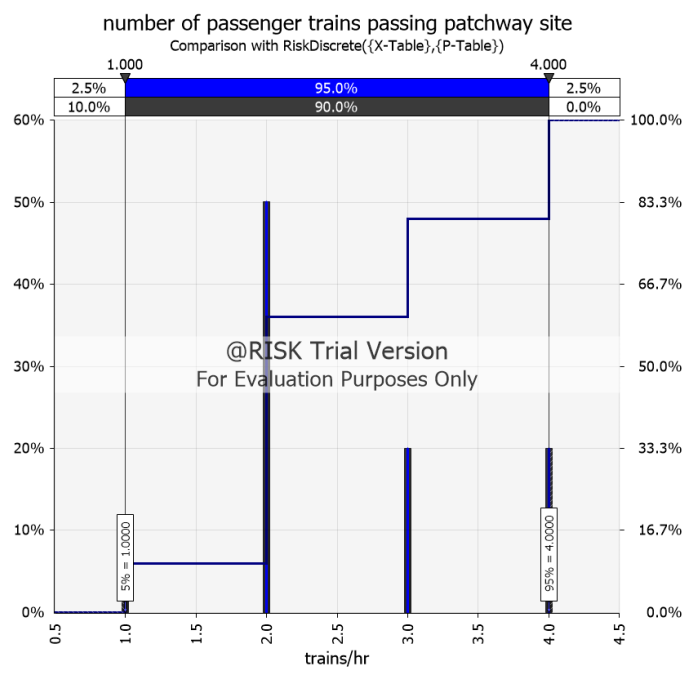



*Figure 8.17. Input distribution for costing parameter 'Number of trains*

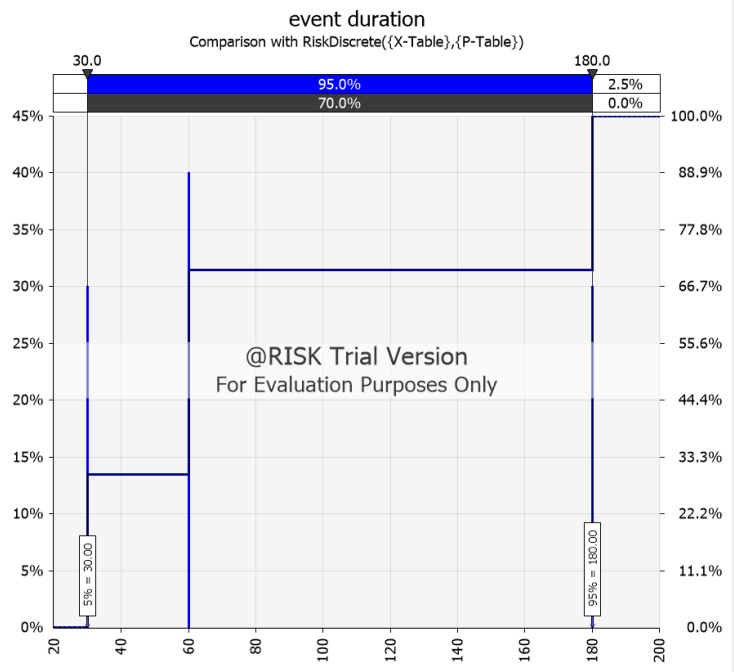



*Figure 8.18. Input distribution for parameter event duration*

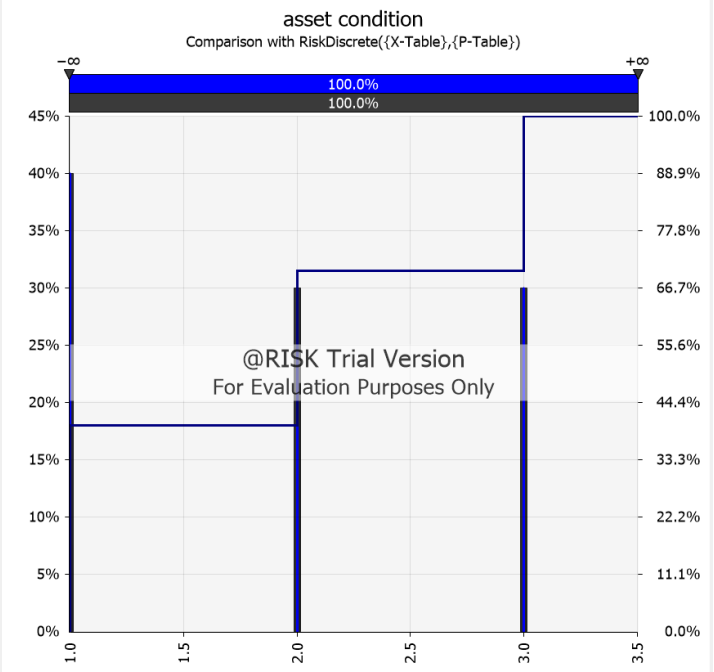



*Figure 8.19. Input distribution for parameter asset condition*

*Table 8.6. Cost parameters used in cost model for monetary damage quantification*

| Cost category | Cost component | Values obtained | units | Source | Relevant assumptions | Assumed distribution to consider uncertainty |
|---|---|---|---|---|---|---|
| Track structure | $C_{T-RB}$ | 2093 | £/m | Data from Track renewal and enhancement team at NR | Where only single point estimate is obtained, the assumption is made that minimum/maximum values are ±30% | Triangular ±30% |
| Drainage | $C_{D-PR}$ | 582 | £/m | Data from Drainage and Lineside asset engineer at NR | ≡ | Triangular ±30% |
| | $C_{D-CR}$ | 1925 | £/chamber | Data from Drainage and Lineside asset engineer at NR | ≡ | Triangular ±30% |
| | $C_{D-L}$ | 25000 | £/shift | Data from Drainage and Lineside asset engineer at NR | ≡ | Triangular ±30% |
| | $L_{D-L}$ | 37.5 | m/shift | Data from Drainage and Lineside asset engineer at NR | ≡ | Triangular ±30% |
| Earthworks | $C_{EW-R}$ | 1560 | £/m | Data from Drainage and Lineside asset engineer at NR | Earthwork type is Rock cutting area according to engineer which affects the used intervention cost value | Triangular ±30% |
| Operational | $C_{OpD-D}$ | [210,250,290] | £/min/train | (Sasidharan et al., 2020) | Route is high importance as reported in Route specification: Western report-provided by drainage and lineside engineer at NR which affects the cost of delay minutes | Triangular three-point estimate |
| | $C_{OpD-C}$ | 7000 | £/train | Assumed | NA | Triangular ±30% |
| | $N_T$ | 2 | train/hr | Data from Route specification: Western report-provided by drainage and lineside engineer at NR | Possible values are hypothetical; giving highest probability to value reported by engineer According to report, only passenger trains are passing the site | Discrete [1,2,3,4] with probabilities [0.1,0.5,0.2,0.2] |
| | $T_{OpD-MP}$ | 17.8 | min/m | Data from drainage and lineside engineer at NR | NA | Triangular ±30% |
| | $S_L$ | 125 | mi/hr | Data from Route specification: Western report-provided by drainage and lineside engineer at NR | NA | Triangular ±30% |
| | $S_R$ | 30 | mi/hr | Control Centre Incident Log provided by Buildings and Civils Engineer at NR technical authority | NA | Triangular ±30% |

*Table 8.7. Exposure parameters used in cost model for damage quantification*

| Damage category | Exposure measure | units | Relevant assumptions | Uncertainty | Uncertainty distribution | Calculated standard deviations |
|---|---|---|---|---|---|---|
| Track | $L_{FT}$ | m | NA | Stems from manual measurement of flooded length | Normal Distribution | Chamber 1234= 4m<br>Chamber 1126: 0.627m |
| Drainage | $N_{FC}$ | Catchpit | Catchpit requiring renewal assumed when flood volume exceeds 100 $m^3$ | No uncertainty is considered in this value as no manual measurement is taken. This is obtained from the simulation output of node flood volumes. | NA | NA |
| | $L_{FP}$ | m | Damaged pipe length requiring renewal is assumed equal to inundated length of track rounded up to the nearest full pipe length in the section as reported in as-built drawings provided by NR | This is an intermediate output calculated from $L_{FT}$ based on the provided as-built pipe lengths. Any uncertainty in 'length of damaged pipes' is propagated from 'length of flooded track' parameter | NA | NA |
| Earthwork | $L_{FEW}$ | m | NA | Stems from manual measurement of 'flooded earthwork length' | Normal distribution | Chamber 1126: 0.782m |
| Operational disruption | $T_{D>0.1}$ | min | According to NR standards, speed restriction is warranted when depth of inundation is 50 mm below rail level and closure is warranted when depth of flood is 100 mm above rail level.<br>It is assumed rail flange is 0.15 m deep (British steel).<br>Therefore, the speed restrictions are warranted when depth >0.1 m<br>Closure is warranted when depth >0.25 m | Since it is a point measurement uncertainty stems from choice of mesh element at which temporal track flood depths are obtained | Normal distribution | Chamber 1234: 6.06min<br>Chamber 1126: 6.65min |
| | $T_C$ | min | NA | Since it is a point measurement uncertainty stems from choice of mesh element at which temporal track flood depths are obtained | Normal distribution | Chamber 1234: 6.06min<br>Chamber 1126: 6.65min |
| | $T_{SR}$ | min | NA | This is an intermediate output calculated as the difference between<br>$T_{D>0.1}$ and $T_C$<br>Uncertainty is propagated from these input parameters | NA | NA |

## 8.6 MCs runs

The damage quantification task entails generating damage charts for each C-D scenario. Therefore, the calculation of damage cost incurred under each individual C-D-S scenario. This requires excluding probabilities of flood sources and treating each scenario as a stand-alone MCs output. A cost distribution for each C-D-S scenario output is then obtained, which accounts for epistemic uncertainties (in costing and exposure parameters). Damage quantification MCs setup design is described through steps 1-4 in Table 8.8. The risk quantification follows from the output of damage quantification through steps 5 & 6 in Table 8.8 to obtain a risk score following the definition: Risk= Probability × Consequence.

As this method involves a large number of calculations going through each individual C-D-S scenario, Chapter 5 proposes an alternative 'shortcut' approach for calculation of total risk in terms of economic damage. The alternative setup for MCs runs is suggested in Table 8.10. The equations are setup to consider possible scenarios of risk sources and their probabilities within the MCs simulations.

*Table 8.8. Methodology 1 for calculating damage cost associated with each C-D-S scenario*

| Objective | Step | Refer to |
|---|---|---|
| MCs design for damage quantification | 1. Create a matrix of damage cost equations for each individual scenario, plugging in the associated scenario exposure parameters and cost components. | Table 8. 9 |
| | 2. Specify 10000 as number of iterations and ran simulations | |
| Scenario damage charts | 3. For each C-D-S scenario, obtain the output damage cost distribution chart and associated output statistics: Mean, Standard deviation, 5% and 95% percentiles in addition to CDF statistics grid. | Section 8.7 for example output Figures 8. 20 & 8. 21<br>Appendix D.2 for all output figures |
| | 4. Generate damage charts for each C-D scenario over the storm events using the mean damage value. Reflect uncertainty using the standard deviation, 5% and 95% percentiles | Section 8.7, Figures 8. 22- 8. 39 |

| | | |
|---|---|---|
| Risk quantification | 5. Calculate the area under each scenario damage cost distribution using the extracted CDF statistics grid, where area equals the product of each reported damage cost and the respective relative density probability. | Appendix D.3 for raw CDF data in Tables A-D1.1 and A-D1.2 |
| | 6. To obtain total risk at location: sum the products of each calculated scenario cost by the respective probability of scenario ($P_C \times P_D \times P_S$) | Section 8.7, Tables 8. 12 & 8. 13 |

*Table 8.9. MCs output matrix format for individual C-D-S scenario damage quantification*

| scenario C-D | C1 D30 | C1 D60 | C1 D180 | C2 D30 | C2 D60 | C2 D180 | C3 D30 | C3 D60 | C3 D180 |
|---|---|---|---|---|---|---|---|---|---|
| S1 | Total Cost associated with each respective C-D-S scenario $C_{C-D-S\ scenario} = C_{Track\ structure\ C-D-S} + C_{Earthworks\ C-D-S} + C_{Drainage\ C-D-S} + C_{operational\ disruptions\ C-D-S}$ | | | | | | | | |
| S2 | | | | | | | | | |
| S5 | | | | | | | | | |
| S10 | | | | | | | | | |
| S30 | | | | | | | | | |
| S50 | | | | | | | | | |
| S100 | | | | | | | | | |
| S200 | | | | | | | | | |

*Table 8.10. Methodology 2 for calculating total risk in monetary terms*

| Objective | Step | Refer to |
|---|---|---|
| MCs design for total risk quantification | 1. Create a table of "If-Then" cost equations in which the three parameters defining a scenario (C-D-S) are considered under each cost category | Table 8. 11 |
| | 2. Specify number of iterations as 10000 and run simulations | |
| Total risk at location | 3. Obtain the output cost distributions chart and the associated output statistics: Mean, Std. Dev., 5% and 95% percentiles to represent total risk and associated uncertainty envelope | Section 8.7, Figures 8. 40 & 8. 41 |

*Table 8.11. MCs output format for total risk quantification*

| Cost category | Cost components | Cost equations |
|---|---|---|
| Track | Cost of formation renewal and re-ballasting | If (C, D, S), Then $C_{Track\ structure}$ |
| Drainage | Cost of catchpit renewal | If (C, D, S), Then $C_{drainage\ category}$ |
| | Cost of pipe renewal | ≡ |
| | Cost of labor | ≡ |
| | Total drainage cost | $\sum C_{drainage\ category}$ |

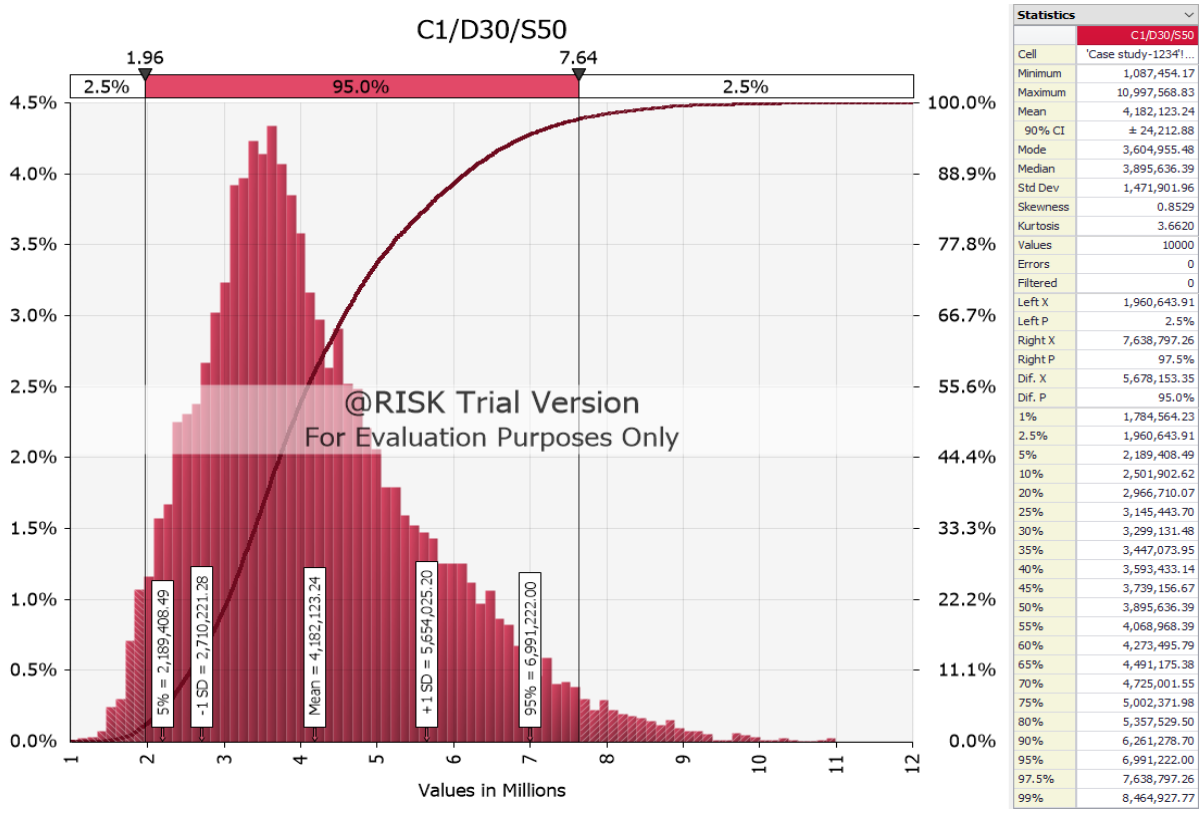
| | | |
|---|---|---|
| Earthwork | Cost of earthwork renewal | If (C, D, S), Then $C_{earthwork}$ |
| Operational | Cost of operational delay due to speed restrictions | If (C, D, S), Then $C_{operational\ distruption\ category}$ |
| | Cost of operational cancellation due to closures | ≡ |
| | Cost of cancellation due to maintenance possessions | ≡ |
| | Total operational disruption cost | $\sum C_{operational\ disruption\ category}$ |
| | Total cost | $\sum C_{components}$ |

## 8.7 Results

Running MCS simulations following steps 1-4 in Table 8.8 produces damage distribution charts for each scenario. A total of 72 scenario distribution outputs are obtained for each location (attached in Appendix D.2). Figures 8.20 and 8.21 show examples of the output distribution for location surrounding chamber "1234" and "1126", respectively. A total of 9 flood damage charts are generated per location, one for each C-D scenario. Each chart uses the mean values from the output distributions, representing the uncertainty with ±1 standard deviation and the 5%-95% percentiles. These charts are shown in Figures 8.22- 8.39.

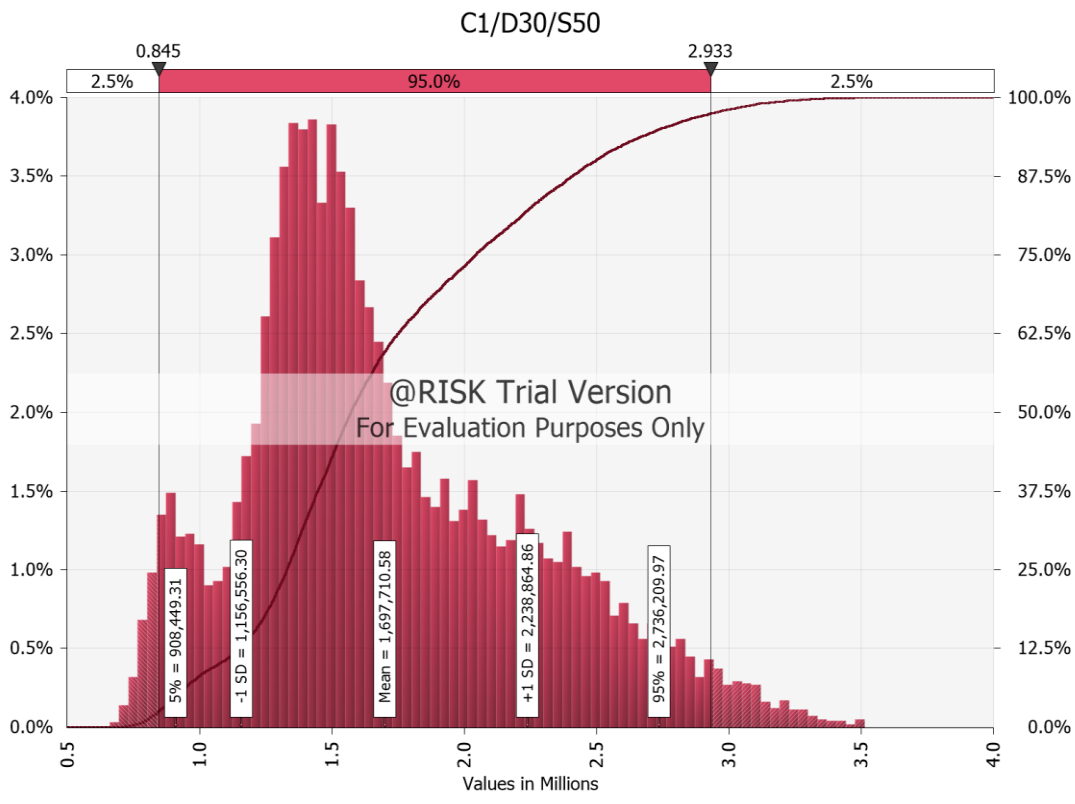
For total risk quantification, following steps 5-6 in Table 8.8 produce the area under each output distribution chart shown in Tables 8. 12 & 8. 13 for "1234" and "1126", respectively. The calculated total flood risk is £2,396,777 at location "1234" and £1,200,153 at location "1126" (Tables 12-13).

The alternative "shortcut" method proposed to obtain total risk directly following steps in Table 8.10 produces the output distribution chart shown in Figure 8.40, in which the two locations "1234" and "1126" are overlaid for comparison. Extracting the mean, ±1 standard deviation and the 5%-95% percentiles, Figure 8.41 is reproduction of the output distribution (Figure 8.40) in the form of uncertainty envelopes. The mean flood damage risk associated with location "1234" is £2,414,082 and the mean flood damage risk associated with location "1126" is £1,205,021.




| Statistics | C1/D30/S50 |
|---|---|
| Cell | 'Case study-1234'!... |
| Minimum | 1,087,454.17 |
| Maximum | 10,997,568.83 |
| Mean | 4,182,123.24 |
| 90% CI | ± 24,212.88 |
| Mode | 3,604,955.48 |
| Median | 3,895,636.39 |
| Std Dev | 1,471,901.96 |
| Skewness | 0.8529 |
| Kurtosis | 3.6620 |
| Values | 10000 |
| Errors | 0 |
| Filtered | 0 |
| Left X | 1,960,643.91 |
| Left P | 2.5% |
| Right X | 7,638,797.26 |
| Right P | 97.5% |
| Dif. X | 5,678,153.35 |
| Dif. P | 95.0% |
| 1% | 1,784,564.23 |
| 2.5% | 1,960,643.91 |
| 5% | 2,189,408.49 |
| 10% | 2,501,902.62 |
| 20% | 2,966,710.07 |
| 25% | 3,145,443.70 |
| 30% | 3,299,131.48 |
| 35% | 3,447,073.95 |
| 40% | 3,593,433.14 |
| 45% | 3,739,156.67 |
| 50% | 3,895,636.39 |
| 55% | 4,068,968.39 |
| 60% | 4,273,495.79 |
| 65% | 4,491,175.38 |
| 70% | 4,725,001.55 |
| 75% | 5,002,371.98 |
| 80% | 5,357,529.50 |
| 90% | 6,261,278.70 |
| 95% | 6,991,222.00 |
| 97.5% | 7,638,797.26 |
| 99% | 8,464,927.77 |

*Figure 8.20. Chamber "1234" MCs damage cost distribution for scenario C1-D3-S50*




| Statistics | C1/D30/TOTAL COST |
|---|---|
| Cell | 'Case study-1126'!D142 |
| Minimum | 658,521.12 |
| Maximum | 3,512,644.84 |
| Mean | 1,697,710.58 |
| 95% CI | ± 10,607.71 |
| Mode | 1,486,824.13 |
| Median | 1,570,687.31 |
| Std Dev | 541,154.28 |
| Skewness | 0.6780 |
| Kurtosis | 2.9603 |
| Values | 10000 |
| Errors | 0 |
| Filtered | 0 |
| Left X | 845,035.37 |
| Left P | 2.5% |
| Right X | 2,932,961.97 |
| Right P | 97.5% |
| Dif. X | 2,087,926.60 |
| Dif. P | 95.0% |
| 1% | 793,290.79 |
| 2.5% | 845,035.37 |
| 5% | 908,449.31 |
| 10% | 1,071,421.44 |
| 20% | 1,275,796.49 |
| 25% | 1,329,231.00 |
| 30% | 1,375,270.14 |
| 35% | 1,422,575.57 |
| 40% | 1,473,336.23 |
| 45% | 1,519,876.39 |
| 50% | 1,570,687.31 |
| 55% | 1,632,451.46 |
| 60% | 1,705,973.08 |
| 65% | 1,801,343.28 |
| 70% | 1,916,842.50 |
| 75% | 2,042,300.17 |
| 80% | 2,181,082.26 |
| 90% | 2,497,372.74 |
| 95% | 2,736,209.97 |
| 97.5% | 2,932,961.97 |
| 99% | 3,109,634.98 |

*Figure 8.21. Chamber "1126" MCs damage cost distribution for scenario C1-D3-S50*

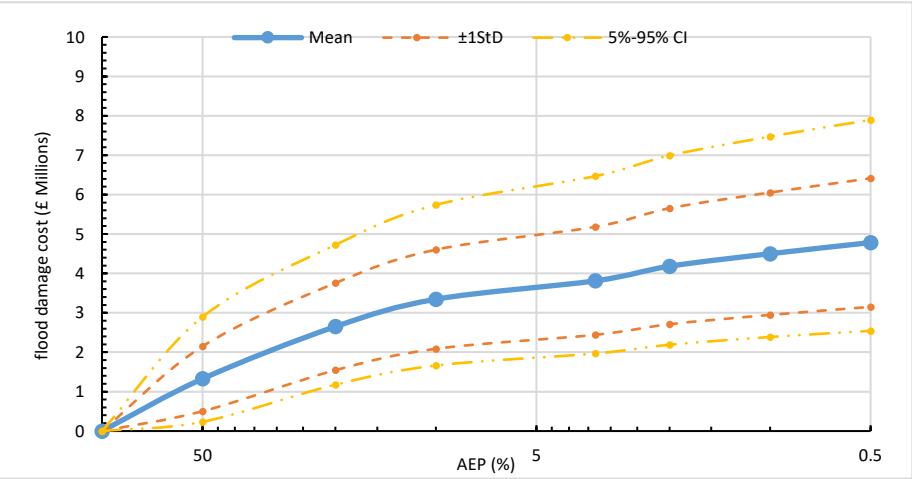



*Figure 8.22. Chamber "1234" C1 D30 Flood damage chart*

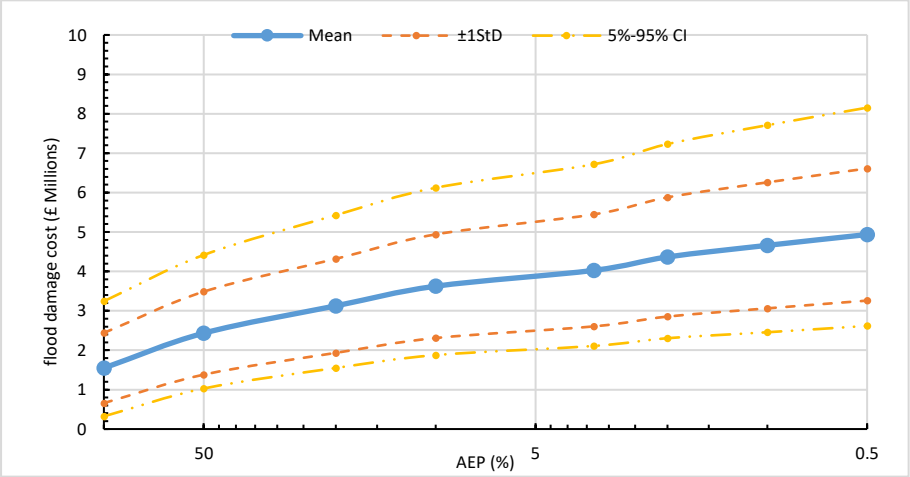



*Figure 8.23. Chamber "1234" C1 D60 Flood damage chart*

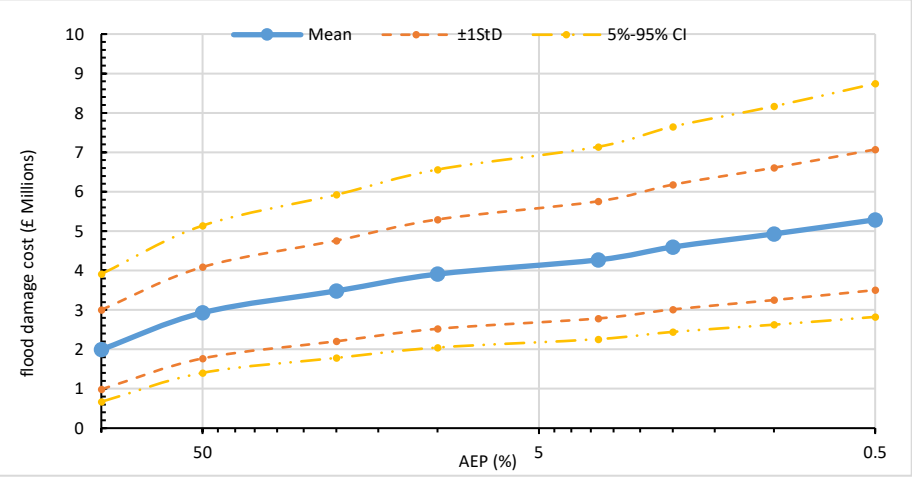



*Figure 8.24. Chamber "1234" C1 D180 flood damage chart*

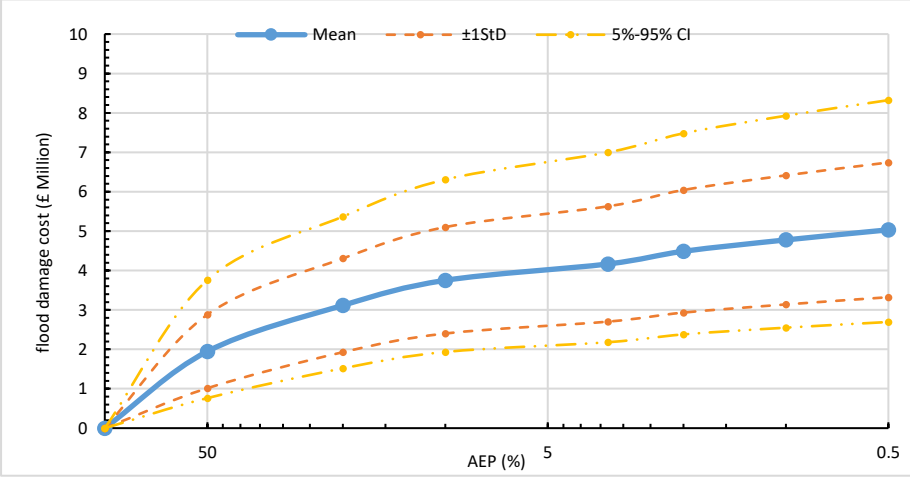



*Figure 8.25. Chamber "1234" C2 D30 flood damage chart*

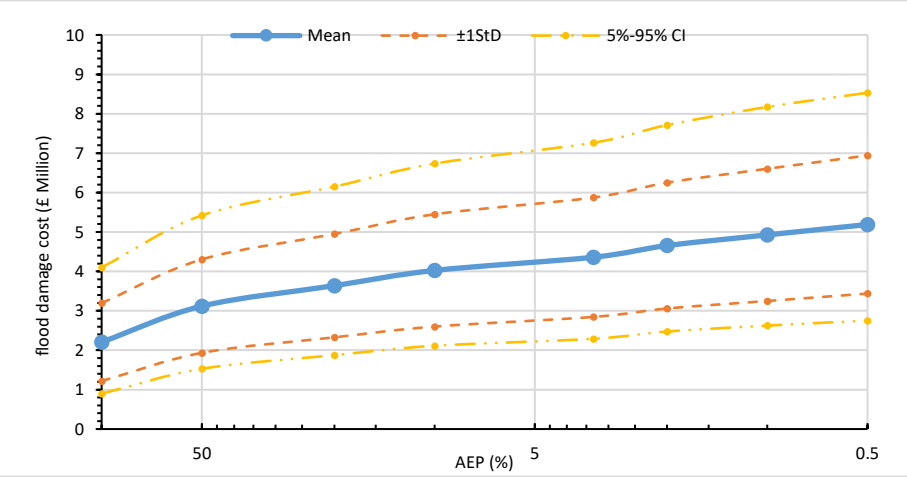



*Figure 8.26. Chamber "1234" C2 D60 flood damage chart*

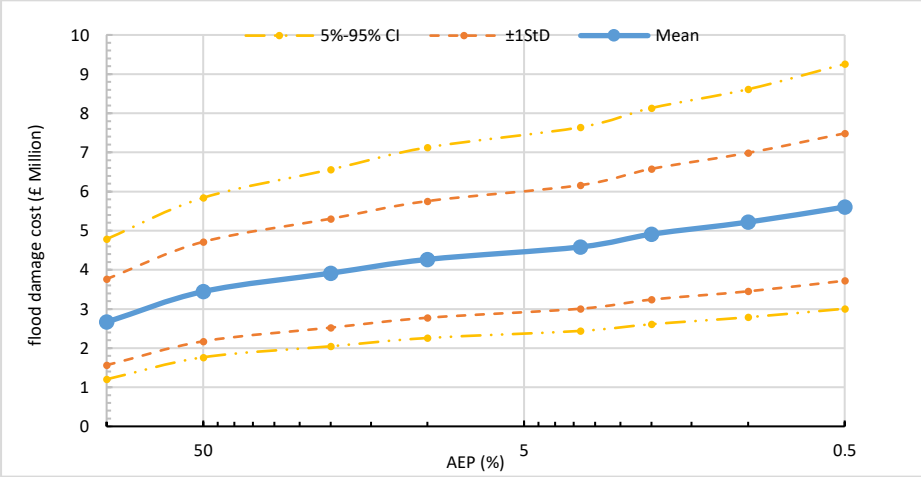



*Figure 8.27. Chamber "1234" C2 D180 flood damage chart*

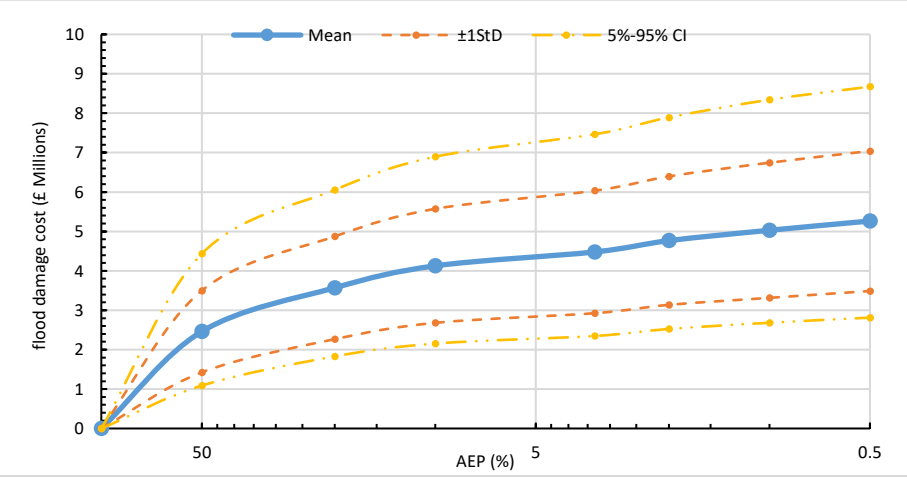



*Figure 8.28. Chamber "1234" C3 D30 flood damage chart*

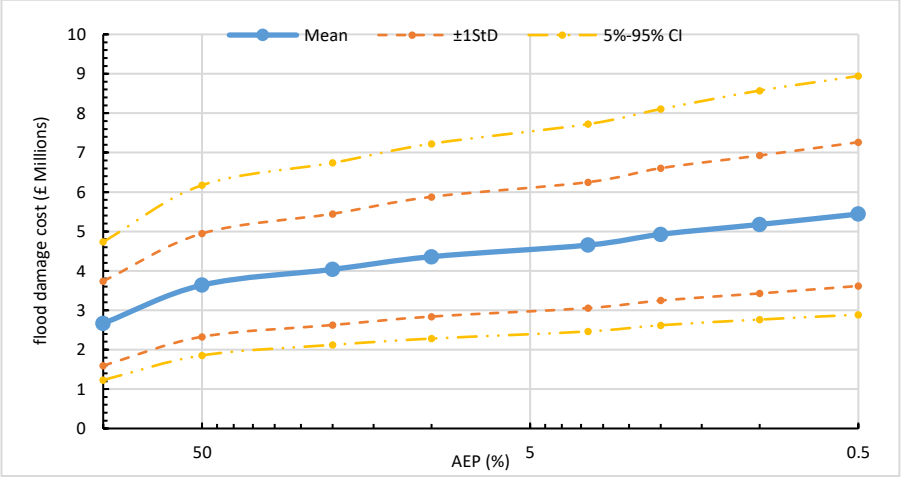



*Figure 8.29. Chamber "1234" C3 D60 flood damage chart*

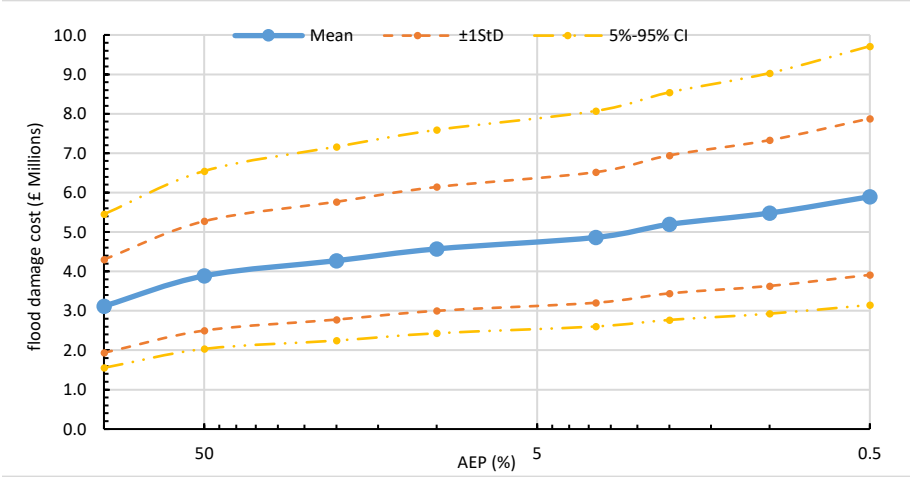



*Figure 8.30. Chamber "1234" C3 D180 flood damage chart*

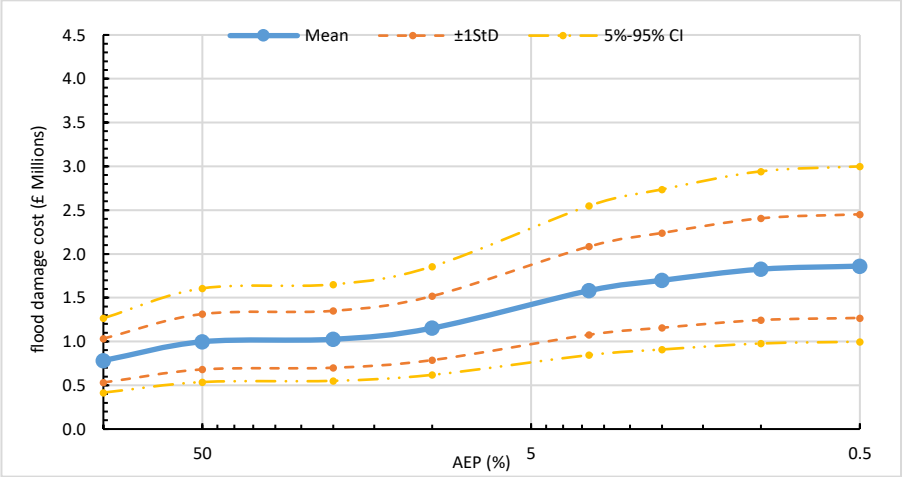



*Figure 8.31. Chamber "1126" C1 D30 flood damage chart*

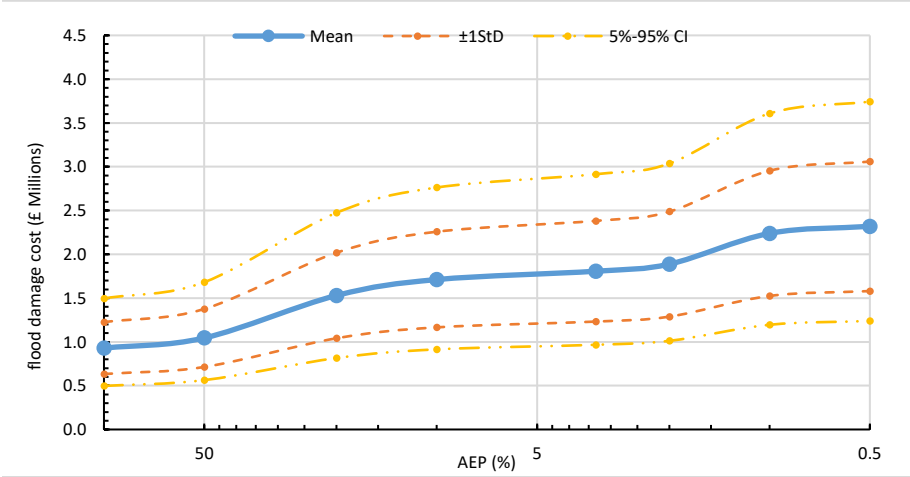



*Figure 8.32. Chamber "1126" C1 D60 flood damage chart*

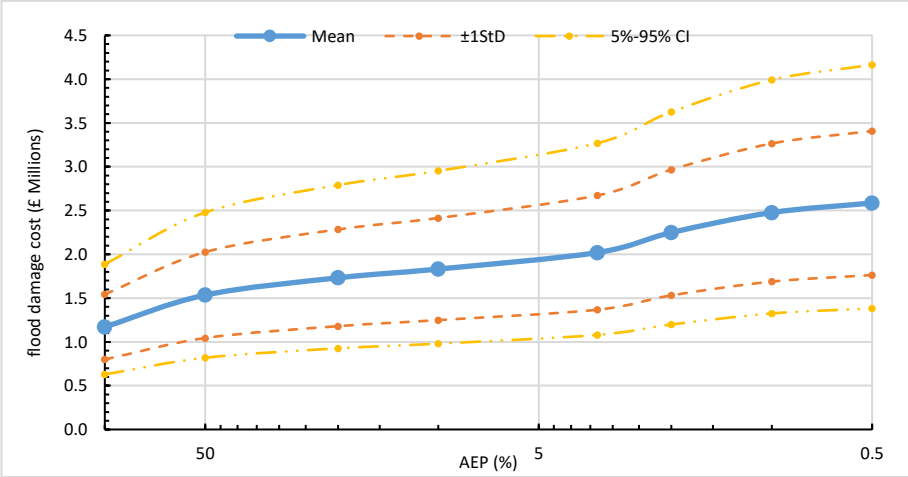



*Figure 8.33. Chamber "1126" C1 D180 flood damage chart*

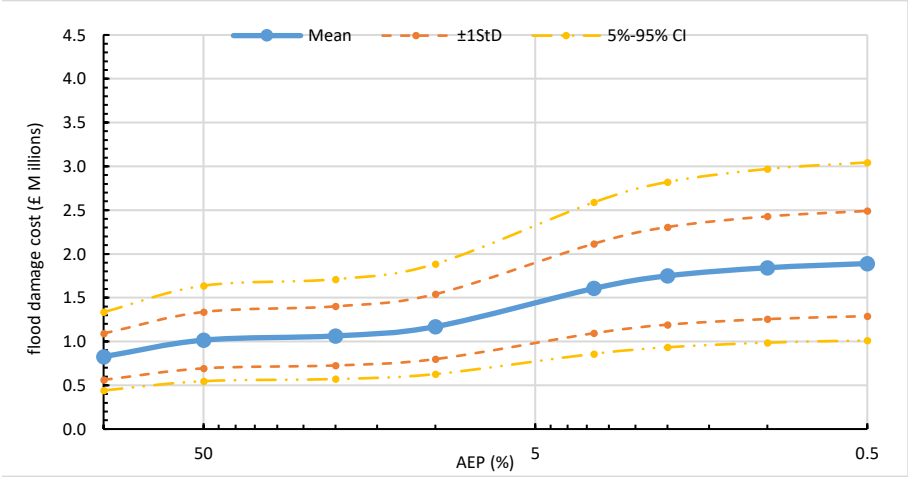



*Figure 8.34. Chamber "1126" C2 D30 flood damage chart*

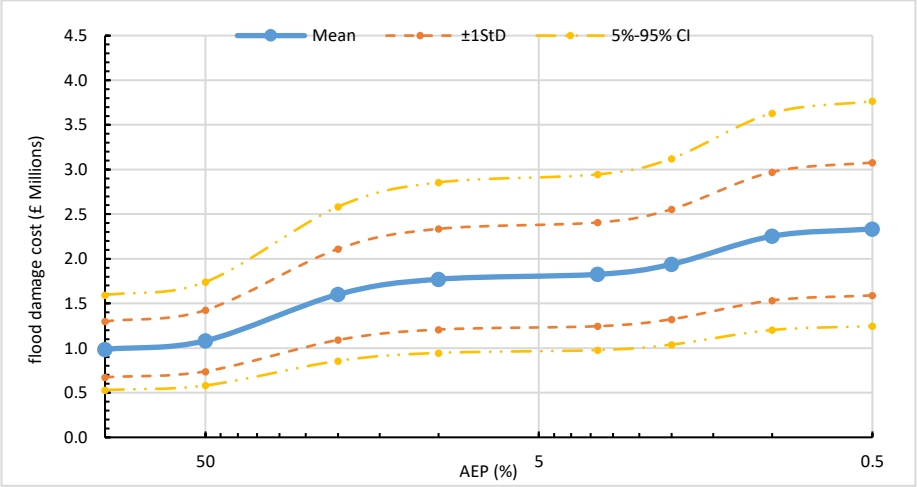



*Figure 8.35. Chamber "1126" C2 D60 flood damage chart*

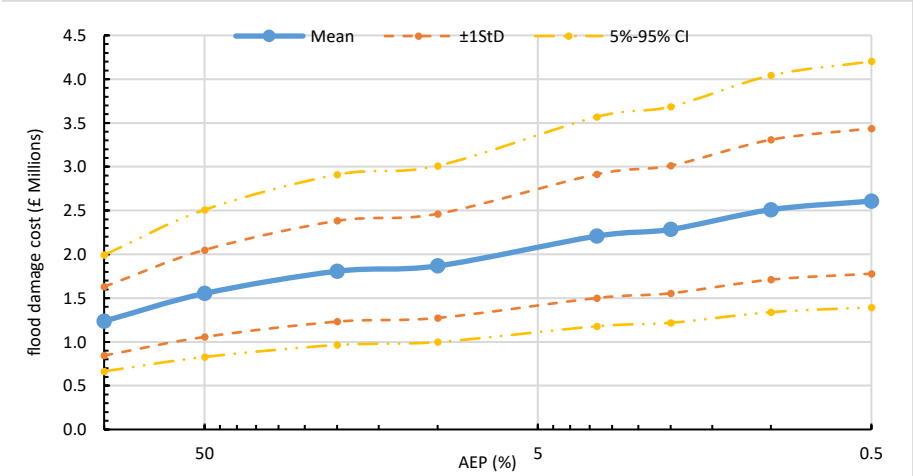



*Figure 8.36. Chamber "1126" C2 D180 flood damage chart*

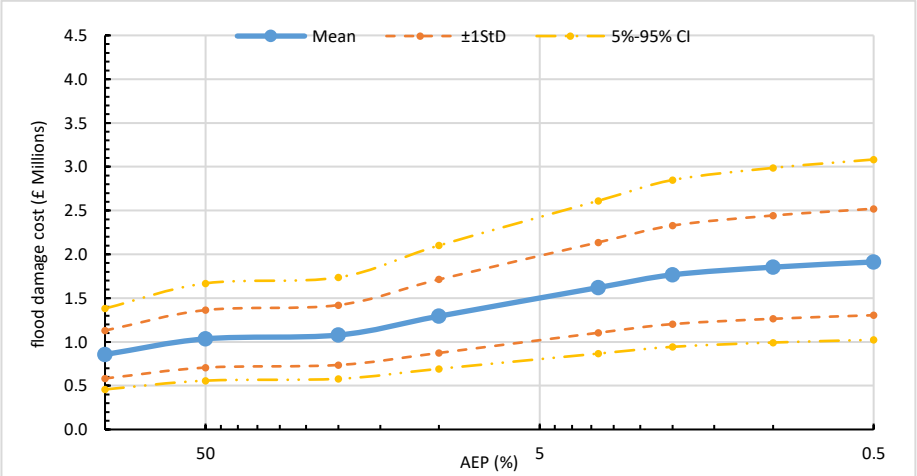



*Figure 8.37. Chamber "1126 C3 D30 flood damage chart*

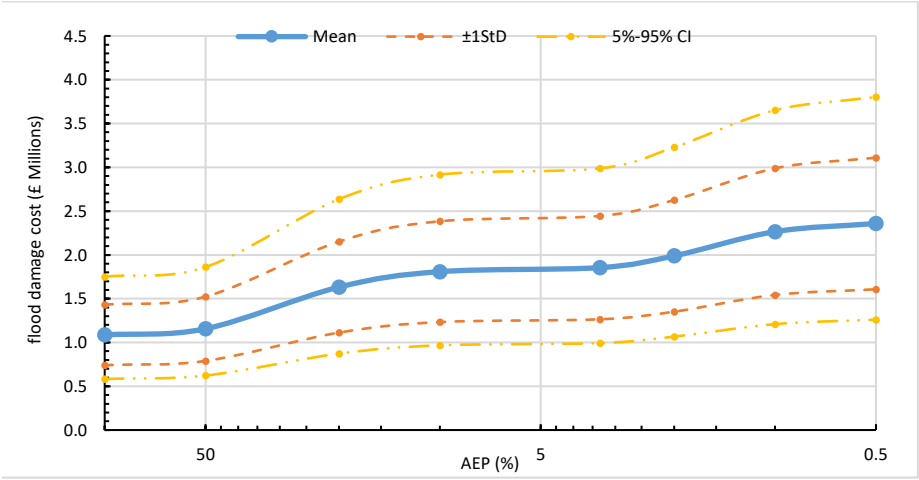



*Figure 8.38. Chamber "1126" C3 D60 flood damage chart*

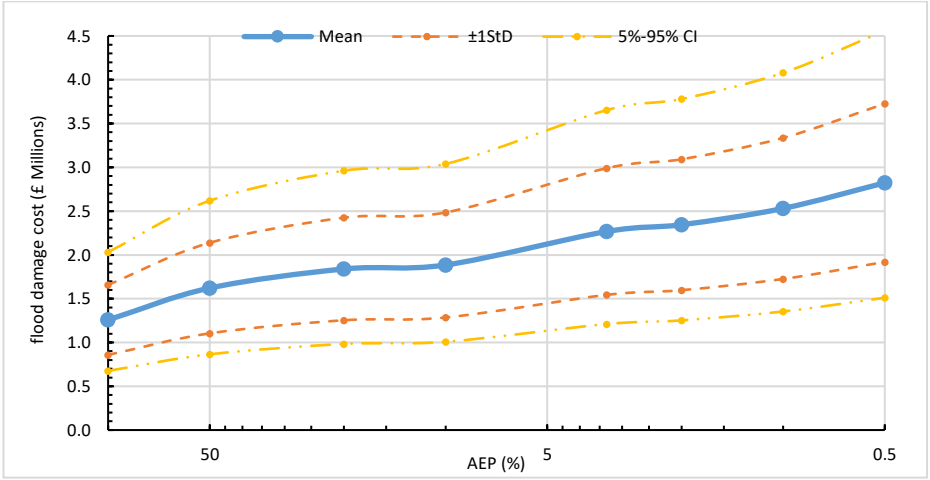



*Figure 8.39. Chamber "1126" C3 D180 flood damage chart*

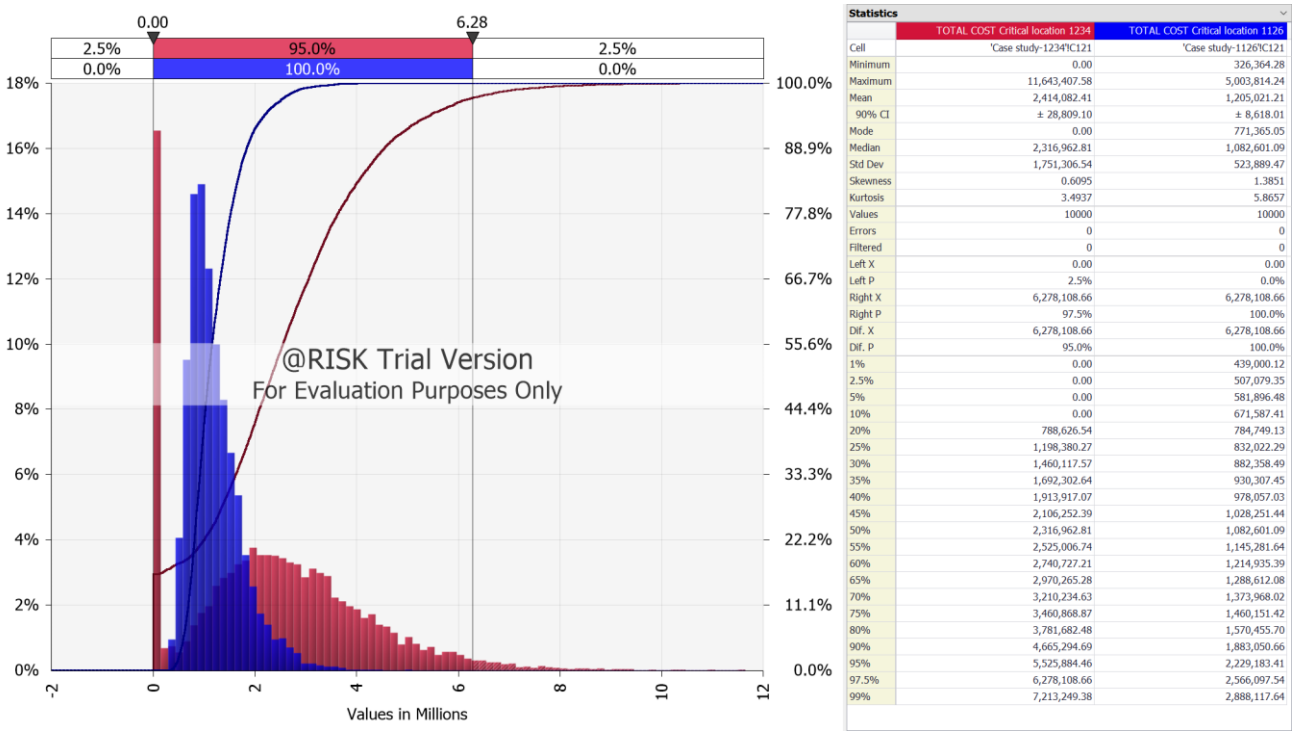
*Table 8.12. Chamber "1234" risk calculation based on damage quantification MCs for individual scenarios*

| C-D scenario | | C1 D30 | C1 D60 | C1 D180 | C2 D30 | C2 D60 | C2 D180 | C3 D30 | C3 D60 | C3 D180 |
|---|---|---|---|---|---|---|---|---|---|---|
| S scenario | Probabilities | 0.12 | 0.16 | 0.12 | 0.09 | 0.12 | 0.09 | 0.09 | 0.12 | 0.09 |
| S1 | 0.54 | £- | £1,610,585 | £2,062,773 | £- | £2,270,511 | £2,735,985 | £- | £2,736,655 | £3,194,044 |
| S2 | 0.27 | £1,385,755 | £2,498,734 | £3,043,379 | £2,008,567 | £3,194,002 | £3,520,281 | £2,526,755 | £3,715,360 | £3,967,791 |
| S5 | 0.1 | £2,720,715 | £3,201,213 | £3,558,698 | £3,188,570 | £3,715,900 | £3,995,822 | £3,648,223 | £4,120,742 | £4,360,106 |
| S10 | 0.054 | £3,423,780 | £3,701,182 | £3,992,286 | £3,833,394 | £4,109,485 | £4,355,453 | £4,213,929 | £4,448,534 | £4,666,262 |
| S30 | 0.018 | £3,897,252 | £4,109,261 | £4,357,686 | £4,250,753 | £4,450,568 | £4,680,811 | £4,571,732 | £4,746,200 | £4,961,185 |
| S50 | 0.01 | £4,269,310 | £4,454,195 | £4,690,194 | £4,580,558 | £4,754,010 | £5,007,573 | £4,863,270 | £5,023,289 | £5,296,122 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| S100 | 0.005 | £4,591,668 | £4,754,609 | £5,029,350 | £4,875,312 | £5,026,611 | £5,318,836 | £5,132,643 | £5,280,770 | £5,586,999 |
| S200 | 0.003 | £4,879,595 | £5,033,116 | £5,393,767 | £5,133,592 | £5,292,232 | £5,714,583 | £5,367,784 | £5,548,945 | £6,012,933 |
| P×C | | £117,786 | £355,478 | £320,847 | £110,724 | £342,074 | £291,667 | £130,256 | £397,434 | £330,508 |
| **Total risk =∑P×C** | | **£2,396,777** | | | | | | | | |

*Table 8.13. Chamber "1126" risk calculation based on damage quantification MCs for individual scenarios*

| C-D scenario | | C1 D30 | C1 D60 | C1 D180 | C2 D30 | C2 D60 | C2 D180 | C3 D30 | C3 D60 | C3 D180 |
|---|---|---|---|---|---|---|---|---|---|---|
| S scenario | Probabilities | 0.12 | 0.16 | 0.12 | 0.09 | 0.12 | 0.09 | 0.09 | 0.12 | 0.09 |
| S1 | 0.54 | £797,333 | £946,438 | £1,193,365 | £842,025 | £1,004,928 | £1,260,243 | £872,330 | £1,106,703 | £1,281,953 |
| S2 | 0.27 | £1,015,850 | £1,064,311 | £1,563,498 | £1,034,164 | £1,102,083 | £1,582,543 | £1,054,298 | £1,178,287 | £1,651,862 |
| S5 | 0.1 | £1,044,310 | £1,559,656 | £1,763,972 | £1,083,399 | £1,631,280 | £1,840,939 | £1,099,019 | £1,663,443 | £1,873,531 |
| S10 | 0.054 | £1,174,127 | £1,744,684 | £1,865,863 | £1,191,684 | £1,804,467 | £1,903,090 | £1,317,586 | £1,842,773 | £1,920,436 |
| S30 | 0.018 | £1,609,176 | £1,841,217 | £2,058,123 | £1,634,302 | £1,860,232 | £2,249,667 | £1,651,172 | £1,889,320 | £2,309,840 |
| S50 | 0.01 | £1,729,535 | £1,923,606 | £2,291,487 | £1,782,410 | £1,974,998 | £2,327,246 | £1,799,444 | £2,026,017 | £2,388,794 |
| S100 | 0.005 | £1,859,842 | £2,281,812 | £2,523,357 | £1,876,898 | £2,295,510 | £2,556,917 | £1,889,036 | £2,308,460 | £2,578,292 |
| S200 | 0.003 | £1,896,020 | £2,363,883 | £2,634,263 | £1,925,510 | £2,378,772 | £2,657,280 | £1,948,868 | £2,403,453 | £2,876,764 |
| P×C | | £112,071 | £179,120 | £170,904 | £87,211 | £140,717 | £133,128 | £89,980 | £150,556 | £136,467 |
| **Total risk =∑P×C** | | **£1,200,153** | | | | | | | | |




Statistics

| | TOTAL COST Critical location 1234 | TOTAL COST Critical location 1126 |
|---|---|---|
| Cell | 'Case study-1234'!C121 | 'Case study-1126'!C121 |
| Minimum | 0.00 | 326,364.28 |
| Maximum | 11,643,407.58 | 5,003,814.24 |
| Mean | 2,414,082.41 | 1,205,021.21 |
| 90% CI | ± 28,809.10 | ± 8,618.01 |
| Mode | 0.00 | 771,365.05 |
| Median | 2,316,962.81 | 1,082,601.09 |
| Std Dev | 1,751,306.54 | 523,889.47 |
| Skewness | 0.6095 | 1.3851 |
| Kurtosis | 3.4937 | 5.8657 |
| Values | 10000 | 10000 |
| Errors | 0 | 0 |
| Filtered | 0 | 0 |
| Left X | 0.00 | 0.00 |
| Left P | 2.5% | 0.0% |
| Right X | 6,278,108.66 | 6,278,108.66 |
| Right P | 97.5% | 100.0% |
| Dif. X | 6,278,108.66 | 6,278,108.66 |
| Dif. P | 95.0% | 100.0% |
| 1% | 0.00 | 439,000.12 |
| 2.5% | 0.00 | 507,079.35 |
| 5% | 0.00 | 581,896.48 |
| 10% | 0.00 | 671,587.41 |
| 20% | 788,626.54 | 784,749.13 |
| 25% | 1,198,380.27 | 832,022.29 |
| 30% | 1,460,117.57 | 882,358.49 |
| 35% | 1,692,302.64 | 930,307.45 |
| 40% | 1,913,917.07 | 978,057.03 |
| 45% | 2,106,252.39 | 1,028,251.44 |
| 50% | 2,316,962.81 | 1,082,601.09 |
| 55% | 2,525,006.74 | 1,145,281.64 |
| 60% | 2,740,727.21 | 1,214,935.39 |
| 65% | 2,970,265.28 | 1,288,612.08 |
| 70% | 3,210,234.63 | 1,373,968.02 |
| 75% | 3,460,868.87 | 1,460,151.42 |
| 80% | 3,781,682.48 | 1,570,455.70 |
| 90% | 4,665,294.69 | 1,883,050.66 |
| 95% | 5,525,884.46 | 2,229,183.41 |
| 97.5% | 6,278,108.66 | 2,566,097.54 |
| 99% | 7,213,249.38 | 2,888,117.64 |

*Figure 8.40. Overlaid damage frequency distributions for locations surrounding chamber "1234" (red) and chamber "1126" (blue) along with CDF curve for each*

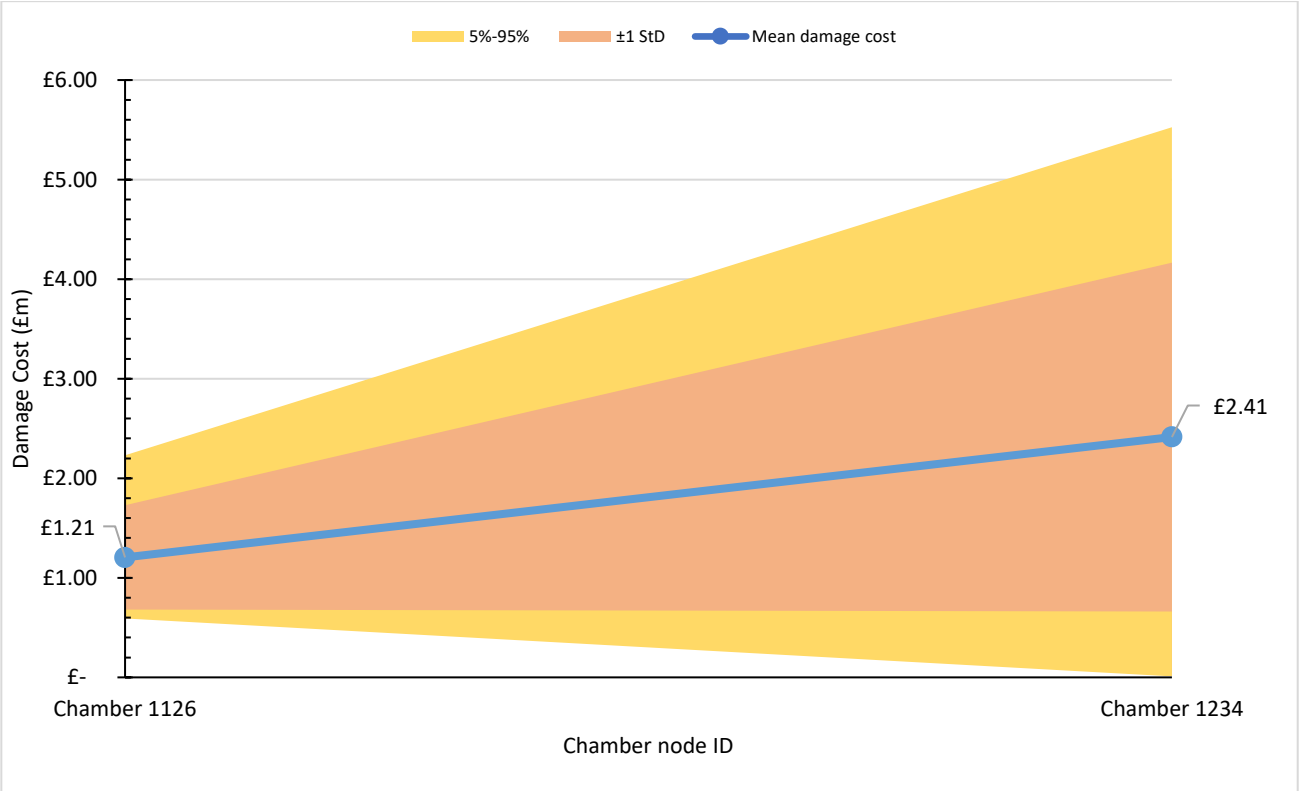



*Figure 8.41. Uncertainty envelope for flood risk at the two critical locations.*

## 8.8 Discussion

### 8.8.1 Damage quantification

The damage charts (Figures 8.22- 8.39) obtained from the damage quantification steps enable to look at each C-D scenario independently and interpolate for intermediate storm events. It also enables infrastructure managers to conduct 'What-If' analyses at specific locations for different types of interventions. These damage charts can then be incorporated as part of Whole Life Cycle Costing (WLCC) assessments.

### 8.8.2 Risk quantification

The risk quantification calculates the flood risk associated with a storm event occurring at least once per year. Following the steps for risk calculation based on the damage quantification shows that location '1234' has a higher flood risk than location '1126'. The results from the second method for risk calculation show a similar conclusion. Figure 8.40 shows that at location surrounding node '1234', more than 16% of the iterations have produced zero damage. This is attributed to the fact that the site floods at a storm event of 1 in 2 return period which, based on the adjustment in table 8.5, translates to the event of a flooding magnitude having a 27% probability of occurrence. Whereas the 1 in1 storm event which is a non-flooding magnitude having a 54%. Conversely, around location '1126' the annual flood damage cost starts at a minimum greater than £300,000. This ties to the fact that chamber '1126' floods at a 1 in 1 storm event which translates to the event of a magnitude resulting in a flood having a 54% of occurrence. Despite this observation, looking at the risk envelope shown in Figure 8.41, location '1234' observes larger overall risk of flood damage compared to '1126', as well as larger uncertainty in the total cost of damage. The larger cost of flood damage at location '1234' overweighs its lower likelihood of a flood occurrence.

Furthermore, the second risk quantification method also shows the risk score at location "1234" entails a larger uncertainty demonstrated by the flatter CDF slope for the location in Figure 8.40 and the larger uncertainty envelope in Figure 8.41. It is crucial for infrastructure managers when studying

risk to understand the uncertainty or confidence in the output rather than make decisions based on single-point evaluation. This is one aspect where the second method for total risk quantification proves more advantageous than the first method. It allows for uncertainties in flood sources to be included as part of the simulations. Another aspect where the second method leads is the lesser number of calculations involved. The first method requires tedious calculations especially when there are a broad range of scenarios or multiple locations being considered. In comparison the second method allows to run simulations for multiple locations and include the various risk scenarios and their probabilities in the run and hence, obtain a total risk score with a confidence range without any follow up calculations. Nonetheless, there is a discussion as to whether variability (i.e., risk scenarios in this case study) should be included in the simulations along with the epistemic uncertainties (i.e., uncertainty in costing and exposure parameters). On this, Vose (2008) suggests that it is not ideal or "is mathematically less correct" to combine the two. They suggest that doing so eliminates the information about how much of the uncertainty in the output distribution is due to inherent variability in the system and how much is due to lack of knowledge. On this, Vose (2008) recommends separation of uncertainty from variability within risk calculation. Where epistemic uncertainties are embedded in simulations and formula calculations are used to consider the variabilities.

On this, since both methods are demonstrated in this case study, the suggestion is to understand what the infrastructure manager requires from the risk score. If the task is a 'what-if' WLCC analysis at a specific location, then quantifying damage to generate damage charts and then calculating risk score based on that is the better option. Also, if there is a need to understand the sensitivity of the damage to various input parameters then the first approach enables infrastructure managers to run sensitivity analyses to understand which parameters are highly influential. Hence, improve the risk estimates by increasing data knowledge on these parameters. However, if the task at-hand is a comparative evaluation of flood risk score between multiple locations then the "shortcut" second setup is suggested as less tedious and provides an uncertainty envelope on the risk score. This setup is useful when multiple sites are identified as critical, and the infrastructure manager requires to make risk-informed decisions about resource prioritisation and budgeting.

### 8.8.3 Sensitivity analysis

In order to put uncertainty under further scrutiny, the output distribution from the damage quantification is used to generate tornado charts to investigate the main sources of uncertainty. A tornado chart shows the effect of various input parameters on the output of the cost for each C-D-S scenario (e.g., Scenario is C1-D30-S10). Figures 8.42 & 8.43 show the tornado charts for the two critical locations. Figures 8.44 and 8.45 show the sensitivity of the models using the regression coefficients for additional analysis.

Looking at the tornado charts for the two locations, 'number of passenger trains', 'train cancellation cost' and 'renewal work possession time' have the biggest impact on the uncertainty in total damage cost at both locations. 'Length of flooded' track appears to cause larger change in output at location '1234'. Each of these parameters is described individually as follows.

**a. Number of passenger trains and train cancellation**

The parameter 'Number of passenger trains passing the site' is present in all equations for the operational disruption category in Table 8.2. Furthermore, the introduced uncertainty in the input parameter is relatively large: -50%, +50% and +100% around the obtained most-likely value -2 trains- (Figure 8.17), compared to other input parameters where the introduced uncertainty is at ±30% (Table 8.6).

Additionally looking at Figures 8.44 & 8.45, the regression coefficients show that number of trains parameter affects cost at location '1126' more so than location '1234'. This is potentially because there are no cancellations warranted at location '1234' as depth of water never rise to the level warranting a closure cancellation, rather only possession cancellation (Tables 8.3 & 8.4). This also explains the observed impact of train cancellation cost parameter; where, despite the fixed uncertainty in the parameter itself at both locations (Figure 8.15), its influence on total cost at location '1126' is greater than at location '1234' (Figure 8.44 & 8.45).

### b. Length of flooded track

The main difference in the sensitivity analysis between the two locations is the size of impact the parameter 'length of flooded track' has on the total cost. It is a significant parameter present in many of the costing terms (see Table 8.2), hence size of uncertainty would have a proportional impact on cost. At location '1234' the parameter had a significant influence on the total cost compared to its negligible impact at '1126'. This is due to the difference in uncertainties introduced in the parameter at either locations, resulting from the previously described difference in zoom scale of the interface when taking the length measurements (Figures 8.2 & 8.3). The larger standard deviation is observed at location '1234', which translates to larger uncertainty in the total damage cost.

### c. Renewal Possession time

'Renewal possession time' has similar significant influence at both locations, albeit slightly more significant at '1126'. This is potentially because the renewal possession time for the location is expressed as part of the operational disruption cost for track, drainage and earthworks, under the assumption the works took place separately. Whereas for location '1234' flooded earthwork damage is not a consideration.

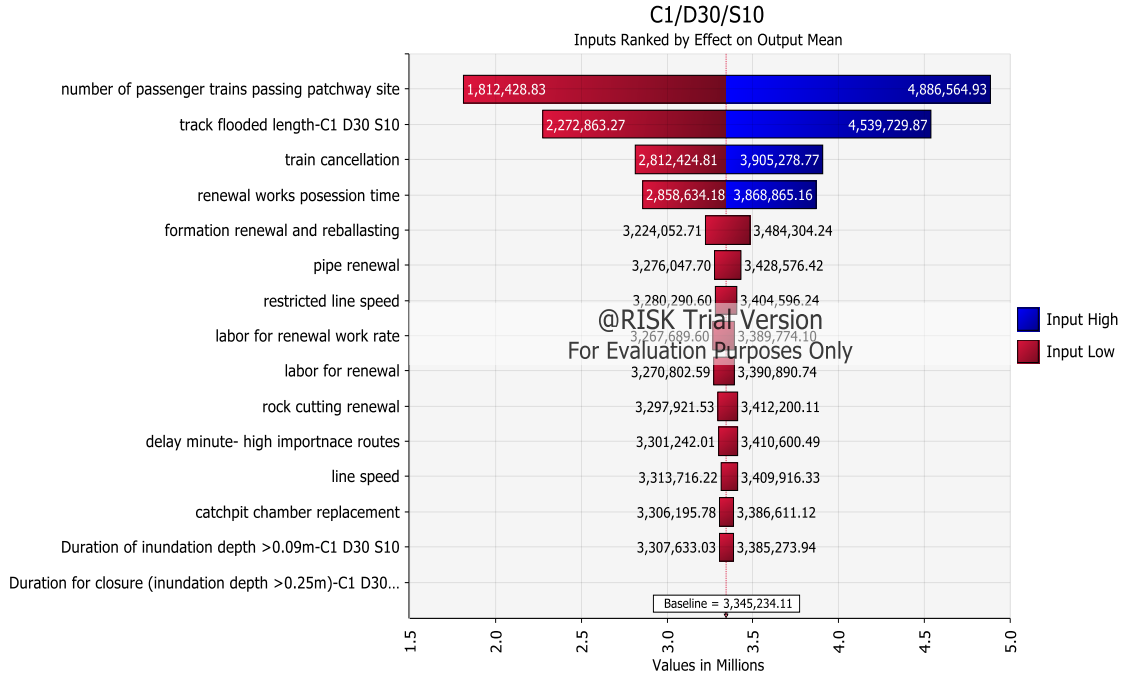



*Figure 8.42. Tornado chart at location "1234" scenario C1-D30-S10*

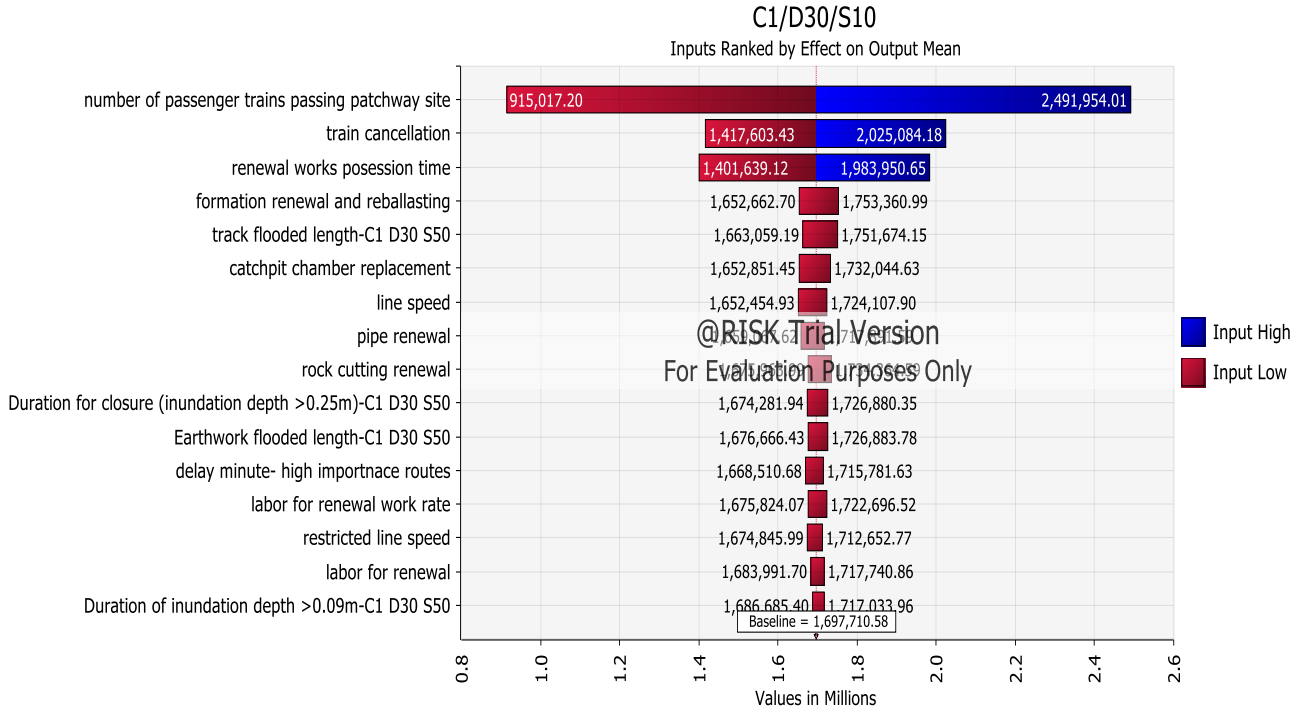



*Figure 8.43. Tornado chart for location "1126" scenario C1-D30-S10*

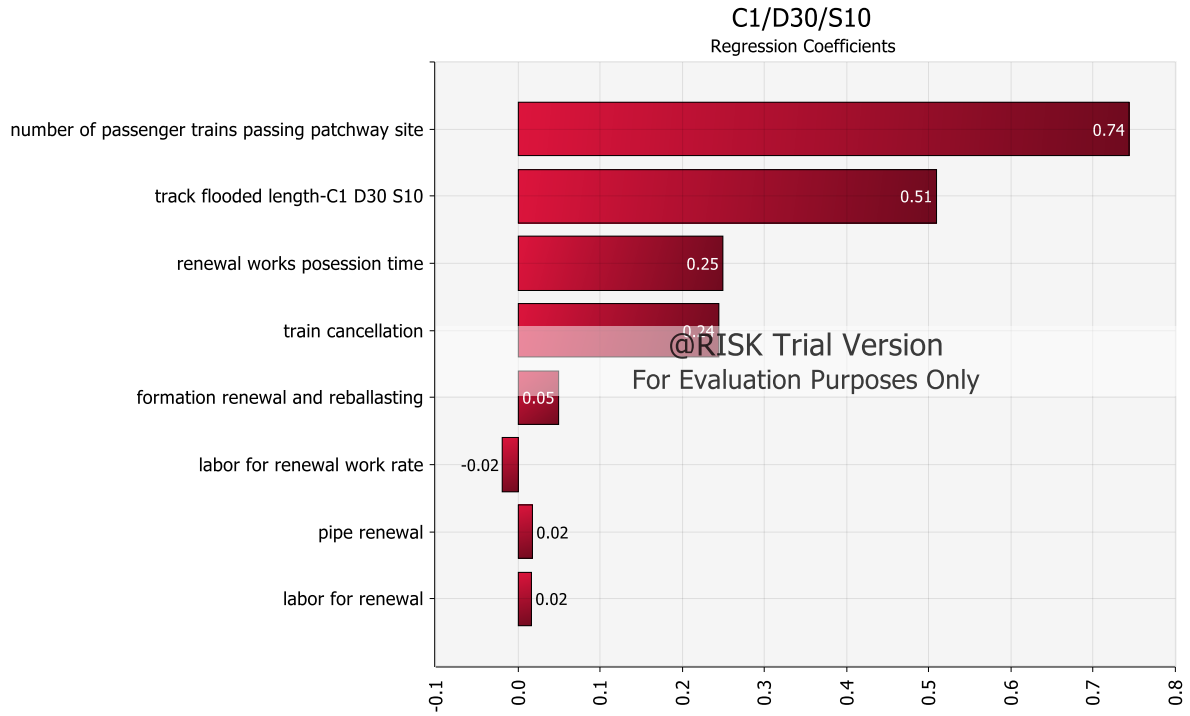



*Figure 8.44. Location "1234" Sensitivity analysis using regression coefficients*

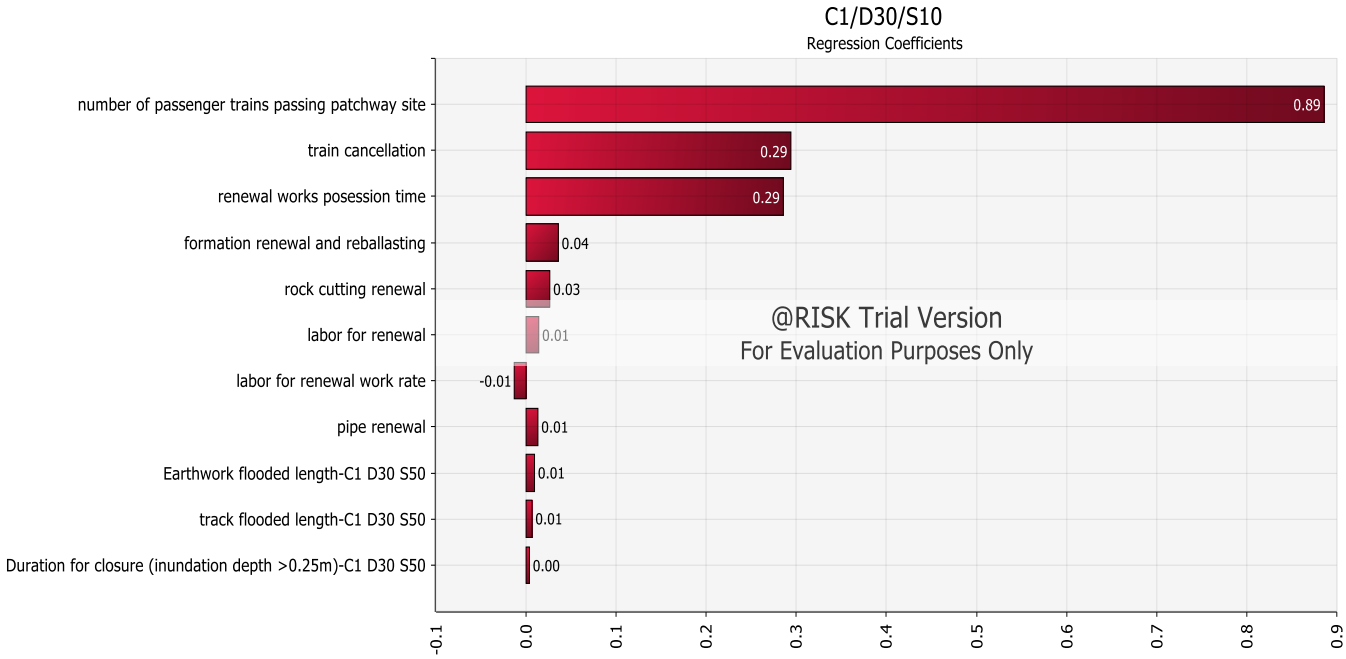



*Figure 8.45. Location "1126" sensitivity analysis using regression coefficients*

## 8.9 Limitations and recommendations

The following are the limitations observed in the case study and recommendations for future applications:

1. One of the main limitations in this study is the assumption that only renewal interventions take places. In the theoretical cost model, more than one intervention type is possible depending on level of exposure to flooding which parallels reality more closely. Therefore, future research should be carried on degradation modelling to describe the type of intervention as a function of flood exposure thresholds for various rail components (Earthworks, track bed and drainage). Examples from previous research looking at levels of damage have been described in Section 3.4.3. Once the damage thresholds are established, unit costs for the different types of intervention are required. This will allow infrastructure managers to predict the level of flood damage and appreciate the level of intervention required which provides better risk estimates of the damage cost incurred.
2. More research is required on monetary quantification of reputational damage caused by the operational disruptions. Similarly, monetary evaluation of environmental damage caused by

the various maintenance activities requires estimates of the emissions volumes caused. Due to time limitation and scarcity of such data, it is not pursued in this research.

3. The cost distributions assumed in this research are based on single-point estimates of costing parameters. This is a major source of epistemic uncertainty. In future applications, better estimates of cost based on historic data and expert opinion are crucial to improve quality of output.
4. Cost model categories, track structure and earthwork intervention are given by aggregate equations. A more disaggregated approach is advisable to ensure uncertainty in risk output is less sensitive to a single cost parameter. For e.g., in the theoretical model, earthwork intervention cost is specified by the cost of labor, cost of equipment and cost of materials. However, such disaggregation is not possible in this demonstration because the obtained unit cost is a lumped value of the intervention. If this value is highly uncertain, it significantly influences the uncertainty in the risk output. Whereas if the uncertainties are distributed across parameters, the assessor will be better able to pin down the source and improve estimates.
5. The cost of operational disruptions accounts for directly incurred delays and cancellations based on the number of trains passing the site. This analysis does not consider the knock-on effect of delays. This may be a difficult task and requires resorting to real-time simulations of rail operations for a more advanced analysis.
6. Finally, the cost estimates in this study do not consider inflation rate. However, to align with the proposed use of this tool, that is prediction of flood risk into the future, it becomes essential to project the present values into the future using the appropriate inflation rate.

## 8.10 Summary

This chapter provides the final stage of the proposed framework which looks at obtaining damage charts and risk scores for comparison of the two critical locations identified in chapter 7. The case study describes the cost model and setups for running MCs simulations. The uncertainties in costing,

exposure and risk sources input parameters are analysed and represented with appropriate distributions. The results show that Location surrounding node '1234' is a higher flood risk location, costed at £2.41m compared to location surrounding node '1126' where flood was costed at £1.21m. Although location '1126' flooded at a rainfall event of higher frequency compared to '1234', the damage associated with '1234' was larger mainly due to greater spread of flooding. Furthermore, location '1234' was associated with larger uncertainty in damage quantification due to larger uncertainty in Flood length exposure parameter. Uncertainty was reflected with a risk uncertainty envelope. A sensitivity analysis of the uncertainties and their sources is presented using tornado charts. The Tornado charts reflected that 'number of passenger trains', 'train cancellation cost' and 'renewal work possession time' have the biggest impact on the uncertainty in total damage cost at both locations.

Furthermore, two setups are proposed for MCs depending on the type of analysis and suggestions are made with regards to which method is advised for which type of analysis. The first method involves separate damage quantification and damage chart generation followed by a risk quantification. This is more suitable for What-If analyses of interventions planning and for understanding sensitivity of the calculated damage to the various cost model inputs. Whereas the second method combines the scenario probability into the MCs run, thus a less tedious approach for comparative risk modelling between multiple locations to inform site prioritisation and budgeting. The chapter is a demonstration of how the presented framework is useful to railway infrastructure managers in various applications like risk-informed budgeting of resources for M&R interventions and WLCC analyses.

# Chapter 9: Discussion

## 9.1 Introduction

The aim of this research was to develop a risk assessment framework for quantitative evaluation of flood risk associated with drainage asset components. This chapter provides a summary of the research and discusses the achievement of the research objectives. It also describes the value of the research and applicability of the framework in railway drainage asset management.

## 9.2 Summary of research

The research methodology carried out in this project is summarised in the following subsection.

a. Review of literature

To identify the specific research need, establish research scope, and inform the development of a comprehensive framework for risk assessment, Chapters 2 and 3 provided background and reviewed standards and studies addressing the following themes:

1) Background on railway drainage systems, current approaches to intervention planning and drainage infrastructure condition modelling applications
2) Asset management concepts and principles, and research studies in the field of railway infrastructure asset management.
3) Risk-informed asset management and risk standards
4) Flood modelling applications

b. Development of theoretical framework

Based on the literature review, Chapter 5 described the development of a risk assessment framework comprising four modules. The following is an overview of these modules.

Module 1: Modelling assets condition

This module proposes the use of data-driven Machine Learning (ML) algorithms for predictive condition modelling of drainage individual assets. The output of the module is the projected condition of an asset.

Module 2: Flood scenario analysis

Scenario analysis is used to evaluate the various potential scenarios of flood risk sources. Two-dimensional (2D) hydraulic modelling is proposed as an agile and user-friendly tool for simulating the two-way interaction between the linear drainage system and catchment surrounding it. The outputs for any scenario are the identification of flooding components and the flood exposure parameters of the surrounding assets.

Module 3: Damage quantification

This module aims to translate the exposure output from the flood modelling results into economic damage charts using a developed cost model. Monte Carlo simulations (MCs) are proposed to reflect the impact of uncertainties in exposure and costing parameters. The output defines the consequence component of risk analysis.

Module 4: risk quantification

This module uses damage quantification output to calculate risk over the various possible scenarios using the mathematical definition of flood risk being the product of the probability of a flood scenario occurring and the value of monetary damage the scenario causes. This provides a comparative economic risk score for the identified flooding components.

c. Case study application of the framework modules

The applicability of the framework for prediction of railway components at highest economic risk was demonstrated through case study applications of each of the four modules. The applications involved the following:

1. Application of ML algorithms for condition modelling of railway drainage pipes with data provided from asset records of the UK railway drainage network.

2. Flood modelling application on a railway track section in Patchway, UK. It involved building a hydraulic model using a 2D hydraulic modelling software (InfoWorks), relying on as-built drawings of drainage system, digital terrain models and land use ordnance survey maps. Scenario analysis was carried out for various combinations of asset conditions, rainfall return period and rainfall durations.
3. Damage and risk quantification application using the developed cost model, exposure results from flood scenario analysis application and cost data from the UK records.

## 9.3 Objectives of research

The achievement of research objectives (see Section 1.3) is described in the following subsections.

### 9.3.1 Achievement of Objective 1: Identify railway drainage system components, performance, and approaches to intervention planning

In Sections 2.2 and 2.3, a review of the railway drainage practices provided by Spink et al. (2014) was found particularly useful to identify current practice in drainage asset management, performance assessment and asset knowledge. Thereby, flagging issues in railway asset knowledge like the subjective and noisy nature of the available inspection data and the need for robust evaluations of performance gaps. Additionally, the section investigated the types of intervention planning (reactive versus proactive approaches). It also reviewed applications of condition-based and predictive maintenance approaches in railway assets. Hence, it highlights the need for a predictive tool for condition assessment of railway drainage assets.

### 9.3.2 Achievement of Objective 2: Identify methods for infrastructure asset condition modelling.

Section 2.3.5 reviewed condition modelling applications for drainage assets in linear water systems like urban drainage and watermain systems. The section reviewed applications of deterministic, statistical, and artificial intelligence methods. Thereby, it nominated Machine Learning algorithms as a data-driven tool to enable predictive assessment of individual asset condition. The review also

identified input factors used in previous studies for training algorithms for stormwater pipe asset condition prediction.

### 9.3.3 Achievement of Objective 3: Review literature on railway asset management.

Section 2.4 provided a review of asset management standards (IAM, 2008b, IAM, 2008a, IAM, 2015, ISO, 2014) to introduce asset management concepts, objectives, prescribed approaches and the asset management hierarchy (strategic planning, tactical programming and operational preparation and operations). Thereon, the section identified the scopes and levels of information quality required for the different levels of asset management. Furthermore, the section reviewed previous studies which looked at different levels of asset management practice for various railway infrastructure assets. Hence, it identifies the paucity in available research particularly for risk-informed drainage asset management.

Thereupon, Section 3.2 looked at benefits of and information required for risk-informed asset management, and reviewed studies on risk-informed railway infrastructure management. Thereby, it established the research scope for developing a risk assessment framework for quantitative evaluation of flood risk in railway drainage systems at component-level to inform operational planning of interventions. Thereby, this section achieved Objective 3 of the research.

### 9.3.4 Achievement of Objective 4: Identify requirements for risk assessment and techniques for quantitative analysis.

To achieve Objective 4, A review of risk standards (ISO, 2018, BSI, 2019b, BSI, 2021, IAM, 2008a) in Section 3.3 provided insight into the sequential process for a risk assessment (identification, analysis and evaluation), requirements for a quantitative analysis (probability and consequence) and an overview of techniques used for the different stages of risk assessment (Section 3.3.4). Furthermore, the section identified sources of flood risk associated with drainage assets (physical performance, and storm event), and the potential consequences of flooding of drainage assets (damage to other assets, pollution, safety and operational disruption), as mentioned in Spink et al. (2014). Thereafter, the section nominated risk assessment techniques for the research. It identified

scenario analysis as a tool for representation of various scenarios of flooding under various potential combinations of flood sources. Moreover, it identified MCs as a statistical tool to quantitatively consider uncertainties in the damage and risk quantification task.

### 9.3.5 Achievement of Objective 5: Identify appropriate methods for modelling flood risk and impacts.

Section 3.4 reviewed flood modelling applications in various systems (urban drainage systems, railway systems and river basins). It summarised these studies in terms of the considered: risk sources and drivers, modelling tools, exposure measures and, if any, damage quantification methods and outputs. Based on these studies, the section identified rainfall event as the main source of flood event characterised by rainfall return period and duration as well as flagging the uncertainty surrounding climate change rainfall projections. Hence, emphasising the need for flood scenario analysis. Moreover, the section recognised catchment properties (i.e., roughness and runoff coefficients), topography and land use as risk drivers which affect both the runoff in the system as well as, in case of flooding, the flood impact patterns onto track and off-track environment surrounding the drainage component. Thereby, recognising the need to represent the catchment to a high level of disaggregate detail. Furthermore, the section highlighted the lack of research on pluvial flood modelling in which the condition of the drainage system components is considered as a source of flood risk.

Therefore, to enable scenario analysis of flood risk, the review of literature established the need for an adaptable tool which enables robust modelling of flood occurrence at asset components as result of the interaction between the linear drainage system and the rainfall runoff. For this purpose, the section proposes the use of 2D hydraulic modelling as an integrated modelling tool to reflect the two-way interaction between the linear drainage system components and the surrounding 2D environment. The section reviewed available hydraulic modelling software and proposed the use of InfoWorks ICM. The learnings from this section were used as basis to develop the flood scenario analysis module in Section 5.4.

### 9.3.6 Achievement of Objective 6: Design a theoretical framework to obtain components for a quantitative flood risk assessment, employing methods identified from literature review.

Chapter 5 achieved Objective 6 of research through development of the four-modules framework for flood risk assessment. The chapter details the stages of each module by describing the methods used and required input data. Each module was presented with a visual flow chart summarising the details of the entailed stages. Section 5.3 described condition modelling module to obtain a condition score for individual drainage assets. This is used to identify the condition as a source of flood risk due to its influence on the asset performance. The section detailed the procedure for choice of candidate methods, namely, metrics reflecting prediction performance, Analytic Hierarchy Process (AHP) for comparison of methods and overall judgment criteria. It also described the required data pre-processing for training and addressing potential issue of class imbalance that is often observed in multi-class real training datasets. Moreover, it detailed the testing and comparison of performance as well as the significance of various inputs towards prediction.

Thereon, Section 5.4 described the flood scenario analysis module. It can visually identify flooding components and the exposure impact of a flood under various scenarios of asset condition and rainfall events. The section described three main stages involving: choice of flood modelling software through comparison of available software capabilities, building the 2D hydraulic model for the linear drainage system, translation of asset condition into capacity loss, and representation of catchment area/potential floodplain to a high level of detail. Thereafter, it detailed the procedure for flood simulations for scenario analysis and generation of flood exposure charts.

Section 5.5 detailed the stages for quantifying flood damage in monetary terms. It described the development of a comprehensive cost model. The general cost model was developed to consider both direct, indirect, tangible, and intangible costs associated with flooding of track structure, earthworks, point assets, signalling and electric assets. The section also addressed the need for uncertainty analysis to represent epistemic uncertainties in costing and exposure parameters using

MCs. Finally, it described the generation of damage charts as a visual reflection of the economic damage over the various scenarios.

Section 5.6 described the method for risk quantification. It entailed the use the scenario damage values from the previous module to obtain a total economic risk score. The study also provided a 'short-cut' method to calculate risk directly from exposure data by incorporating risk sources uncertainties within MCs damage calculations. From the case study application, the first method involves separate damage quantification and damage chart generation, therefore it is more suitable for What-If analyses of mitigation planning and for understanding sensitivity of the calculated damage to the various cost model inputs for future data collection. Whereas the 'short-cut' method is a less tedious approach for comparative risk modelling between multiple locations to inform site prioritisation and budgeting. From the case study, both methods achieved similar risk scores for either locations, where risk at '1234' was quantified at £2.41m and at '1126' risk was quantified at £1.21m. Although the short-cut method provides the risk in the form of uncertainty envelopes rather than a point-value of risk, which would be more relevant for decision-making.

### 9.3.7 Achievement of objective 7: Perform case study demonstrations of designed theoretical framework for component-level railway drainage quantitative flood risk assessment.

Chapters 6, 7 and 8 demonstrated the use of the framework for quantitative risk assessment through application of each module using railway drainage case study data. Chapter 6 demonstrated the detailed stages of Module 1 through a case study on structural and service condition modelling of railway drainage pipe components (short pipe sections) using railway drainage asset records from the UK. Chapter 7 demonstrated Module 2 through the application of 2D hydraulic modelling for flood scenario analysis using a case study of a railway track section located in Patchway, Bristol, UK. The case study identified two critical components and generated exposure charts for each component. Chapter 8 demonstrated Modules 3 and 4 for damage and risk quantification using exposure output from Chapter 6 and damage cost data from the UK. The output was an economic

risk score for the two identified critical sites to compare criticality. These applications successfully demonstrated the downstream flow of each module output into the subsequent module towards achieving an economic component-level risk score.

## 9.4 Value of research and applicability of tool to industry

The research developed a comprehensive generalisable framework utilising various techniques that can be easily streamlined into in-place asset management systems to enhance, systematise, and speed operational decision-making. The presented modular structure, by which output from each preceding module is used as downstream input into the next module, gives assets managers the flexibility to adjust methods, assumptions, and decision thresholds as well as to pinpoint uncertainties and control their propagation. The techniques chosen for obtaining the components for risk assessment are chosen such that the modules mainly rely on continually increasing asset inventory data and historic maintenance records, with minimal reliance on subjective judgment, albeit not entirely avoided when there is a lack of data.

In addition to identifying the condition of asset as a potential source of component flooding, the proposed use of data-driven ML algorithms leverage noisy and imprecise asset data records for continual prognosis of asset condition, thereby, to provide early warnings of maintenance needs. Furthermore, use of data-driven algorithms enables the constant feed into training datasets with newly collected data for the continual improvement of prediction performance. The application provides a base for Big Data integration into predictive railway drainage asset management.

For risk analysis, the framework proposed the use of 2D hydraulic modelling for scenario analysis as it offers an interactive, user-friendly, and agile environment to reflect various, present or future, scenarios of flood risk sources and various layouts of surrounding geography. This enables the systematic identification of flooding components and the quantification of consequent flood exposure of various elements in both track and off-track environment. It also enables predictive outlook of impact of risk mitigation alternatives like structural measures, vegetation, or land use planning at specific locations. Thereby, it supports early-on intervention decision-making.

Furthermore, the proposed representation of the as-built drainage system in a 2D model for evaluation of performance provides an example of how Digital Twins can be incorporated for improving railway drainage asset management. A digital twin is a virtual representation of a physical asset, i.e. the drainage assets, to obtain a full picture of the drainage asset information, its performance, and impacts of interventions over its lifecycle from procurement through operation and maintenance until end-of-life. This informs operational level decision-making to enable optimised and cost-effective asset management processes as described above. The hydraulic modelling can be extended to regional and national levels provided accurate and well-connected asset data is available to validate the model. However, from the UK application, obtaining well-connected and reliable drainage asset drawings may be a challenge. Additionally since the assets are buried and often old, the as-built drawings may not b representative of the current layout, particularly with regards to asset slopes, unless they've been reprofiled and the drawings have been updated. The benefit of 2D hydraulic modelling is mainly realised at an operational level for short-term intervention prioritisation within routes and potentially regions as it is a detailed level of analysis. It can also inform medium-term climate change adaptation and resilience measures to be tested for impact, such as green covers and retaining structures.

Furthermore, the developed cost model is designed to identify costs incurred in a reactive sense to - or as a consequence of- a certain flood incident. The model could be incoporated as a part of a Whole Life Cycle Appraisal in which other life cycle costs are included, such as cyclic inspection and maintenance activities.

This enables infrastructure managers to embed risk-informed decision-making within Asset management plans to achieve improved levels of service through comparison of intervention criticality of various locations against performance thresholds and the mitigation of the impacts of severe weather events.

## 9.5 Limitations and recommendations

The limitations of research were mainly related to the demonstrated applications of the modules. Limitations associated with each module application were discussed in Sections 6.9, 7.8 and 8.9. In summary, the notable limitation in condition modelling to be further investigated is the attainment of a probabilistic output from condition modelling algorithms. For flood simulations, the main limitation relates to calibration of the developed flood model against actual measurements of flood data. For damage quantification, future research should address the development of exposure-damage level charts for accurate predictions of potential damage. Furthermore, as the research addresses the first two stage of risk assessment, risk evaluation remains a prospect for further research. It entails the definition of bespoke risk tolerance thresholds in collaboration with infrastructure managers. Such criteria enable operational intervention planning to be streamlined and thus, improve decision-making process.

## 9.6 Summary

This chapter provided an overview of the research methodology, reviewed achievement of objectives throughout the research and highlighted the value of research to the industry as well as main limitations and recommendations for future development. The proposed comprehensive framework leverages available technologies for quantitative evaluation of drainage flood risk at component level. Thus, enabling proactive planning of interventions and optimal allocation of resources.

# Chapter 10: Conclusion

## 10.1 Accomplished work

The research developed a detailed four-module framework for assessment of risks associated with railway drainage assets at component-level. The framework provides a set of tools for railway drainage infrastructure managers to obtain a quantitative risk score to inform operational level of planning, prioritisation of and allocation of resources for interventions. The objectives outlined in Chapter 1 have been demonstrated in the research through:

1) Literature review of (Chapters 2 and 3):
    a. Railway drainage system,
    b. Condition modelling applications of drainage infrastructure assets,
    c. Asset management principles and concepts, current practice in railway drainage and previous studies on railway infrastructure management and risk-informed infrastructure management in particular,
    d. Risk assessment standards and practice in railway drainage,
    e. Flood risk modelling applications.
2) Development of a risk assessment theoretical framework which uses quantitative techniques identified from the literature review (Chapter 5).
3) Case study demonstrations of the framework modules for attainment of a quantitative risk score (Chapters 6, 7 and 8).

## 10.2 Findings

It was found that for a quantitative component level drainage risk assessment, a combination of tools and techniques are applicable to work in sequence for obtaining elements of a risk assessment and ultimately, attainment of a monetary risk score. The following summarise the suitable tools and techniques.

1) Machine Learning algorithms offer high-performance tools for condition modelling of individual drainage assets. They are fit to deal with subjective, incomplete and/or inconsistent drainage asset records. Furthermore, they enable the continual training and performance improvement with the regular collection of new inspection data, thereby, allowing the continual prognosis of problem areas to advise on potential intervention needs early on. The work entailed in this research on developing the machine learning data-driven approach to predict the condition of individual railway drainage pipes was reported in Aljafari et al. (2022) (Appendix A).
2) The significant factors for drainage pipes structural and service condition prediction amongst the used factors are previous condition and years since previous condition. In addition to length being pertinent to structural condition prediction and whether maintenance took place being a significant factor for service condition prediction.
3) Scenario analysis is an applicable tool for identification of risk scenarios in response to various combinations of risk sources as well as the analysis of consequence of flood risk.
4) The use of 2D hydraulic modelling software offers a highly adaptable and user-friendly scenario analysis tool that is based on robust mathematical hydraulic equations for visualisation of flooding and associated consequences for various scenarios of risk sources and drivers. The advantages of 2D hydraulic modelling for scenario analysis are particularly prominent in consideration of the composite nature of the railway system, in which the topographic layout and elements at risk vary significantly both spatially and temporally. Through modelling the two-way interaction between the drainage system and the surrounding area, a 2D hydraulic modelling software offers an agile environment to reflect the continually variable risk parameters (sources and drivers).
5) Exposure charts offer a suitable visual representation of inundation exposure of various damage receptors under the various tested flood risk scenarios.
6) For economic quantification of flood consequence, a comprehensive cost model, which considers both direct, indirect, tangible, and ‘monetised’ intangible damage, should be

customised-according to infrastructure managers' needs, in terms of unit costs and inundation exposure parameters (obtained from hydraulic simulations). The cost model may include M&R costs for various assets affected by flooding, operational disruption compensations, off-track land compensations and safety costs.

7) Monte Carlo simulation is found a suitable statistical tool for quantitative evaluation of uncertainty in the damage quantification stage, which returns frequency distribution of damage as an output. Monte Carlo enables the random sampling of uncertain parameters through representing their potential values and associated occurrence probabilities with appropriate statistical distribution charts.
8) Representation of flood scenario consequence using damage charts with uncertainty envelopes for the various scenarios offers a useful visual representation of the 'consequence' component of risk. This is particularly useful for 'What-If' scenario analyses at a particular location for comparison of potential economic damages, thereby advising on suitability of specific comparable intervention measures.
9) Representation of risk sources as discrete uncertainty distributions given by their probabilities of occurrence enables direct calculation of monetary risk distribution using MCs. This approach is advised to inform prioritisation decision, in which a comparative monetary risk score is sought for various locations.
10) Operational level quantitative risk calculation is recommended to rely mainly on historic data records. However, for instances where there is a paucity in historic data, expert opinion becomes essential, particularly regarding asset data for building the hydraulic model and uncertainty distributions for damage quantification. Expert input is also important when establishing scenarios for modelling various risk sources like climatic projections.

## 10.3 Conclusions

1) The proposed framework is suitable for achieving monetary risk scores associated with individual drainage components to inform comparative intervention prioritisation and planning at an operational level of management.
2) Component-level risk-informed operational asset management can be applied for short-term intervention through planning and prioritisation based on current or near-future condition predictions, climate conditions, and as-built environment. Furthermore, it can also be applied for long-term evaluation of potential risk mitigation measures, where, based on prediction of future asset condition and climatic projections, 2D hydraulic simulations can be implemented in a 'What-If' scenario analysis of potential mitigations measures (e.g. structural installations, vegetation planting or land-use planning). Thereby, enabling cost-benefit analyses of these measures.
3) The framework proposes the use of a combination of available data-driven technologies for risk-assessment. Leveraging current available technology for the benefit of improving current asset management through increased reliance on data and digital techniques enables drainage asset management to be streamlined for efficiency in decision-making, improved system performance and thus, improved level of service. Through optimisation of use of intervention windows, improved planning and aggregation of intervention works, reduction of unnecessary proactive interventions in line with risk tolerance thresholds, cost-effective asset management practice can be achieved.

## 10.4 Recommendations for further research

Limitations of this work have been thoroughly discussed in Sections 6.9, 7.8 and 8.9. In summary, future research and application of the framework should address:

1) The need for probabilistic output from ML algorithms to quantify probability of asset condition as an uncertain source of flood risk.

2) The need for flooding incident data collection for calibration of the flood simulation model.
3) Scope to consider climatic projection factors within the simulated rainfall events.
4) Scope to source drainage system asset data at national level for widespread hydraulic modelling.
5) The need for stage-damage charts for accurate quantification of damage. This can be developed in collaboration with infrastructure managers.
6) The need for subsequent risk evaluation through establishment of risk tolerance thresholds in collaboration with infrastructure managers.
7) Scope for consideration of ground water as a source of water damage within the track structure and for its impact to be considered within the risk assessment. Furthermore, scope for consideration of impact of surrounding waterbodies like rivers or in coastal locations on the railway infrastructure.
8) Need for well-connected as-built asset data to expand the scope of the hydraulic modelling to a national level of application.

## 11.References


ADADI, A. & BERRADA, M. 2018. Peeking Inside the Black-Box: A Survey on Explainable Artificial Intelligence (XAI). *IEEE Access,* 6**,** 52138-52160.

AHMED, M., KHALEF, R., ALI, G. & EL-ADAWAY, I. 2021. Evaluating Deterioration of Tunnels Using Computational Machine Learning Algorithms. *Journal of Construction Engineering and Management,* 147**,** 1-15.

ALAVEZ-VARGAS, M., BIRKEL, C., CORONA, A. & BREÑA-NARANJO, J. A. 2021. Land cover change induced sediment transport behaviour in a large tropical Mexican catchment. *Hydrological Sciences Journal,* 66**,** 1069-1082.

ALAWAD, H., KAEWUNRUEN, S. & AN, M. 2020. Learning From Accidents: Machine Learning for Safety at Railway Stations. *IEEE Access,* 8**,** 633-648.

ALLAH BUKHSH, Z., SAEED, A., STIPANOVIC, I. & DOREE, A. G. 2019. Predictive maintenance using tree-based classification techniques: A case of railway switches. *Transportation Research Part C: Emerging Technologies,* 101**,** 35-54.

ALTARABSHEH, A., KANDIL, A. & VENTRESCA, M. 2016. Multi-Objective Optimization Algorithm for Sewer Network Rehabilitation Using Life Cycle Cost Analysis and Semi-Markov Deterioration Models. *Construction Research Congress 2016: Old and New Construction Technologies Converge in Historic San Juan***,** 2089-2099.

AN, M., CHEN, Y. & BAKER, C. J. 2011. A fuzzy reasoning and fuzzy-analytical hierarchy process based approach to the process of railway risk information: A railway risk management system. *Information Sciences,* 181**,** 3946-3966.

ANA, E. V. & BAUWENS, W. 2010. Modeling the structural deterioration of urban drainage pipes: the state-of-the-art in statistical methods. *Urban Water Journal,* 7**,** 47-59.

ANBAZHAGAN, P., BHARATHA, T. & AMARAJEEVI, G. 2012. Study of ballast fouling in railway track formations. *Indian Geotechnical Journal,* 42**,** 87-99.

ANGARITA, H., NIÑO, P., VARGAS, D., HERNÁNDEZ, N. & TORRES, A. 2017. Identifying explanatory variables of structural state for optimum asset management of urban drainage networks: a pilot study for the city of Bogota. *Ingeniería e Investigación,* 37**,** 6-16.

APEL, H., MERZ, B. & THIEKEN, A. H. 2008. Quantification of uncertainties in flood risk assessments. *International Journal of River Basin Management,* 6**,** 149-162.

ARCHETTI, R., BOLOGNESI, A., CASADIO & MAGLIONICO, M. 2011. Development of flood probability charts for urban drainage network in coastal areas through a simplified joint assessment approach. *Hydrology and Earth System Sciences,* 15**,** 3115-3122.

ARRIGHI, C. & CAMPO, L. 2019. Effects of Digital Terrain Model uncertainties on high-resolution urban flood damage assessment. *Journal of Flood Risk Management,* 12**,** e12530.

ARRIGHI, C., MAZZANTI, B., PISTONE, F. & CASTELLI, F. 2020. Empirical flash flood vulnerability functions for residential buildings. *SN Applied Sciences,* 2**,** 904.

ARRIGHI, C., PREGNOLATO, M. & CASTELLI, F. 2021. Indirect flood impacts and cascade risk across interdependent linear infrastructures. *Nat. Hazards Earth Syst. Sci.,* 21**,** 1955-1969.

ARRIGHI, C., ROSSI, L., TRASFORINI, E., RUDARI, R., FERRARIS, L., BRUGIONI, M., FRANCESCHINI, S. & CASTELLI, F. 2018. Quantification of flood risk mitigation benefits: A building-scale damage assessment through the RASOR platform. *Journal of Environmental Management,* 207**,** 92-104.

ARSHAD, M. & AHMED, M. 2021. Train Delay Estimation in Indian Railways by Including Weather Factors Through Machine Learning Techniques. *Recent Advances in Computer Science and Communications* 14**,** 1300-1307.

ASADI, P., GINDY, M. & ALVAREZ, M. 2019. A Machine Learning Based Approach for Automatic Rebar Detection and Quantification of Deterioration in Concrete Bridge Deck Ground Penetrating Radar B-scan Images. *KSCE Journal of Civil Engineering,* 23**,** 2618-2627.

ASNAASHARI, A., MCBEAN, E. A., GHARABAGHI, B. & TUTT, D. 2013. Forecasting watermain failure using artificial neural network modelling. *Canadian Water Resources Journal,* 38**,** 24-33.

ASSAAD, R. & EL-ADAWAY, I. H. 2020. Bridge Infrastructure Asset Management System: Comparative Computational Machine Learning Approach for Evaluating and Predicting Deck Deterioration Conditions. *Journal of Infrastructure Systems,* 26**,** 04020032.

BAIK, H. S., JEONG, H. S. & ABRAHAM, D. M. 2006. Estimating transition probabilities in Markov chain-based deterioration models for management of wastewater systems. *Journal of Water Resources Planning and Management-Asce,* 132**,** 15-24.

BAILEY, O., ZLATANOVIC, L., VAN DER HOEK, J. P., KAPELAN, Z., BLOKKER, M., ARNOT, T. & HOFMAN, J. 2020. A stochastic model to predict flow, nutrient and temperature changes in a sewer under water conservation scenarios. *Water,* 12**,** 1187.

BAUR, R. & HERZ, R. 2002. Selective inspection planning with ageing forecast for sewer types. *Water Science and Technology,* 46**,** 389-396.

BEN, L., CONGCONG, S., PALMA, R., JOSEPH-DURAN, B., MESEGUER, J., CEMBRANO, G. & PUIG, V. 2019. A Feedback Simulation Procedure for Real-time Control of Urban Drainage Systems. *IFAC-PapersOnLine,* 52**,** 101-106.

BENN, J. 2013. Railway bridge failure during flooding in the UK and Ireland. *Proceedings of the Institution of Civil Engineers - Forensic Engineering,* 166**,** 163-170.

BENTLEY. 2021. *OpenFlows CivilStorm* [Online]. Available: https://www.bentley.com/software/openflows-civilstorm/ [Accessed].

BIEGER, K., HÖRMANN, G. & FOHRER, N. 2015. The impact of land use change in the Xiangxi Catchment (China) on water balance and sediment transport. *Regional Environmental Change,* 15**,** 485-498.

BLANC, J., HALL, J. W., ROCHE, N., DAWSON, R. J., CESSES, Y., BURTON, A. & KILSBY, C. G. 2012. Enhanced efficiency of pluvial flood risk estimation in urban areas using spatial–temporal rainfall simulations. *Flood Risk Managment,* 5**,** 143-152.

BRITISH STEEL 2017. *Dimensions and properties: flat-bottomed vignole rail.*

BSI 2019a. BS EN IEC 31010:2019 Risk management. Risk assessment techniques. UK: BSI.

BSI 2019b. Risk management. *Risk assessment techniques.* UK: British Standards Institution.

BSI 2021. Risk management. *Code of practice and guidance for implementation of BS ISO 31000:2018.* UK: British Standards Institution.
BUBECK, P., DILLENARDT, L., ALFIERI, L., FEYEN, L., THIEKEN, A. H. & KELLERMANN, P. 2019. Global warming to increase flood risk on European railways. *Climatic Change,* 155**,** 19-36.
BUCKLAND, M. & GEY, F. 1994. The relationship between Recall and Precision. *Journal of the American Society for Information Science,* 45**,** 12-19.
BUDA, M., MAKI, A. & MAZUROWSKI, M. A. 2018. A systematic study of the class imbalance problem in convolutional neural networks. *Neural Networks,* 106**,** 249-259.
BURROW, M. P. N., NAITO, S. & EVDORIDES, H. T. 2009. Network-Level Railway Track Maintenance Management Model. *Transportation Research Record,* 2117**,** 66-76.
CARADOT, N., RIECHEL, M., FESNEAU, M., HERNANDEZ, N., TORRES, A., SONNENBERG, H., ECKERT, E., LENGEMANN, N., WASCHNEWSKI, J. & ROUAULT, P. 2018. Practical benchmarking of statistical and machine learning models for predicting the condition of sewer pipes in Berlin, Germany. *Journal of Hydroinformatics,* 20**,** 1131-1147.
CHAWLA, N. V., BOWYER, K. W., HALL, L. O. & KEGELMEYER, W. P. 2002. SMOTE: synthetic minority over-sampling technique. *Journal of artificial intelligence research,* 16**,** 321-357.
CHEETHAM, M., CHIROUZE, F. & BREDIER, L. RISK VIP: Evaluation of Flood Risk on the French Railway Network Using an Innovative GIS Approach. E3S Web of Conferences, 2016. EDP Sciences, 10004.
CHENG, N. N., HE, H., YANG, S., LU, Y. J. & JING, Z. W. 2017a. Impacts of topography on sediment discharge in Loess Plateau, China. *Quaternary International,* 440.
CHENG, T., XU, Z., HONG, S. & SONG, S. 2017b. Flood Risk Zoning by Using 2D Hydrodynamic Modeling: A Case Study in Jinan City. *Mathematical Problems in Engineering,* 2017**,** 1-8.
CHI. 2021. *PCSWMM* [Online]. CHI. Available: https://www.pcswmm.com/ [Accessed].
CHOW, V. T. 1959. Open-channel hydraulics. *McGraw-Hill civil engineering series*.
CIWEM 2016. Rainfall Modelling Guide.
CONSILVIO, A., FEBBRARO, A. D. & SACCO, N. Stochastic scheduling approach for predictive risk-based railway maintenance. 2016 IEEE International Conference on Intelligent Rail Transportation (ICIRT), 23-25 Aug. 2016 2016. 197-203.
DASHEPOUR, K. 2018. *A risk based stochastic modelling approach to inform maintenance expenditure on railway infrastructure.* PhD, University of Birmingham.
DAVIES, J. P., CLARKE, B. A., WHITER, J. T. & CUNNINGHAM, R. J. 2001a. Factors influencing the structural deterioration and collapse of rigid sewer pipes. *Urban Water,* 3**,** 73-89.
DAVIES, J. P., CLARKE, B. A., WHITER, J. T., CUNNINGHAM, R. J. & LEIDI, A. 2001b. The structural condition of rigid sewer pipes: a statistical investigation. *Urban Water,* 3**,** 277-286.
DAVIS, J. & GOADRICH, M. 2006. The relationship between Precision-Recall and ROC curves. *Proceedings of the 23rd international conference on Machine learning.* Pittsburgh, Pennsylvania, USA: Association for Computing Machinery.

DAWOOD, T., ZHU, Z. & ZAYED, T. 2018. Computer Vision–Based Model for Moisture Marks Detection and Recognition in Subway Networks. *Journal of Computing in Civil Engineering,* 32**,** 04017079.
DEFRA 2021. River modelling: technical standards and assessment. *Hydraulic modelling: best practice (model approach).* UK.
DEVAN, O. 2019. TrackWater: Optimising railway drainage maintenance using IoT sensors. *Permanent Way Institution,* 137**,** 37-40.
DEVINNE, N., DEBOLD, R., FORDE, M. C. & HO, C. L. Impact of climate change on railway construction, maintenance and safety in the United Kingdom. Eleventh International Conference on the Bearing Capacity of Roads, Railways and Airfields, Volume 2, 2022. CRC Press, 62-80.
DHI. 2021. *MIKE FLOOD* [Online]. DHI. Available: https://www.mikepoweredbydhi.com/products/mike-flood [Accessed].
DIGIMAP. 2022a. *Lidar,* 1:1 250. University of Edinburgh.
DIGIMAP. 2022b. *Ordnance survey,* 1:1 250. University of Edinburgh.
DINDAR, S. & KAEWUNRUEN, S. 2022. 16 - Risk-based maintenance of turnout systems. *In:* CALÇADA, R. & KAEWUNRUEN, S. (eds.) *Rail Infrastructure Resilience.* Woodhead Publishing.
DINDAR, S., KAEWUNRUEN, S., AN, M. & SUSSMAN, J. M. 2018. Bayesian Network-based probability analysis of train derailments caused by various extreme weather patterns on railway turnouts. *Safety science,* 110**,** 20-30.
DINMOHAMMADI, F. 2019. A risk-based modelling approach to maintenance optimization of railway rolling stock. *Journal of Quality in Maintenance Engineering,* 25**,** 272-293.
DIONISIO, C. S. 2018. *A Project Manager's Book of Tools and Techniques,* John Wiley & Sons.
DPTI 2018. Track and Civil Infrastructure-Drainage-Train System. Australia: DPTI.
ELCHEIKH, M. & BURROW, M. P. N. 2017. Uncertainties in Forecasting Maintenance Costs for Asset Management: Application to an Aging Canal System. *ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part A: Civil Engineering,* 3**,** 04016014.
ELLIS, E., YU, H.-S., MCDOWELL, G., DAWSON, A. & THOM, N. 2008. *Advances in transportation geotechnics,* Boca Raton, Boca Raton : CRC Press.
ELLIS, J. B. & VIAVATTENE, C. 2014. Sustainable Urban Drainage System Modeling for Managing Urban Surface Water Flood Risk. *CLEAN – Soil, Air, Water,* 42**,** 153-159.
ERGU, D., KOU, G., PENG, Y. & SHI, Y. 2011. A simple method to improve the consistency ratio of the pair-wise comparison matrix in ANP. *European Journal of Operational Research,* 213**,** 246-259.
FATHI, A., MAZARI, M., SAGHAFI, M., HOSSEINI, A. & KUMAR, S. 2019. Parametric Study of Pavement Deterioration Using Machine Learning Algorithms. *Airfield and Highway Pavements 2019.*
FECAROTTI, C. & ANDREWS, J. 2017. Optimising strategy selection for the management of railway assets.
FERGUSON, C. R. & FENNER, R. A. 2020. The potential for natural flood management to maintain free discharge at urban drainage outfalls. *Journal of Flood Risk Management,* 13**,** e12617.

FERREÑO, D., SAINZ-AJA, J. A., CARRASCAL, I. A., CUARTAS, M., POMBO, J., CASADO, J. A. & DIEGO, S. 2021. Prediction of mechanical properties of rail pads under in-service conditions through machine learning algorithms. *Advances in Engineering Software,* 151**,** 102927.
FERRER, L. 2022. Analysis and comparison of classification metrics. *arXiv preprint arXiv:2209.05355*.
FIRLIK, B., STAŚKIEWICZ, T. & SŁOWIŃSKI, M. 2023. Thermal imaging of the wheel-rail interface. *Proceedings of the Institution of Mechanical Engineers. Part F, Journal of rail and rapid transit*.
FLO-2D. 2021. *FLO-2D Pro* [Online]. Available: https://flo-2d.com/flo-2d-pro/ [Accessed].
FORERO-ORTIZ, E., MARTÍNEZ-GOMARIZ, E., CAÑAS PORCUNA, M., LOCATELLI, L. & RUSSO, B. 2020. Flood Risk Assessment in an Underground Railway System under the Impact of Climate Change—A Case Study of the Barcelona Metro. 12**,** 5291.
FOUDI, S., OSÉS-ERASO, N. & TAMAYO, I. 2015. Integrated spatial flood risk assessment: The case of Zaragoza. *Land Use Policy,* 42**,** 278-292.
FURTADO, F. & RIBEIRO, D. 2023. Railway Bridge Management System Based on Visual Inspections with Semi-Markov Continuous Time Process. *KSCE journal of civil engineering,* 27**,** 233-250.
GARROTE, J., ALVARENGA, F. M. & DÍEZ-HERRERO, A. 2016. Quantification of flash flood economic risk using ultra-detailed stage–damage functions and 2-D hydraulic models. *Journal of Hydrology,* 541**,** 611-625.
GHATAORA, G. & RUSHTON, K. 2012. Movement of Water Through Ballast and Subballast for Dual-Line Railway Track. *Transportation Research Record: Journal of the Transportation Research Board***,** 78-86.
GOEL, M. K. 2011. Runoff Coefficient. *In:* SINGH, V. P., SINGH, P. & HARITASHYA, U. K. (eds.) *Encyclopedia of Snow, Ice and Glaciers.* Dordrecht: Springer Netherlands.
GOLIGHTLY, D. & DADASHI, N. 2017. The characteristics of railway service disruption: implications for disruption management. *Ergonomics,* 60**,** 307-320.
GONG, Y., QIAN, Y. & FANUCCI, F. 2023. Investigation on the drainage condition within the ballast layer based on 3D CFD simulations. *Transportation Geotechnics,* 39**,** 100939.
GOULDBY, B., SAYERS, P., MULET-MARTI, J., HASSAN, M. & BENWELL, D. 2008. A methodology for regional-scale risk assessment. *Proceedings of The Institution of Civil Engineers-water Management* 161**,** 169-182.
GRANDINI, M., BAGLI, E. & VISANI, G. 2020. Metrics for multi-class classification: an overview. *arXiv preprint arXiv:2008.05756*.
GULER, H., JOVANOVIC, S. & EVREN, G. 2011. Modelling railway track geometry deterioration. 164**,** 65-75.
GUO, H. & VIKTOR, H. L. 2004. Learning from imbalanced data sets with boosting and data generation: the DataBoost-IM approach. *SIGKDD Explor. Newsl.,* 6**,** 30–39.
HALFF 2021. Software Evaluation and Analysis for Stormwater Infrastructure Modeling. *Technical Memorandum.* Houston, Texas: Halff Associates, Inc.
HAMARAT, M., PAPAELIAS, M. & KAEWUNRUEN, S. 2021. Train-track interactions over vulnerable railway turnout systems exposed to flooding conditions. *Engineering Failure Analysis,* 127**,** 105459.

HARRINGTON, R. M., LIMA, A. D. O., FOX-IVEY, R., NGUYEN, T., LAURENT, J., DERSCH, M. S. & EDWARDS, J. R. 2023. Use of deep convolutional neural networks and change detection technology for railway track inspections. *Proceedings of the Institution of Mechanical Engineers. Part F, Journal of rail and rapid transit,* 237**,** 137-145.

HARVEY, R. R. & MCBEAN, E. A. 2014. Predicting the structural condition of individual sanitary sewer pipes with random forests. *Canadian Journal of Civil Engineering,* 41**,** 294-303.

HASTIE, T., TIBSHIRANI, R. & FRIEDMAN, J. 2009. Random Forests. *In:* HASTIE, T., TIBSHIRANI, R. & FRIEDMAN, J. (eds.) *The Elements of Statistical Learning: Data Mining, Inference, and Prediction.* New York, NY: Springer New York.

HE, Q., LI, H., BHATTACHARJYA, D., PARIKH, D. P. & HAMPAPUR, A. 2015. Track geometry defect rectification based on track deterioration modelling and derailment risk assessment. *Journal of the Operational Research Society,* 66**,** 392-404.

HONG, L., OUYANG, M., PEETA, S., HE, X. & YAN, Y. 2015. Vulnerability assessment and mitigation for the Chinese railway system under floods. *Reliability Engineering & System Safety,* 137**,** 58-68.

IAM 2008a. Asset management. *Specification for the optimised management of physical assets.* UK: BSI.

IAM 2008b. Asset management *Guidlines for the application of PAS 55-1.* UK: British Standards Institution.

IAM 2015. An Anatomy of Asset Management. Britsol, UK: Institute of Asset Management.

INNOVYZE. 2021a. *Infoworks ICM* [Online]. Innovyze. Available: https://store.innovyze.com/StormwaterSewerFlood/InfoWoICM?cclcl=en_US [Accessed].

INNOVYZE 2021b. Infoworks ICM version 2021.9 Help.

IPWEA 2011. International Infrastructure Manual (IIMM). Australia: Institute of Public Works Engineering Australia.

ISHIZAKA, A. & LABIB, A. 2011. Review of the main developments in the analytic hierarchy process. *Expert Systems with Applications,* 38**,** 14336-14345.

ISO 2014. Asset management. *Management systems. Requirements.* UK: British Standards Institution.

ISO 2018. Risk management *Guidelines.* UK: British Standards Institution.

JAMSHIDI, A., HAJIZADEH, S., SU, Z., NAEIMI, M., NÚÑEZ, A., DOLLEVOET, R., DE SCHUTTER, B. & LI, Z. 2018. A decision support approach for condition-based maintenance of rails based on big data analysis. *Transportation Research Part C: Emerging Technologies,* 95**,** 185-206.

JOHNSTON, I., MURPHY, W. & HOLDEN, J. 2021. A review of floodwater impacts on the stability of transportation embankments. *Earth-Science Reviews,* 215**,** 103553.

JOVANOVIC, S., GULER, H. & COKO, B. 2015. Track degradation analysis in the scope of railway infrastructure maintenance management systems. *Gradevinar,* 67**,** 247-257.

JUNG, Y. & MERWADE, V. 2012. Uncertainty Quantification in Flood Inundation Mapping Using Generalized Likelihood Uncertainty Estimate and Sensitivity Analysis. *Journal of Hydrologic Engineering,* 17**,** 507-520.

KAEWUNRUEN & TANG 2019. Idealisations of Dynamic Modelling for Railway Ballast in Flood Conditions. *Applied Sciences,* 9**,** 1785.
KAEWUNRUEN, S. & CHIENGSON, C. 2018. Railway track inspection and maintenance priorities due to dynamic coupling effects of dipped rails and differential track settlements. *Engineering Failure Analysis,* 93**,** 157-171.
KALATHAS, I. & PAPOUTSIDAKIS, M. 2021. Predictive Maintenance Using Machine Learning and Data Mining: A Pioneer Method Implemented to Greek Railways. *Designs,* 5**,** 5.
KANNAPIRAN, A., CHANAN, A., SINGH, G., TAMBOSIS, P., JEYAKUMARAN, J. & KANDASAMY, J. 2008. Strategic asset management planning of stormwater drainage systems. *Water Practice and Technology,* 3**,** wpt2008065.
KELLAGHER, R., CESSES, Y., DI MAURO, M. & GOULDBY, B. 2009. An urban drainage flood risk procedure-a comprehensive approach. *The WaPUG Annual Conference.*
KELLERMANN, P., SCHOBEL, A., KUNDELA, G. & THIEKEN, A. H. 2015. Estimating flood damage to railway infrastructure - the case study of the March River flood in 2006 at the Austrian Northern Railway. *Natural Hazards and Earth System Sciences,* 15**,** 2485-2496.
KIRITSIS, D., EMMANOUILIDIS, C., KORONIOS, A. & MATHEW, J. Engineering Asset Management. World Congress on Engineering Asset Management (WCEAM), 2009 UK. Springer Books.
KLEINER, Y., SADIQ, R. & RAJANI, B. 2006. Modelling the deterioration of buried infrastructure as a fuzzy Markov process. *Journal of Water Supply: Research and Technology - Aqua,* 55**,** 67-80.
KOCZKODAJ, W. W. & SZAREK, S. J. 2010. On distance-based inconsistency reduction algorithms for pairwise comparisons. *Logic Journal of the IGPL,* 18**,** 859-869.
KOKS, E. E., ROZENBERG, J., ZORN, C., TARIVERDI, M., VOUSDOUKAS, M., FRASER, S. A., HALL, J. W. & HALLEGATTE, S. 2019. A global multi-hazard risk analysis of road and railway infrastructure assets. *Nature Communications,* 10**,** 2677.
KONIG, A. 2005. CARE-S WP2 External corrosion model description. *SINTEF Technology and Society, Trondheim, Norway*.
KOVACEVIC, M., GAVIN, K., OSLAKOVIC, I. S. & BACIC, M. 2016. A new methodology for assessment of railway infrastructure condition. *Transportation research procedia,* 14**,** 1930-1939.
KUŁAKOWSKI, K. 2015. Notes on order preservation and consistency in AHP. *European Journal of Operational Research,* 245**,** 333-337.
LA PAGLIA, I., CARNEVALE, M., CORRADI, R., DI GIALLEONARDO, E., FACCHINETTI, A. & LISI, S. 2023. Condition monitoring of vertical track alignment by bogie acceleration measurements on commercial high-speed vehicles. *Mechanical systems and signal processing,* 186**,** 109869.
LANDIS. 2022. *Soilscapes*. Cranfield Soil and Agrifood Institute.
LE, B., ANDREWS, J. & FECAROTTI, C. 2017. A Petri net model for railway bridge maintenance. *Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability,* 231**,** 306-323.
LE GAT, Y. 2008. Modelling the deterioration process of drainage pipelines. *Urban Water Journal,* 5**,** 97-106.

LE PEN, L. & POWRIE, W. 2022. The Railway Track System: Performance and Trackbed Design. *In:* BLAINEY, S. & PRESTON, J. (eds.) *Sustainable Railway Engineering and Operations*. Emerald Publishing Limited.
LEE, J., PARK, C. Y., BAEK, S., HAN, S. H. & YUN, S. 2021. Risk-Based Prioritization of Sewer Pipe Inspection from Infrastructure Asset Management Perspective. *Sustainability,* 13**,** 7213.
LEE, J. S., HWANG, S. H., CHOI, I. Y. & KIM, I. K. 2018. Prediction of Track Deterioration Using Maintenance Data and Machine Learning Schemes. *Journal of Transportation Engineering, Part A: Systems,* 144**,** 04018045.
LEKUTHAI, A. & VONGVISESSOMJAI, S. 2001. Intangible Flood Damage Quantification. *Water Resources Management,* 15**,** 343-362.
LI, D., HYSLIP, J., SUSSMANN, T. & CHRISMER, S. 2015. *Railway geotechnics,* Boca Raton, Fla. [u.a., CRC Press/Spon Press.
LI, D. & SELIG, E. 1995. Evaluation of railway subgrade problems. *Transportation research record,* 1489**,** 17.
LIANG, P. K. P., BURROW, M. P. N., SASIDHARAN, M., TORBAGHAN, M. E. & GHATAORA, G. S. 2022. A rational framework for post-flood road network condition recovery. *Infrastructure Asset Management***,** 1-14.
LINARDATOS, P., PAPASTEFANOPOULOS, V. & KOTSIANTIS, S. 2020. Explainable AI: A Review of Machine Learning Interpretability Methods. *Entropy (Basel),* 23.
LIU, K., WANG, M., CAO, Y., ZHU, W. & YANG, G. 2018. Susceptibility of existing and planned Chinese railway system subjected to rainfall-induced multi-hazards. *Transportation Research Part A: Policy and Practice,* 117**,** 214-226.
LIU, Y., MA, X., LI, Y., TIE, Y., ZHANG, Y. & GAO, J. 2019. Water Pipeline Leakage Detection Based on Machine Learning and Wireless Sensor Networks. *Sensors,* 19**,** 5086.
MADANAT, S., KARLAFTIS, M. G. & MCCARTHY, P. S. 1997. Probabilistic infrastructure deterioration models with panel data. *Journal of Infrastructure Systems,* 3**,** 4.
MAHMOODIAN, M., JAIRO, A., TORRES-MATALLANA, J. A., LEOPOLD, U., SCHUTZ, G. & CLEMENS, F. 2018. A Data-Driven Surrogate Modelling Approach for Acceleration of Short-Term Simulations of a Dynamic Urban Drainage Simulator. *Water,* 2018.
MAHMOUD, S. H. & ALAZBA, A. A. 2015. Hydrological Response to Land Cover Changes and Human Activities in Arid Regions Using a Geographic Information System and Remote Sensing. *PLOS ONE,* 10**,** e0125805.
MARSH, B. 2016. Multivariate Analysis of the Vector Boson Fusion Higgs Boson.
MARTINOVIĆ, K., GAVIN, K. & REALE, C. 2016. Assessing the vulnerability of Irish Rail network earthworks. *Transportation Research Procedia,* 14**,** 1904-1913.
MATHWORKS. 2022. *MATLAB 2020a* [Online]. Available: https://www.mathworks.com/products/matlab.html [Accessed].
MAZARI, M. & RODRIGUEZ, D. D. 2016. Prediction of pavement roughness using a hybrid gene expression programming-neural network technique. *Journal of Traffic and Transportation Engineering (English Edition),* 3**,** 448-455.
MCMAHON, P., ZHANG, T. & DWIGHT, R. 2020. Requirements for Big Data Adoption for Railway Asset Management. *IEEE Access,* 8**,** 15543-15564.

MEEGODA, J. N., JULIANO, T. M., AYOOLA, M. G. & DHAR, S. 2004. A Methodology to Predict the Remaining Service Life of CSCPs. *International Conference on Case Histories in Geotechnical Engineering.*
MERZ, B., KREIBICH, H., SCHWARZE, R. & THIEKEN, A. 2010. Review article "Assessment of economic flood damage". *Nat. Hazards Earth Syst. Sci.*, 10**,** 1697-1724.
MICEVSKI, T., KUCZERA, G. & COOMBES, P. 2002. Markov Model for Storm Water Pipe Deterioration. *Journal of Infrastructure Systems*, 8**,** 49-56.
MICHIO. 2020. *michio (2020). Oversampling Imbalanced Data: SMOTE related algorithms (https://github.com/minoue-xx/Oversampling-Imbalanced-Data/releases/tag/1.0.1), GitHub. Retrieved October 9, 2020.* [Online]. [Accessed].
MILLER, P. J., LUBKE, G. H., MCARTOR, D. B. & BERGEMAN, C. S. 2016. Finding structure in data using multivariate tree boosting. *Psychological methods*, 21**,** 583-602.
MITTAL, S. & RAO, D. 2017. Vision based railway track monitoring using deep learning. *arXiv preprint arXiv:.06423*.
MOGHTADERNEJAD, S., HUBER, G., HACKL, J. & ADEY, B. T. 2021. Data-driven estimation of deterioration curves: a railway supporting structures case study. *Infrastructure Asset Management***,** 1-15.
MOHAMMADI, M. M., NAJAFI, M., SALEHABADI, N., SERAJIANTEHRANI, R. & KAUSHAL, V. 2020. Predicting Condition of Sanitary Sewer Pipes with Gradient Boosting Tree. *Pipelines 2020.*
MOLINAS, A. & MOMMANDI, A. 2012. Modeling Ballasted Tracks for Runoff Coefficient C. Colorado. DTD Applied Research and Innovation Branch.
MOLNAR, C., CASALICCHIO, G. & BISCHL, B. Interpretable Machine Learning – A Brief History, State-of-the-Art and Challenges. *In:* KOPRINSKA, I., KAMP, M., APPICE, A., LOGLISCI, C., ANTONIE, L., ZIMMERMANN, A., GUIDOTTI, R., ÖZGÖBEK, Ö., RIBEIRO, R. P., GAVALDÀ, R., GAMA, J., ADILOVA, L., KRISHNAMURTHY, Y., FERREIRA, P. M., MALERBA, D., MEDEIROS, I., CECI, M., MANCO, G., MASCIARI, E., RAS, Z. W., CHRISTEN, P., NTOUTSI, E., SCHUBERT, E., ZIMEK, A., MONREALE, A., BIECEK, P., RINZIVILLO, S., KILLE, B., LOMMATZSCH, A. & GULLA, J. A., eds. ECML PKDD 2020 Workshops, 2020// 2020 Cham. Springer International Publishing, 417-431.
MURPHY, A. T., GOULDBY, B., COLE, S. J., MOORE, R. J. & KENDALL, H. Real-time flood inundation forecasting and mapping for key railway infrastructure: a UK case study. E3S Web of Conferences, 2016. EDP Sciences.
MUSHAR, S. H. M., AHMAD, S. S. S., KASMIN, F. & KASMURI, E. 2019. Flood Damage Assessment: A Preliminary Study. *Environmental Research, Engineering & Management*, 75**,** 55-71.
NÉELZ, S. & PENDER, G. 2010. Benchmarking of 2D hydraulic modelling packages.
NETWORK RAIL 2017. Weather Resilience and Climate Chnage Adaptation Strategy 2017-2019.
NETWORK RAIL 2018. Railway drainage systems manual. Bracknell.
NETWORK RAIL 2021. Network Rail expenditure in 2019/20. *In:* RAIL, N. (ed.). UK: Network Rail.

NOFAL, O. M. & VAN DE LINDT, J. W. 2021. High-resolution flood risk approach to quantify the impact of policy change on flood losses at community-level. *International Journal of Disaster Risk Reduction,* 62**,** 102429.
O'CONNOR, P. & KLEYNER, A. 2012. *Practical reliability engineering*, John Wiley & Sons.
OLDEN, J. D., JOY, M. K. & DEATH, R. G. 2004. An accurate comparison of methods for quantifying variable importance in artificial neural networks using simulated data. *Ecological Modelling,* 178**,** 389-397.
OSLAKOVIC, I. S., TER MAAT, H., HARTMANN, A. & DEWULF, G. Risk assessment of climate change impacts on railway infrastructure. EPOC 2013 Conference, 2013.
PALIN, E. J., STIPANOVIC OSLAKOVIC, I., GAVIN, K. & QUINN, A. 2021. Implications of climate change for railway infrastructure. *WIREs Climate Change,* 12.
PALISADE. 2022. *@RISK* [Online]. USA. [Accessed].
PAPATHANASIOU, N. & ADEY, B. T. 2021. Making comparable risk estimates for railway assets of different types. 8**,** 53-74.
PARVIN, H., ALIZADEH, H. & MINAEI, B. 2008. MKNN: Modified k-nearest neighbor. *Lecture Notes in Engineering and Computer Science,* 2173.
PERRIZO, W., DING, Q. & DENTON, A. Lazy Classifiers Using P-trees. CAINE, 2002a. Citeseer, 176-179.
PERRIZO, W., DING, Q. & DENTON, A. 2002b. *Lazy Classifiers Using P-trees*.
PHILLIPS, B., YU, S., THOMPSON, G. & DE SILVA, N. 1D and 2D modelling of urban drainage systems using XP-SWMM and TUFLOW. 10th international conference on urban drainage, Copenhagen, Denmark, 2005. Citeseer, 21-26.
PIRYONESI, S. M. & EL-DIRABY, T. E. 2021. Using Machine Learning to Examine Impact of Type of Performance Indicator on Flexible Pavement Deterioration Modeling. *Journal of Infrastructure Systems,* 27**,** 04021005.
POWER, C., MIAN, J., SPINK, T., ABBOTT, S. & EDWARDS, M. 2016. Development of an evidence-based geotechnical asset management policy for network rail, Great Britain. *Procedia engineering,* 143**,** 726-733.
PREGNOLATO, M., FORD, A., WILKINSON, S. M. & DAWSON, R. J. 2017. The impact of flooding on road transport: A depth-disruption function. *Transportation Research Part D: Transport and Environment,* 55**,** 67-81.
QUINLAN, J. R. 1990. Decision trees and decision-making. *IEEE Transactions on Systems, Man, and Cybernetics,* 20**,** 339-346.
RAGHAVAN, V., BOLLMANN, P. & JUNG, G. S. 1989. A critical investigation of recall and precision as measures of retrieval system performance. *ACM Trans. Inf. Syst.,* 7**,** 205–229.
RAILCORP 2009. Engineering Manual: Track Drainage Australia.
RAJANI, B. & KLEINER, Y. 2001. Comprehensive review of structural deterioration of water mains: physically based models. *Urban Water,* 3**,** 151-164.
RAMA, D. & ANDREWS, J. D. 2016. Railway infrastructure asset management: the whole-system life cost analysis. *IET Intelligent Transport Systems,* 10**,** 58-64.
REZAEI, S. Z. 2020. *A network level railway drainage risk management tool* PhD, University of Birmingham.

ROKSTAD, M. M. & UGARELLI, R. M. 2015. Evaluating the role of deterioration models for condition assessment of sewers. *Journal of Hydroinformatics,* 17**,** 789-804.
RUSHTON, K. R. & GHATAORA, G. Design for efficient drainage of railway track foundations. Proceedings of the Institution of Civil Engineers-Transport, 2014. Thomas Telford Ltd, 3-14.
RUSSO, B., MALGRAT, P., VELASCO, M. & THEIAS, H. 2014. Flood risk assessment of climate change impacts using a detailed 1d/2d coupled model. Application to barcelona case study. *International Conerence on Flood Managment* Brazil
SAATY, R. W. 1987. The analytic hierarchy process—what it is and how it is used. *Mathematical Modelling,* 9**,** 161-176.
SAATY, T. L. 1977. A scaling method for priorities in hierarchical structures. *Journal of Mathematical Psychology,* 15**,** 234-281.
SAATY, T. L. 2013. On the measurement of intengibles. A principal eigenvector approach to relative measurement derived from paired comparisons. *Notices of the American Mathematical Society,* 60**,** 192-208.
SALINAS-RODRIGUEZ, C., GERSONIUS, B., ZEVENBERGEN, C., SERRANO, D. & ASHLEY, R. 2018. A Semi Risk-Based Approach for Managing Urban Drainage Systems under Extreme Rainfall. *Water,* 10**,** 384.
SAÑUDO, R., MIRANDA, M., GARCÍA, C. & GARCÍA-SANCHEZ, D. 2019. Drainage in railways. *Construction and Building Materials,* 210**,** 391-412.
SASIDHARAN, M., BURROW, M. P. N. & GHATAORA, G. S. 2020. A whole life cycle approach under uncertainty for economically justifiable ballasted railway track maintenance. *Research in Transportation Economics,* 80.
SASIDHARAN, M., BURROW, M. P. N., GHATAORA, G. S. & MARATHU, R. 2022. A risk-informed decision support tool for the strategic asset management of railway track infrastructure. *Proceedings of the Institution of Mechanical Engineers, Part F: Journal of Rail and Rapid Transit,* 236**,** 183-197.
SELIG, E. T. & WATERS, J. M. 1994. *Track geotechnology and substructure management* London, Telford.
SHARMA, S., CUI, Y., HE, Q., MOHAMMADI, R. & LI, Z. 2018. Data-driven optimization of Railway maintenance for track geometry. *Transportation Research Part C: Emerging Technologies,* 90**,** 34-58.
SHAW, L. Y. 1993. Stormwater management for transportation facilities. *Transportation Research Board,* 174.
SHREEMALI, J., MALVIYA, L., PALIWAL, P., CHAKRABARTI, P., PODDAR, S., JINDAL, B. & CHAUBISA, H. 2021. Comparing performance of multiple classifiers for regression and classification machine learning problems using structured datasets. *Materials Today: Proceedings*.
SINGH, D. & SINGH, B. 2020. Investigating the impact of data normalization on classification performance. *Applied Soft Computing,* 97**,** 105524.
SOKOLOVA, M. & LAPALME, G. 2009. A systematic analysis of performance measures for classification tasks. *Information Processing & Management,* 45**,** 427-437.
SOLOMATINE, D. P. & OSTFELD, A. 2008. Data-driven modelling: some past experiences and new approaches. *Journal of Hydroinformatics,* 10**,** 3-22.
SPINK, T., DUNCAN, I., TODD, A. & LAWRANCE, A. 2014. Transport infrastructure drainage: condition appraisal and remedial treatment. London, UK: CIRIA.

SRESAKOOLCHAI, J., HAMARAT, M. & KAEWUNRUEN, S. 2023. Automated machine learning recognition to diagnose flood resilience of railway switches and crossings. *Sci Rep,* 13**,** 2106.
STENSTRÖM, C., NORRBIN, P., PARIDA, A. & KUMAR, U. 2016. Preventive and corrective maintenance – cost comparison and cost–benefit analysis. *Structure and Infrastructure Engineering,* 12**,** 603-617.
STREAMLINE TECHNOLOGIES. 2021. *ICPR-4* [Online]. Available: https://streamnologies.com/content/index.php/about-icpr-4/ [Accessed].
SU, Z., JAMSHIDI, A., NÚÑEZ, A., BALDI, S. & DE SCHUTTER, B. 2017. Multi-level condition-based maintenance planning for railway infrastructures – A scenario-based chance-constrained approach. *Transportation Research Part C: Emerging Technologies,* 84**,** 92-123.
SURUCU, O., GADSDEN, S. A. & YAWNEY, J. 2023. Condition Monitoring using Machine Learning: A Review of Theory, Applications, and Recent Advances. *Expert Systems with Applications,* 221**,** 119738.
SVOZIL, D., KVASNICKA, V. & POSPICHAL, J. Í. 1997. Introduction to multi-layer feed-forward neural networks. *Chemometrics and Intelligent Laboratory Systems,* 39**,** 43-62.
TAPIA-SILVA, F.-O., ITZEROTT, S., FOERSTER, S., KUHLMANN, B. & KREIBICH, H. 2011. Estimation of flood losses to agricultural crops using remote sensing. *Physics and Chemistry of the Earth, Parts A/B/C,* 36**,** 253-265.
TEN VELDHUIS, J. A. E. & CLEMENS, F. H. L. R. 2010. Flood risk modelling based on tangible and intangible urban flood damage quantification. *Water Science and Technology,* 62**,** 189-195.
THADURI, A., GALAR, D. & KUMAR, U. 2015. Railway assets: A potential domain for big data analytics. *Procedia Computer Science,* 53**,** 457-467.
TRAN, NG, A. W. M., PERERA, B. J. C., BURN, S. & DAVIS, P. 2006. Application of probabilistic neural networks in modelling structural deterioration of stormwater pipes. *Urban Water Journal,* 3**,** 175-184.
TRAN, PERERA, B. J. C. & NG, A. W. M. 2009. Comparison of Structural Deterioration Models for Stormwater Drainage Pipes. *Computer-Aided Civil and Infrastructure Engineering,* 24**,** 145-156.
TRAN, D. H., NG, A. W. M., MCMANUS, K. J. & BURN, S. 2008. Prediction models for serviceability deterioration of stormwater pipes. *Structure and Infrastructure Engineering,* 4**,** 287-295.
TRAN, D. H., NG, A. W. M. & PERERA, B. J. C. 2007. Neural networks deterioration models for serviceability condition of buried stormwater pipes. *Engineering Applications of Artificial Intelligence,* 20**,** 1144-1151.
TRAN, H. D. 2007. *Investigation of deterioration models for stormwater pipe systems* Doctor of Philosophy Degree, Victoria University.
TRAN, H. D., PERERA, B. J. C. & NG, A. W. M. 2010. Markov and Neural Network Models for Prediction of Structural Deterioration of Storm-Water Pipe Assets. *Journal of Infrastructure Systems,* 16**,** 167-171.
TSAKIRIS, G. 2014. Flood risk assessment: concepts, modelling, applications. *Natural Hazards and Earth System Sciences,* 14**,** 1361-1369.
TSUBAKI, R., BRICKER, J. D., ICHII, K. & KAWAHARA, Y. 2016. Development of fragility curves for railway embankment and ballast scour due to overtopping flood flow. *Nat. Hazards Earth Syst. Sci.,* 16**,** 2455-2472.

TSUBAKI, R., KAWAHARA, Y. & UEDA, Y. J. N. H. 2017. Railway embankment failure due to ballast layer breach caused by inundation flows. 87**,** 717-738.
TZANAKAKIS, K. 2013. *The railway track and its long term behaviour: a handbook for a railway track of high quality*, Springer Science & Business Media.
UGARELLI, R. M., SELSETH, I., LE GAT, Y., ROSTUM, J. & KROGH, A. H. 2013. Wastewater pipes in Oslo: from condition monitoring to rehabilitation planning. *Water Practice and Technology,* 8**,** 487-494.
USMAN, K. 2020. *The Development of a Risk-Informed Framework for the Appraisal of Drainage Maintenance of Ballasted Railway Track.* PhD, University of Birmingham.
USMAN, K., PETER NICHOLAS BURROW, M., SINGH GHATAORA, G. & SASIDHARAN, M. 2021. Using Probabilistic Fault Tree Analysis and Monte Carlo Simulation to Examine the Likelihood of Risks Associated with Ballasted Railway Drainage Failure. *Transportation Research Record: Journal of the Transportation Research Board,* 2675**,** 70-89.
VAIDYA, O. S. & KUMAR, S. 2006. Analytic hierarchy process: An overview of applications. *European Journal of Operational Research,* 169**,** 1-29.
VALE, C. & RIBEIRO, I. M. 2014. Railway condition-based maintenance model with stochastic deterioration. *Journal of Civil Engineering and Management,* 20**,** 686-692.
VAN DAU, Q., KUNTIYAWICHAI, K. & PLERMKAMON, V. 2017. Quantification of Flood Damage under Potential Climate Change Impacts in Central Vietnam. *Irrigation & Drainage,* 66**,** 842-854.
VAN DER WESTHUIZEN, N. & GRÄBE, P. 2013. The integration of railway asset management information to ensure maintenance effectiveness. *Journal of the South African Institution of Civil Engineering,* 55**,** 18-29.
VARGAS, L. G. 1990. An overview of the analytic hierarchy process and its applications. *European Journal of Operational Research,* 48**,** 2-8.
VINET, F. 2008. Geographical analysis of damage due to flash floods in southern France: The cases of 12–13 November 1999 and 8–9 September 2002. *Applied Geography,* 28**,** 323-336.
VOLLERSTEN, J. & KÖNIG, A. 2005. WP2 Report D6: Model testing and evaluation, Computer Aided REhabilitation of Sewer networks (Care-S). *SINTEF Technology and Society, Trondheim, Norway*.
VOSE, D. 2008. *Risk analysis: a quantitative guide*, John Wiley & Sons.
WALLINGFORD, H. 1981. The Wallingford Procedure - for design and analysis of urban storm drainage. *Volume 1- Principles, methods and practice.* UK: Department of Environement.
WANG, G. 2019. *An investigation of the suitability of smartphone devices for road condition assessment.* University of Birmingham.
WANG, G., BURROW, M. & GHATAORA, G. 2020a. Study of the Factors Affecting Road Roughness Measurement Using Smartphones. *Journal of Infrastructure Systems,* 26**,** 04020020.
WANG, Q., LIN, S., LI, T. & HE, Z. 2020b. Intelligent Proactive Maintenance System for High-Speed Railway Traction Power Supply System. *IEEE Transactions on Industrial Informatics,* 16**,** 6729-6739.

WANG, Q., LIU, K., WANG, M. & KOKS, E. E. 2021. A River Flood and Earthquake Risk Assessment of Railway Assets along the Belt and Road. *International Journal of Disaster Risk Science,* 12**,** 553-567.

WANG, X., LIU, X. & EUSTON, T. L. 2023. Relationship between track geometry defect occurrence and substructure condition: A case study on one passenger railroad in the United States. *Construction & building materials,* 365**,** 130066.

WARIS, M., PANIGRAHI, S., MENGAL, A., SOOMRO, M. I., MIRJAT, N. H., ULLAH, M., AZLAN, Z. S. & KHAN, A. 2019. An Application of Analytic Hierarchy Process (AHP) for Sustainable Procurement of Construction Equipment: Multicriteria-Based Decision Framework for Malaysia. *Mathematical Problems in Engineering,* 2019**,** 6391431.

WIRAHADIKUSUMAH, R., ABRAHAM, D. & ISELEY, T. 2001. Challenging Issues in Modeling Deterioration of Combined Sewers. *Journal of Infrastructure Systems,* 7**,** 77-84.

WU, W., LIU, Z. & HE, Y. 2015. Classification of defects with ensemble methods in the automated visual inspection of sewer pipes. *Pattern Analysis and Applications,* 18**,** 263-276.

WU, W., LU, L., HUANG, X., SHANGGUAN, H. & WEI, Z. 2021a. An automatic calibration framework based on the InfoWorks ICM model: the effect of multiple objectives during multiple water pollutant modeling. *Environmental Science and Pollution Research,* 28**,** 31814-31830.

WU, X., GAO, A., WEN, Z., WU, S., HE, S., CHI, M. & LIANG, S. 2023. Online estimation of fatigue damage of railway bogie frame based on axle box accelerations. *Vehicle system dynamics,* 61**,** 286-308.

WU, Y., TAIT, S., NICHOLS, A. & RAJA, J. 2021b. Simulation of Railway Drainage Asset Service Condition Degradation in the UK Using a Markov Chain–Based Approach. *Journal of Infrastructure Systems,* 27**,** 04021023.

XIE, J., HUANG, J., ZENG, C., JIANG, S.-H. & PODLICH, N. 2020. Systematic Literature Review on Data-Driven Models for Predictive Maintenance of Railway Track: Implications in Geotechnical Engineering. *Geosciences,* 10**,** 425.

XU, H. & SINHA, S. K. 2020. Applying Survival Analysis to Pipeline Data: Gaps and Challenges. *Pipelines***,** 148-158.

XU, H. & SINHA, S. K. 2021. Modeling Pipe Break Data Using Survival Analysis with Machine Learning Imputation Methods. *Journal of Performance of Constructed Facilities,* 35**,** 04021071.

XU, H., SINHA, S. K. & VISHWAKARMA, A. 2020. Development of a Fuzzy Inference Performance Rating System for Water Pipelines Using a Comprehensive List of Input Variables. *Pipelines.*

YANG, H., TONG, X. & GOU, D. Study on the waterlogging operation effects of InfoWorks ICM dispatching strategies. E3S Web of Conferences, 2021. EDP Sciences, 01009.

YANG, J. 2004. Road crack condition performance modeling using recurrent Markov chains and artificial neural networks.

YAZDI, J., HEYDARI MOFRAD, H. & HEYDARI MOFRAD, M. 2022. Development of a risk-based optimization approach to improve the performance of urban drainage systems. *Hydrological Sciences Journal***,** 1-14.

ZANELLI, F., SABBIONI, E., CARNEVALE, M., MAURI, M., TARSITANO, D., CASTELLI-DEZZA, F. & DEBATTISTI, N. 2023. Wireless sensor nodes for

freight trains condition monitoring based on geo-localized vibration measurements. *Proceedings of the Institution of Mechanical Engineers. Part F, Journal of rail and rapid transit,* 237**,** 193-204.
ZHANG, Z. 2016. Introduction to machine learning: k-nearest neighbors. *Annals of translational medicine,* 4**,** 218-218.
ZHOU, Q., PANDURO, T. E., THORSEN, B. J. & ARNBJERG-NIELSEN, K. 2013. Adaption to Extreme Rainfall with Open Urban Drainage System: An Integrated Hydrological Cost-Benefit Analysis. *Environmental Management,* 51**,** 586-601.
ZHU, W., LIU, K., WANG, M., WARD, P. J. & KOKS, E. E. 2021. System vulnerability and risk assessment of railway systems to flooding. *Nat. Hazards Earth Syst. Sci. Discuss.*, 2021**,** 1-48.
ZHU, Z., CHEN, Z., CHEN, X. & HE, P. 2016. Approach for evaluating inundation risks in urban drainage systems. *Science of The Total Environment,* 553**,** 1-12.

# Appendices

## Appendix A: Published journal paper



ASCE

### Condition Modeling of Railway Drainage Pipes

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**Abstract:** Condition of drainage asset systems can have substantial impact on the structural and operational integrity of railway tracks. It is therefore important to ensure that the various components of the drainage system are well-maintained. To this end, decision makers in the railway industry have been moving toward predictive, risk-informed drainage asset management. The approach aims to optimize the allocation of the limited time and financial resources for maintenance works. To achieve this more research is required to develop predictive condition models for railway drainage assets. This paper describes the development of data-driven condition prediction models using drainage pipe asset records. The models were tested for both structural and service condition prediction. Nine input factors were considered in the prediction models. Significance of the factors was evaluated using connection weight analysis. Four machine learning (ML) algorithms, namely neural networks, decision trees, bagged trees, and *k*-nearest neighbor, were compared based on their condition prediction performance for pipe drainage assets. The models were developed and tested using field data collected from the UK owner of rail assets, Network Rail. The results demonstrated that bagged trees performed best on a balanced data set with 87% overall accuracy for structural condition prediction and 72% accuracy for service condition prediction. It was found that pipe length, previous condition, years since previous condition, and maintenance were the most significant factors in predicting condition. **DOI: 10.1061/(ASCE)IS.1943-555X.0000708.** © *2022 American Society of Civil Engineers.*

#### Introduction and Background

Although the impact of poor drainage on railway track is well known, only a few researchers, e.g., Usman et al. (2017) and Sañudo et al. (2019), have focused on understanding the failure modes of drainage assets and their impact on a track. According to the UK railway drainage standards, performance of drainage system describes the physical ability of the system to carry flow from rainfall and runoff from adjacent areas and groundwater as to not disturb the stable operation of other rail infrastructure. Further, the drainage system should prevent any pollutants from leaving the system in uncontrolled manner. Poor performance of a drainage system causes myriad problems including ballast deterioration, subgrade failure (Usman et al. 2015), loss of track geometry degradation, corrosion of track elements, earthwork failures, electric system failures, and even derailments (Sañudo et al. 2019). Poor drainage performance is not only caused by incidental defects and collapses of drainage assets, but it also occurs because of natural deterioration experienced by the drainage assets (Ana and Bauwens 2010). Level of performance for a drainage asset is usually reflected through a condition scoring system, where asset inspectors allocate a condition score depending on the observed condition of the asset.

Asset management is a complex process consisting of periodic inspections, routine and emergency maintenance, enhancement, and renewal activities with a direct impact on reliability and safety of railway operation (Fecarotti and Andrews 2017). These activities need to be arranged or strategized efficiently such that to maintain a given level of service and safety within budget constraints (Fecarotti and Andrews 2017; Jovanonic and Guler 2006). Jovanonic and Guler (2006) stated that for efficient management of railway assets, work on two items is crucial: (1) improvement of performance monitoring, and (2) having reliable condition assessment and prediction leading to optimized maintenance and rehabilitation planning and resource allocation. For the first, Kovacevic et al. (2016) developed a methodology to asses railway infrastructure using ground-penetrating radar (GPR), seismic refraction, and drones to evaluate track performance features including ballast fouling, soil water content, slope geometry, and drainage condition. Although this is important to move away from subjective assessments of railway assets, there is still a gap in predictive condition modeling for railway drainage assets. Wu et al. (2021) utilized the statistical Markov chains for assessment of rail drainage asset service condition at cohort level. However, it is prudent to address structural condition in addition to service condition. Further, through development of a two-stage framework for railway track geometry maintenance optimization, Fecarotti and Andrews (2017) emphasized the importance of individual asset condition assessment prior to any network-level strategy evaluation.

Currently, there is shift from corrective or reactive maintenance strategies toward proactive and condition-based strategies. Predictive condition models are a step in this direction. Consilvio et al. (2016)

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## Appendix B.1: MATLAB codes for trained algorithms

NN

```
function [trainedClassifier, validationAccuracy] = NNSIG30CODE(ALLBALSMOT_ST_SUF)
% [trainedClassifier, validationAccuracy] = trainClassifier(trainingData)
% Returns a trained classifier and its accuracy. This code recreates the
% classification model trained in Classification Learner app. Use the
% generated code to automate training the same model with new data, or to
% learn how to programmatically train models.
%
%  Input:
%      trainingData: A table containing the same predictor and response
%       columns as those imported into the app.
%
%  Output:
%      trainedClassifier: A struct containing the trained classifier. The
%       struct contains various fields with information about the trained
%       classifier.
%
%      trainedClassifier.predictFcn: A function to make predictions on new
%       data.
%
%      validationAccuracy: A double containing the accuracy as a
%       percentage. In the app, the Models pane displays this overall
%       accuracy score for each model.
%
```

```
% Use the code to train the model with new data. To retrain your
% classifier, call the function from the command line with your original
% data or new data as the input argument trainingData.
%
% For example, to retrain a classifier trained with the original data set
% T, enter:
%   [trainedClassifier, validationAccuracy] = trainClassifier(T)
%
% To make predictions with the returned 'trainedClassifier' on new data T2,
% use
%   yfit = trainedClassifier.predictFcn(T2)
%
% T2 must be a table containing at least the same predictor columns as used
% during training. For details, enter:
%   trainedClassifier.HowToPredict

% Auto-generated by MATLAB on 08-Feb-2022 19:27:15


% Extract predictors and response
% This code processes the data into the right shape for training the
% model.
inputTable = ALLBALSMOT_ST_SUF;
predictorNames = {'L100', 'effluent', 'topgraphy', 'pipesize', 'material', 'shape', 'PREVIOUSRECORDEDSTRUCTURALCONDITION',
'YEARSFROMPREVIOUSMATCH', 'MAINTENANCE'};
predictors = inputTable(:, predictorNames);
response = inputTable.Drainagestrcutralcondition;
isCategoricalPredictor = [false, false, false, false, false, false, false, false, false];

% Train a classifier
% This code specifies all the classifier options and trains the classifier.
classificationNeuralNetwork = fitcnet(...
    predictors, ...
    response, ...
    'LayerSizes', 30, ...
    'Activations', 'sigmoid', ...
    'Lambda', 0, ...
    'IterationLimit', 1000, ...
    'Standardize', true, ...
    'ClassNames', [1; 2; 3; 4; 5]);

% Create the result struct with predict function
predictorExtractionFcn = @(t) t(:, predictorNames);
neuralNetworkPredictFcn = @(x) predict(classificationNeuralNetwork, x);
trainedClassifier.predictFcn = @(x) neuralNetworkPredictFcn(predictorExtractionFcn(x));

% Add additional fields to the result struct
trainedClassifier.RequiredVariables = {'L100', 'MAINTENANCE', 'PREVIOUSRECORDEDSTRUCTURALCONDITION',
'YEARSFROMPREVIOUSMATCH', 'effluent', 'material', 'pipesize', 'shape', 'topgraphy'};
trainedClassifier.ClassificationNeuralNetwork = classificationNeuralNetwork;
trainedClassifier.About = 'This struct is a trained model exported from Classification Learner R2021b.';
trainedClassifier.HowToPredict = sprintf('To make predictions on a new table, T, use: \n  yfit = c.predictFcn(T) \nreplacing "c" with the name of the variable
that is this struct, e.g. "trainedModel". \n \nThe table, T, must contain the variables returned by: \n  c.RequiredVariables \nVariable formats (e.g. matrix/vector,
datatype) must match the original training data. \nAdditional variables are ignored. \n \nFor more information, see <a href="matlab:helpview(fullfile(docroot,
"stats", "stats.map"), "appclassification_exportmodeltoworkspace")">How to predict using an exported model</a>.');

% Extract predictors and response
% This code processes the data into the right shape for training the
% model.
inputTable = ALLBALSMOT_ST_SUF;
predictorNames = {'L100', 'effluent', 'topgraphy', 'pipesize', 'material', 'shape', 'PREVIOUSRECORDEDSTRUCTURALCONDITION',
'YEARSFROMPREVIOUSMATCH', 'MAINTENANCE'};
predictors = inputTable(:, predictorNames);
response = inputTable.Drainagestrcutralcondition;
isCategoricalPredictor = [false, false, false, false, false, false, false, false, false];

% Set up holdout validation
cvp = cvpartition(response, 'Holdout', 0.25);
trainingPredictors = predictors(cvp.training, :);
trainingResponse = response(cvp.training, :);
trainingIsCategoricalPredictor = isCategoricalPredictor;

% Train a classifier
% This code specifies all the classifier options and trains the classifier.
classificationNeuralNetwork = fitcnet(...
    trainingPredictors, ...
    trainingResponse, ...
    'LayerSizes', 50, ...
    'Activations', 'sigmoid', ...
    'Lambda', 0, ...
    'IterationLimit', 1000, ...
    'Standardize', true, ...
    'ClassNames', [1; 2; 3; 4; 5]);

% Create the result struct with predict function
neuralNetworkPredictFcn = @(x) predict(classificationNeuralNetwork, x);
```

```
validationPredictFcn = @(x) neuralNetworkPredictFcn(x);

% Add additional fields to the result struct


% Compute validation predictions
validationPredictors = predictors(cvp.test, :);
validationResponse = response(cvp.test, :);
[validationPredictions, validationScores] = validationPredictFcn(validationPredictors);

% Compute validation accuracy
correctPredictions = (validationPredictions == validationResponse);
isMissing = isnan(validationResponse);
correctPredictions = correctPredictions(~isMissing);
validationAccuracy = sum(correctPredictions)/length(correctPredictions);
```

DT

```
function [trainedClassifier, validationAccuracy] = trainClassifier(trainingData)
% [trainedClassifier, validationAccuracy] = trainClassifier(trainingData)
% Returns a trained classifier and its accuracy. This code recreates the
% classification model trained in Classification Learner app. Use the
% generated code to automate training the same model with new data, or to
% learn how to programmatically train models.
%
%  Input:
%      trainingData: A table containing the same predictor and response
%       columns as those imported into the app.
%
%  Output:
%      trainedClassifier: A struct containing the trained classifier. The
%       struct contains various fields with information about the trained
%       classifier.
%
%      trainedClassifier.predictFcn: A function to make predictions on new
%       data.
%
%      validationAccuracy: A double containing the accuracy as a
%       percentage. In the app, the Models pane displays this overall
%       accuracy score for each model.
%
% Use the code to train the model with new data. To retrain your
% classifier, call the function from the command line with your original
% data or new data as the input argument trainingData.
%
% For example, to retrain a classifier trained with the original data set
% T, enter:
%   [trainedClassifier, validationAccuracy] = trainClassifier(T)
%
% To make predictions with the returned 'trainedClassifier' on new data T2,
% use
%   yfit = trainedClassifier.predictFcn(T2)
%
% T2 must be a table containing at least the same predictor columns as used
% during training. For details, enter:
%   trainedClassifier.HowToPredict

% Auto-generated by MATLAB on 08-Feb-2022 19:26:05


% Extract predictors and response
% This code processes the data into the right shape for training the
% model.
inputTable = trainingData;
predictorNames = {'L100', 'effluent', 'topgraphy', 'pipesize', 'material', 'shape', 'PREVIOUSRECORDEDSTRUCTURALCONDITION',
'YEARSFROMPREVIOUSMATCH', 'MAINTENANCE'};
predictors = inputTable(:, predictorNames);
response = inputTable.Drainagestrcutralcondition;
isCategoricalPredictor = [false, false, false, false, false, false, false, false, false];

% Train a classifier
% This code specifies all the classifier options and trains the classifier.
classificationTree = fitctree(...
    predictors, ...
    response, ...
    'SplitCriterion', 'gdi', ...
    'MaxNumSplits', 356910, ...
    'Surrogate', 'off', ...
    'ClassNames', [1; 2; 3; 4; 5]);

% Create the result struct with predict function
predictorExtractionFcn = @(t) t(:, predictorNames);
treePredictFcn = @(x) predict(classificationTree, x);
trainedClassifier.predictFcn = @(x) treePredictFcn(predictorExtractionFcn(x));

% Add additional fields to the result struct
trainedClassifier.RequiredVariables = {'L100', 'MAINTENANCE', 'PREVIOUSRECORDEDSTRUCTURALCONDITION',
'YEARSFROMPREVIOUSMATCH', 'effluent', 'material', 'pipesize', 'shape', 'topgraphy'};
```

```
trainedClassifier.ClassificationTree = classificationTree;
trainedClassifier.About = 'This struct is a trained model exported from Classification Learner R2021b.';
trainedClassifier.HowToPredict = sprintf('To make predictions on a new table, T, use: \n  yfit = c.predictFcn(T) \nreplacing "c" with the name of the variable that is this struct, e.g. "trainedModel". \n \nThe table, T, must contain the variables returned by: \n  c.RequiredVariables \nVariable formats (e.g. matrix/vector, datatype) must match the original training data. \nAdditional variables are ignored. \n \nFor more information, see <a href="matlab:helpview(fullfile(docroot, "stats", "stats.map"), "appclassification_exportmodeltoworkspace")">How to predict using an exported model</a>.');

% Extract predictors and response
% This code processes the data into the right shape for training the
% model.
inputTable = trainingData;
predictorNames = {'L100', 'effluent', 'topgraphy', 'pipesize', 'material', 'shape', 'PREVIOUSRECORDEDSTRUCTURALCONDITION', 'YEARSFROMPREVIOUSMATCH', 'MAINTENANCE'};
predictors = inputTable(:, predictorNames);
response = inputTable.Drainagestrcutralcondition;
isCategoricalPredictor = [false, false, false, false, false, false, false, false, false];

% Set up holdout validation
cvp = cvpartition(response, 'Holdout', 0.25);
trainingPredictors = predictors(cvp.training, :);
trainingResponse = response(cvp.training, :);
trainingIsCategoricalPredictor = isCategoricalPredictor;

% Train a classifier
% This code specifies all the classifier options and trains the classifier.
classificationTree = fitctree(...
    trainingPredictors, ...
    trainingResponse, ...
    'SplitCriterion', 'gdi', ...
    'MaxNumSplits', 356910, ...
    'Surrogate', 'off', ...
    'ClassNames', [1; 2; 3; 4; 5]);

% Create the result struct with predict function
treePredictFcn = @(x) predict(classificationTree, x);
validationPredictFcn = @(x) treePredictFcn(x);

% Add additional fields to the result struct


% Compute validation predictions
validationPredictors = predictors(cvp.test, :);
validationResponse = response(cvp.test, :);
[validationPredictions, validationScores] = validationPredictFcn(validationPredictors);

% Compute validation accuracy
correctPredictions = (validationPredictions == validationResponse);
isMissing = isnan(validationResponse);
correctPredictions = correctPredictions(~isMissing);
validationAccuracy = sum(correctPredictions)/length(correctPredictions);
```

KNN:

```
Function [trainedClassifier, validationAccuracy] = trainClassifier(trainingData)
% [trainedClassifier, validationAccuracy] = trainClassifier(trainingData)
% Returns a trained classifier and its accuracy. This code recreates the
% classification model trained in Classification Learner app. Use the
% generated code to automate training the same model with new data, or to
% learn how to programmatically train models.
%
%  Input:
%      trainingData: A table containing the same predictor and response
%       columns as those imported into the app.
%
%  Output:
%      trainedClassifier: A struct containing the trained classifier. The
%       struct contains various fields with information about the trained
%       classifier.
%
%      trainedClassifier.predictFcn: A function to make predictions on new
%       data.
%
%      validationAccuracy: A double containing the accuracy as a
%       percentage. In the app, the Models pane displays this overall
%       accuracy score for each model.
%
% Use the code to train the model with new data. To retrain your
% classifier, call the function from the command line with your original
% data or new data as the input argument trainingData.
%
% For example, to retrain a classifier trained with the original data set
% T, enter:
%   [trainedClassifier, validationAccuracy] = trainClassifier(T)
%
% To make predictions with the returned 'trainedClassifier' on new data T2,
% use
%   yfit = trainedClassifier.predictFcn(T2)
%
```

```
% T2 must be a table containing at least the same predictor columns as used
% during training. For details, enter:
%   trainedClassifier.HowToPredict

% Auto-generated by MATLAB on 08-Feb-2022 19:23:46


% Extract predictors and response
% This code processes the data into the right shape for training the
% model.
inputTable = trainingData;
predictorNames = {'L100', 'effluent', 'topgraphy', 'pipesize', 'material', 'shape', 'PREVIOUSRECORDEDSTRUCTURALCONDITION',
'YEARSFROMPREVIOUSMATCH', 'MAINTENANCE'};
predictors = inputTable(:, predictorNames);
response = inputTable.Drainagestrcutralcondition;
isCategoricalPredictor = [false, false, false, false, false, false, false, false, false];

% Train a classifier
% This code specifies all the classifier options and trains the classifier.
classificationKNN = fitcknn(...
    predictors, ...
    response, ...
    'Distance', 'Euclidean', ...
    'Exponent', [], ...
    'NumNeighbors', 3, ...
    'DistanceWeight', 'Equal', ...
    'Standardize', true, ...
    'ClassNames', [1; 2; 3; 4; 5]);

% Create the result struct with predict function
predictorExtractionFcn = @(t) t(:, predictorNames);
knnPredictFcn = @(x) predict(classificationKNN, x);
trainedClassifier.predictFcn = @(x) knnPredictFcn(predictorExtractionFcn(x));

% Add additional fields to the result struct
trainedClassifier.RequiredVariables = {'L100', 'MAINTENANCE', 'PREVIOUSRECORDEDSTRUCTURALCONDITION',
'YEARSFROMPREVIOUSMATCH', 'effluent', 'material', 'pipesize', 'shape', 'topgraphy'};
trainedClassifier.ClassificationKNN = classificationKNN;
trainedClassifier.About = 'This struct is a trained model exported from Classification Learner R2021b.';
trainedClassifier.HowToPredict = sprintf('To make predictions on a new table, T, use: \n  yfit = c.predictFcn(T) \nreplacing "c" with the name of the variable
that is this struct, e.g. "trainedModel". \n \nThe table, T, must contain the variables returned by: \n  c.RequiredVariables \nVariable formats (e.g. matrix/vector,
datatype) must match the original training data. \nAdditional variables are ignored. \n \nFor more information, see <a href="matlab:helpview(fullfile(docroot,
"stats", "stats.map"), "appclassification_exportmodeltoworkspace")">How to predict using an exported model</a>.');

% Extract predictors and response
% This code processes the data into the right shape for training the
% model.
inputTable = trainingData;
predictorNames = {'L100', 'effluent', 'topgraphy', 'pipesize', 'material', 'shape', 'PREVIOUSRECORDEDSTRUCTURALCONDITION',
'YEARSFROMPREVIOUSMATCH', 'MAINTENANCE'};
predictors = inputTable(:, predictorNames);
response = inputTable.Drainagestrcutralcondition;
isCategoricalPredictor = [false, false, false, false, false, false, false, false, false];

% Set up holdout validation
cvp = cvpartition(response, 'Holdout', 0.25);
trainingPredictors = predictors(cvp.training, :);
trainingResponse = response(cvp.training, :);
trainingIsCategoricalPredictor = isCategoricalPredictor;

% Train a classifier
% This code specifies all the classifier options and trains the classifier.
classificationKNN = fitcknn(...
    trainingPredictors, ...
    trainingResponse, ...
    'Distance', 'Euclidean', ...
    'Exponent', [], ...
    'NumNeighbors', 3, ...
    'DistanceWeight', 'Equal', ...
    'Standardize', true, ...
    'ClassNames', [1; 2; 3; 4; 5]);

% Create the result struct with predict function
knnPredictFcn = @(x) predict(classificationKNN, x);
validationPredictFcn = @(x) knnPredictFcn(x);

% Add additional fields to the result struct


% Compute validation predictions
validationPredictors = predictors(cvp.test, :);
validationResponse = response(cvp.test, :);
[validationPredictions, validationScores] = validationPredictFcn(validationPredictors);

% Compute validation accuracy
correctPredictions = (validationPredictions == validationResponse);
```

```
isMissing = isnan(validationResponse);
correctPredictions = correctPredictions(~isMissing);
validationAccuracy = sum(correctPredictions)/length(correctPredictions);
```

Bagged trees

```
function [trainedClassifier, validationAccuracy] = BAGGED30CODE(trainingData)
% [trainedClassifier, validationAccuracy] = trainClassifier(trainingData)
% Returns a trained classifier and its accuracy. This code recreates the
% classification model trained in Classification Learner app. Use the
% generated code to automate training the same model with new data, or to
% learn how to programmatically train models.
%
%  Input:
%      trainingData: A table containing the same predictor and response
%       columns as those imported into the app.
%
%  Output:
%      trainedClassifier: A struct containing the trained classifier. The
%       struct contains various fields with information about the trained
%       classifier.
%
%      trainedClassifier.predictFcn: A function to make predictions on new
%       data.
%
%      validationAccuracy: A double containing the accuracy as a
%       percentage. In the app, the Models pane displays this overall
%       accuracy score for each model.
%
% Use the code to train the model with new data. To retrain your
% classifier, call the function from the command line with your original
% data or new data as the input argument trainingData.
%
% For example, to retrain a classifier trained with the original data set
% T, enter:
%   [trainedClassifier, validationAccuracy] = trainClassifier(T)
%
% To make predictions with the returned 'trainedClassifier' on new data T2,
% use
%   yfit = trainedClassifier.predictFcn(T2)
%
% T2 must be a table containing at least the same predictor columns as used
% during training. For details, enter:
%   trainedClassifier.HowToPredict

% Auto-generated by MATLAB on 08-Feb-2022 19:25:04


% Extract predictors and response
% This code processes the data into the right shape for training the
% model.
inputTable = trainingData;
predictorNames = {'L100', 'effluent', 'topgraphy', 'pipesize', 'material', 'shape', 'PREVIOUSRECORDEDSTRUCTURALCONDITION',
'YEARSFROMPREVIOUSMATCH', 'MAINTENANCE'};
predictors = inputTable(:, predictorNames);
response = inputTable.Drainagestrcutralcondition;
isCategoricalPredictor = [false, false, false, false, false, false, false, false, false];

% Train a classifier
% This code specifies all the classifier options and trains the classifier.
template = templateTree(...
    'MaxNumSplits', 356910);
classificationEnsemble = fitcensemble(...
    predictors, ...
    response, ...
    'Method', 'Bag', ...
    'NumLearningCycles', 30, ...
    'Learners', template, ...
    'ClassNames', [1; 2; 3; 4; 5]);

% Create the result struct with predict function
predictorExtractionFcn = @(t) t(:, predictorNames);
ensemblePredictFcn = @(x) predict(classificationEnsemble, x);
trainedClassifier.predictFcn = @(x) ensemblePredictFcn(predictorExtractionFcn(x));

% Add additional fields to the result struct
trainedClassifier.RequiredVariables = {'L100', 'MAINTENANCE', 'PREVIOUSRECORDEDSTRUCTURALCONDITION',
'YEARSFROMPREVIOUSMATCH', 'effluent', 'material', 'pipesize', 'shape', 'topgraphy'};
trainedClassifier.ClassificationEnsemble = classificationEnsemble;
trainedClassifier.About = 'This struct is a trained model exported from Classification Learner R2021b.';
trainedClassifier.HowToPredict = sprintf('To make predictions on a new table, T, use: \n  yfit = c.predictFcn(T) \nreplacing "c" with the name of the variable
that is this struct, e.g. "trainedModel". \n \nThe table, T, must contain the variables returned by: \n  c.RequiredVariables \nVariable formats (e.g. matrix/vector,
datatype) must match the original training data. \nAdditional variables are ignored. \n \nFor more information, see <a href="matlab:helpview(fullfile(docroot,
"stats", "stats.map"), "appclassification_exportmodeltoworkspace")">How to predict using an exported model</a>.');

% Extract predictors and response
% This code processes the data into the right shape for training the
% model.
```

```
inputTable = trainingData;
predictorNames = {'L100', 'effluent', 'topgraphy', 'pipesize', 'material', 'shape', 'PREVIOUSRECORDEDSTRUCTURALCONDITION',
'YEARSFROMPREVIOUSMATCH', 'MAINTENANCE'};
predictors = inputTable(:, predictorNames);
response = inputTable.Drainagestrcutralcondition;
isCategoricalPredictor = [false, false, false, false, false, false, false, false, false];

% Set up holdout validation
cvp = cvpartition(response, 'Holdout', 0.25);
trainingPredictors = predictors(cvp.training, :);
trainingResponse = response(cvp.training, :);
trainingIsCategoricalPredictor = isCategoricalPredictor;

% Train a classifier
% This code specifies all the classifier options and trains the classifier.
template = templateTree(...
    'MaxNumSplits', 356910);
classificationEnsemble = fitcensemble(...
    trainingPredictors, ...
    trainingResponse, ...
    'Method', 'Bag', ...
    'NumLearningCycles', 30, ...
    'Learners', template, ...
    'ClassNames', [1; 2; 3; 4; 5],'OOBPrediction','on');

% Create the result struct with predict function
ensemblePredictFcn = @(x) predict(classificationEnsemble, x);
validationPredictFcn = @(x) ensemblePredictFcn(x);

% Add additional fields to the result struct


% Compute validation predictions
validationPredictors = predictors(cvp.test, :);
validationResponse = response(cvp.test, :);
[validationPredictions, validationScores] = validationPredictFcn(validationPredictors);

% Compute validation accuracy
correctPredictions = (validationPredictions == validationResponse);
isMissing = isnan(validationResponse);
correctPredictions = correctPredictions(~isMissing);
validationAccuracy = sum(correctPredictions)/length(correctPredictions);
```

Boosted Trees

```
function [trainedClassifier, validationAccuracy] = trainClassifier(trainingData)
% [trainedClassifier, validationAccuracy] = trainClassifier(trainingData)
% Returns a trained classifier and its accuracy. This code recreates the
% classification model trained in Classification Learner app. Use the
% generated code to automate training the same model with new data, or to
% learn how to programmatically train models.
%
%  Input:
%      trainingData: A table containing the same predictor and response
%       columns as those imported into the app.
%
%  Output:
%      trainedClassifier: A struct containing the trained classifier. The
%       struct contains various fields with information about the trained
%       classifier.
%
%      trainedClassifier.predictFcn: A function to make predictions on new
%       data.
%
%      validationAccuracy: A double containing the accuracy as a
%       percentage. In the app, the Models pane displays this overall
%       accuracy score for each model.
%
% Use the code to train the model with new data. To retrain your
% classifier, call the function from the command line with your original
% data or new data as the input argument trainingData.
%
% For example, to retrain a classifier trained with the original data set
% T, enter:
%   [trainedClassifier, validationAccuracy] = trainClassifier(T)
%
% To make predictions with the returned 'trainedClassifier' on new data T2,
% use
%   yfit = trainedClassifier.predictFcn(T2)
%
% T2 must be a table containing at least the same predictor columns as used
% during training. For details, enter:
%   trainedClassifier.HowToPredict

% Auto-generated by MATLAB on 08-Feb-2022 19:25:38


% Extract predictors and response
```

```
% This code processes the data into the right shape for training the
% model.
inputTable = trainingData;
predictorNames = {'L100', 'effluent', 'topgraphy', 'pipesize', 'material', 'shape', 'PREVIOUSRECORDEDSTRUCTURALCONDITION',
'YEARSFROMPREVIOUSMATCH', 'MAINTENANCE'};
predictors = inputTable(:, predictorNames);
response = inputTable.Drainagestrcutralcondition;
isCategoricalPredictor = [false, false, false, false, false, false, false, false, false];

% Train a classifier
% This code specifies all the classifier options and trains the classifier.
template = templateTree(...
    'MaxNumSplits', 356910);
classificationEnsemble = fitcensemble(...
    predictors, ...
    response, ...
    'Method', 'RUSBoost', ...
    'NumLearningCycles', 30, ...
    'Learners', template, ...
    'LearnRate', 0.1, ...
    'ClassNames', [1; 2; 3; 4; 5]);

% Create the result struct with predict function
predictorExtractionFcn = @(t) t(:, predictorNames);
ensemblePredictFcn = @(x) predict(classificationEnsemble, x);
trainedClassifier.predictFcn = @(x) ensemblePredictFcn(predictorExtractionFcn(x));

% Add additional fields to the result struct
trainedClassifier.RequiredVariables = {'L100', 'MAINTENANCE', 'PREVIOUSRECORDEDSTRUCTURALCONDITION',
'YEARSFROMPREVIOUSMATCH', 'effluent', 'material', 'pipesize', 'shape', 'topgraphy'};
trainedClassifier.ClassificationEnsemble = classificationEnsemble;
trainedClassifier.About = 'This struct is a trained model exported from Classification Learner R2021b.';
trainedClassifier.HowToPredict = sprintf('To make predictions on a new table, T, use: \n  yfit = c.predictFcn(T) \nreplacing "c" with the name of the variable
that is this struct, e.g. "trainedModel". \n \nThe table, T, must contain the variables returned by: \n  c.RequiredVariables \nVariable formats (e.g. matrix/vector,
datatype) must match the original training data. \nAdditional variables are ignored. \n \nFor more information, see <a href="matlab:helpview(fullfile(docroot,
"stats", "stats.map"), "appclassification_exportmodeltoworkspace")">How to predict using an exported model</a>.');

% Extract predictors and response
% This code processes the data into the right shape for training the
% model.
inputTable = trainingData;
predictorNames = {'L100', 'effluent', 'topgraphy', 'pipesize', 'material', 'shape', 'PREVIOUSRECORDEDSTRUCTURALCONDITION',
'YEARSFROMPREVIOUSMATCH', 'MAINTENANCE'};
predictors = inputTable(:, predictorNames);
response = inputTable.Drainagestrcutralcondition;
isCategoricalPredictor = [false, false, false, false, false, false, false, false, false];

% Set up holdout validation
cvp = cvpartition(response, 'Holdout', 0.25);
trainingPredictors = predictors(cvp.training, :);
trainingResponse = response(cvp.training, :);
trainingIsCategoricalPredictor = isCategoricalPredictor;

% Train a classifier
% This code specifies all the classifier options and trains the classifier.
template = templateTree(...
    'MaxNumSplits', 356910);
classificationEnsemble = fitcensemble(...
    trainingPredictors, ...
    trainingResponse, ...
    'Method', 'RUSBoost', ...
    'NumLearningCycles', 30, ...
    'Learners', template, ...
    'LearnRate', 0.1, ...
    'ClassNames', [1; 2; 3; 4; 5]);

% Create the result struct with predict function
ensemblePredictFcn = @(x) predict(classificationEnsemble, x);
validationPredictFcn = @(x) ensemblePredictFcn(x);

% Add additional fields to the result struct


% Compute validation predictions
validationPredictors = predictors(cvp.test, :);
validationResponse = response(cvp.test, :);
[validationPredictions, validationScores] = validationPredictFcn(validationPredictors);

% Compute validation accuracy
correctPredictions = (validationPredictions == validationResponse);
isMissing = isnan(validationResponse);
correctPredictions = correctPredictions(~isMissing);
validationAccuracy = sum(correctPredictions)/length(correctPredictions);
```

# Appendix B.2: Raw connections weights data from NN for CWA

*Table A-B.1. STRC connection weight between layers*

| connection weight from / to | HN | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Input factor | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 |
| Length | -0.70 | -1.86 | 0.02 | -0.93 | -5.06 | -0.60 | 0.69 | -0.46 | -2.09 | 1.06 | -1.58 | -11.46 | -3.81 | 2.91 | 13.09 | 0.96 | 5.59 | -1.66 | -3.76 | -1.55 |
| Effluent | 0.75 | 0.22 | 0.46 | 3.19 | -0.28 | -0.45 | -0.77 | 0.55 | 1.81 | -2.17 | 1.07 | -0.25 | 2.25 | -0.68 | -1.04 | -2.31 | -4.28 | 3.71 | -2.01 | 0.56 |
| Topography | -1.36 | -1.08 | 0.03 | -0.72 | -0.25 | -0.24 | -0.83 | -0.12 | -3.01 | -1.91 | 4.06 | -0.85 | 1.65 | -2.12 | 1.58 | 1.54 | -5.94 | -1.43 | -0.10 | -0.16 |
| Size | 1.40 | 0.14 | -0.31 | 3.21 | -0.87 | 1.01 | 1.02 | 0.88 | 0.97 | -5.26 | -10.02 | 1.23 | -1.68 | 0.83 | 0.10 | -0.34 | -0.66 | -1.12 | -0.20 | -0.54 |
| Material | -0.21 | 0.36 | 0.19 | -1.20 | -1.84 | 0.03 | -0.12 | -0.07 | 0.06 | 1.58 | -1.76 | 1.06 | -0.58 | -1.81 | 2.21 | -0.36 | -0.75 | -2.23 | 2.75 | -0.25 |
| Shape | -2.42 | -0.24 | 0.44 | 0.76 | -1.14 | -0.90 | 0.77 | -1.01 | 3.00 | 2.59 | -3.65 | 4.61 | -4.82 | 1.03 | -1.00 | 7.82 | -4.08 | 2.27 | 2.26 | -0.50 |
| Previous recorded condition | -3.70 | -5.25 | -2.28 | -3.21 | 3.86 | 8.35 | -0.01 | -1.75 | -4.85 | -6.86 | 2.98 | 0.20 | -1.57 | -3.41 | 0.23 | -1.70 | 2.07 | -7.22 | 3.06 | -0.25 |
| Years from previous recorded condition | 2.94 | -4.08 | 1.60 | -4.09 | 0.60 | 0.13 | -1.55 | -0.99 | 1.87 | -3.19 | 7.72 | -2.23 | 3.76 | -2.64 | -0.45 | 5.36 | 1.33 | 3.68 | 2.55 | -0.50 |
| maintenance | 1.53 | 3.34 | 0.78 | 1.10 | 0.50 | -1.31 | 2.11 | 0.68 | 2.12 | 2.93 | -5.21 | 4.08 | -0.23 | -1.31 | -7.57 | -0.82 | -2.15 | -0.95 | -0.67 | 2.48 |
| connection weight from/ to | HN | | | | | | | | | | | | | | | | | | | |
| Output condition | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 |
| condition 1 | 0.11 | -0.31 | 3.49 | -2.77 | 2.63 | -3.60 | 1.65 | 2.45 | -1.00 | -1.06 | -0.44 | -1.77 | -1.15 | 0.28 | -1.94 | 1.91 | -1.57 | 0.30 | 1.90 | 4.28 |
| condition 2 | -2.17 | 0.97 | 4.77 | -2.56 | 1.92 | 3.81 | 0.28 | 2.98 | -0.79 | -1.20 | -0.37 | -1.67 | -1.38 | 0.62 | -2.42 | 2.32 | -1.45 | 0.01 | 1.17 | -1.17 |
| condition 3 | -2.97 | 2.87 | 0.62 | -2.26 | 1.27 | 2.60 | -0.07 | 0.57 | -2.61 | -1.37 | 0.05 | -1.61 | -2.01 | -0.51 | -3.17 | 1.26 | -1.73 | 1.00 | 1.09 | -3.19 |
| condition 4 | 1.15 | 2.27 | 0.21 | -1.00 | 1.57 | 1.15 | -4.43 | -6.61 | -2.34 | -0.70 | -1.23 | -0.87 | -2.93 | 2.07 | -2.30 | -6.21 | -1.22 | 0.66 | -0.08 | -4.93 |
| condition 5 | 4.75 | -7.53 | -10.18 | 6.79 | -6.44 | -3.39 | 2.67 | 0.96 | 6.56 | 3.93 | 4.56 | 4.94 | 8.68 | -2.13 | 9.93 | 0.58 | 4.06 | -1.24 | -2.45 | 3.23 |

*Table A-B.2. STRC calculation of input significance using CWA*

| Input Factor | Local Significance | | | | | overall significance |
|---|---|---|---|---|---|---|
| | C1 | C2 | C3 | C4 | C5 | |

| | | | | | | |
|---|---|---|---|---|---|---|
| Length | -27.5 | -24.1 | -31.5 | -15.4 | 87.1 | 37.1 |
| Effluent | -4.6 | -10.2 | -7.6 | 7.1 | 21.7 | 10.2 |
| Topography | 11.0 | 11.3 | 17.6 | -10.7 | -3.5 | 10.8 |
| Size | -5.7 | 2.9 | -3.3 | 12.0 | -35.8 | 11.9 |
| Material | -4.5 | -3.9 | -4.4 | -4.4 | 13.9 | 6.2 |
| Shape | 17.8 | 22.0 | 17.1 | -33.2 | -37.5 | 25.5 |
| Previous recorded condition | -15.0 | 41.3 | 44.6 | 27.4 | -71.8 | 40.0 |
| Years since last recorded condition | 24.5 | 17.6 | 1.7 | -42.3 | 45.0 | 26.2 |
| maintenance | 25.3 | 4.7 | 2.3 | 0.0 | -61.9 | 18.9 |

*Table A-B.3. SRVC connection weight between layers*

| connection weight from / to | HN | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Input factor | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 |
| Length | -0.38 | 0.08 | -1.16 | -0.05 | 0.90 | 0.48 | -0.28 | 0.66 | 0.90 | 0.08 | 0.88 | 0.65 | -0.33 | -0.21 | -0.32 | 0.46 | -0.03 | 0.03 | -0.39 | 0.40 |
| Effluent | 0.02 | -0.09 | 0.04 | 0.43 | -0.07 | 1.74 | -0.52 | 0.77 | -0.36 | 0.17 | -0.32 | 0.14 | -0.49 | -0.05 | -0.74 | 0.09 | -0.37 | -0.57 | 0.54 | 0.13 |
| Topography | -0.30 | 1.32 | 0.87 | -0.39 | 0.24 | 0.76 | -0.57 | -0.38 | -0.44 | 0.17 | 1.11 | 0.10 | 1.28 | -0.07 | -0.62 | -2.11 | -0.27 | -0.13 | -0.13 | 0.20 |
| Size | -0.22 | 0.83 | -0.72 | 0.90 | -0.04 | -2.14 | -0.57 | 0.90 | -1.41 | 0.22 | 0.10 | -0.05 | -1.20 | -0.04 | -1.12 | 1.22 | -0.15 | -0.21 | 0.15 | 0.81 |
| Material | -0.14 | -0.74 | -0.67 | -0.79 | 0.47 | 0.27 | -0.42 | -2.40 | -0.21 | -0.07 | 2.64 | -0.04 | -0.79 | -0.08 | 0.72 | 0.38 | 0.16 | 0.24 | 0.17 | -0.02 |
| Shape | 0.00 | 0.93 | 0.17 | -0.09 | -0.88 | 0.75 | 0.72 | -0.42 | 1.01 | -0.19 | 1.75 | -0.19 | -2.81 | 0.27 | -0.07 | 0.78 | -0.21 | 0.50 | -0.80 | 0.71 |
| Previous recorded condition | 3.72 | 0.38 | 0.54 | -0.54 | 3.85 | 0.48 | 0.79 | -0.82 | -1.43 | 4.68 | 0.21 | 4.33 | 0.28 | -4.01 | -0.11 | -0.11 | 1.72 | 1.21 | 0.07 | -0.01 |
| Years from previous recorded condition | -0.39 | 0.80 | 0.04 | 1.03 | -0.08 | -0.97 | -0.83 | 0.65 | -0.83 | -0.23 | -0.09 | 0.25 | 1.45 | -0.02 | -0.80 | -0.42 | -1.60 | 0.64 | 3.71 | 0.17 |
| maintenance | 0.09 | -0.34 | -0.85 | -1.93 | 2.09 | -0.46 | -1.92 | 0.34 | 4.28 | -0.92 | -0.35 | -0.32 | -0.70 | 0.34 | 0.03 | 0.64 | -1.27 | -1.92 | -0.07 | 1.66 |
| connection weight from/ to | HN | | | | | | | | | | | | | | | | | | | |
| Output condition | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 |
| condition 1 | 2.36 | -0.05 | -0.77 | -0.72 | 0.91 | 1.10 | -1.38 | -1.57 | 1.99 | -2.89 | -0.22 | -3.57 | 1.98 | 0.50 | -1.18 | 1.93 | -0.62 | -2.02 | -0.44 | 2.59 |
| condition 2 | 0.79 | -0.62 | -0.70 | -0.57 | 0.65 | 0.36 | -0.03 | -0.57 | 0.95 | 1.72 | 0.16 | -0.96 | 0.49 | 3.08 | 0.15 | 0.86 | -0.84 | -1.37 | 0.65 | 0.55 |
| condition 3 | -0.08 | 0.66 | 0.52 | 0.11 | 0.49 | -0.26 | -0.45 | -0.22 | -0.43 | 1.17 | 0.76 | 2.90 | 0.67 | 2.14 | -0.08 | 1.00 | -0.73 | -0.68 | -1.02 | -0.75 |

| | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| condition 4 | -0.80 | -0.16 | 0.53 | 0.37 | -3.43 | -1.05 | 2.01 | -0.01 | 1.22 | 1.29 | 0.21 | 1.20 | -0.35 | -4.02 | -0.57 | 0.13 | -0.59 | -0.63 | -0.18 | -1.65 |
| condition 5 | -1.34 | -1.35 | 0.40 | 2.05 | 2.56 | 0.49 | -0.15 | 0.30 | -3.23 | -0.66 | -1.08 | 0.25 | -0.89 | -2.52 | 0.60 | -1.53 | 3.00 | 2.69 | 3.06 | -0.59 |

*Table A-B.4. SRVC calculation of input significance using CWA*

| Input Factor | Local Significance | | | | | overall significance |
|---|---|---|---|---|---|---|
| | C1 | C2 | C3 | C4 | C5 | |
| Length | 1.5 | 0.9 | 1.9 | -1.7 | -2.6 | 1.7 |
| Effluent | 1.0 | 0.9 | -0.2 | -1.5 | 2.3 | 1.2 |
| Topography | -0.5 | -1.9 | 2.0 | -2.5 | -0.5 | 1.5 |
| Size | -3.2 | -1.8 | 1.6 | 0.0 | 1.8 | 1.7 |
| Material | 2.8 | 2.6 | 1.0 | -3.0 | 0.3 | 1.9 |
| Shape | -0.1 | -0.2 | -0.5 | 3.5 | -10.1 | 2.9 |
| Previous recorded condition | -24.0 | -7.1 | 10.0 | 8.7 | 24.3 | 14.8 |
| Years since last recorded condition | -3.2 | -0.5 | -0.7 | -1.2 | 11.4 | 3.4 |
| maintenance | 27.2 | 11.6 | -1.1 | -10.0 | -22.8 | 14.5 |

# Appendix C.1: Simulation outputs: Point-in-time image of flood scenario for lengths

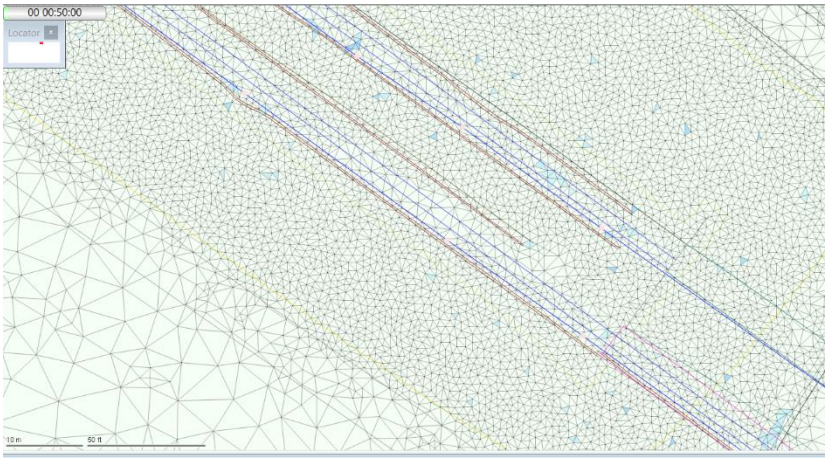



*Figure A-C. 1. Simulation output: Image of flood location surrounding node BSW 1234 U6FT, Scenario C1-D30-S1*

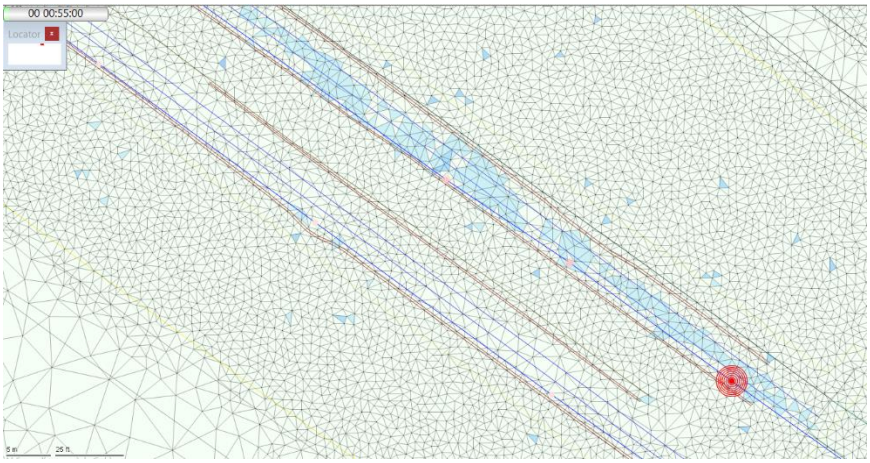



*Figure A-C. 2. Simulation output: Image of flood location surrounding node BSW 1234 U6FT, Scenario C1-D30-S2*




*Figure A-C. 3. Simulation output: Image of flood location surrounding node BSW 1234 U6FT, Scenario C1-D30-S5*

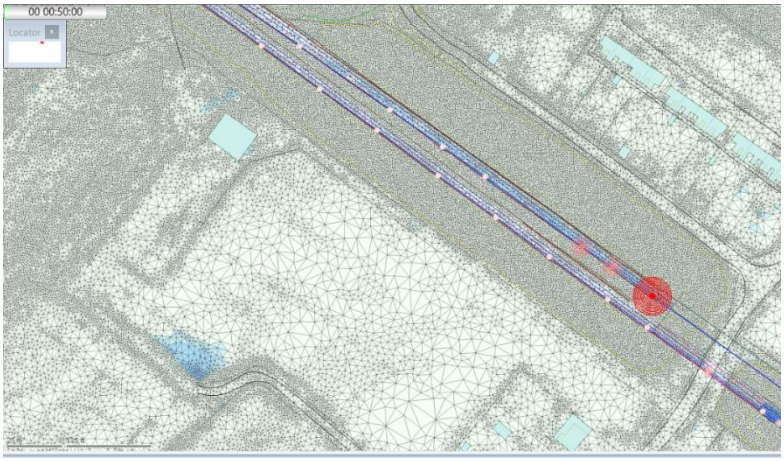



*Figure A-C. 4. Simulation output: Image of flood location surrounding node BSW 1234 U6FT, Scenario C1-D30-S10*




*Figure A-C. 5. Simulation output: Image of flood location surrounding node BSW 1234 U6FT, Scenario C1-D30-S30*

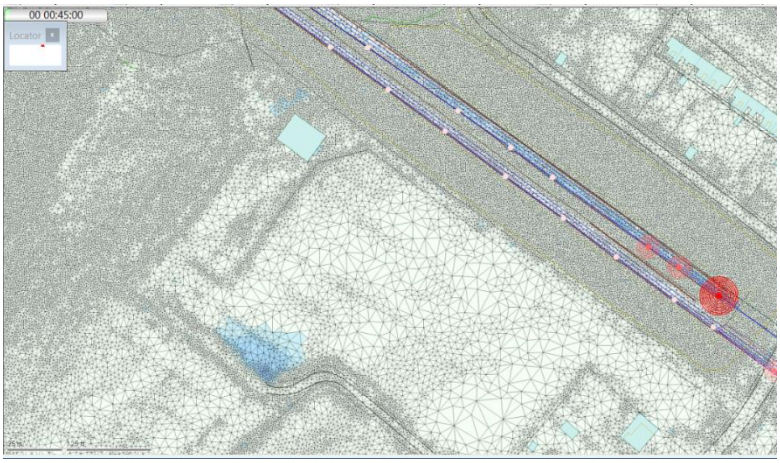



*Figure A-C. 6. Simulation output: Image of flood location surrounding node BSW 1234 U6FT, Scenario C1-D30-S50*




*Figure A-C. 7. Simulation output: Image of flood location surrounding node BSW 1234 U6FT, Scenario C1-D30-S100*

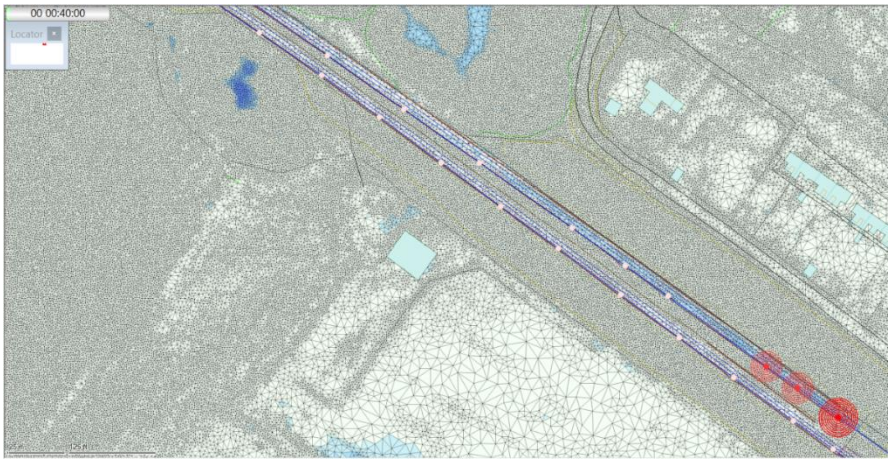



*Figure A-C. 8. Simulation output: Image of flood location surrounding node BSW 1234 U6FT, Scenario C1-D30-S200*

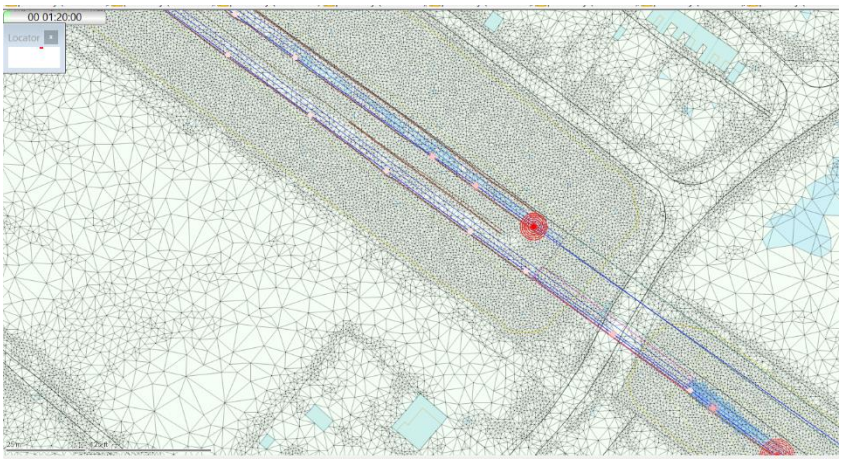



*Figure A-C. 9. Simulation output: Image of flood location surrounding node BSW 1234 U6FT, Scenario C1-D60-S1*

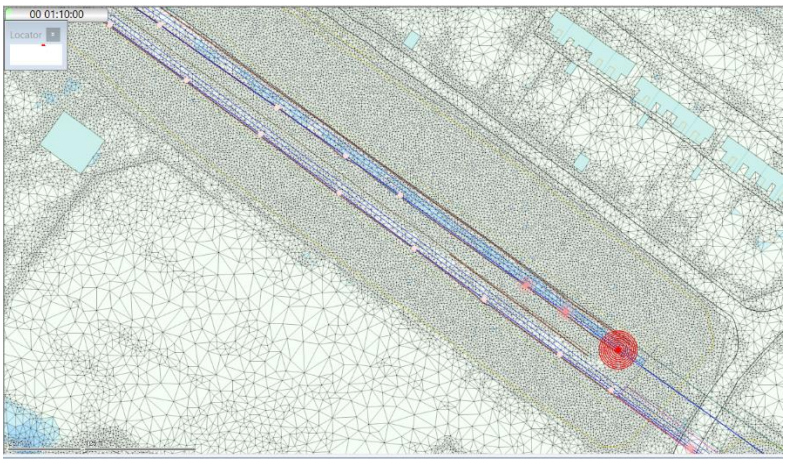



*Figure A-C. 10. Simulation output: Image of flood location surrounding node BSW 1234 U6FT, Scenario C1-D60-S2*

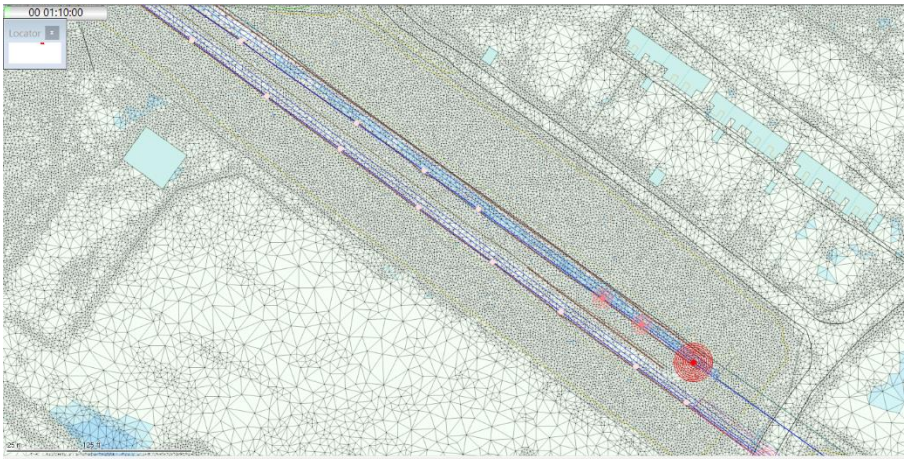



*Figure A-C. 11. Simulation output: Image of flood location surrounding node BSW 1234 U6FT, Scenario C1-D60-S5*

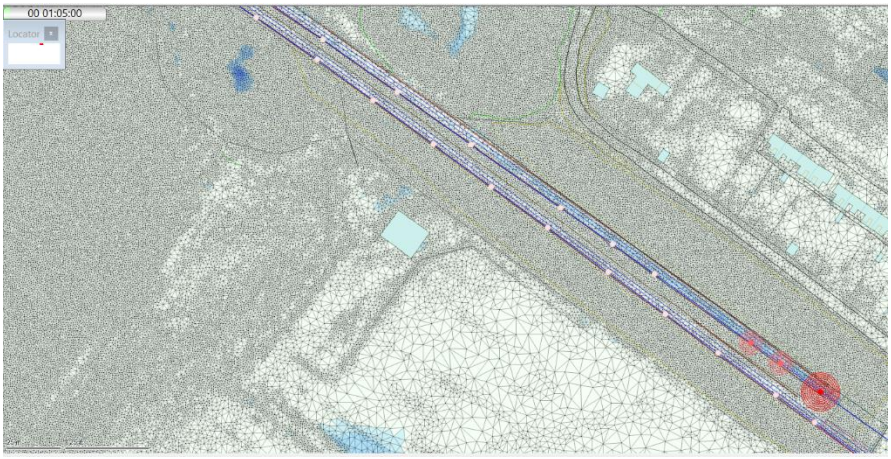



*Figure A-C. 12. Simulation output: Image of flood location surrounding node BSW 1234 U6FT, Scenario C1-D60-S10*

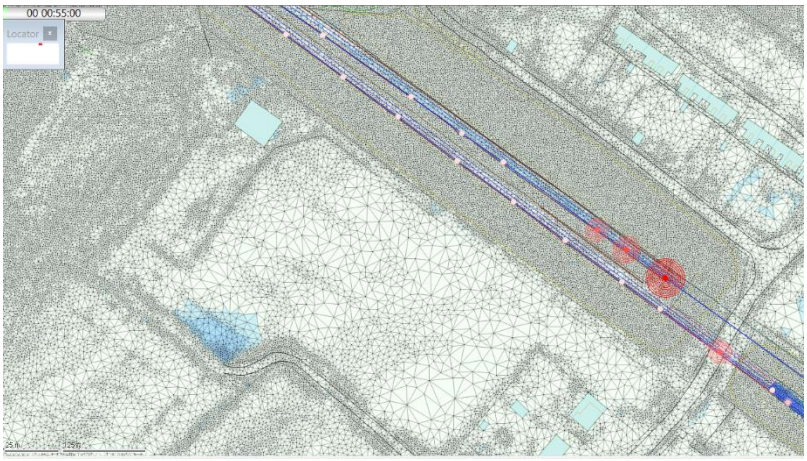



*Figure A-C. 13. Simulation output: Image of flood location surrounding node BSW 1234 U6FT, Scenario C1-D60-S30*




*Figure A-C. 14. Simulation output: Image of flood location surrounding node BSW 1234 U6FT, Scenario C1-D60-S50*

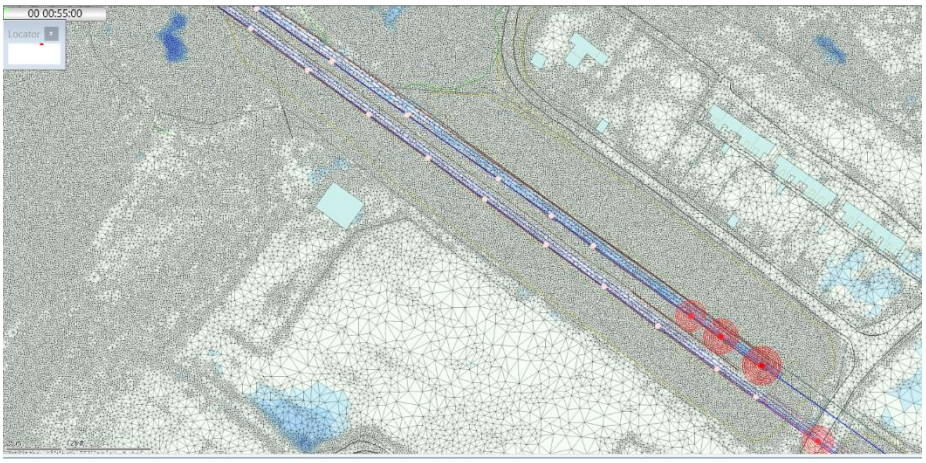



*Figure A-C. 15. Simulation output: Image of flood location surrounding node BSW 1234 U6FT, Scenario C1-D60-S100*




*Figure A-C. 16. Simulation output: Image of flood location surrounding node BSW 1234 U6FT, Scenario C1-D60-S200*

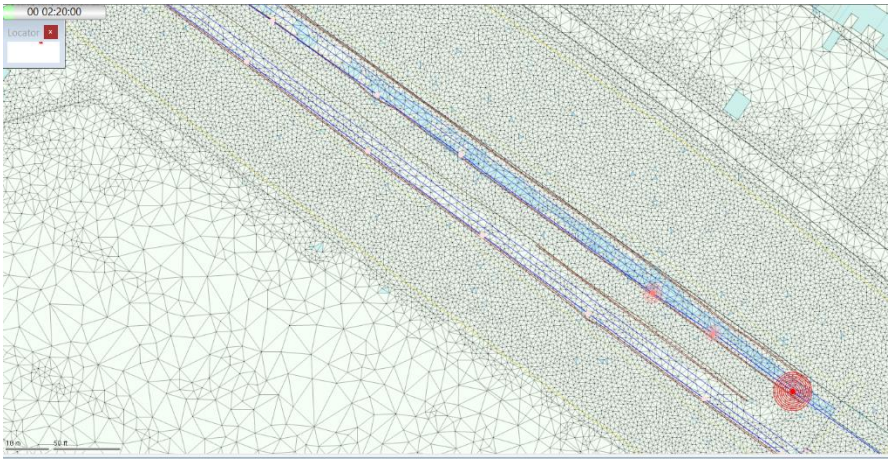



*Figure A-C. 17. Simulation output: Image of flood location surrounding node BSW 1234 U6FT, Scenario C1-D180-S1*

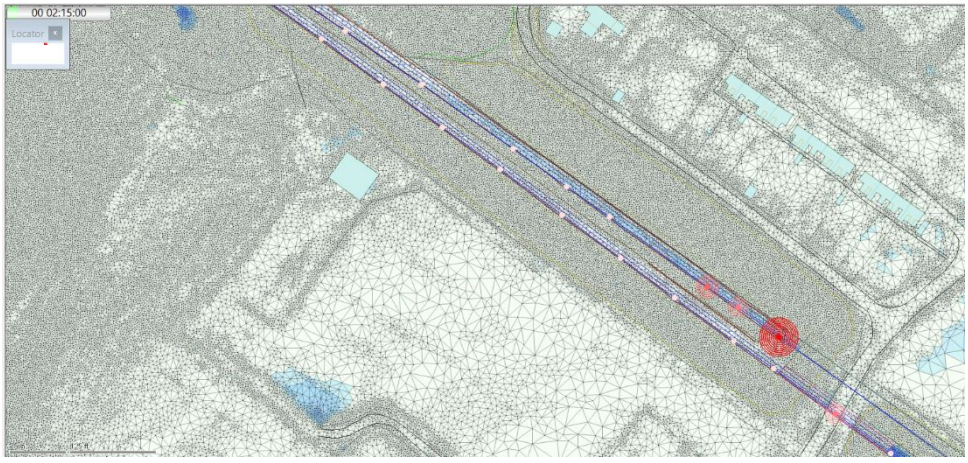



*Figure A-C. 18. Simulation output: Image of flood location surrounding node BSW 1234 U6FT, Scenario C1-D180-S2*

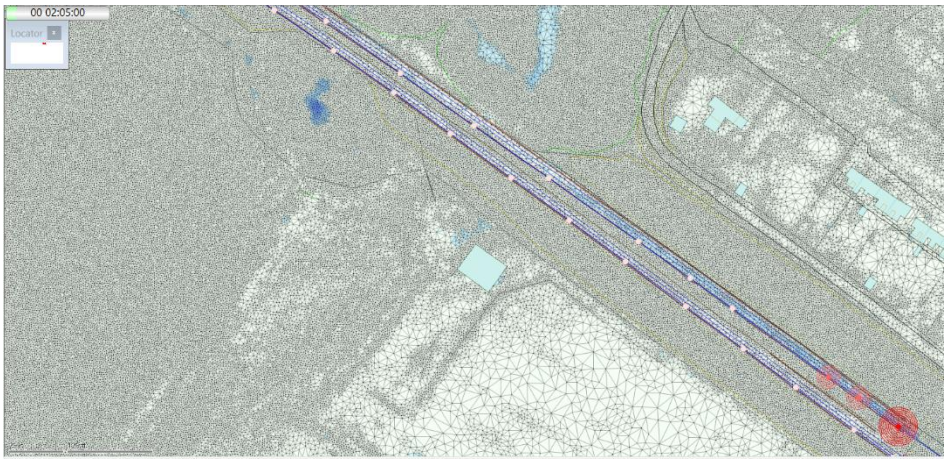



*Figure A-C. 19. Simulation output: Image of flood location surrounding node BSW 1234 U6FT, Scenario C1-D180-S5*

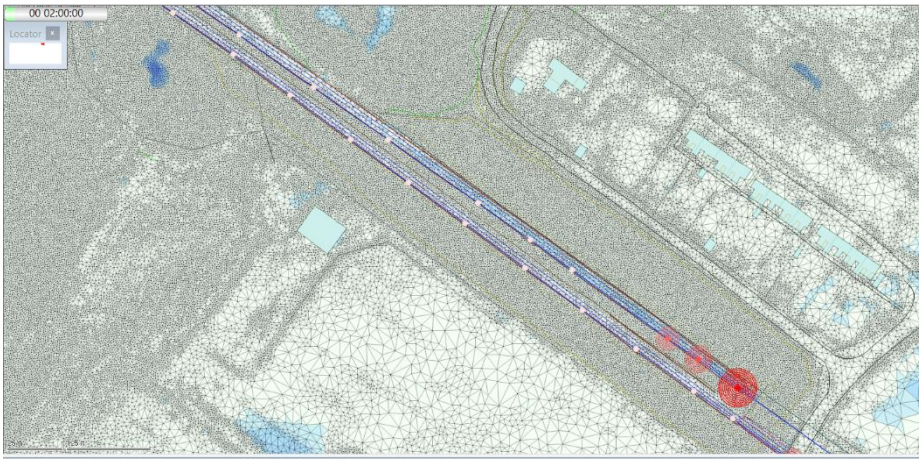



*Figure A-C. 20. Simulation output: Image of flood location surrounding node BSW 1234 U6FT, Scenario C1-D180-S10*

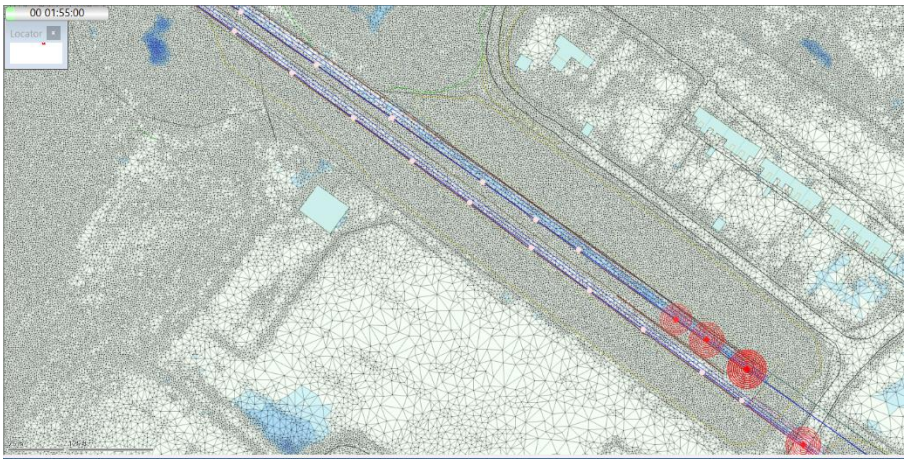



*Figure A-C. 21. Simulation output: Image of flood location surrounding node  BSW 1234 U6FT, Scenario C1-D180-S30*

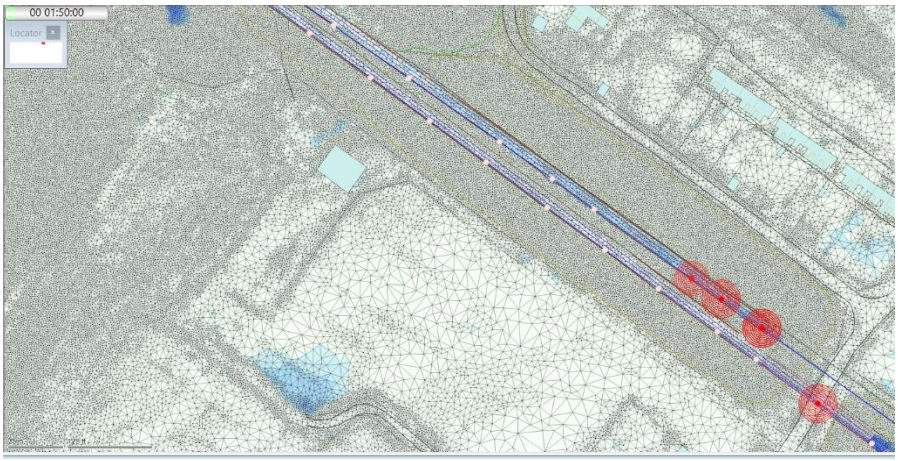



*Figure A-C. 22. Simulation output: Image of flood location surrounding node BSW 1234 U6FT, Scenario C1-D180-S50*




*Figure A-C. 23. Simulation output: Image of flood location surrounding node  BSW 1234 U6FT, Scenario C1-D180-S100*




*Figure A-C. 24. Simulation output: Image of flood location surrounding node BSW 1234 U6FT, Scenario C1-D180-S200*

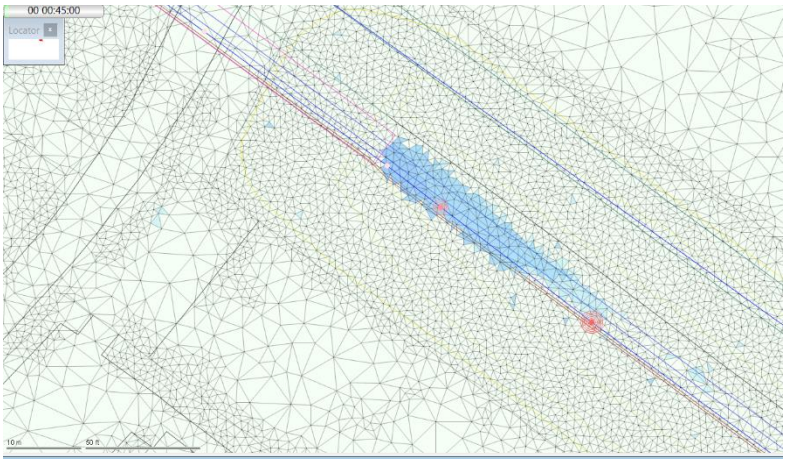



*Figure A-C. 25. Simulation output: Image of flood location surrounding node BSW 1126 DCE, Scenario C1-D30-S1*

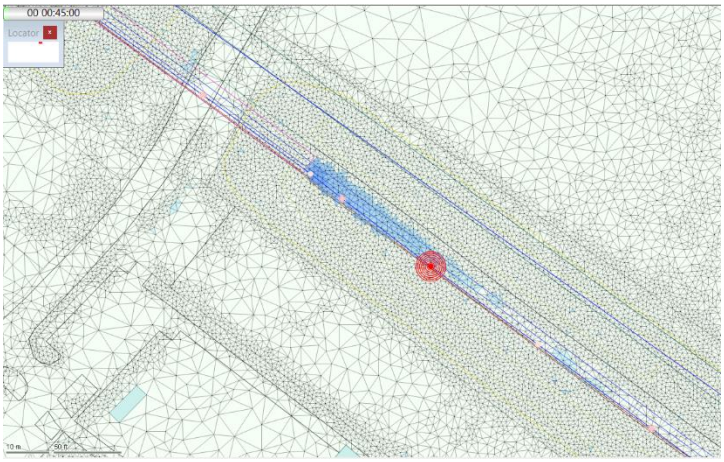



*Figure A-C. 26. Simulation output: Image of flood location surrounding node BSW 1126 DCE, Scenario C1-D30-S2*

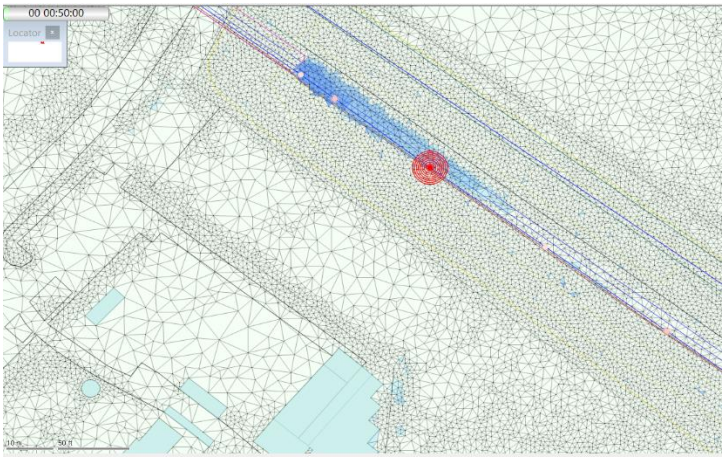



*Figure A-C. 27. Simulation output: Image of flood location surrounding node BSW 1126 DCE, Scenario C1-D30-S5*

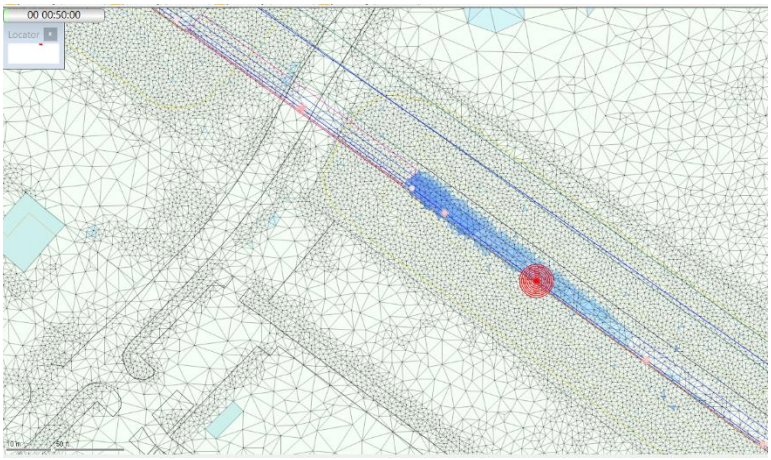



*Figure A-C. 28. Simulation output: Image of flood location surrounding node BSW 1126 DCE, Scenario C1-D30-S10*




*Figure A-C. 29. Simulation output: Image of flood location surrounding node BSW 1126 DCE, Scenario C1-D30-S30*

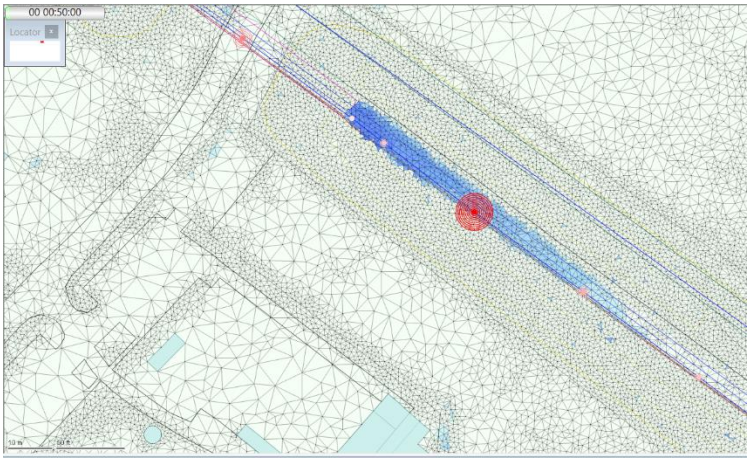



*Figure A-C. 30. Simulation output: Image of flood location surrounding node BSW 1126 DCE, Scenario C1-D30-S50*

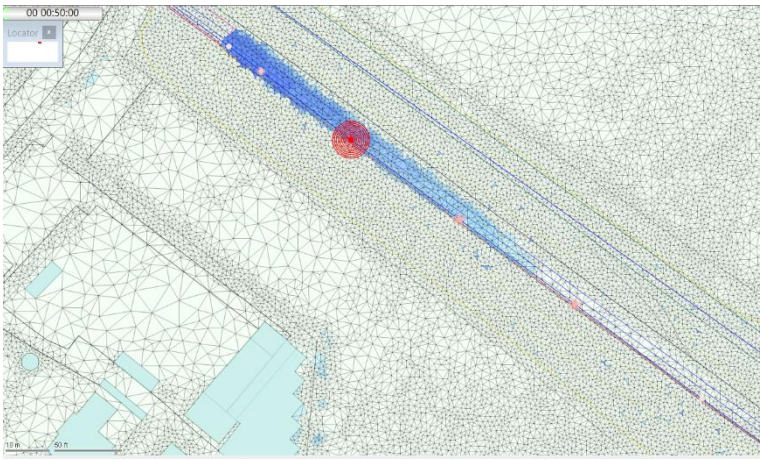



*Figure A-C. 31. Simulation output: Image of flood location surrounding node BSW 1126 DCE, Scenario C1-D30-S100*




*Figure A-C. 32. Simulation output: Image of flood location surrounding node BSW 1126 DCE, Scenario C1-D30-S200*

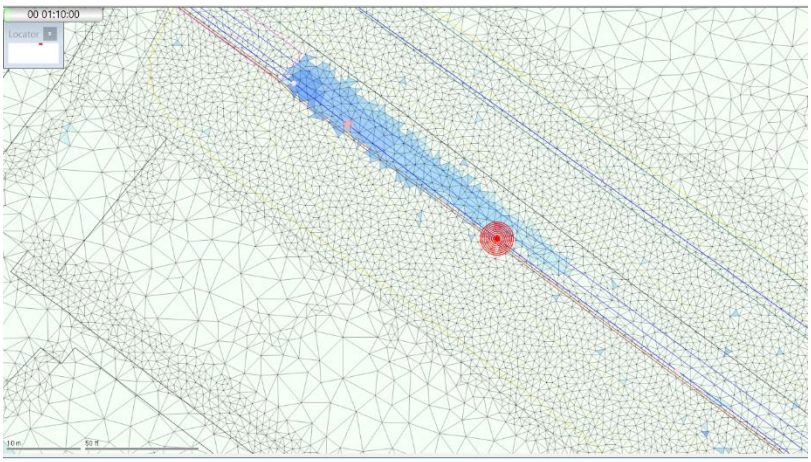



*Figure A-C. 33. Simulation output: Image of flood location surrounding node BSW 1126 DCE, Scenario C1-D60-S1*

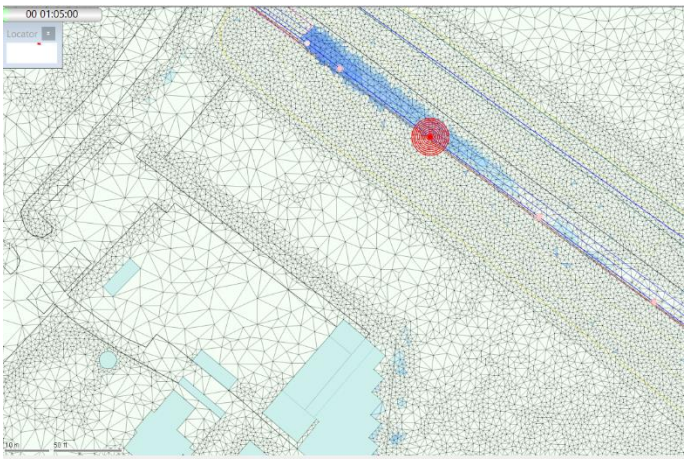



*Figure A-C. 34. Simulation output: Image of flood location surrounding node BSW 1126 DCE, Scenario C1-D60-S2*

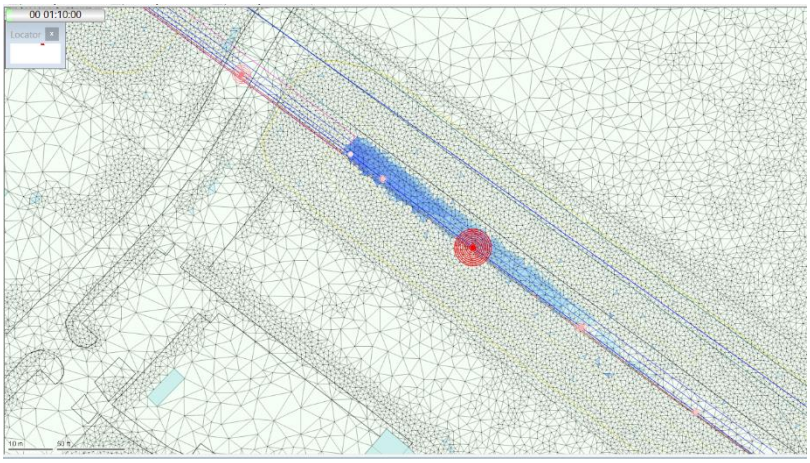



*Figure A-C. 35. Simulation output: Image of flood location surrounding node BSW 1126 DCE, Scenario C1-D60-S5*

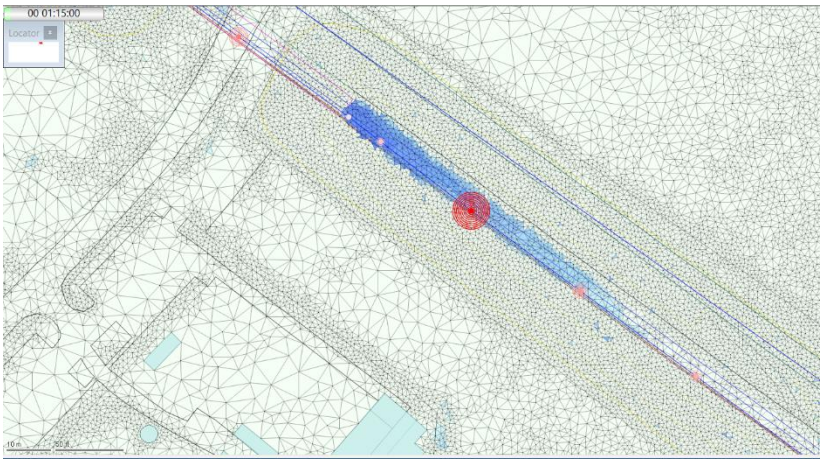



*Figure A-C. 36. Simulation output: Image of flood location surrounding node BSW 1126 DCE, Scenario C1-D60-S10*

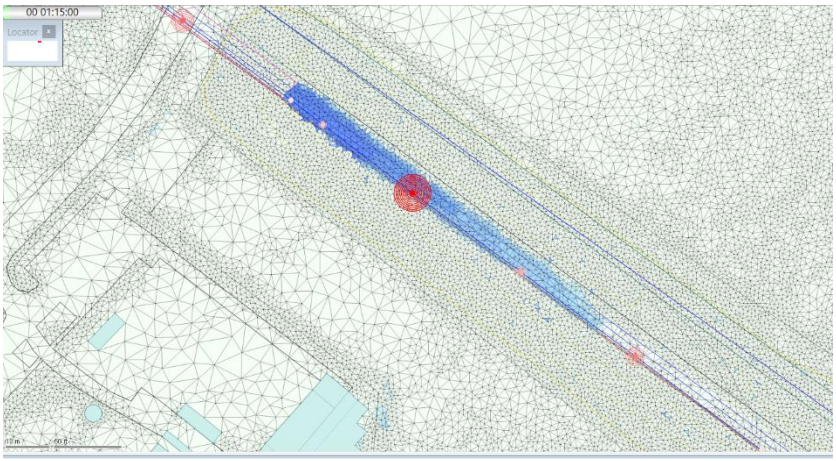



*Figure A-C. 37. Simulation output: Image of flood location surrounding node BSW 1126 DCE, Scenario C1-D60-S30*

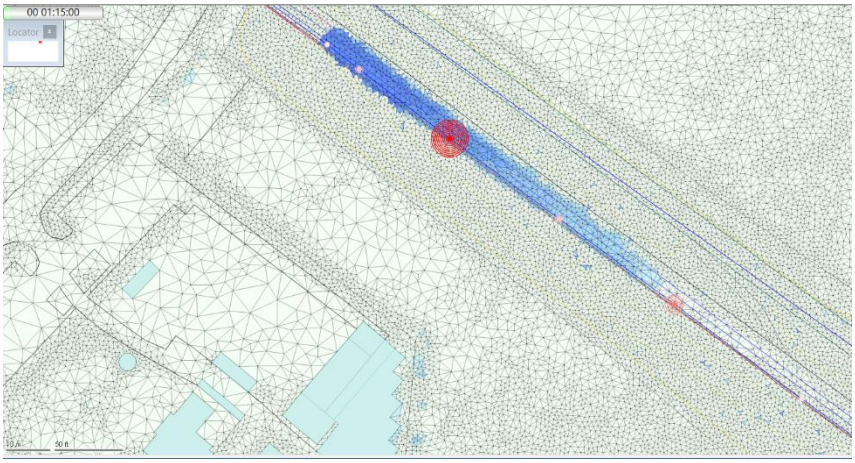



*Figure A-C. 38. Simulation output: Image of flood location surrounding node BSW 1126 DCE, Scenario C1-D60-S50*

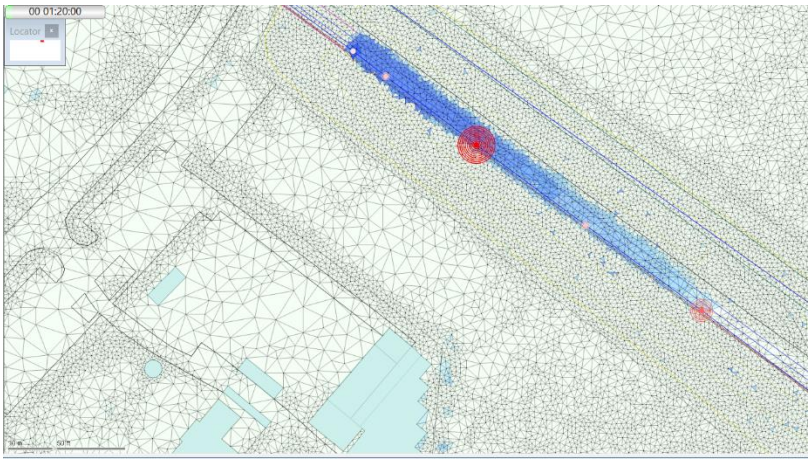



*Figure A-C. 39. Simulation output: Image of flood location surrounding node BSW 1126 DCE, Scenario C1-D60-S100*

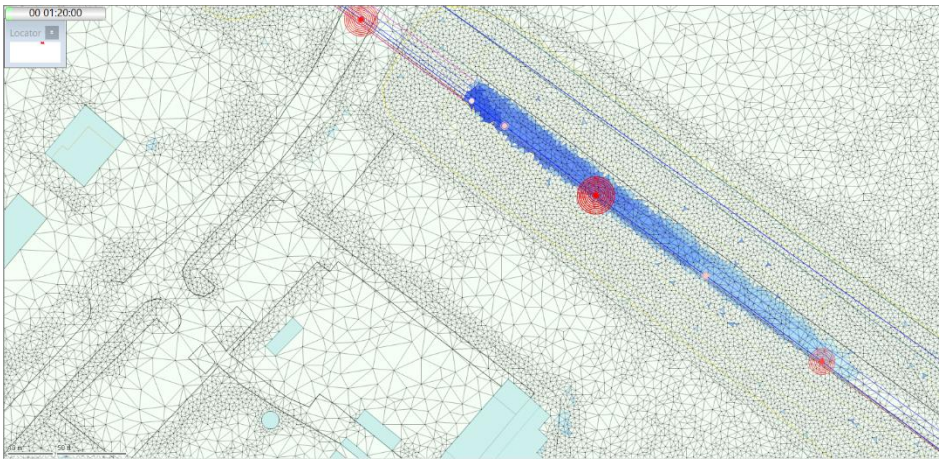



*Figure A-C. 40. Simulation output: Image of flood location surrounding node BSW 1126 DCE, Scenario C1-D60-S200*




*Figure A-C. 41. Simulation output: Image of flood location surrounding node BSW 1126 DCE, Scenario C1-D180-S1*

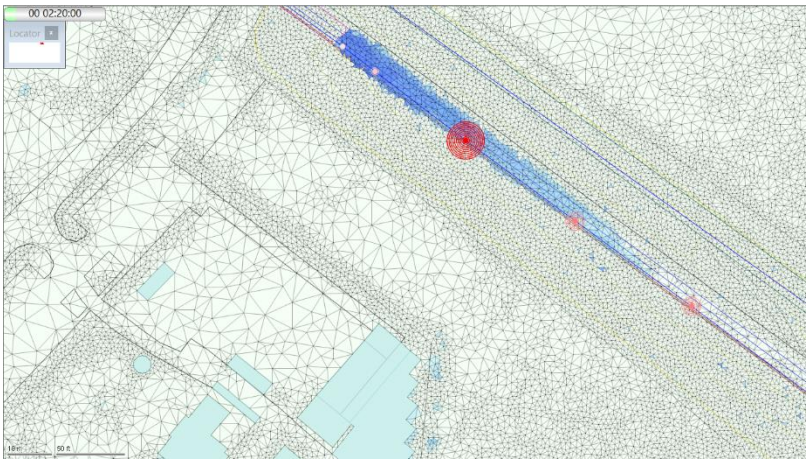



*Figure A-C. 42. Simulation output: Image of flood location surrounding node BSW 1126 DCE, Scenario C1-D180-S2*

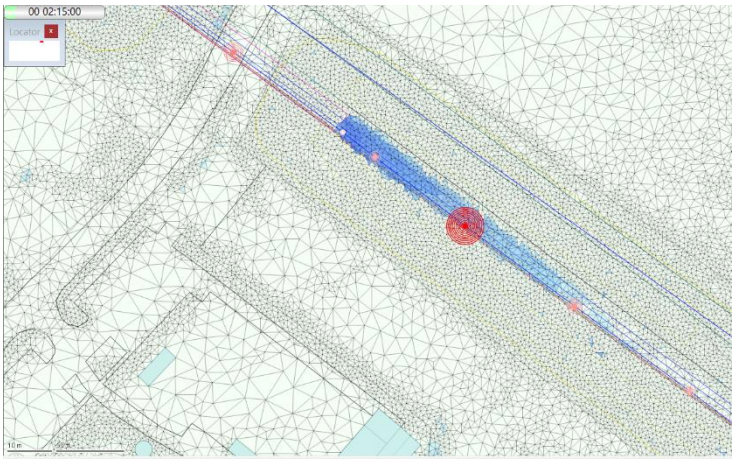



*Figure A-C. 43. Simulation output: Image of flood location surrounding node BSW 1126 DCE, Scenario C1-D180-S5*

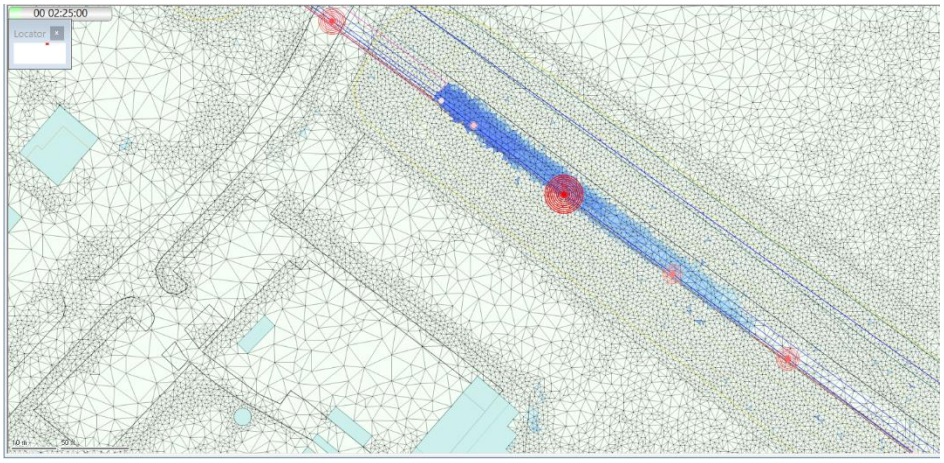



*Figure A-C. 44. Simulation output: Image of flood location surrounding node BSW 1126 DCE, Scenario C1-D180-S10*

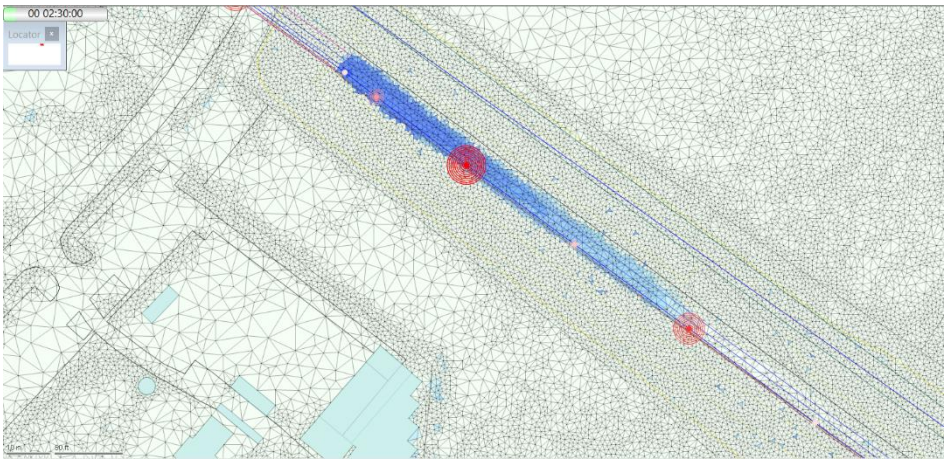



*Figure A-C. 45. Simulation output: Image of flood location surrounding node BSW 1126 DCE, Scenario C1-D180-S30*

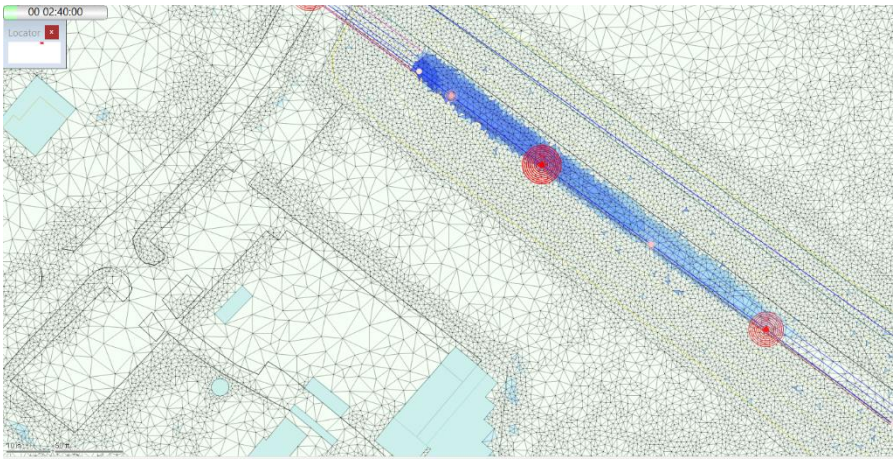



*Figure A-C. 46. Simulation output: Image of flood location surrounding node BSW 1126 DCE, Scenario C1-D180-S50*

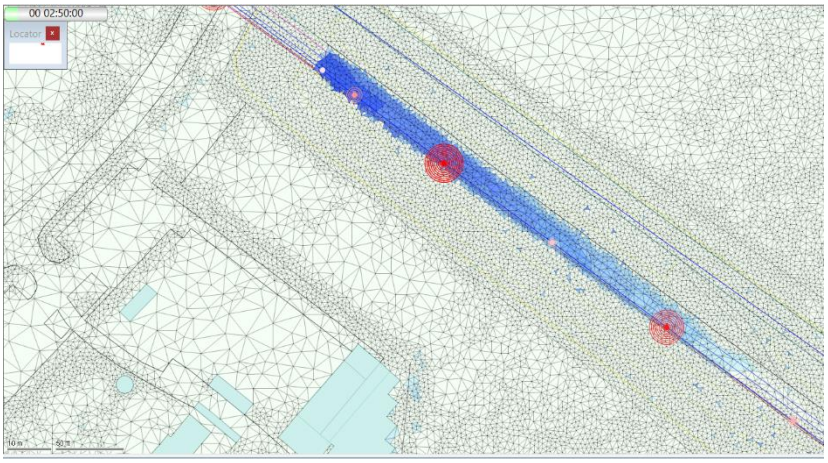



*Figure A-C. 47. Simulation output: Image of flood location surrounding node BSW 1126 DCE, Scenario C1-D180-S100*

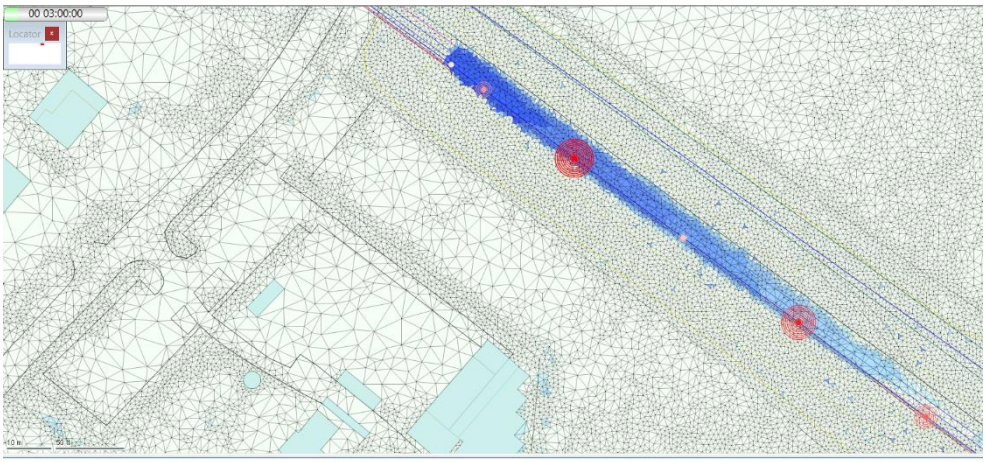



*Figure A-C. 48. Simulation output: Image of flood location surrounding node BSW 1126 DCE, Scenario C1-D180-S200*

# Appendix C.2: Simulation outputs: Time-Depth tables

*Table A-C 1 Simulation output: time-depth table for on-track element 898421 surrounding node BSW 007 1234 U6FT, scenario where pipe downstream from node is in condition 1*

| Scenario | C1-D30-S1 | C1-D30-S2 | C1-D30-S5 | C1-D30-S10 | C1-D30-S30 | C1-D30-S50 | C1-D30-S100 | C1-D30-S200 | C1-D60-S1 | C1-D60-S2 | C1-D60-S5 | C1-D60-S10 | C1-D60-S30 | C1-D60-S50 | C1-D60-S100 | C1-D60-S200 | C1-D180-S1 | C1-D180-S2 | C1-D180-S5 | C1-D180-S10 | C1-D180-S30 | C1-D180-S50 | C1-D180-S100 | C1-D180-S200 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 00 00:00:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 00 00:05:00 | 0 | 0.001 | 0.001 | 0.001 | 0.001 | 0.002 | 0.002 | 0.003 | 0 | 0 | 0 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 00 00:10:00 | 0.002 | 0.003 | 0.004 | 0.006 | 0.009 | 0.012 | 0.016 | 0.023 | 0.001 | 0.001 | 0.001 | 0.002 | 0.003 | 0.003 | 0.004 | 0.006 | 0 | 0 | 0 | 0 | 0.001 | 0.001 | 0.001 | 0.001 |
| 00 00:15:00 | 0.014 | 0.021 | 0.039 | 0.045 | 0.052 | 0.054 | 0.057 | 0.062 | 0.001 | 0.002 | 0.003 | 0.004 | 0.007 | 0.009 | 0.013 | 0.03 | 0 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.002 | 0.003 |
| 00 00:20:00 | 0.044 | 0.047 | 0.051 | 0.054 | 0.058 | 0.061 | 0.067 | 0.079 | 0.003 | 0.004 | 0.008 | 0.01 | 0.031 | 0.031 | 0.033 | 0.034 | 0.001 | 0.001 | 0.001 | 0.001 | 0.002 | 0.003 | 0.003 | 0.005 |
| 00 00:25:00 | 0.028 | 0.03 | 0.041 | 0.051 | 0.066 | 0.073 | 0.08 | 0.093 | 0.008 | 0.013 | 0.032 | 0.032 | 0.037 | 0.037 | 0.039 | 0.043 | 0.001 | 0.001 | 0.002 | 0.002 | 0.003 | 0.004 | 0.006 | 0.008 |
| 00 00:30:00 | 0.039 | 0.048 | 0.059 | 0.063 | 0.079 | 0.086 | 0.181 | 0.198 | 0.035 | 0.04 | 0.042 | 0.045 | 0.052 | 0.054 | 0.06 | 0.07 | 0.001 | 0.002 | 0.002 | 0.003 | 0.005 | 0.006 | 0.008 | 0.026 |
| 00 00:35:00 | 0.038 | 0.05 | 0.057 | 0.101 | 0.186 | 0.197 | 0.207 | 0.209 | 0.039 | 0.043 | 0.047 | 0.052 | 0.064 | 0.073 | 0.087 | 0.1 | 0.001 | 0.002 | 0.003 | 0.004 | 0.007 | 0.01 | 0.025 | 0.025 |
| 00 00:40:00 | 0.037 | 0.047 | 0.141 | 0.176 | 0.192 | 0.202 | 0.208 | 0.212 | 0.031 | 0.044 | 0.053 | 0.061 | 0.075 | 0.083 | 0.096 | 0.172 | 0.002 | 0.003 | 0.004 | 0.006 | 0.022 | 0.024 | 0.025 | 0.027 |
| 00 00:45:00 | 0.039 | 0.077 | 0.179 | 0.186 | 0.198 | 0.203 | 0.205 | 0.208 | 0.044 | 0.053 | 0.061 | 0.066 | 0.163 | 0.192 | 0.207 | 0.218 | 0.003 | 0.004 | 0.006 | 0.008 | 0.024 | 0.025 | 0.027 | 0.027 |
| 00 00:50:00 | 0.04 | 0.108 | 0.183 | 0.192 | 0.197 | 0.201 | 0.202 | 0.204 | 0.047 | 0.054 | 0.117 | 0.173 | 0.2 | 0.205 | 0.212 | 0.224 | 0.003 | 0.005 | 0.008 | 0.024 | 0.026 | 0.027 | 0.027 | 0.028 |
| 00 00:55:00 | 0.039 | 0.129 | 0.183 | 0.192 | 0.196 | 0.199 | 0.199 | 0.202 | 0.047 | 0.108 | 0.172 | 0.19 | 0.206 | 0.21 | 0.215 | 0.22 | 0.005 | 0.007 | 0.024 | 0.025 | 0.027 | 0.027 | 0.028 | 0.036 |
| 00 01:00:00 | 0.037 | 0.121 | 0.173 | 0.19 | 0.194 | 0.197 | 0.197 | 0.2 | 0.047 | 0.118 | 0.188 | 0.194 | 0.206 | 0.209 | 0.212 | 0.216 | 0.006 | 0.019 | 0.025 | 0.026 | 0.027 | 0.028 | 0.036 | 0.038 |
| 00 01:05:00 | 0.034 | 0.12 | 0.163 | 0.188 | 0.192 | 0.195 | 0.196 | 0.198 | 0.047 | 0.172 | 0.19 | 0.198 | 0.203 | 0.205 | 0.208 | 0.211 | 0.008 | 0.024 | 0.026 | 0.027 | 0.031 | 0.036 | 0.038 | 0.041 |
| 00 01:10:00 | 0.031 | 0.087 | 0.131 | 0.184 | 0.19 | 0.194 | 0.194 | 0.197 | 0.119 | 0.18 | 0.194 | 0.197 | 0.201 | 0.203 | 0.205 | 0.208 | 0.024 | 0.026 | 0.027 | 0.028 | 0.037 | 0.038 | 0.042 | 0.051 |
| 00 01:15:00 | 0.028 | 0.088 | 0.094 | 0.178 | 0.189 | 0.192 | 0.193 | 0.196 | 0.104 | 0.171 | 0.193 | 0.195 | 0.199 | 0.201 | 0.203 | 0.206 | 0.026 | 0.028 | 0.029 | 0.036 | 0.04 | 0.043 | 0.052 | 0.056 |
| 00 01:20:00 | 0.026 | 0.035 | 0.097 | 0.156 | 0.187 | 0.191 | 0.192 | 0.194 | 0.127 | 0.161 | 0.191 | 0.194 | 0.197 | 0.199 | 0.201 | 0.204 | 0.029 | 0.029 | 0.037 | 0.041 | 0.046 | 0.054 | 0.058 | 0.063 |
| 00 01:25:00 | 0.025 | 0.028 | 0.062 | 0.098 | 0.186 | 0.19 | 0.191 | 0.193 | 0.116 | 0.143 | 0.19 | 0.192 | 0.196 | 0.198 | 0.2 | 0.203 | 0.03 | 0.036 | 0.042 | 0.045 | 0.057 | 0.06 | 0.066 | 0.132 |
| 00 01:30:00 | 0.024 | 0.025 | 0.053 | 0.057 | 0.185 | 0.189 | 0.19 | 0.192 | 0.085 | 0.116 | 0.187 | 0.191 | 0.195 | 0.196 | 0.198 | 0.202 | 0.035 | 0.044 | 0.047 | 0.056 | 0.064 | 0.08 | 0.147 | 0.199 |
| 00 01:35:00 | 0.023 | 0.023 | 0.025 | 0.03 | 0.184 | 0.188 | 0.189 | 0.192 | 0.078 | 0.114 | 0.18 | 0.189 | 0.193 | 0.195 | 0.197 | 0.2 | 0.043 | 0.045 | 0.057 | 0.062 | 0.136 | 0.168 | 0.202 | 0.214 |
| 00 01:40:00 | 0.023 | 0.023 | 0.024 | 0.025 | 0.179 | 0.187 | 0.188 | 0.191 | 0.031 | 0.087 | 0.151 | 0.188 | 0.192 | 0.194 | 0.196 | 0.199 | 0.042 | 0.053 | 0.06 | 0.117 | 0.186 | 0.201 | 0.213 | 0.226 |
| 00 01:45:00 | 0.022 | 0.022 | 0.022 | 0.023 | 0.168 | 0.187 | 0.188 | 0.191 | 0.026 | 0.07 | 0.108 | 0.186 | 0.191 | 0.193 | 0.195 | 0.198 | 0.051 | 0.056 | 0.127 | 0.18 | 0.202 | 0.21 | 0.222 | 0.229 |
| 00 01:50:00 | 0.022 | 0.022 | 0.022 | 0.022 | 0.048 | 0.184 | 0.188 | 0.19 | 0.024 | 0.055 | 0.068 | 0.183 | 0.19 | 0.192 | 0.194 | 0.197 | 0.052 | 0.12 | 0.177 | 0.194 | 0.21 | 0.216 | 0.222 | 0.227 |
| 00 01:55:00 | 0 | 0 | 0 | 0.021 | 0.023 | 0.179 | 0.187 | 0.19 | 0.025 | 0.026 | 0.061 | 0.178 | 0.189 | 0.191 | 0.193 | 0.197 | 0.053 | 0.159 | 0.19 | 0.2 | 0.211 | 0.215 | 0.219 | 0.223 |
| 00 02:00:00 | 0 | 0 | 0 | 0 | 0.022 | 0.154 | 0.186 | 0.189 | 0.023 | 0.024 | 0.025 | 0.164 | 0.188 | 0.19 | 0.192 | 0.197 | 0.135 | 0.183 | 0.196 | 0.203 | 0.209 | 0.212 | 0.216 | 0.22 |
| 00 02:05:00 | 0 | 0 | 0 | 0 | 0.021 | 0.026 | 0.186 | 0.189 | 0.023 | 0.023 | 0.024 | 0.059 | 0.187 | 0.189 | 0.192 | 0.196 | 0.155 | 0.187 | 0.199 | 0.202 | 0.207 | 0.21 | 0.213 | 0.217 |
| 00 02:10:00 | 0 | 0 | 0 | 0 | 0 | 0.022 | 0.185 | 0.189 | 0.022 | 0.023 | 0.023 | 0.025 | 0.186 | 0.189 | 0.191 | 0.196 | 0.169 | 0.191 | 0.198 | 0.201 | 0.205 | 0.208 | 0.211 | 0.214 |
| 00 02:15:00 | 0 | 0 | 0 | 0 | 0 | 0.021 | 0.182 | 0.188 | 0.022 | 0.022 | 0.022 | 0.022 | 0.185 | 0.188 | 0.191 | 0.195 | 0.158 | 0.192 | 0.197 | 0.2 | 0.204 | 0.206 | 0.209 | 0.212 |
| 00 02:20:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0.175 | 0.188 | 0.021 | 0.021 | 0.022 | 0.022 | 0.184 | 0.187 | 0.19 | 0.195 | 0.163 | 0.19 | 0.196 | 0.199 | 0.203 | 0.205 | 0.207 | 0.21 |
| 00 02:25:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0.104 | 0.187 | 0.021 | 0.021 | 0.021 | 0.021 | 0.181 | 0.187 | 0.189 | 0.194 | 0.152 | 0.186 | 0.195 | 0.198 | 0.202 | 0.204 | 0.206 | 0.209 |
| 00 02:30:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0.023 | 0.187 | 0 | 0 | 0 | 0 | 0.171 | 0.186 | 0.189 | 0.194 | 0.13 | 0.183 | 0.194 | 0.197 | 0.201 | 0.203 | 0.205 | 0.208 |
| 00 02:35:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0.021 | 0.187 | 0 | 0 | 0 | 0 | 0.055 | 0.185 | 0.188 | 0.193 | 0.133 | 0.176 | 0.193 | 0.196 | 0.2 | 0.202 | 0.205 | 0.208 |
| 00 02:40:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.186 | 0 | 0 | 0 | 0 | 0.022 | 0.184 | 0.188 | 0.193 | 0.123 | 0.146 | 0.192 | 0.195 | 0.2 | 0.202 | 0.204 | 0.207 |
| 00 02:45:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.185 | 0 | 0 | 0 | 0 | 0.021 | 0.182 | 0.188 | 0.192 | 0.096 | 0.127 | 0.191 | 0.195 | 0.199 | 0.201 | 0.204 | 0.207 |
| 00 02:50:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.184 | 0 | 0 | 0 | 0 | 0.021 | 0.176 | 0.187 | 0.192 | 0.108 | 0.122 | 0.19 | 0.194 | 0.199 | 0.201 | 0.204 | 0.206 |
| 00 02:55:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.179 | 0 | 0 | 0 | 0 | 0.021 | 0.147 | 0.187 | 0.192 | 0.083 | 0.1 | 0.189 | 0.193 | 0.198 | 0.2 | 0.203 | 0.206 |
| 00 03:00:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.153 | 0 | 0 | 0 | 0 | 0.021 | 0.025 | 0.187 | 0.192 | 0.085 | 0.108 | 0.186 | 0.193 | 0.198 | 0.2 | 0.203 | 0.206 |
| 00 03:05:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.025 | 0 | 0 | 0 | 0 | 0.021 | 0.021 | 0.186 | 0.191 | 0.068 | 0.088 | 0.18 | 0.191 | 0.197 | 0.199 | 0.202 | 0.205 |
| 00 03:10:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.021 | 0 | 0 | 0 | 0 | 0 | 0 | 0.185 | 0.191 | 0.064 | 0.092 | 0.159 | 0.191 | 0.196 | 0.198 | 0.201 | 0.204 |
| 00 03:15:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.185 | 0.191 | 0.032 | 0.073 | 0.106 | 0.189 | 0.195 | 0.198 | 0.201 | 0.203 |
| 00 03:20:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.183 | 0.191 | 0.027 | 0.074 | 0.082 | 0.188 | 0.195 | 0.197 | 0.2 | 0.203 |
| 00 03:25:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.179 | 0.19 | 0.029 | 0.058 | 0.081 | 0.186 | 0.194 | 0.196 | 0.199 | 0.202 |

| | | | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 00 03:30:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.166 | 0.19 | 0.028 | 0.049 | 0.068 | 0.181 | 0.193 | 0.196 | 0.199 | 0.201 |
| 00 03:35:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.029 | 0.19 | 0.026 | 0.026 | 0.058 | 0.168 | 0.192 | 0.195 | 0.198 | 0.201 |
| 00 03:40:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.022 | 0.189 | 0.025 | 0.026 | 0.049 | 0.098 | 0.191 | 0.194 | 0.197 | 0.2 |
| 00 03:45:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.021 | 0.189 | 0.024 | 0.025 | 0.025 | 0.054 | 0.19 | 0.193 | 0.196 | 0.199 |
| 00 03:50:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.188 | 0.024 | 0.024 | 0.024 | 0.038 | 0.189 | 0.192 | 0.196 | 0.198 |
| 00 03:55:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.188 | 0.023 | 0.023 | 0.024 | 0.026 | 0.188 | 0.192 | 0.195 | 0.198 |
| 00 04:00:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.187 | 0.023 | 0.023 | 0.023 | 0.024 | 0.188 | 0.191 | 0.194 | 0.197 |
| 00 04:05:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.187 | 0.022 | 0.022 | 0.023 | 0.022 | 0.187 | 0.19 | 0.194 | 0.197 |
| 00 04:10:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.184 | 0.022 | 0.022 | 0.022 | 0.022 | 0.186 | 0.19 | 0.193 | 0.197 |
| 00 04:15:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.179 | 0.021 | 0.021 | 0.022 | 0.022 | 0.185 | 0.189 | 0.193 | 0.196 |
| 00 04:20:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.154 | 0.021 | 0.021 | 0.021 | 0.021 | 0.185 | 0.188 | 0.192 | 0.196 |
| 00 04:25:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.026 | 0 | 0 | 0 | 0 | 0.184 | 0.188 | 0.192 | 0.195 |
| 00 04:30:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.179 | 0.188 | 0.191 | 0.195 |
| 00 04:35:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.169 | 0.187 | 0.191 | 0.194 |
| 00 04:40:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.066 | 0.187 | 0.19 | 0.194 |
| 00 04:45:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.022 | 0.186 | 0.19 | 0.193 |
| 00 04:50:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.021 | 0.186 | 0.189 | 0.193 |
| 00 04:55:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.185 | 0.189 | 0.193 |
| 00 05:00:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.184 | 0.189 | 0.192 |
| 00 05:05:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.18 | 0.189 | 0.191 |
| 00 05:10:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.172 | 0.188 | 0.191 |
| 00 05:15:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.101 | 0.188 | 0.191 |
| 00 05:20:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.023 | 0.188 | 0.191 |
| 00 05:25:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.021 | 0.187 | 0.191 |
| 00 05:30:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.187 | 0.19 |
| 00 05:35:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.186 | 0.19 |
| 00 05:40:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.186 | 0.19 |
| 00 05:45:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.185 | 0.19 |
| 00 05:50:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.184 | 0.189 |
| 00 05:55:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.182 | 0.189 |
| 00 06:00:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.175 | 0.189 |
| 00 06:05:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.142 | 0.189 |
| 00 06:10:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.024 | 0.188 |
| 00 06:15:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.021 | 0.188 |
| 00 06:20:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.021 | 0.188 |
| 00 06:25:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.187 |
| 00 06:30:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.187 |
| 00 06:35:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.186 |
| 00 06:40:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.186 |
| 00 06:45:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.185 |
| 00 06:50:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.184 |
| 00 06:55:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.182 |
| 00 07:00:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.176 |
| 00 07:05:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.145 |
| 00 07:10:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.025 |
| 00 07:15:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.021 |
| 00 07:20:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

*Table A-C. 2. Simulation output: time-depth table for on-track element 898421 surrounding node BSW 007 1234 U6FT, scenario where pipe downstream from node is in condition 2*

| Scenario | C2-D30-S1 | C2-D30-S2 | C2-D30-S5 | C2-D30-S10 | C2-D30-S30 | C2-D30-S50 | C2-D30-S100 | C2-D30-S200 | C2-D60-S1 | C2-D60-S2 | C2-D60-S5 | C2-D60-S10 | C2-D60-S30 | C2-D60-S50 | C2-D60-S100 | C2-D60-S200 | C2-D180-S1 | C2-D180-S2 | C2-D180-S5 | C2-D180-S10 | C2-D180-S30 | C2-D180-S50 | C2-D180-S100 | C2-D180-S200 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 00 00:00:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 00 00:05:00 | 0 | 0.001 | 0.001 | 0.001 | 0.001 | 0.002 | 0.002 | 0.003 | 0 | 0 | 0 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 00 00:10:00 | 0.002 | 0.003 | 0.004 | 0.006 | 0.009 | 0.012 | 0.016 | 0.023 | 0.001 | 0.001 | 0.001 | 0.002 | 0.003 | 0.003 | 0.004 | 0.006 | 0 | 0 | 0 | 0 | 0.001 | 0.001 | 0.001 | 0.001 |
| 00 00:15:00 | 0.014 | 0.021 | 0.039 | 0.045 | 0.052 | 0.054 | 0.057 | 0.062 | 0.001 | 0.002 | 0.003 | 0.004 | 0.007 | 0.009 | 0.013 | 0.03 | 0 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.002 | 0.003 |
| 00 00:20:00 | 0.044 | 0.047 | 0.051 | 0.054 | 0.058 | 0.061 | 0.067 | 0.079 | 0.003 | 0.004 | 0.008 | 0.01 | 0.031 | 0.031 | 0.033 | 0.034 | 0.001 | 0.001 | 0.001 | 0.001 | 0.002 | 0.003 | 0.003 | 0.005 |
| 00 00:25:00 | 0.028 | 0.03 | 0.041 | 0.051 | 0.066 | 0.073 | 0.08 | 0.093 | 0.008 | 0.013 | 0.032 | 0.032 | 0.037 | 0.037 | 0.039 | 0.043 | 0.001 | 0.001 | 0.002 | 0.002 | 0.003 | 0.004 | 0.006 | 0.008 |
| 00 00:30:00 | 0.039 | 0.048 | 0.059 | 0.063 | 0.079 | 0.086 | 0.189 | 0.204 | 0.035 | 0.04 | 0.042 | 0.045 | 0.052 | 0.054 | 0.06 | 0.07 | 0.001 | 0.002 | 0.002 | 0.003 | 0.005 | 0.006 | 0.008 | 0.026 |
| 00 00:35:00 | 0.038 | 0.05 | 0.057 | 0.096 | 0.193 | 0.202 | 0.21 | 0.216 | 0.039 | 0.043 | 0.047 | 0.052 | 0.064 | 0.073 | 0.087 | 0.1 | 0.001 | 0.002 | 0.003 | 0.004 | 0.007 | 0.01 | 0.025 | 0.025 |
| 00 00:40:00 | 0.037 | 0.047 | 0.151 | 0.183 | 0.2 | 0.208 | 0.215 | 0.219 | 0.031 | 0.044 | 0.053 | 0.061 | 0.075 | 0.083 | 0.096 | 0.177 | 0.002 | 0.003 | 0.004 | 0.006 | 0.022 | 0.024 | 0.025 | 0.027 |
| 00 00:45:00 | 0.039 | 0.097 | 0.186 | 0.193 | 0.206 | 0.209 | 0.212 | 0.214 | 0.044 | 0.053 | 0.061 | 0.066 | 0.169 | 0.197 | 0.215 | 0.224 | 0.003 | 0.004 | 0.006 | 0.008 | 0.024 | 0.025 | 0.027 | 0.028 |
| 00 00:50:00 | 0.04 | 0.119 | 0.191 | 0.198 | 0.205 | 0.207 | 0.209 | 0.211 | 0.047 | 0.054 | 0.127 | 0.183 | 0.207 | 0.212 | 0.221 | 0.23 | 0.003 | 0.005 | 0.008 | 0.024 | 0.026 | 0.027 | 0.027 | 0.028 |
| 00 00:55:00 | 0.039 | 0.138 | 0.191 | 0.2 | 0.203 | 0.205 | 0.206 | 0.209 | 0.047 | 0.118 | 0.18 | 0.198 | 0.213 | 0.218 | 0.223 | 0.226 | 0.005 | 0.007 | 0.024 | 0.025 | 0.027 | 0.027 | 0.028 | 0.036 |
| 00 01:00:00 | 0.037 | 0.131 | 0.176 | 0.198 | 0.201 | 0.203 | 0.204 | 0.207 | 0.047 | 0.128 | 0.194 | 0.202 | 0.213 | 0.216 | 0.219 | 0.222 | 0.006 | 0.019 | 0.025 | 0.026 | 0.027 | 0.028 | 0.036 | 0.038 |
| 00 01:05:00 | 0.034 | 0.13 | 0.17 | 0.196 | 0.2 | 0.201 | 0.203 | 0.205 | 0.06 | 0.18 | 0.199 | 0.206 | 0.211 | 0.213 | 0.215 | 0.218 | 0.008 | 0.024 | 0.026 | 0.027 | 0.031 | 0.036 | 0.038 | 0.041 |
| 00 01:10:00 | 0.031 | 0.104 | 0.126 | 0.192 | 0.198 | 0.2 | 0.202 | 0.204 | 0.129 | 0.188 | 0.201 | 0.205 | 0.208 | 0.21 | 0.212 | 0.215 | 0.024 | 0.026 | 0.027 | 0.028 | 0.037 | 0.038 | 0.042 | 0.051 |
| 00 01:15:00 | 0.028 | 0.093 | 0.125 | 0.184 | 0.197 | 0.198 | 0.2 | 0.203 | 0.115 | 0.178 | 0.2 | 0.203 | 0.207 | 0.208 | 0.21 | 0.212 | 0.026 | 0.028 | 0.029 | 0.036 | 0.04 | 0.043 | 0.052 | 0.056 |
| 00 01:20:00 | 0.026 | 0.06 | 0.09 | 0.143 | 0.195 | 0.197 | 0.199 | 0.201 | 0.136 | 0.172 | 0.199 | 0.202 | 0.205 | 0.207 | 0.209 | 0.211 | 0.029 | 0.029 | 0.037 | 0.041 | 0.046 | 0.054 | 0.058 | 0.063 |
| 00 01:25:00 | 0.025 | 0.028 | 0.088 | 0.099 | 0.194 | 0.196 | 0.198 | 0.201 | 0.128 | 0.153 | 0.197 | 0.2 | 0.204 | 0.205 | 0.207 | 0.209 | 0.03 | 0.036 | 0.042 | 0.045 | 0.057 | 0.06 | 0.066 | 0.14 |
| 00 01:30:00 | 0.024 | 0.025 | 0.062 | 0.069 | 0.193 | 0.195 | 0.197 | 0.2 | 0.1 | 0.122 | 0.194 | 0.199 | 0.203 | 0.204 | 0.206 | 0.208 | 0.035 | 0.044 | 0.047 | 0.056 | 0.064 | 0.091 | 0.156 | 0.208 |
| 00 01:35:00 | 0.023 | 0.023 | 0.026 | 0.05 | 0.192 | 0.194 | 0.196 | 0.199 | 0.095 | 0.125 | 0.189 | 0.197 | 0.201 | 0.203 | 0.205 | 0.207 | 0.043 | 0.045 | 0.057 | 0.062 | 0.144 | 0.179 | 0.209 | 0.221 |
| 00 01:40:00 | 0.023 | 0.023 | 0.024 | 0.025 | 0.187 | 0.194 | 0.196 | 0.199 | 0.031 | 0.106 | 0.179 | 0.196 | 0.2 | 0.202 | 0.204 | 0.206 | 0.042 | 0.054 | 0.06 | 0.128 | 0.193 | 0.209 | 0.22 | 0.233 |
| 00 01:45:00 | 0.022 | 0.022 | 0.022 | 0.023 | 0.168 | 0.193 | 0.195 | 0.198 | 0.026 | 0.087 | 0.128 | 0.194 | 0.199 | 0.201 | 0.203 | 0.205 | 0.051 | 0.056 | 0.137 | 0.185 | 0.209 | 0.218 | 0.229 | 0.236 |
| 00 01:50:00 | 0.022 | 0.022 | 0.022 | 0.022 | 0.034 | 0.191 | 0.195 | 0.198 | 0.025 | 0.064 | 0.085 | 0.192 | 0.198 | 0.2 | 0.202 | 0.204 | 0.052 | 0.133 | 0.185 | 0.201 | 0.217 | 0.223 | 0.229 | 0.234 |
| 00 01:55:00 | 0.021 | 0.021 | 0.021 | 0.021 | 0.023 | 0.187 | 0.194 | 0.197 | 0.024 | 0.026 | 0.071 | 0.186 | 0.197 | 0.199 | 0.201 | 0.203 | 0.058 | 0.166 | 0.197 | 0.208 | 0.218 | 0.222 | 0.226 | 0.23 |
| 00 02:00:00 | 0 | 0 | 0 | 0 | 0.021 | 0.16 | 0.194 | 0.197 | 0.023 | 0.025 | 0.051 | 0.147 | 0.196 | 0.198 | 0.2 | 0.203 | 0.145 | 0.19 | 0.204 | 0.211 | 0.217 | 0.219 | 0.223 | 0.227 |
| 00 02:05:00 | 0 | 0 | 0 | 0 | 0 | 0.026 | 0.193 | 0.197 | 0.023 | 0.023 | 0.024 | 0.061 | 0.195 | 0.197 | 0.2 | 0.202 | 0.162 | 0.194 | 0.206 | 0.21 | 0.214 | 0.217 | 0.22 | 0.224 |
| 00 02:10:00 | 0 | 0 | 0 | 0 | 0 | 0.022 | 0.192 | 0.197 | 0.022 | 0.022 | 0.022 | 0.024 | 0.194 | 0.197 | 0.199 | 0.202 | 0.177 | 0.199 | 0.206 | 0.209 | 0.213 | 0.215 | 0.218 | 0.221 |
| 00 02:15:00 | 0 | 0 | 0 | 0 | 0 | 0.021 | 0.19 | 0.196 | 0.022 | 0.022 | 0.022 | 0.023 | 0.193 | 0.196 | 0.199 | 0.201 | 0.163 | 0.2 | 0.205 | 0.207 | 0.211 | 0.213 | 0.216 | 0.219 |
| 00 02:20:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0.184 | 0.196 | 0.021 | 0.021 | 0.022 | 0.022 | 0.192 | 0.195 | 0.198 | 0.201 | 0.173 | 0.197 | 0.204 | 0.206 | 0.21 | 0.212 | 0.215 | 0.218 |
| 00 02:25:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0.157 | 0.196 | 0 | 0 | 0.021 | 0.021 | 0.189 | 0.195 | 0.197 | 0.2 | 0.161 | 0.194 | 0.203 | 0.205 | 0.209 | 0.211 | 0.214 | 0.217 |
| 00 02:30:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0.025 | 0.195 | 0 | 0 | 0 | 0 | 0.18 | 0.194 | 0.197 | 0.2 | 0.143 | 0.191 | 0.202 | 0.205 | 0.208 | 0.21 | 0.213 | 0.216 |
| 00 02:35:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0.021 | 0.195 | 0 | 0 | 0 | 0 | 0.062 | 0.193 | 0.196 | 0.199 | 0.138 | 0.184 | 0.201 | 0.204 | 0.208 | 0.21 | 0.212 | 0.215 |
| 00 02:40:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.194 | 0 | 0 | 0 | 0 | 0.022 | 0.193 | 0.196 | 0.199 | 0.135 | 0.156 | 0.2 | 0.203 | 0.207 | 0.209 | 0.212 | 0.214 |
| 00 02:45:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.194 | 0 | 0 | 0 | 0 | 0.021 | 0.19 | 0.196 | 0.198 | 0.108 | 0.139 | 0.199 | 0.202 | 0.207 | 0.209 | 0.211 | 0.214 |
| 00 02:50:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.193 | 0 | 0 | 0 | 0 | 0 | 0.183 | 0.195 | 0.198 | 0.118 | 0.135 | 0.198 | 0.202 | 0.206 | 0.208 | 0.211 | 0.214 |
| 00 02:55:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.191 | 0 | 0 | 0 | 0 | 0 | 0.112 | 0.195 | 0.198 | 0.106 | 0.111 | 0.197 | 0.201 | 0.206 | 0.208 | 0.211 | 0.213 |
| 00 03:00:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.189 | 0 | 0 | 0 | 0 | 0 | 0.023 | 0.194 | 0.198 | 0.085 | 0.12 | 0.194 | 0.2 | 0.205 | 0.207 | 0.21 | 0.213 |
| 00 03:05:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.178 | 0 | 0 | 0 | 0 | 0 | 0.021 | 0.194 | 0.197 | 0.093 | 0.105 | 0.188 | 0.199 | 0.204 | 0.207 | 0.209 | 0.212 |
| 00 03:10:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.056 | 0 | 0 | 0 | 0 | 0 | 0 | 0.193 | 0.197 | 0.071 | 0.1 | 0.172 | 0.198 | 0.204 | 0.206 | 0.209 | 0.212 |
| 00 03:15:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.022 | 0 | 0 | 0 | 0 | 0 | 0 | 0.193 | 0.197 | 0.06 | 0.095 | 0.118 | 0.197 | 0.203 | 0.205 | 0.208 | 0.211 |
| 00 03:20:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.021 | 0 | 0 | 0 | 0 | 0 | 0 | 0.19 | 0.197 | 0.029 | 0.089 | 0.097 | 0.196 | 0.202 | 0.205 | 0.208 | 0.21 |
| 00 03:25:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.185 | 0.197 | 0.027 | 0.073 | 0.098 | 0.195 | 0.202 | 0.204 | 0.207 | 0.209 |
| 00 03:30:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.167 | 0.196 | 0.027 | 0.064 | 0.082 | 0.19 | 0.201 | 0.203 | 0.206 | 0.209 |
| 00 03:35:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.03 | 0.196 | 0.026 | 0.029 | 0.07 | 0.172 | 0.2 | 0.202 | 0.206 | 0.208 |
| 00 03:40:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.021 | 0.195 | 0.025 | 0.028 | 0.063 | 0.089 | 0.199 | 0.202 | 0.205 | 0.207 |
| 00 03:45:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.195 | 0.024 | 0.024 | 0.027 | 0.059 | 0.198 | 0.201 | 0.204 | 0.207 |
| 00 03:50:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.195 | 0.024 | 0.024 | 0.023 | 0.039 | 0.197 | 0.2 | 0.203 | 0.206 |

| | | | | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 00 03:55:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.194 | 0.023 | 0.024 | 0.024 | 0.026 | 0.196 | 0.199 | 0.203 | 0.205 |
| 00 04:00:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.194 | 0.023 | 0.023 | 0.023 | 0.024 | 0.196 | 0.199 | 0.202 | 0.205 |
| 00 04:05:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.193 | 0.022 | 0.022 | 0.022 | 0.022 | 0.195 | 0.198 | 0.202 | 0.205 |
| 00 04:10:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.192 | 0.022 | 0.022 | 0.022 | 0.022 | 0.194 | 0.198 | 0.201 | 0.204 |
| 00 04:15:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.189 | 0.021 | 0.021 | 0.022 | 0.022 | 0.193 | 0.197 | 0.201 | 0.204 |
| 00 04:20:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.181 | 0 | 0 | 0.021 | 0.021 | 0.192 | 0.196 | 0.2 | 0.203 |
| 00 04:25:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.13 | 0 | 0 | 0 | 0 | 0.19 | 0.196 | 0.2 | 0.203 |
| 00 04:30:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.024 | 0 | 0 | 0 | 0 | 0.186 | 0.195 | 0.199 | 0.203 |
| 00 04:35:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.021 | 0 | 0 | 0 | 0 | 0.168 | 0.195 | 0.199 | 0.202 |
| 00 04:40:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.031 | 0.194 | 0.198 | 0.202 |
| 00 04:45:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.022 | 0.194 | 0.198 | 0.201 |
| 00 04:50:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.021 | 0.193 | 0.198 | 0.201 |
| 00 04:55:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.193 | 0.197 | 0.2 |
| 00 05:00:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.191 | 0.197 | 0.2 |
| 00 05:05:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.186 | 0.197 | 0.199 |
| 00 05:10:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.17 | 0.197 | 0.199 |
| 00 05:15:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.026 | 0.196 | 0.199 |
| 00 05:20:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.022 | 0.196 | 0.199 |
| 00 05:25:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.021 | 0.195 | 0.198 |
| 00 05:30:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.195 | 0.198 |
| 00 05:35:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.195 | 0.198 |
| 00 05:40:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.194 | 0.198 |
| 00 05:45:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.194 | 0.198 |
| 00 05:50:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.193 | 0.197 |
| 00 05:55:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.192 | 0.197 |
| 00 06:00:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.189 | 0.197 |
| 00 06:05:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.181 | 0.197 |
| 00 06:10:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.13 | 0.196 |
| 00 06:15:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.024 | 0.196 |
| 00 06:20:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.021 | 0.196 |
| 00 06:25:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.195 |
| 00 06:30:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.195 |
| 00 06:35:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.194 |
| 00 06:40:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.194 |
| 00 06:45:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.193 |
| 00 06:50:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.192 |
| 00 06:55:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.188 |
| 00 07:00:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.18 |
| 00 07:05:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.111 |
| 00 07:10:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.023 |
| 00 07:15:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.021 |
| 00 07:20:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

*Table A-C. 3. Simulation output: time-depth table for on-track element 898421 surrounding node BSW 007 1234 U6FT, scenario where pipe downstream from node is in condition 3*

| Scenario | C3-D30-S1 | C3-D30-S2 | C3-D30-S5 | C3-D30-S10 | C3-D30-S30 | C3-D30-S50 | C3-D30-S100 | C3-D30-S200 | C3-D60-S1 | C3-D60-S2 | C3-D60-S5 | C3-D60-S10 | C3-D60-S30 | C3-D60-S50 | C3-D60-S100 | C3-D60-S200 | C3-D180-S1 | C3-D180-S2 | C3-D180-S5 | C3-D180-S10 | C3-D180-S30 | C3-D180-S50 | C3-D180-S100 | C3-D180-S200 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 00 00:00:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 00 00:05:00 | 0 | 0.001 | 0.001 | 0.001 | 0.001 | 0.002 | 0.002 | 0.003 | 0 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 00 00:10:00 | 0.002 | 0.003 | 0.004 | 0.006 | 0.009 | 0.012 | 0.016 | 0.023 | 0.001 | 0.002 | 0.003 | 0.002 | 0.003 | 0.003 | 0.004 | 0.006 | 0 | 0 | 0 | 0 | 0.001 | 0.001 | 0.001 | 0.001 |
| 00 00:15:00 | 0.014 | 0.021 | 0.039 | 0.045 | 0.052 | 0.054 | 0.057 | 0.062 | 0.001 | 0.004 | 0.008 | 0.004 | 0.007 | 0.009 | 0.013 | 0.03 | 0 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.002 | 0.003 |

| | | | | | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 00 00:20:00 | 0.044 | 0.047 | 0.051 | 0.054 | 0.058 | 0.061 | 0.067 | 0.079 | 0.003 | 0.013 | 0.032 | 0.01 | 0.031 | 0.031 | 0.033 | 0.034 | 0.001 | 0.001 | 0.001 | 0.001 | 0.002 | 0.003 | 0.003 | 0.005 |
| 00 00:25:00 | 0.028 | 0.03 | 0.041 | 0.051 | 0.066 | 0.073 | 0.08 | 0.093 | 0.008 | 0.04 | 0.042 | 0.032 | 0.037 | 0.037 | 0.039 | 0.043 | 0.001 | 0.001 | 0.002 | 0.002 | 0.003 | 0.004 | 0.006 | 0.008 |
| 00 00:30:00 | 0.039 | 0.048 | 0.059 | 0.063 | 0.079 | 0.086 | 0.202 | 0.217 | 0.035 | 0.043 | 0.047 | 0.045 | 0.052 | 0.054 | 0.06 | 0.07 | 0.001 | 0.002 | 0.002 | 0.003 | 0.005 | 0.006 | 0.008 | 0.026 |
| 00 00:35:00 | 0.038 | 0.05 | 0.057 | 0.132 | 0.207 | 0.215 | 0.22 | 0.227 | 0.039 | 0.044 | 0.053 | 0.052 | 0.064 | 0.073 | 0.087 | 0.1 | 0.001 | 0.002 | 0.003 | 0.004 | 0.007 | 0.01 | 0.025 | 0.025 |
| 00 00:40:00 | 0.037 | 0.047 | 0.16 | 0.195 | 0.211 | 0.219 | 0.225 | 0.229 | 0.031 | 0.053 | 0.061 | 0.061 | 0.075 | 0.083 | 0.096 | 0.19 | 0.002 | 0.003 | 0.004 | 0.006 | 0.022 | 0.024 | 0.025 | 0.027 |
| 00 00:45:00 | 0.039 | 0.123 | 0.198 | 0.204 | 0.217 | 0.22 | 0.223 | 0.225 | 0.044 | 0.054 | 0.148 | 0.066 | 0.183 | 0.212 | 0.225 | 0.234 | 0.003 | 0.004 | 0.006 | 0.008 | 0.024 | 0.025 | 0.027 | 0.028 |
| 00 00:50:00 | 0.04 | 0.137 | 0.201 | 0.209 | 0.217 | 0.218 | 0.22 | 0.222 | 0.047 | 0.132 | 0.192 | 0.192 | 0.219 | 0.222 | 0.23 | 0.241 | 0.003 | 0.005 | 0.008 | 0.024 | 0.026 | 0.027 | 0.027 | 0.028 |
| 00 00:55:00 | 0.039 | 0.154 | 0.203 | 0.211 | 0.215 | 0.216 | 0.218 | 0.22 | 0.047 | 0.144 | 0.204 | 0.209 | 0.224 | 0.229 | 0.233 | 0.237 | 0.005 | 0.007 | 0.024 | 0.025 | 0.027 | 0.027 | 0.028 | 0.036 |
| 00 01:00:00 | 0.037 | 0.147 | 0.191 | 0.21 | 0.213 | 0.214 | 0.216 | 0.218 | 0.087 | 0.192 | 0.209 | 0.215 | 0.224 | 0.227 | 0.23 | 0.233 | 0.006 | 0.019 | 0.025 | 0.026 | 0.027 | 0.028 | 0.036 | 0.038 |
| 00 01:05:00 | 0.034 | 0.147 | 0.182 | 0.208 | 0.212 | 0.213 | 0.215 | 0.217 | 0.088 | 0.199 | 0.213 | 0.217 | 0.222 | 0.224 | 0.226 | 0.229 | 0.008 | 0.024 | 0.026 | 0.027 | 0.031 | 0.036 | 0.038 | 0.041 |
| 00 01:10:00 | 0.031 | 0.122 | 0.156 | 0.204 | 0.21 | 0.212 | 0.213 | 0.215 | 0.145 | 0.191 | 0.212 | 0.216 | 0.22 | 0.221 | 0.224 | 0.226 | 0.024 | 0.026 | 0.027 | 0.028 | 0.037 | 0.038 | 0.042 | 0.051 |
| 00 01:15:00 | 0.028 | 0.116 | 0.127 | 0.198 | 0.209 | 0.21 | 0.212 | 0.214 | 0.134 | 0.183 | 0.211 | 0.215 | 0.218 | 0.22 | 0.222 | 0.224 | 0.026 | 0.028 | 0.029 | 0.036 | 0.04 | 0.043 | 0.052 | 0.056 |
| 00 01:20:00 | 0.029 | 0.087 | 0.126 | 0.17 | 0.207 | 0.209 | 0.211 | 0.213 | 0.153 | 0.166 | 0.209 | 0.213 | 0.217 | 0.218 | 0.22 | 0.222 | 0.029 | 0.029 | 0.037 | 0.041 | 0.046 | 0.054 | 0.058 | 0.063 |
| 00 01:25:00 | 0.025 | 0.028 | 0.102 | 0.122 | 0.206 | 0.208 | 0.21 | 0.212 | 0.143 | 0.142 | 0.206 | 0.212 | 0.215 | 0.217 | 0.219 | 0.221 | 0.03 | 0.036 | 0.042 | 0.045 | 0.057 | 0.06 | 0.101 | 0.158 |
| 00 01:30:00 | 0.024 | 0.024 | 0.089 | 0.095 | 0.205 | 0.207 | 0.209 | 0.212 | 0.12 | 0.141 | 0.201 | 0.21 | 0.214 | 0.216 | 0.218 | 0.22 | 0.035 | 0.044 | 0.047 | 0.056 | 0.064 | 0.125 | 0.169 | 0.219 |
| 00 01:35:00 | 0.023 | 0.023 | 0.023 | 0.073 | 0.204 | 0.206 | 0.209 | 0.211 | 0.113 | 0.124 | 0.19 | 0.209 | 0.213 | 0.215 | 0.216 | 0.219 | 0.043 | 0.045 | 0.057 | 0.062 | 0.16 | 0.187 | 0.22 | 0.232 |
| 00 01:40:00 | 0.023 | 0.023 | 0.024 | 0.022 | 0.2 | 0.206 | 0.208 | 0.21 | 0.056 | 0.103 | 0.148 | 0.208 | 0.212 | 0.213 | 0.215 | 0.217 | 0.042 | 0.054 | 0.06 | 0.144 | 0.205 | 0.219 | 0.231 | 0.244 |
| 00 01:45:00 | 0.022 | 0.022 | 0.023 | 0.024 | 0.19 | 0.205 | 0.208 | 0.21 | 0.044 | 0.101 | 0.109 | 0.206 | 0.211 | 0.212 | 0.214 | 0.217 | 0.051 | 0.056 | 0.15 | 0.198 | 0.219 | 0.228 | 0.24 | 0.247 |
| 00 01:50:00 | 0.022 | 0.022 | 0.022 | 0.022 | 0.107 | 0.203 | 0.207 | 0.209 | 0.027 | 0.045 | 0.095 | 0.203 | 0.21 | 0.211 | 0.213 | 0.216 | 0.052 | 0.144 | 0.197 | 0.213 | 0.228 | 0.234 | 0.239 | 0.245 |
| 00 01:55:00 | 0.021 | 0.021 | 0.021 | 0.021 | 0.023 | 0.199 | 0.207 | 0.209 | 0.025 | 0.025 | 0.059 | 0.198 | 0.209 | 0.211 | 0.213 | 0.215 | 0.093 | 0.179 | 0.209 | 0.22 | 0.229 | 0.233 | 0.237 | 0.241 |
| 00 02:00:00 | 0 | 0 | 0 | 0 | 0.022 | 0.187 | 0.206 | 0.209 | 0.023 | 0.024 | 0.025 | 0.179 | 0.208 | 0.21 | 0.212 | 0.215 | 0.158 | 0.203 | 0.216 | 0.222 | 0.228 | 0.23 | 0.234 | 0.238 |
| 00 02:05:00 | 0 | 0 | 0 | 0 | 0.021 | 0.066 | 0.205 | 0.208 | 0.023 | 0.022 | 0.024 | 0.101 | 0.207 | 0.209 | 0.212 | 0.214 | 0.175 | 0.206 | 0.218 | 0.221 | 0.226 | 0.228 | 0.231 | 0.235 |
| 00 02:10:00 | 0 | 0 | 0 | 0 | 0 | 0.023 | 0.205 | 0.208 | 0.022 | 0.022 | 0.022 | 0.054 | 0.206 | 0.209 | 0.211 | 0.213 | 0.189 | 0.211 | 0.217 | 0.22 | 0.224 | 0.226 | 0.229 | 0.232 |
| 00 02:15:00 | 0 | 0 | 0 | 0 | 0 | 0.021 | 0.202 | 0.208 | 0.022 | 0.021 | 0.022 | 0.024 | 0.205 | 0.208 | 0.21 | 0.213 | 0.178 | 0.212 | 0.216 | 0.219 | 0.223 | 0.225 | 0.227 | 0.23 |
| 00 02:20:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0.197 | 0.207 | 0.021 | 0.021 | 0.021 | 0.022 | 0.205 | 0.207 | 0.21 | 0.213 | 0.183 | 0.209 | 0.215 | 0.218 | 0.222 | 0.223 | 0.226 | 0.229 |
| 00 02:25:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0.17 | 0.207 | 0 | 0 | 0 | 0.021 | 0.202 | 0.207 | 0.209 | 0.212 | 0.174 | 0.206 | 0.214 | 0.217 | 0.221 | 0.222 | 0.225 | 0.228 |
| 00 02:30:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0.03 | 0.206 | 0 | 0 | 0 | 0 | 0.195 | 0.206 | 0.209 | 0.212 | 0.154 | 0.203 | 0.214 | 0.216 | 0.22 | 0.222 | 0.224 | 0.227 |
| 00 02:35:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0.021 | 0.206 | 0 | 0 | 0 | 0 | 0.154 | 0.205 | 0.208 | 0.211 | 0.157 | 0.195 | 0.213 | 0.215 | 0.219 | 0.221 | 0.224 | 0.226 |
| 00 02:40:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.205 | 0 | 0 | 0 | 0 | 0.027 | 0.204 | 0.208 | 0.211 | 0.149 | 0.174 | 0.212 | 0.215 | 0.219 | 0.221 | 0.223 | 0.226 |
| 00 02:45:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.204 | 0 | 0 | 0 | 0 | 0.021 | 0.202 | 0.208 | 0.211 | 0.128 | 0.146 | 0.211 | 0.214 | 0.218 | 0.22 | 0.223 | 0.225 |
| 00 02:50:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.2 | 0 | 0 | 0 | 0 | 0 | 0.196 | 0.207 | 0.21 | 0.136 | 0.152 | 0.21 | 0.213 | 0.218 | 0.22 | 0.222 | 0.225 |
| 00 02:55:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.19 | 0 | 0 | 0 | 0 | 0 | 0.166 | 0.207 | 0.21 | 0.119 | 0.132 | 0.209 | 0.212 | 0.217 | 0.219 | 0.222 | 0.225 |
| 00 03:00:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.102 | 0 | 0 | 0 | 0 | 0 | 0.029 | 0.207 | 0.21 | 0.119 | 0.133 | 0.206 | 0.212 | 0.217 | 0.219 | 0.222 | 0.225 |
| 00 03:05:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.023 | 0 | 0 | 0 | 0 | 0 | 0.021 | 0.206 | 0.21 | 0.108 | 0.127 | 0.201 | 0.211 | 0.216 | 0.218 | 0.221 | 0.224 |
| 00 03:10:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.021 | 0 | 0 | 0 | 0 | 0 | 0 | 0.206 | 0.21 | 0.104 | 0.115 | 0.185 | 0.21 | 0.215 | 0.218 | 0.22 | 0.223 |
| 00 03:15:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.205 | 0.209 | 0.068 | 0.119 | 0.138 | 0.209 | 0.215 | 0.217 | 0.22 | 0.222 |
| 00 03:20:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.203 | 0.209 | 0.053 | 0.109 | 0.119 | 0.208 | 0.214 | 0.216 | 0.219 | 0.222 |
| 00 03:25:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.199 | 0.209 | 0.026 | 0.103 | 0.119 | 0.206 | 0.213 | 0.216 | 0.219 | 0.221 |
| 00 03:30:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.186 | 0.209 | 0.026 | 0.08 | 0.107 | 0.202 | 0.213 | 0.215 | 0.218 | 0.22 |
| 00 03:35:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.063 | 0.208 | 0.028 | 0.056 | 0.098 | 0.19 | 0.212 | 0.214 | 0.217 | 0.22 |
| 00 03:40:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.022 | 0.208 | 0.025 | 0.029 | 0.068 | 0.13 | 0.211 | 0.213 | 0.216 | 0.219 |
| 00 03:45:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.021 | 0.207 | 0.024 | 0.026 | 0.042 | 0.095 | 0.21 | 0.213 | 0.216 | 0.218 |
| 00 03:50:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.207 | 0.024 | 0.024 | 0.026 | 0.077 | 0.209 | 0.212 | 0.215 | 0.218 |
| 00 03:55:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.207 | 0.023 | 0.023 | 0.025 | 0.025 | 0.208 | 0.211 | 0.215 | 0.217 |
| 00 04:00:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.207 | 0.023 | 0.023 | 0.023 | 0.025 | 0.208 | 0.211 | 0.214 | 0.217 |
| 00 04:05:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.206 | 0.022 | 0.022 | 0.023 | 0.023 | 0.207 | 0.21 | 0.214 | 0.216 |
| 00 04:10:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.205 | 0.022 | 0.022 | 0.022 | 0.022 | 0.206 | 0.21 | 0.213 | 0.216 |
| 00 04:15:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.204 | 0.021 | 0.021 | 0.022 | 0.022 | 0.205 | 0.209 | 0.213 | 0.216 |
| 00 04:20:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.2 | 0 | 0 | 0.021 | 0.021 | 0.205 | 0.208 | 0.212 | 0.215 |
| 00 04:25:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.19 | 0 | 0 | 0 | 0 | 0.203 | 0.208 | 0.212 | 0.215 |
| 00 04:30:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.104 | 0 | 0 | 0 | 0 | 0.198 | 0.208 | 0.211 | 0.214 |
| 00 04:35:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.023 | 0 | 0 | 0 | 0 | 0.182 | 0.207 | 0.211 | 0.214 |

| | | | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 00 04:40:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.021 | 0 | 0 | 0 | 0 | 0.06 | 0.207 | 0.21 | 0.214 |
| 00 04:45:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.022 | 0.206 | 0.21 | 0.213 |
| 00 04:50:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.021 | 0.206 | 0.21 | 0.213 |
| 00 04:55:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.205 | 0.209 | 0.212 |
| 00 05:00:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.204 | 0.209 | 0.212 |
| 00 05:05:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.201 | 0.209 | 0.211 |
| 00 05:10:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.194 | 0.209 | 0.211 |
| 00 05:15:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.148 | 0.208 | 0.211 |
| 00 05:20:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.023 | 0.208 | 0.211 |
| 00 05:25:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.021 | 0.208 | 0.21 |
| 00 05:30:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.207 | 0.21 |
| 00 05:35:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.207 | 0.21 |
| 00 05:40:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.207 | 0.21 |
| 00 05:45:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.206 | 0.21 |
| 00 05:50:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.205 | 0.209 |
| 00 05:55:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.204 | 0.209 |
| 00 06:00:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.202 | 0.209 |
| 00 06:05:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.195 | 0.209 |
| 00 06:10:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.158 | 0.208 |
| 00 06:15:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.023 | 0.208 |
| 00 06:20:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.021 | 0.208 |
| 00 06:25:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.207 |
| 00 06:30:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.207 |
| 00 06:35:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.206 |
| 00 06:40:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.206 |
| 00 06:45:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.205 |
| 00 06:50:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.204 |
| 00 06:55:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.2 |
| 00 07:00:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.191 |
| 00 07:05:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.11 |
| 00 07:10:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.023 |
| 00 07:15:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.021 |
| 00 07:20:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

*Table A-C. 4. Simulation output: time-depth table for on-track element 904283 surrounding node BSW 007 1126 DCE, scenario where pipe downstream from node is in condition 1*

| Scenario | C1-D30-S1 | C1-D30-S2 | C1-D30-S5 | C1-D30-S10 | C1-D30-S30 | C1-D30-S50 | C1-D30-S100 | C1-D30-S200 | C1-D60-S1 | C1-D60-S2 | C1-D60-S5 | C1-D60-S10 | C1-D60-S30 | C1-D60-S50 | C1-D60-S100 | C1-D60-S200 | C1-D180-S1 | C1-D180-S2 | C1-D180-S5 | C1-D180-S10 | C1-D180-S30 | C1-D180-S50 | C1-D180-S100 | C1-D180-S200 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 00 00:00:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 00 00:05:00 | 0 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.003 | 0 | 0 | 0 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 00 00:10:00 | 0.001 | 0.002 | 0.004 | 0.006 | 0.01 | 0.011 | 0.013 | 0.014 | 0.001 | 0.001 | 0.001 | 0.001 | 0.002 | 0.003 | 0.004 | 0.007 | 0 | 0 | 0 | 0 | 0.001 | 0.001 | 0.001 | 0.001 |
| 00 00:15:00 | 0.013 | 0.016 | 0.026 | 0.034 | 0.045 | 0.05 | 0.058 | 0.066 | 0.001 | 0.001 | 0.003 | 0.004 | 0.007 | 0.008 | 0.009 | 0.017 | 0 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.002 |
| 00 00:20:00 | 0.038 | 0.047 | 0.071 | 0.091 | 0.109 | 0.114 | 0.172 | 0.271 | 0.003 | 0.005 | 0.007 | 0.008 | 0.018 | 0.021 | 0.026 | 0.041 | 0.001 | 0.001 | 0.001 | 0.001 | 0.002 | 0.002 | 0.003 | 0.005 |
| 00 00:25:00 | 0.062 | 0.081 | 0.099 | 0.126 | 0.262 | 0.33 | 0.436 | 0.548 | 0.008 | 0.01 | 0.02 | 0.025 | 0.056 | 0.06 | 0.079 | 0.086 | 0.001 | 0.001 | 0.001 | 0.001 | 0.003 | 0.004 | 0.005 | 0.007 |
| 00 00:30:00 | 0.079 | 0.1 | 0.164 | 0.254 | 0.405 | 0.481 | 0.591 | 0.7 | 0.025 | 0.032 | 0.057 | 0.08 | 0.098 | 0.11 | 0.134 | 0.192 | 0.001 | 0.001 | 0.002 | 0.003 | 0.005 | 0.005 | 0.01 | 0.013 |
| 00 00:35:00 | 0.091 | 0.139 | 0.254 | 0.345 | 0.496 | 0.569 | 0.672 | 0.775 | 0.046 | 0.08 | 0.102 | 0.126 | 0.266 | 0.339 | 0.434 | 0.522 | 0.001 | 0.002 | 0.003 | 0.004 | 0.008 | 0.01 | 0.013 | 0.029 |
| 00 00:40:00 | 0.106 | 0.198 | 0.318 | 0.405 | 0.55 | 0.62 | 0.717 | 0.816 | 0.08 | 0.101 | 0.191 | 0.289 | 0.455 | 0.536 | 0.649 | 0.752 | 0.001 | 0.002 | 0.004 | 0.006 | 0.011 | 0.013 | 0.016 | 0.033 |
| 00 00:45:00 | 0.118 | 0.238 | 0.357 | 0.443 | 0.584 | 0.651 | 0.745 | 0.842 | 0.097 | 0.161 | 0.307 | 0.41 | 0.584 | 0.667 | 0.774 | 0.878 | 0.002 | 0.003 | 0.007 | 0.009 | 0.013 | 0.014 | 0.027 | 0.038 |
| 00 00:50:00 | 0.085 | 0.234 | 0.361 | 0.448 | 0.585 | 0.656 | 0.749 | 0.854 | 0.131 | 0.249 | 0.395 | 0.498 | 0.668 | 0.746 | 0.851 | 0.955 | 0.003 | 0.004 | 0.009 | 0.011 | 0.014 | 0.015 | 0.031 | 0.054 |
| 00 00:55:00 | 0.043 | 0.17 | 0.31 | 0.402 | 0.541 | 0.616 | 0.714 | 0.835 | 0.197 | 0.32 | 0.461 | 0.562 | 0.724 | 0.801 | 0.904 | 1.008 | 0.004 | 0.008 | 0.01 | 0.013 | 0.015 | 0.027 | 0.04 | 0.064 |
| 00 01:00:00 | 0.005 | 0.065 | 0.229 | 0.329 | 0.481 | 0.563 | 0.667 | 0.796 | 0.246 | 0.373 | 0.511 | 0.611 | 0.767 | 0.842 | 0.945 | 1.048 | 0.007 | 0.01 | 0.012 | 0.014 | 0.02 | 0.034 | 0.053 | 0.075 |

| | | | | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 00 01:05:00 | 0.003 | 0.004 | 0.113 | 0.234 | 0.414 | 0.508 | 0.62 | 0.756 | 0.264 | 0.404 | 0.543 | 0.642 | 0.797 | 0.872 | 0.973 | 1.075 | 0.009 | 0.011 | 0.014 | 0.016 | 0.033 | 0.041 | 0.065 | 0.089 |
| 00 01:10:00 | 0.002 | 0.003 | 0.024 | 0.115 | 0.333 | 0.44 | 0.562 | 0.707 | 0.236 | 0.4 | 0.556 | 0.663 | 0.819 | 0.893 | 0.993 | 1.094 | 0.011 | 0.014 | 0.017 | 0.019 | 0.049 | 0.065 | 0.081 | 0.118 |
| 00 01:15:00 | 0.002 | 0.002 | 0.002 | 0.023 | 0.236 | 0.358 | 0.494 | 0.65 | 0.181 | 0.367 | 0.541 | 0.666 | 0.832 | 0.907 | 1.006 | 1.107 | 0.015 | 0.017 | 0.021 | 0.038 | 0.07 | 0.084 | 0.107 | 0.212 |
| 00 01:20:00 | 0.001 | 0.001 | 0.002 | 0.002 | 0.122 | 0.266 | 0.418 | 0.59 | 0.107 | 0.31 | 0.496 | 0.633 | 0.821 | 0.902 | 1.008 | 1.112 | 0.018 | 0.022 | 0.043 | 0.065 | 0.091 | 0.113 | 0.189 | 0.336 |
| 00 01:25:00 | 0 | 0 | 0.001 | 0.001 | 0.028 | 0.153 | 0.328 | 0.524 | 0.036 | 0.23 | 0.434 | 0.579 | 0.779 | 0.866 | 0.978 | 1.091 | 0.023 | 0.046 | 0.076 | 0.089 | 0.134 | 0.221 | 0.33 | 0.472 |
| 00 01:30:00 | 0 | 0 | 0 | 0 | 0.001 | 0.037 | 0.228 | 0.446 | 0.004 | 0.117 | 0.358 | 0.519 | 0.727 | 0.818 | 0.933 | 1.053 | 0.058 | 0.079 | 0.098 | 0.128 | 0.278 | 0.371 | 0.48 | 0.62 |
| 00 01:35:00 | 0 | 0 | 0 | 0 | 0.001 | 0.001 | 0.107 | 0.358 | 0.003 | 0.025 | 0.263 | 0.448 | 0.676 | 0.771 | 0.889 | 1.016 | 0.08 | 0.1 | 0.171 | 0.267 | 0.429 | 0.52 | 0.635 | 0.769 |
| 00 01:40:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0.024 | 0.259 | 0.002 | 0.002 | 0.155 | 0.363 | 0.617 | 0.718 | 0.841 | 0.973 | 0.098 | 0.166 | 0.297 | 0.395 | 0.56 | 0.65 | 0.762 | 0.895 |
| 00 01:45:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0.001 | 0.143 | 0.001 | 0.002 | 0.035 | 0.268 | 0.551 | 0.657 | 0.787 | 0.928 | 0.144 | 0.268 | 0.401 | 0.498 | 0.664 | 0.75 | 0.861 | 0.994 |
| 00 01:50:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.029 | 0 | 0.001 | 0.001 | 0.156 | 0.478 | 0.593 | 0.73 | 0.881 | 0.23 | 0.355 | 0.484 | 0.581 | 0.742 | 0.826 | 0.938 | 1.07 |
| 00 01:55:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.001 | 0 | 0 | 0 | 0.036 | 0.394 | 0.524 | 0.67 | 0.832 | 0.301 | 0.422 | 0.55 | 0.645 | 0.801 | 0.884 | 0.996 | 1.128 |
| 00 02:00:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.001 | 0.3 | 0.445 | 0.604 | 0.779 | 0.358 | 0.476 | 0.603 | 0.694 | 0.847 | 0.93 | 1.041 | 1.173 |
| 00 02:05:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.191 | 0.355 | 0.534 | 0.722 | 0.4 | 0.519 | 0.644 | 0.733 | 0.885 | 0.966 | 1.077 | 1.207 |
| 00 02:10:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.066 | 0.255 | 0.456 | 0.662 | 0.425 | 0.551 | 0.676 | 0.764 | 0.915 | 0.996 | 1.106 | 1.235 |
| 00 02:15:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.004 | 0.138 | 0.368 | 0.598 | 0.416 | 0.566 | 0.696 | 0.79 | 0.94 | 1.022 | 1.131 | 1.259 |
| 00 02:20:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.001 | 0.027 | 0.269 | 0.529 | 0.381 | 0.552 | 0.7 | 0.808 | 0.961 | 1.044 | 1.153 | 1.279 |
| 00 02:25:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.001 | 0.001 | 0.153 | 0.45 | 0.336 | 0.526 | 0.694 | 0.815 | 0.978 | 1.063 | 1.172 | 1.298 |
| 00 02:30:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.031 | 0.362 | 0.281 | 0.492 | 0.673 | 0.805 | 0.987 | 1.077 | 1.188 | 1.314 | |
| 00 02:35:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.001 | 0.262 | 0.219 | 0.45 | 0.647 | 0.787 | 0.982 | 1.084 | 1.202 | 1.33 |
| 00 02:40:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.146 | 0.148 | 0.405 | 0.621 | 0.764 | 0.976 | 1.087 | 1.213 | 1.344 |
| 00 02:45:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.03 | 0.075 | 0.354 | 0.587 | 0.739 | 0.963 | 1.077 | 1.222 | 1.356 |
| 00 02:50:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.002 | 0.04 | 0.299 | 0.55 | 0.711 | 0.946 | 1.067 | 1.223 | 1.367 |
| 00 02:55:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.001 | 0.011 | 0.237 | 0.512 | 0.679 | 0.931 | 1.056 | 1.222 | 1.376 |
| 00 03:00:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.009 | 0.168 | 0.467 | 0.646 | 0.909 | 1.039 | 1.218 | 1.382 |
| 00 03:05:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.008 | 0.092 | 0.417 | 0.608 | 0.885 | 1.023 | 1.207 | 1.38 |
| 00 03:10:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.007 | 0.054 | 0.361 | 0.567 | 0.86 | 1.005 | 1.197 | 1.373 |
| 00 03:15:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.006 | 0.013 | 0.299 | 0.52 | 0.827 | 0.979 | 1.177 | 1.361 |
| 00 03:20:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.005 | 0.005 | 0.224 | 0.461 | 0.786 | 0.945 | 1.147 | 1.333 |
| 00 03:25:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.004 | 0.004 | 0.122 | 0.389 | 0.737 | 0.903 | 1.112 | 1.3 |
| 00 03:30:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.003 | 0.003 | 0.031 | 0.299 | 0.679 | 0.855 | 1.071 | 1.266 |
| 00 03:35:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.002 | 0.003 | 0.003 | 0.191 | 0.618 | 0.804 | 1.028 | 1.229 |
| 00 03:40:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.002 | 0.002 | 0.002 | 0.066 | 0.55 | 0.749 | 0.982 | 1.19 |
| 00 03:45:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.001 | 0.001 | 0.002 | 0.002 | 0.477 | 0.69 | 0.934 | 1.15 |
| 00 03:50:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.001 | 0.001 | 0.001 | 0.393 | 0.628 | 0.885 | 1.108 |
| 00 03:55:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.299 | 0.561 | 0.832 | 1.063 |
| 00 04:00:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.191 | 0.489 | 0.776 | 1.016 |
| 00 04:05:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.066 | 0.406 | 0.717 | 0.968 |
| 00 04:10:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.001 | 0.313 | 0.654 | 0.917 |
| 00 04:15:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.206 | 0.587 | 0.864 |
| 00 04:20:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.081 | 0.516 | 0.809 |
| 00 04:25:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.004 | 0.435 | 0.751 |
| 00 04:30:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.344 | 0.689 |
| 00 04:35:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.24 | 0.623 |
| 00 04:40:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.119 | 0.553 |
| 00 04:45:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.022 | 0.477 |
| 00 04:50:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.001 | 0.39 |
| 00 04:55:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.292 |
| 00 05:00:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.18 |
| 00 05:05:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.051 |
| 00 05:10:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.001 |

*Table A-C. 5. Simulation output: time-depth table for on-track element 904283 surrounding node BSW 007 1126 DCE, scenario where pipe downstream from node is in condition 2*

| Scenario | C2-D30-S1 | C2-D30-S2 | C2-D30-S5 | C2-D30-S10 | C2-D30-S30 | C2-D30-S50 | C2-D30-S100 | C2-D30-S200 | C2-D60-S1 | C2-D60-S2 | C2-D60-S5 | C2-D60-S10 | C2-D60-S30 | C2-D60-S50 | C2-D60-S100 | C2-D60-S200 | C2-D180-S1 | C2-D180-S2 | C2-D180-S5 | C2-D180-S10 | C2-D180-S30 | C2-D180-S50 | C2-D180-S100 | C2-D180-S200 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 00 00:00:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 00 00:05:00 | 0 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.003 | 0 | 0 | 0 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 00 00:10:00 | 0.001 | 0.002 | 0.004 | 0.006 | 0.01 | 0.011 | 0.013 | 0.014 | 0.001 | 0.001 | 0.001 | 0.001 | 0.002 | 0.003 | 0.004 | 0.007 | 0 | 0 | 0 | 0 | 0.001 | 0.001 | 0.001 | 0.001 |
| 00 00:15:00 | 0.013 | 0.016 | 0.026 | 0.034 | 0.045 | 0.05 | 0.058 | 0.066 | 0.001 | 0.001 | 0.003 | 0.004 | 0.007 | 0.008 | 0.009 | 0.017 | 0 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.002 |
| 00 00:20:00 | 0.038 | 0.047 | 0.079 | 0.095 | 0.111 | 0.119 | 0.177 | 0.272 | 0.003 | 0.005 | 0.007 | 0.008 | 0.018 | 0.021 | 0.026 | 0.042 | 0.001 | 0.001 | 0.001 | 0.001 | 0.002 | 0.002 | 0.003 | 0.005 |
| 00 00:25:00 | 0.07 | 0.086 | 0.102 | 0.128 | 0.261 | 0.332 | 0.441 | 0.55 | 0.008 | 0.01 | 0.02 | 0.025 | 0.057 | 0.065 | 0.081 | 0.093 | 0.001 | 0.001 | 0.001 | 0.001 | 0.003 | 0.004 | 0.005 | 0.007 |
| 00 00:30:00 | 0.085 | 0.1 | 0.169 | 0.255 | 0.405 | 0.483 | 0.603 | 0.702 | 0.025 | 0.032 | 0.059 | 0.086 | 0.104 | 0.112 | 0.137 | 0.199 | 0.001 | 0.001 | 0.002 | 0.003 | 0.005 | 0.005 | 0.01 | 0.013 |
| 00 00:35:00 | 0.093 | 0.135 | 0.259 | 0.346 | 0.497 | 0.571 | 0.683 | 0.776 | 0.05 | 0.086 | 0.1 | 0.129 | 0.277 | 0.344 | 0.437 | 0.528 | 0.001 | 0.002 | 0.003 | 0.004 | 0.008 | 0.01 | 0.013 | 0.03 |
| 00 00:40:00 | 0.105 | 0.199 | 0.322 | 0.406 | 0.551 | 0.622 | 0.727 | 0.818 | 0.086 | 0.107 | 0.2 | 0.294 | 0.463 | 0.541 | 0.65 | 0.756 | 0.001 | 0.002 | 0.004 | 0.006 | 0.011 | 0.013 | 0.021 | 0.046 |
| 00 00:45:00 | 0.118 | 0.237 | 0.361 | 0.444 | 0.585 | 0.653 | 0.754 | 0.844 | 0.101 | 0.17 | 0.316 | 0.414 | 0.591 | 0.671 | 0.776 | 0.882 | 0.002 | 0.003 | 0.007 | 0.009 | 0.013 | 0.014 | 0.029 | 0.053 |
| 00 00:50:00 | 0.085 | 0.228 | 0.361 | 0.448 | 0.588 | 0.664 | 0.763 | 0.855 | 0.142 | 0.257 | 0.403 | 0.501 | 0.674 | 0.75 | 0.853 | 0.958 | 0.003 | 0.004 | 0.009 | 0.011 | 0.014 | 0.016 | 0.048 | 0.061 |
| 00 00:55:00 | 0.043 | 0.161 | 0.308 | 0.4 | 0.546 | 0.634 | 0.738 | 0.836 | 0.209 | 0.328 | 0.468 | 0.565 | 0.73 | 0.804 | 0.906 | 1.011 | 0.004 | 0.008 | 0.01 | 0.013 | 0.015 | 0.029 | 0.039 | 0.068 |
| 00 01:00:00 | 0.005 | 0.052 | 0.225 | 0.326 | 0.487 | 0.583 | 0.694 | 0.797 | 0.257 | 0.38 | 0.517 | 0.613 | 0.772 | 0.845 | 0.946 | 1.051 | 0.007 | 0.01 | 0.012 | 0.014 | 0.026 | 0.046 | 0.066 | 0.077 |
| 00 01:05:00 | 0.003 | 0.004 | 0.109 | 0.229 | 0.421 | 0.529 | 0.646 | 0.758 | 0.274 | 0.41 | 0.549 | 0.645 | 0.802 | 0.875 | 0.974 | 1.078 | 0.009 | 0.011 | 0.014 | 0.016 | 0.034 | 0.059 | 0.076 | 0.089 |
| 00 01:10:00 | 0.002 | 0.003 | 0.019 | 0.11 | 0.341 | 0.462 | 0.589 | 0.709 | 0.246 | 0.409 | 0.565 | 0.665 | 0.823 | 0.895 | 0.994 | 1.097 | 0.011 | 0.014 | 0.017 | 0.019 | 0.061 | 0.071 | 0.091 | 0.111 |
| 00 01:15:00 | 0.002 | 0.002 | 0.002 | 0.019 | 0.245 | 0.383 | 0.524 | 0.652 | 0.191 | 0.377 | 0.554 | 0.67 | 0.838 | 0.91 | 1.006 | 1.11 | 0.015 | 0.017 | 0.021 | 0.039 | 0.077 | 0.087 | 0.117 | 0.201 |
| 00 01:20:00 | 0.001 | 0.001 | 0.002 | 0.002 | 0.133 | 0.292 | 0.451 | 0.592 | 0.117 | 0.321 | 0.51 | 0.641 | 0.835 | 0.913 | 0.996 | 1.114 | 0.018 | 0.022 | 0.044 | 0.074 | 0.095 | 0.11 | 0.23 | 0.327 |
| 00 01:25:00 | 0 | 0 | 0.001 | 0.001 | 0.026 | 0.185 | 0.366 | 0.525 | 0.036 | 0.242 | 0.449 | 0.589 | 0.799 | 0.889 | 0.958 | 1.093 | 0.023 | 0.048 | 0.082 | 0.093 | 0.139 | 0.214 | 0.363 | 0.465 |
| 00 01:30:00 | 0 | 0 | 0 | 0 | 0.001 | 0.061 | 0.27 | 0.448 | 0.004 | 0.13 | 0.374 | 0.53 | 0.75 | 0.845 | 0.917 | 1.055 | 0.066 | 0.083 | 0.101 | 0.132 | 0.285 | 0.365 | 0.506 | 0.614 |
| 00 01:35:00 | 0 | 0 | 0 | 0 | 0 | 0.002 | 0.158 | 0.36 | 0.003 | 0.024 | 0.283 | 0.461 | 0.698 | 0.796 | 0.875 | 1.017 | 0.086 | 0.102 | 0.178 | 0.272 | 0.435 | 0.516 | 0.656 | 0.764 |
| 00 01:40:00 | 0 | 0 | 0 | 0 | 0 | 0.001 | 0.034 | 0.261 | 0.002 | 0.002 | 0.175 | 0.378 | 0.64 | 0.742 | 0.825 | 0.974 | 0.1 | 0.176 | 0.303 | 0.399 | 0.565 | 0.647 | 0.78 | 0.89 |
| 00 01:45:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0.001 | 0.146 | 0.001 | 0.002 | 0.051 | 0.286 | 0.574 | 0.683 | 0.77 | 0.929 | 0.148 | 0.278 | 0.406 | 0.502 | 0.668 | 0.747 | 0.877 | 0.99 |
| 00 01:50:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.027 | 0.001 | 0.001 | 0.001 | 0.177 | 0.505 | 0.621 | 0.712 | 0.882 | 0.235 | 0.362 | 0.488 | 0.585 | 0.746 | 0.824 | 0.952 | 1.067 |
| 00 01:55:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.001 | 0 | 0 | 0 | 0.052 | 0.424 | 0.553 | 0.65 | 0.832 | 0.305 | 0.43 | 0.554 | 0.648 | 0.804 | 0.882 | 1.009 | 1.125 |
| 00 02:00:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.001 | 0.333 | 0.479 | 0.583 | 0.78 | 0.362 | 0.483 | 0.606 | 0.697 | 0.851 | 0.928 | 1.054 | 1.169 |
| 00 02:05:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.23 | 0.394 | 0.512 | 0.723 | 0.404 | 0.525 | 0.647 | 0.735 | 0.888 | 0.964 | 1.089 | 1.204 |
| 00 02:10:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.109 | 0.299 | 0.431 | 0.663 | 0.428 | 0.557 | 0.679 | 0.767 | 0.918 | 0.994 | 1.118 | 1.232 |
| 00 02:15:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.017 | 0.19 | 0.34 | 0.599 | 0.419 | 0.571 | 0.701 | 0.792 | 0.943 | 1.02 | 1.142 | 1.255 |
| 00 02:20:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.001 | 0.062 | 0.237 | 0.53 | 0.384 | 0.559 | 0.711 | 0.809 | 0.964 | 1.041 | 1.164 | 1.276 |
| 00 02:25:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.001 | 0.116 | 0.452 | 0.339 | 0.533 | 0.707 | 0.809 | 0.981 | 1.059 | 1.183 | 1.294 |
| 00 02:30:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.018 | 0.363 | 0.284 | 0.499 | 0.686 | 0.797 | 0.991 | 1.074 | 1.199 | 1.311 |
| 00 02:35:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.001 | 0.263 | 0.222 | 0.457 | 0.66 | 0.778 | 0.986 | 1.08 | 1.213 | 1.326 |
| 00 02:40:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.147 | 0.151 | 0.413 | 0.635 | 0.755 | 0.98 | 1.075 | 1.225 | 1.34 |
| 00 02:45:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.027 | 0.076 | 0.361 | 0.602 | 0.73 | 0.967 | 1.069 | 1.234 | 1.353 |
| 00 02:50:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.001 | 0.046 | 0.307 | 0.565 | 0.701 | 0.949 | 1.057 | 1.238 | 1.364 |
| 00 02:55:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.018 | 0.245 | 0.528 | 0.67 | 0.934 | 1.042 | 1.237 | 1.373 |
| 00 03:00:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.009 | 0.177 | 0.484 | 0.636 | 0.912 | 1.031 | 1.234 | 1.38 |
| 00 03:05:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.008 | 0.101 | 0.436 | 0.598 | 0.889 | 1.012 | 1.223 | 1.38 |
| 00 03:10:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.007 | 0.054 | 0.381 | 0.557 | 0.866 | 0.992 | 1.212 | 1.373 |
| 00 03:15:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.006 | 0.022 | 0.32 | 0.508 | 0.834 | 0.971 | 1.195 | 1.358 |
| 00 03:20:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.005 | 0.005 | 0.247 | 0.45 | 0.793 | 0.935 | 1.164 | 1.333 |
| 00 03:25:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.004 | 0.004 | 0.149 | 0.376 | 0.745 | 0.89 | 1.128 | 1.3 |
| 00 03:30:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.003 | 0.003 | 0.034 | 0.284 | 0.688 | 0.844 | 1.089 | 1.265 |
| 00 03:35:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.002 | 0.003 | 0.003 | 0.174 | 0.626 | 0.793 | 1.046 | 1.228 |
| 00 03:40:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.002 | 0.002 | 0.002 | 0.047 | 0.558 | 0.736 | 1.001 | 1.19 |
| 00 03:45:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.001 | 0.001 | 0.002 | 0.002 | 0.486 | 0.678 | 0.954 | 1.15 |
| 00 03:50:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.001 | 0.001 | 0.402 | 0.615 | 0.905 | 1.108 |

| | | | | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 00 03:55:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.31 | 0.547 | 0.853 | 1.063 |
| 00 04:00:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.204 | 0.472 | 0.798 | 1.016 |
| 00 04:05:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.079 | 0.387 | 0.74 | 0.968 |
| 00 04:10:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.01 | 0.292 | 0.679 | 0.917 |
| 00 04:15:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.181 | 0.614 | 0.865 |
| 00 04:20:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.053 | 0.544 | 0.809 |
| 00 04:25:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.002 | 0.467 | 0.751 |
| 00 04:30:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.001 | 0.379 | 0.689 |
| 00 04:35:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.281 | 0.623 |
| 00 04:40:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.168 | 0.553 |
| 00 04:45:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.038 | 0.477 |
| 00 04:50:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.001 | 0.39 |
| 00 04:55:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.293 |
| 00 05:00:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.18 |
| 00 05:05:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.05 |
| 00 05:10:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.001 |

*Table A-C. 6. Simulation output: time-depth table for on-track element 904283 surrounding node BSW 007 1126 DCE, scenario where pipe downstream from node is in condition 3*

| Scenario | C3-D30-S1 | C3-D30-S2 | C3-D30-S5 | C3-D30-S10 | C3-D30-S30 | C3-D30-S50 | C3-D30-S100 | C3-D30-S200 | C3-D60-S1 | C3-D60-S2 | C3-D60-S5 | C3-D60-S10 | C3-D60-S30 | C3-D60-S50 | C3-D60-S100 | C3-D60-S200 | C3-D180-S1 | C3-D180-S2 | C3-D180-S5 | C3-D180-S10 | C3-D180-S30 | C3-D180-S50 | C3-D180-S100 | C3-D180-S200 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 00 00:00:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 00 00:05:00 | 0 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.003 | 0 | 0 | 0 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 00 00:10:00 | 0.001 | 0.002 | 0.004 | 0.006 | 0.01 | 0.011 | 0.013 | 0.014 | 0.001 | 0.001 | 0.001 | 0.001 | 0.002 | 0.003 | 0.004 | 0.007 | 0 | 0 | 0 | 0 | 0.001 | 0.001 | 0.001 | 0.001 |
| 00 00:15:00 | 0.013 | 0.016 | 0.026 | 0.034 | 0.045 | 0.05 | 0.058 | 0.067 | 0.001 | 0.001 | 0.003 | 0.004 | 0.007 | 0.008 | 0.009 | 0.017 | 0 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.002 |
| 00 00:20:00 | 0.049 | 0.063 | 0.085 | 0.101 | 0.117 | 0.128 | 0.184 | 0.277 | 0.003 | 0.005 | 0.007 | 0.019 | 0.033 | 0.036 | 0.042 | 0.064 | 0.001 | 0.001 | 0.001 | 0.001 | 0.002 | 0.002 | 0.003 | 0.005 |
| 00 00:25:00 | 0.083 | 0.092 | 0.1 | 0.135 | 0.272 | 0.34 | 0.443 | 0.562 | 0.01 | 0.023 | 0.036 | 0.044 | 0.077 | 0.086 | 0.096 | 0.101 | 0.001 | 0.001 | 0.001 | 0.001 | 0.004 | 0.009 | 0.016 | 0.024 |
| 00 00:30:00 | 0.091 | 0.104 | 0.183 | 0.268 | 0.413 | 0.489 | 0.597 | 0.711 | 0.039 | 0.049 | 0.082 | 0.098 | 0.108 | 0.115 | 0.158 | 0.225 | 0.001 | 0.001 | 0.002 | 0.003 | 0.011 | 0.017 | 0.028 | 0.035 |
| 00 00:35:00 | 0.097 | 0.152 | 0.274 | 0.363 | 0.503 | 0.576 | 0.678 | 0.79 | 0.078 | 0.097 | 0.108 | 0.144 | 0.296 | 0.374 | 0.453 | 0.55 | 0.001 | 0.002 | 0.003 | 0.005 | 0.019 | 0.027 | 0.032 | 0.049 |
| 00 00:40:00 | 0.109 | 0.214 | 0.344 | 0.429 | 0.557 | 0.626 | 0.722 | 0.831 | 0.095 | 0.11 | 0.216 | 0.314 | 0.477 | 0.562 | 0.662 | 0.772 | 0.001 | 0.002 | 0.004 | 0.008 | 0.025 | 0.03 | 0.046 | 0.067 |
| 00 00:45:00 | 0.128 | 0.251 | 0.379 | 0.47 | 0.59 | 0.657 | 0.75 | 0.858 | 0.109 | 0.198 | 0.328 | 0.429 | 0.602 | 0.691 | 0.787 | 0.895 | 0.002 | 0.003 | 0.007 | 0.015 | 0.031 | 0.042 | 0.06 | 0.068 |
| 00 00:50:00 | 0.089 | 0.243 | 0.361 | 0.461 | 0.59 | 0.668 | 0.761 | 0.866 | 0.174 | 0.281 | 0.414 | 0.515 | 0.683 | 0.768 | 0.863 | 0.971 | 0.003 | 0.004 | 0.011 | 0.02 | 0.031 | 0.043 | 0.058 | 0.075 |
| 00 00:55:00 | 0.036 | 0.177 | 0.301 | 0.407 | 0.544 | 0.643 | 0.74 | 0.837 | 0.242 | 0.349 | 0.478 | 0.577 | 0.738 | 0.821 | 0.916 | 1.022 | 0.004 | 0.008 | 0.015 | 0.025 | 0.047 | 0.061 | 0.07 | 0.08 |
| 00 01:00:00 | 0.005 | 0.067 | 0.214 | 0.331 | 0.484 | 0.594 | 0.697 | 0.799 | 0.288 | 0.399 | 0.526 | 0.624 | 0.78 | 0.862 | 0.956 | 1.062 | 0.007 | 0.01 | 0.021 | 0.03 | 0.046 | 0.063 | 0.075 | 0.086 |
| 00 01:05:00 | 0.003 | 0.004 | 0.093 | 0.234 | 0.419 | 0.54 | 0.65 | 0.761 | 0.303 | 0.428 | 0.557 | 0.655 | 0.81 | 0.891 | 0.983 | 1.088 | 0.009 | 0.014 | 0.027 | 0.033 | 0.066 | 0.072 | 0.082 | 0.095 |
| 00 01:10:00 | 0.002 | 0.003 | 0.007 | 0.115 | 0.338 | 0.476 | 0.595 | 0.711 | 0.283 | 0.426 | 0.569 | 0.675 | 0.83 | 0.911 | 1.003 | 1.107 | 0.011 | 0.022 | 0.037 | 0.05 | 0.073 | 0.081 | 0.092 | 0.12 |
| 00 01:15:00 | 0.002 | 0.002 | 0.002 | 0.014 | 0.242 | 0.398 | 0.531 | 0.653 | 0.234 | 0.394 | 0.554 | 0.681 | 0.843 | 0.925 | 1.016 | 1.119 | 0.02 | 0.032 | 0.046 | 0.063 | 0.087 | 0.093 | 0.111 | 0.22 |
| 00 01:20:00 | 0.001 | 0.001 | 0.001 | 0.001 | 0.128 | 0.31 | 0.458 | 0.592 | 0.162 | 0.338 | 0.51 | 0.654 | 0.831 | 0.923 | 1.017 | 1.123 | 0.032 | 0.046 | 0.076 | 0.085 | 0.1 | 0.109 | 0.227 | 0.343 |
| 00 01:25:00 | 0 | 0 | 0 | 0 | 0.016 | 0.205 | 0.373 | 0.524 | 0.061 | 0.26 | 0.448 | 0.603 | 0.791 | 0.889 | 0.986 | 1.103 | 0.049 | 0.067 | 0.091 | 0.099 | 0.156 | 0.218 | 0.362 | 0.477 |
| 00 01:30:00 | 0 | 0 | 0 | 0 | 0.001 | 0.084 | 0.279 | 0.447 | 0.006 | 0.153 | 0.374 | 0.543 | 0.739 | 0.842 | 0.942 | 1.065 | 0.072 | 0.093 | 0.104 | 0.149 | 0.3 | 0.368 | 0.505 | 0.625 |
| 00 01:35:00 | 0 | 0 | 0 | 0 | 0 | 0.009 | 0.168 | 0.358 | 0.003 | 0.027 | 0.282 | 0.476 | 0.687 | 0.793 | 0.898 | 1.027 | 0.093 | 0.111 | 0.189 | 0.289 | 0.447 | 0.518 | 0.654 | 0.772 |
| 00 01:40:00 | 0 | 0 | 0 | 0 | 0 | 0.001 | 0.039 | 0.259 | 0.002 | 0.002 | 0.175 | 0.394 | 0.628 | 0.741 | 0.852 | 0.984 | 0.112 | 0.211 | 0.312 | 0.413 | 0.574 | 0.649 | 0.778 | 0.897 |
| 00 01:45:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0.001 | 0.143 | 0.001 | 0.002 | 0.047 | 0.303 | 0.562 | 0.682 | 0.798 | 0.94 | 0.197 | 0.307 | 0.414 | 0.514 | 0.676 | 0.749 | 0.876 | 0.996 |
| 00 01:50:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.019 | 0 | 0.001 | 0.003 | 0.197 | 0.491 | 0.619 | 0.742 | 0.894 | 0.279 | 0.388 | 0.495 | 0.595 | 0.752 | 0.824 | 0.951 | 1.072 |
| 00 01:55:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.001 | 0 | 0 | 0.001 | 0.072 | 0.408 | 0.55 | 0.682 | 0.845 | 0.346 | 0.452 | 0.56 | 0.657 | 0.811 | 0.883 | 1.008 | 1.13 |
| 00 02:00:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.006 | 0.316 | 0.476 | 0.617 | 0.792 | 0.4 | 0.503 | 0.612 | 0.705 | 0.856 | 0.928 | 1.053 | 1.174 |
| 00 02:05:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.001 | 0.21 | 0.39 | 0.548 | 0.736 | 0.44 | 0.544 | 0.652 | 0.743 | 0.893 | 0.965 | 1.088 | 1.208 |
| 00 02:10:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.085 | 0.294 | 0.471 | 0.676 | 0.461 | 0.575 | 0.684 | 0.774 | 0.923 | 0.994 | 1.117 | 1.236 |
| 00 02:15:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.009 | 0.184 | 0.385 | 0.613 | 0.45 | 0.589 | 0.707 | 0.799 | 0.948 | 1.02 | 1.141 | 1.26 |
| 00 02:20:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.001 | 0.054 | 0.288 | 0.545 | 0.414 | 0.576 | 0.718 | 0.816 | 0.968 | 1.042 | 1.163 | 1.28 |
| 00 02:25:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.001 | 0.176 | 0.469 | 0.369 | 0.552 | 0.715 | 0.824 | 0.986 | 1.061 | 1.182 | 1.299 |

| | | | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 00 02:30:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.044 | 0.382 | 0.316 | 0.517 | 0.694 | 0.817 | 0.997 | 1.077 | 1.198 | 1.315 |
| 00 02:35:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.001 | 0.286 | 0.257 | 0.476 | 0.668 | 0.798 | 0.997 | 1.087 | 1.212 | 1.33 |
| 00 02:40:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.174 | 0.188 | 0.432 | 0.643 | 0.779 | 0.99 | 1.092 | 1.224 | 1.344 |
| 00 02:45:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.042 | 0.111 | 0.381 | 0.611 | 0.757 | 0.981 | 1.087 | 1.233 | 1.357 |
| 00 02:50:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.001 | 0.052 | 0.327 | 0.575 | 0.728 | 0.963 | 1.075 | 1.236 | 1.368 |
| 00 02:55:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.033 | 0.266 | 0.537 | 0.701 | 0.946 | 1.064 | 1.236 | 1.376 |
| 00 03:00:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.019 | 0.199 | 0.494 | 0.67 | 0.929 | 1.05 | 1.233 | 1.382 |
| 00 03:05:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.008 | 0.123 | 0.446 | 0.634 | 0.904 | 1.031 | 1.222 | 1.382 |
| 00 03:10:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.007 | 0.054 | 0.392 | 0.596 | 0.878 | 1.014 | 1.211 | 1.375 |
| 00 03:15:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.006 | 0.034 | 0.332 | 0.552 | 0.85 | 0.989 | 1.193 | 1.36 |
| 00 03:20:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.005 | 0.005 | 0.26 | 0.497 | 0.809 | 0.954 | 1.163 | 1.335 |
| 00 03:25:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.004 | 0.004 | 0.164 | 0.43 | 0.759 | 0.913 | 1.126 | 1.302 |
| 00 03:30:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.003 | 0.003 | 0.041 | 0.347 | 0.703 | 0.866 | 1.088 | 1.268 |
| 00 03:35:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.002 | 0.003 | 0.003 | 0.249 | 0.642 | 0.815 | 1.044 | 1.231 |
| 00 03:40:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.002 | 0.002 | 0.002 | 0.134 | 0.576 | 0.761 | 0.999 | 1.193 |
| 00 03:45:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.001 | 0.001 | 0.002 | 0.019 | 0.507 | 0.703 | 0.953 | 1.153 |
| 00 03:50:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.001 | 0.001 | 0.426 | 0.641 | 0.904 | 1.111 |
| 00 03:55:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.336 | 0.575 | 0.852 | 1.067 |
| 00 04:00:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.234 | 0.505 | 0.797 | 1.02 |
| 00 04:05:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.114 | 0.424 | 0.739 | 0.971 |
| 00 04:10:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.013 | 0.333 | 0.678 | 0.921 |
| 00 04:15:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.001 | 0.23 | 0.613 | 0.869 |
| 00 04:20:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.107 | 0.543 | 0.813 |
| 00 04:25:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.01 | 0.466 | 0.755 |
| 00 04:30:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.001 | 0.378 | 0.694 |
| 00 04:35:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.28 | 0.628 |
| 00 04:40:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.166 | 0.558 |
| 00 04:45:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.033 | 0.483 |
| 00 04:50:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.001 | 0.397 |
| 00 04:55:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.3 |
| 00 05:00:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.189 |
| 00 05:05:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.057 |
| 00 05:10:00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.001 |

# Appendix D.1: Exposure parameters input distributions

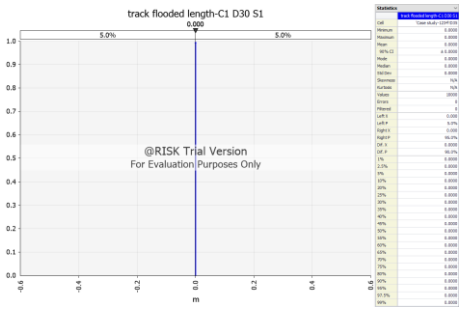



*Figure A-D1. 49. Chamber "1234" track flooded length input distribution C1-D30-S1*

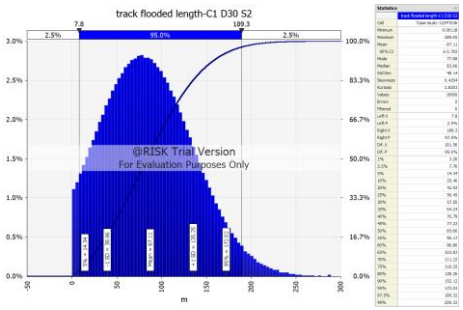



*Figure A-D1. 50. Chamber "1234" track flooded length input distribution C1-D30-S2*

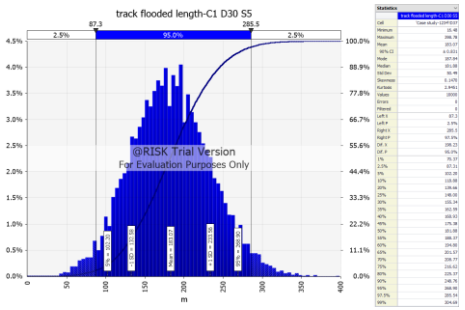



*Figure A-D1. 51. Chamber "1234" track flooded length input distribution C1-D30-S5*

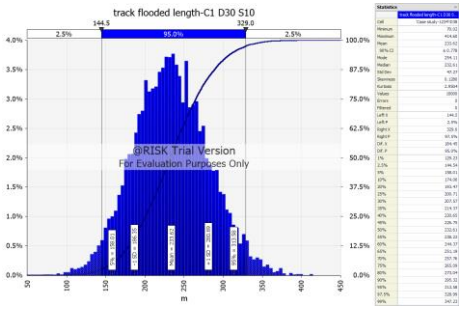



*Figure A-D1. 52. Chamber "1234" track flooded length input distribution C1-D30-S10*

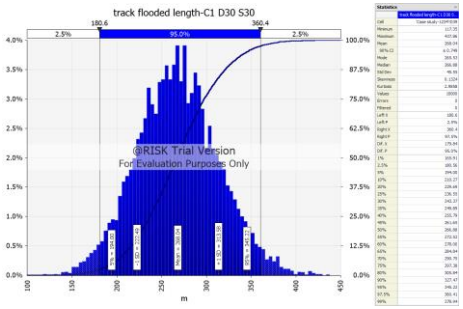



*Figure A-D1. 53. Chamber "1234" track flooded length input distribution C1-D30-S30*

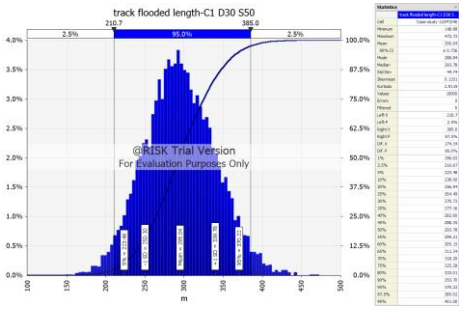



*Figure A-D1. 54. Chamber "1234" track flooded length input distribution C1-D30-S50*

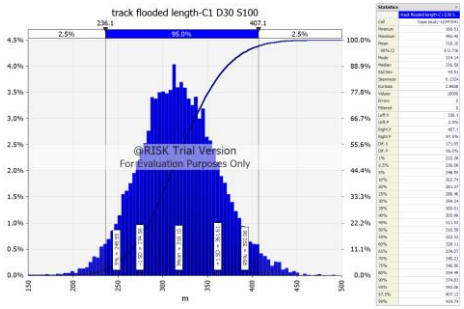



*Figure A-D1. 55. Chamber "1234" track flooded length input distribution C1-D30-S100*

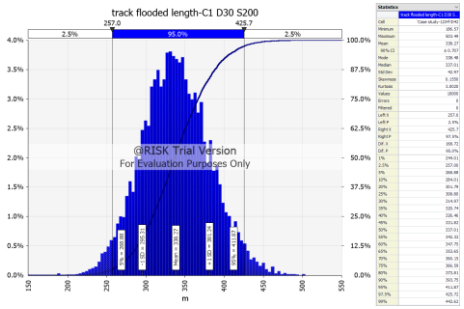



*Figure A-D1. 56. Chamber "1234" track flooded length input distribution C1-D30-S200*

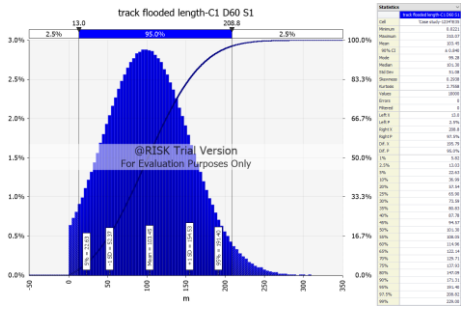



Figure A-D1. 57. Chamber "1234" track flooded length input distribution C1-D60-S1

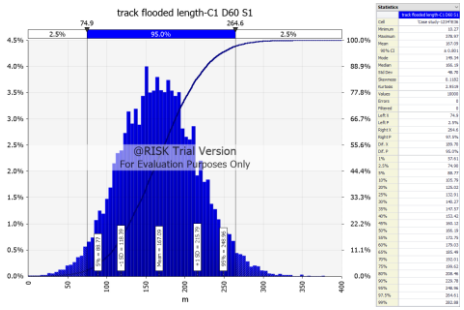



*Figure A-D1. 58. Chamber "1234" track flooded length input distribution C1-D60-S2*

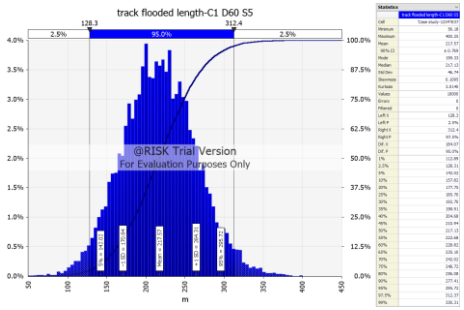



*Figure A-D1. 59. Chamber "1234" track flooded length input distribution C1-D60-S5*

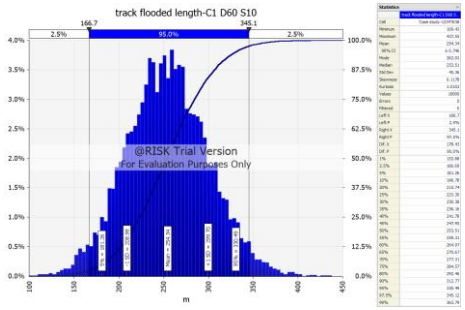



Figure A-D1. 60. Chamber "1234" track flooded length input distribution C1-D60-S10

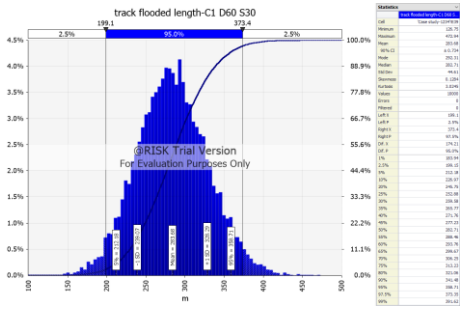



*Figure A-D1. 61. Chamber "1234" track flooded length input distribution C1-D60-S30*

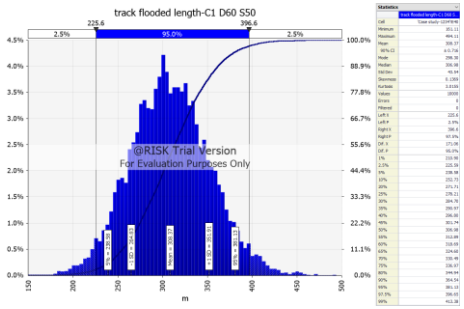



*Figure A-D1. 62. Chamber "1234" track flooded length input distribution C1-D60-S50*

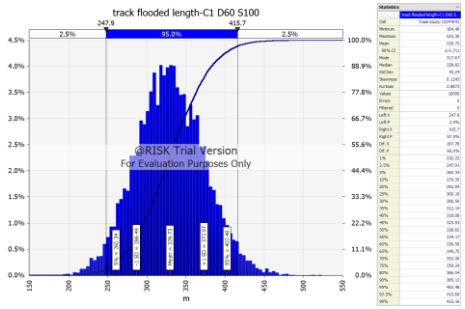



Figure A-D1. 63. Chamber "1234" track flooded length input distribution C1-D60-S100

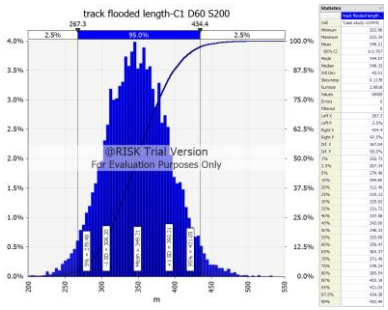



*Figure A-D1. 64. Chamber "1234" track flooded length input distribution C1-D60-S200*

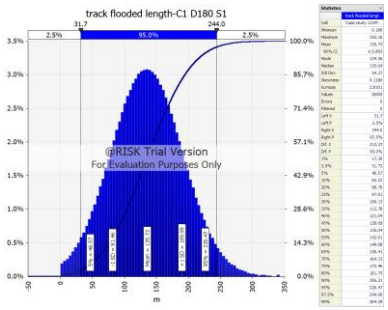



*Figure A-D1. 65. Chamber "1234" track flooded length input distribution C1-D180-S1*

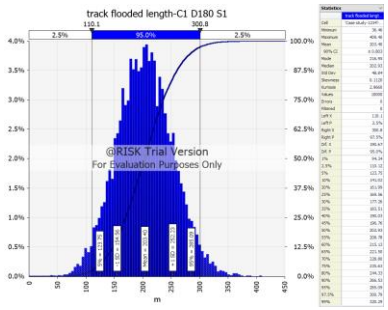



Figure A-D1. 66. Chamber "1234" track flooded length input distribution C1-D180-S2

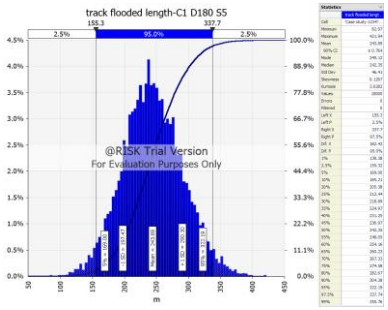



*Figure A-D1. 67. Chamber "1234" track flooded length input distribution C1-D180-S5*

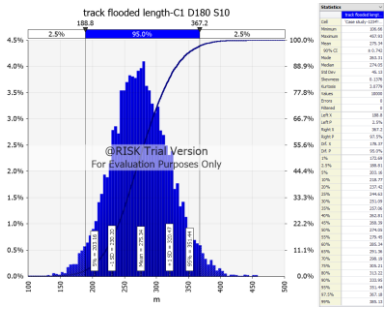



*Figure A-D1. 68. Chamber "1234" track flooded length input distribution C1-D180-S10*

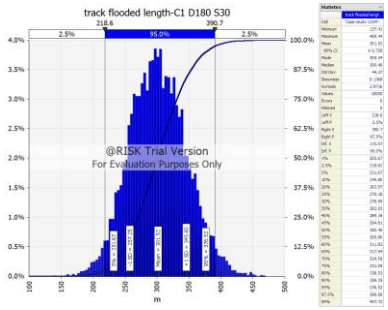



Figure A-D1. 69. Chamber "1234" track flooded length input distribution C1-D180-S30

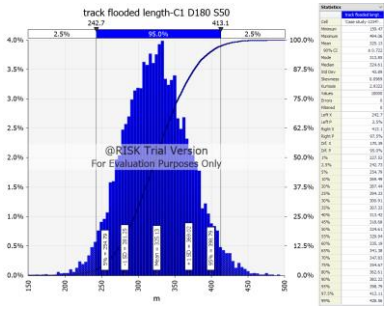



*Figure A-D1. 70. Chamber "1234" track flooded length input distribution C1-D180-S50*

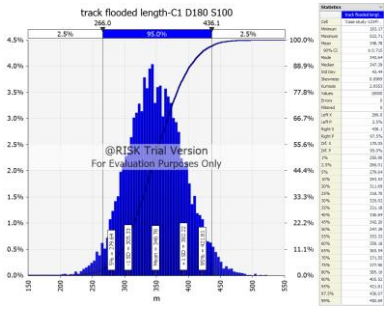



*Figure A-D1. 71. Chamber "1234" track flooded length input distribution C1-D180-S100*

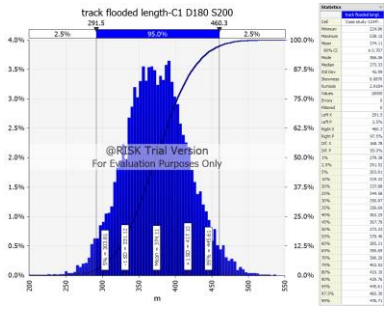



Figure A-D1. 72. Chamber "1234" track flooded length input distribution C1-D180-S200

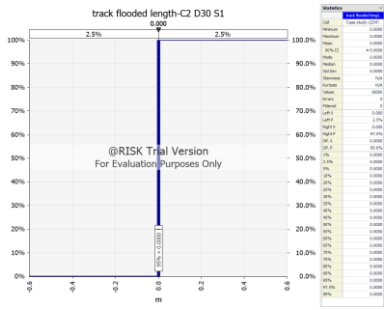



*Figure A-D1. 73. Chamber "1234" track flooded length input distribution C2-D30-S1*

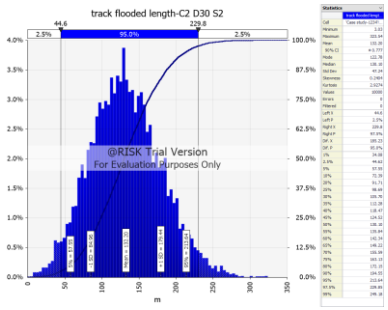



*Figure A-D1. 74. Chamber "1234" track flooded length input distribution C2-D30-S2*

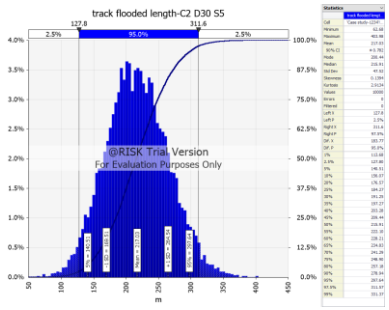



Figure A-D1. 75. Chamber "1234" track flooded length input distribution C2-D30-S5

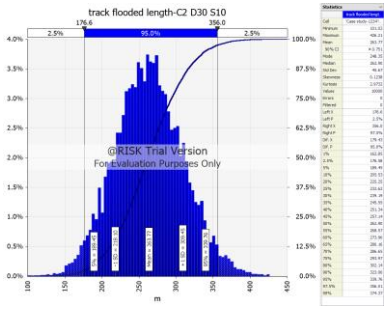



*Figure A-D1. 76. Chamber "1234" track flooded length input distribution C2-D30-S10*

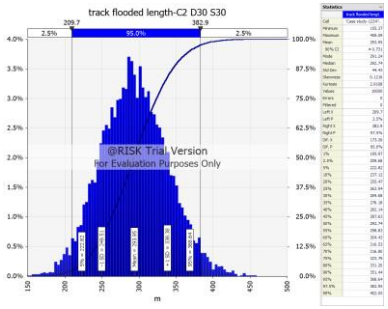



*Figure A-D1. 77. Chamber "1234" track flooded length input distribution C2-D30-S30*

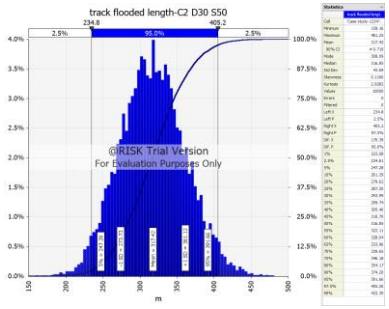



Figure A-D1. 78. Chamber "1234" track flooded length input distribution C2-D30-S50

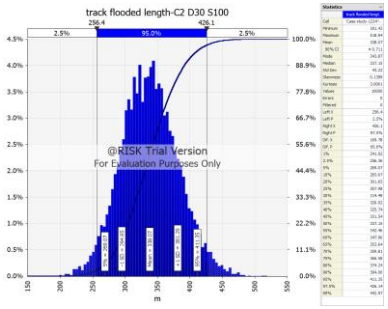



*Figure A-D1. 79. Chamber "1234" track flooded length input distribution C2-D30-S100*

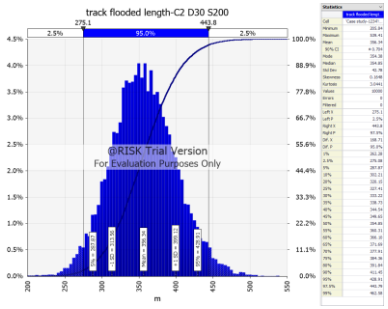



*Figure A-D1. 80. Chamber "1234" track flooded length input distribution C2-D30-S200*

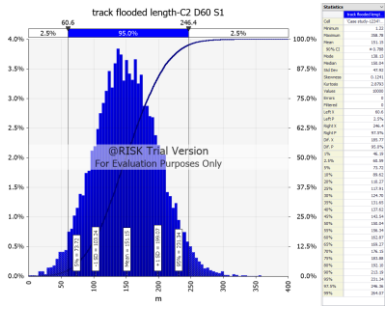



Figure A-D1. 81. Chamber "1234" track flooded length input distribution C2-D60-S1

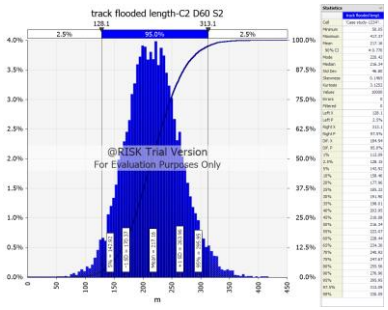



*Figure A-D1. 82. Chamber "1234" track flooded length input distribution C2-D60-S2*

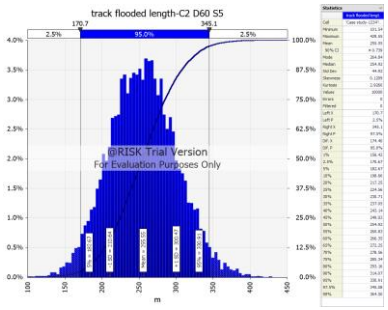



*Figure A-D1. 83. Chamber "1234" track flooded length input distribution C2-D60-S5*

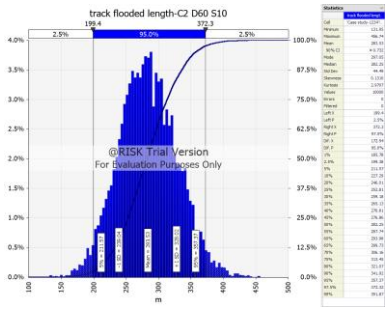



Figure A-D1. 84. Chamber "1234" track flooded length input distribution C2-D60-S10

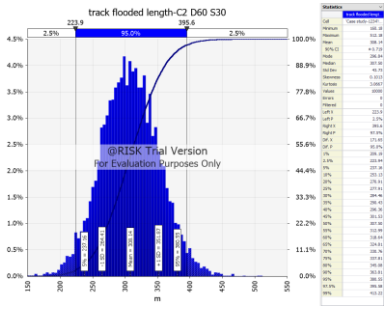



*Figure A-D1. 85. Chamber "1234" track flooded length input distribution C2-D60-S30*

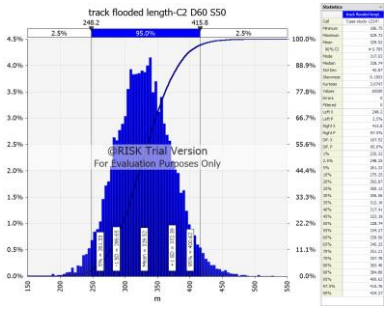



*Figure A-D1. 86. Chamber "1234" track flooded length input distribution C2-D60-S50*

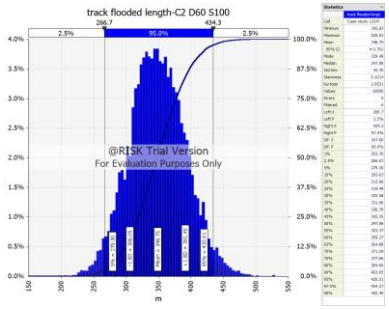



Figure A-D1. 87. Chamber "1234" track flooded length input distribution C2-D60-S100

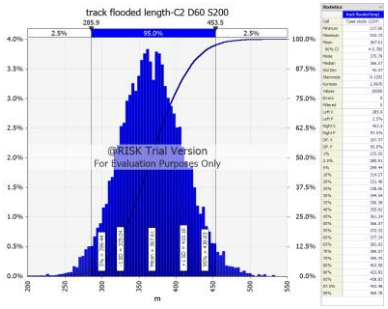



*Figure A-D1. 88. Chamber "1234" track flooded length input distribution C2-D60-S200*

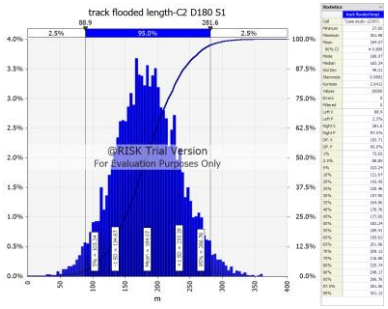



*Figure A-D1. 89. Chamber "1234" track flooded length input distribution C2-D180-S1*

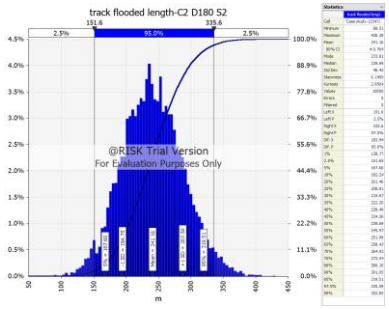



Figure A-D1. 90. Chamber "1234" track flooded length input distribution C2-D180-S2

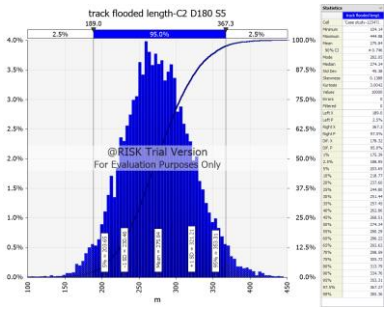



*Figure A-D1. 91. Chamber "1234" track flooded length input distribution C2-D180-S5*

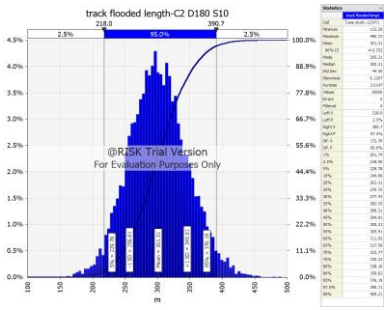



*Figure A-D1. 92. Chamber "1234" track flooded length input distribution C2-D180-S10*

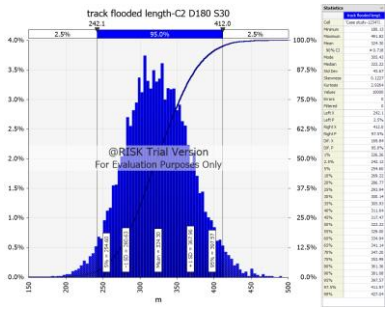



Figure A-D1. 93. Chamber "1234" track flooded length input distribution C2-D180-S30

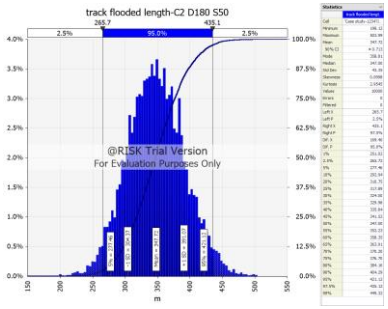



*Figure A-D1. 94. Chamber "1234" track flooded length input distribution C2-D180-S50*

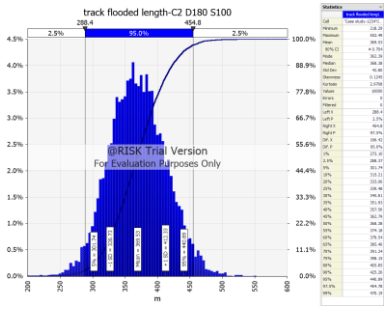



*Figure A-D1. 95. Chamber "1234" track flooded length input distribution C2-D180-S100*

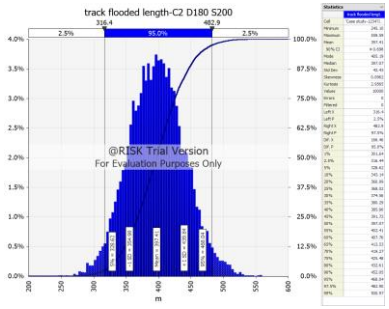



Figure A-D1. 96. Chamber "1234" track flooded length input distribution C2-D180-S200

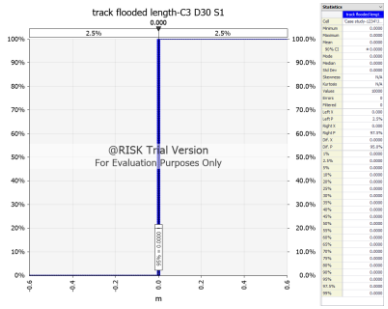



*Figure A-D1. 97. Chamber "1234" track flooded length input distribution C3-D30-S1*

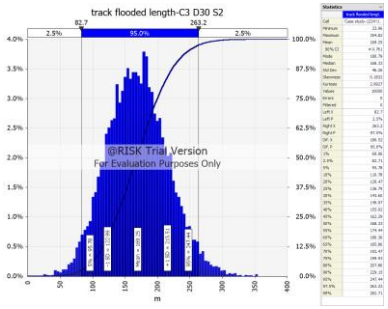



*Figure A-D1. 98. Chamber "1234" track flooded length input distribution C3-D30-S2*

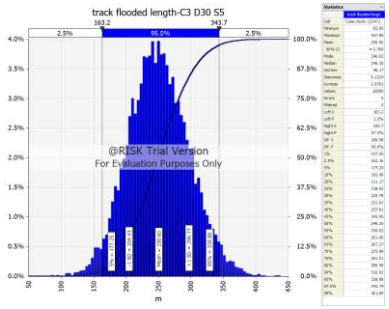



Figure A-D1. 99. Chamber "1234" track flooded length input distribution C3-D30-S5

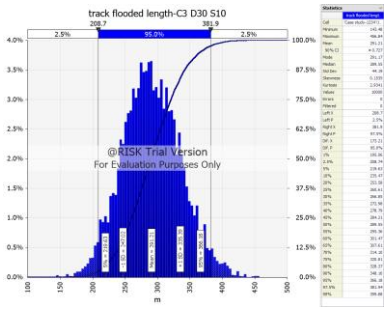



*Figure A-D1. 100. Chamber "1234" track flooded length input distribution C3-D30-S10*

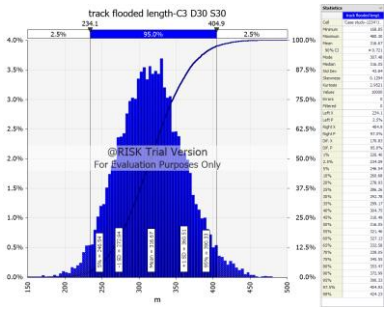



*Figure A-D1. 101. Chamber "1234" track flooded length input distribution C3-D30-S30*

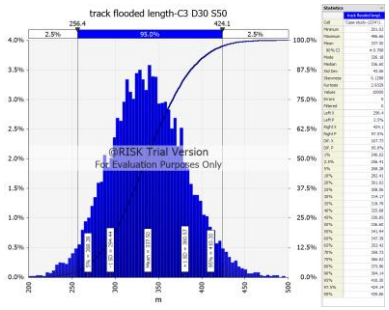



Figure A-D1. 102. Chamber "1234" track flooded length input distribution C3-D30-S50

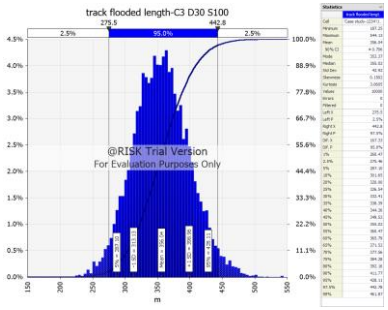



*Figure A-D1. 103. Chamber "1234" track flooded length input distribution C3-D30-S100*

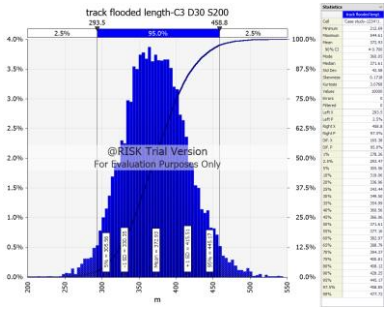



*Figure A-D1. 104. Chamber "1234" track flooded length input distribution C3-D30-S200*

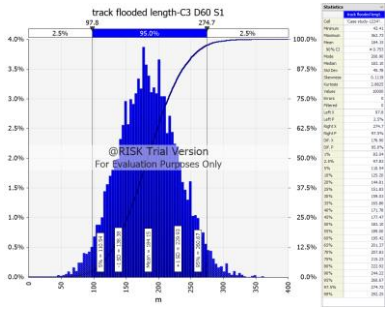



Figure A-D1. 105. Chamber "1234" track flooded length input distribution C3-D60-S1

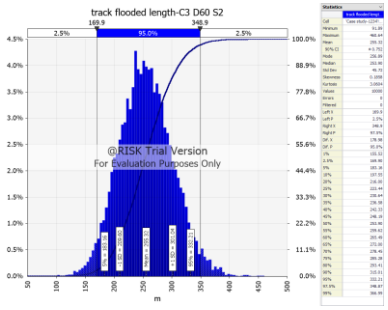



*Figure A-D1. 106. Chamber "1234" track flooded length input distribution C3-D60-S2*

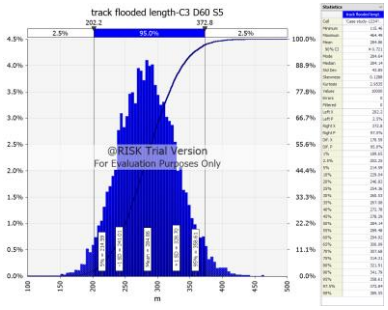



*Figure A-D1. 107. Chamber "1234" track flooded length input distribution C3-D60-S5*

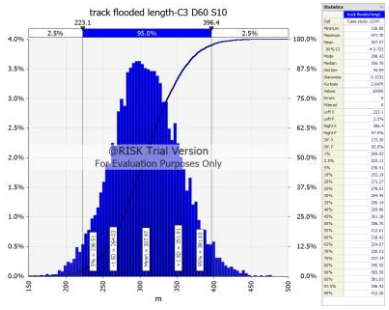



Figure A-D1. 108. Chamber "1234" track flooded length input distribution C3-D60-S10

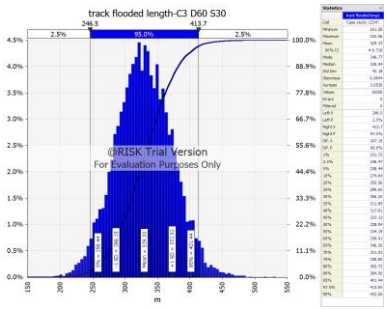



*Figure A-D1. 109. Chamber "1234" track flooded length input distribution C3-D60-S30*

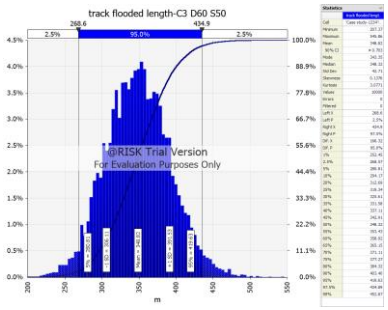



*Figure A-D1. 110. Chamber "1234" track flooded length input distribution C3-D60-S50*

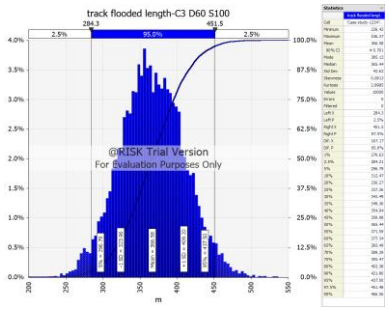



Figure A-D1. 111. Chamber "1234" track flooded length input distribution C3-D60-S100

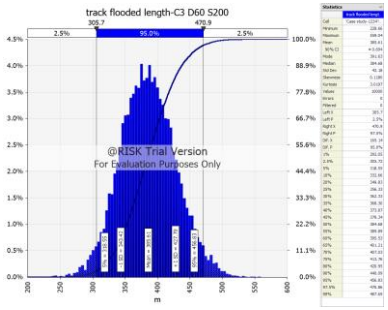



*Figure A-D1. 112. Chamber "1234" track flooded length input distribution C3-D60-S200*

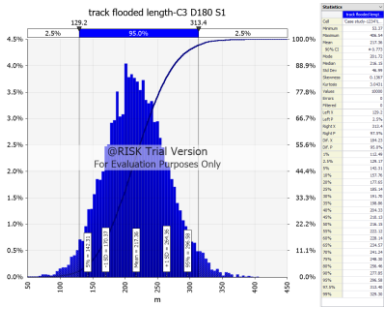



*Figure A-D1. 113. Chamber "1234" track flooded length input distribution C3-D180-S1*

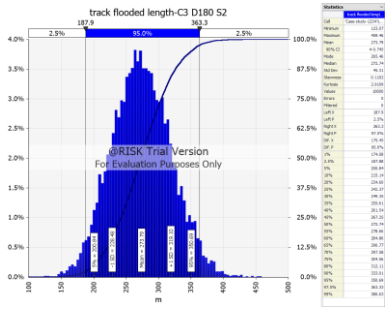



Figure A-D1. 114. Chamber "1234" track flooded length input distribution C3-D180-S2

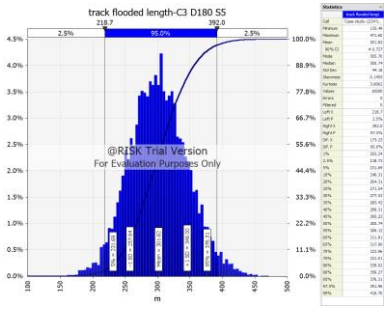



*Figure A-D1. 115. Chamber "1234" track flooded length input distribution C3-D180-S5*

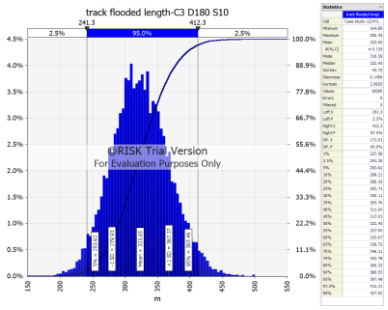



*Figure A-D1. 116. Chamber "1234" track flooded length input distribution C3-D180-S10*

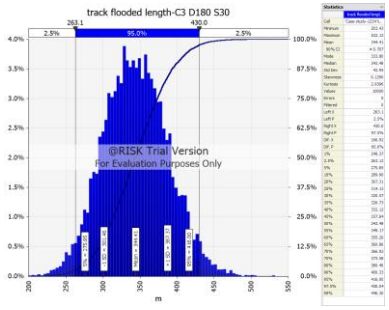



Figure A-D1. 117. Chamber "1234" track flooded length input distribution C3-D180-S30

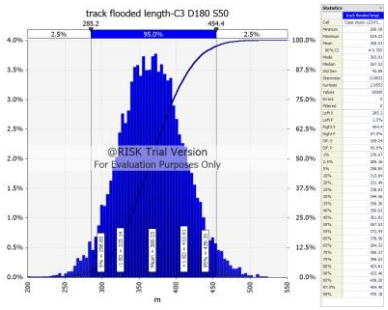



*Figure A-D1. 118. Chamber "1234" track flooded length input distribution C3-D180-S50*

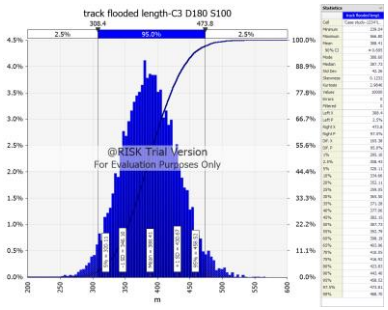



*Figure A-D1. 119. Chamber "1234" track flooded length input distribution C3-D180-S100*

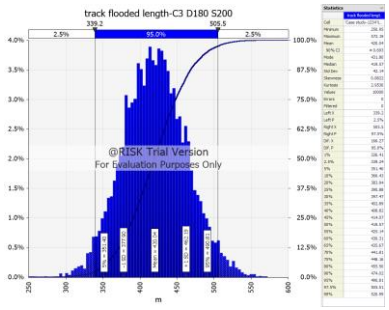



Figure A-D1. 120. Chamber "1234" track flooded length input distribution C3-D180-S200

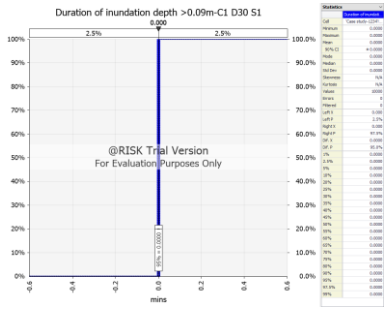



*Figure A-D1. 121. Chamber "1234" duration of inundation depth >0.09 m input distribution C1-D30-S1*

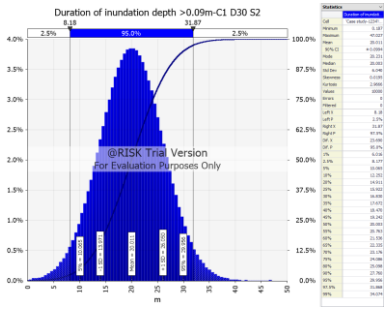



*Figure A-D1. 122. Chamber "1234" duration of inundation depth >0.09 m input distribution C1-D30-S2*

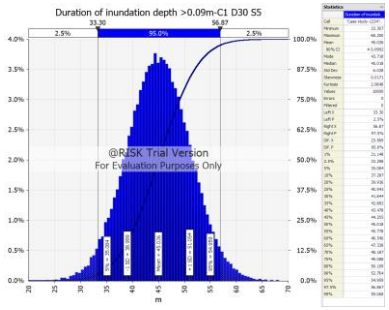



Figure A-D1. 123. Chamber "1234" duration of inundation depth >0.09 m input distribution C1-D30-S5

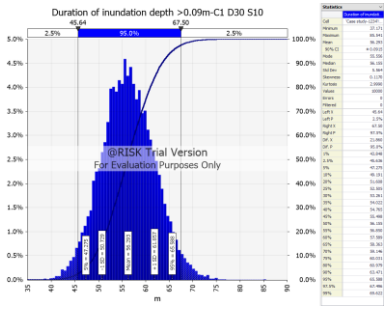



*Figure A-D1. 124. Chamber "1234" duration of inundation depth >0.09 m input distribution C1-D30-S10*

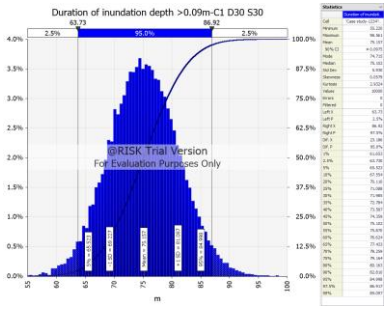



*Figure A-D1. 125. Chamber "1234" duration of inundation depth >0.09 m input distribution C1-D30-S30*

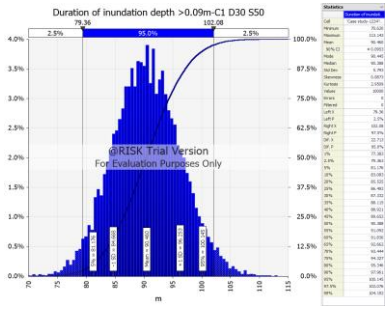



Figure A-D1. 126. Chamber "1234" duration of inundation depth >0.09 m input distribution C1-D30-S50

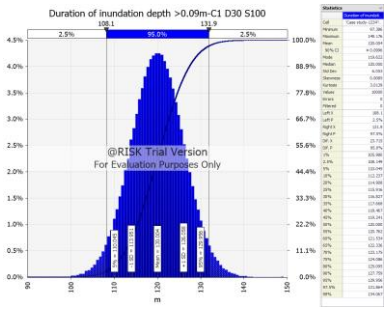



*Figure A-D1. 127. Chamber "1234" duration of inundation depth >0.09 m input distribution C1-D30-S100*

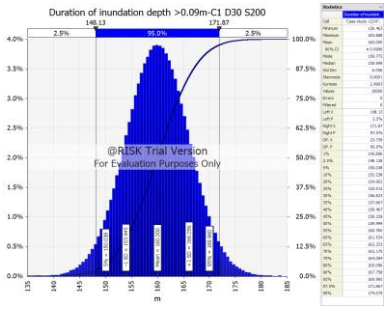



*Figure A-D1. 128. Chamber "1234" duration of inundation depth >0.09 m input distribution C1-D30-S200*

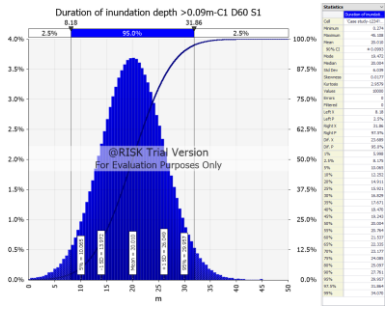



Figure A-D1. 129. Chamber "1234" duration of inundation depth >0.09 m input distribution C1-D60-S1

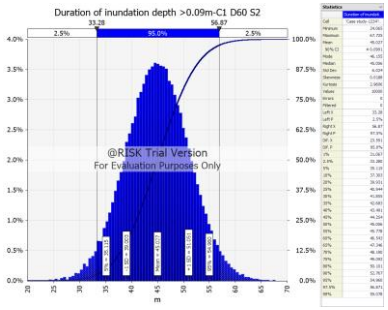



*Figure A-D1. 130. Chamber "1234" duration of inundation depth >0.09 m input distribution C1-D60-S2*

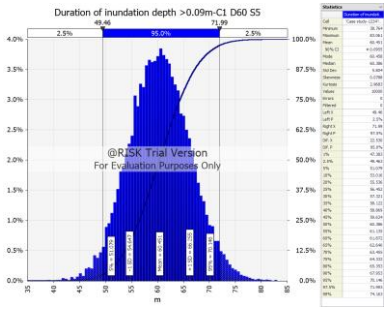



*Figure A-D1. 131. Chamber "1234" duration of inundation depth >0.09 m input distribution C1-D60-S5*

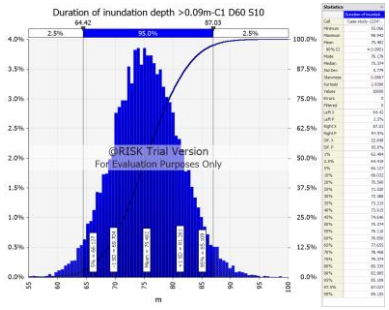



Figure A-D1. 132. Chamber "1234" duration of inundation depth >0.09 m input distribution C1-D60-S10

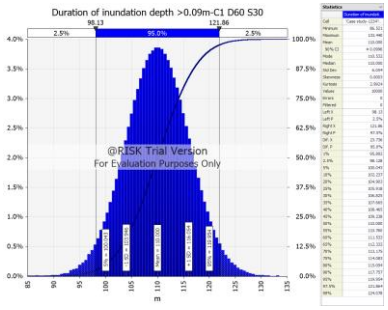



*Figure A-D1. 133. Chamber "1234" duration of inundation depth >0.09 m input distribution C1-D60-S30*

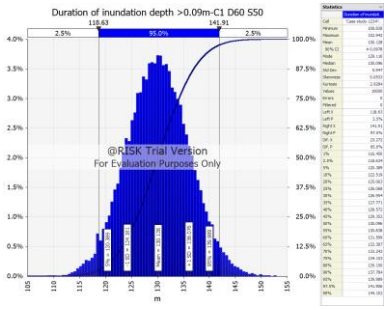



*Figure A-D1. 134. Chamber "1234" duration of inundation depth >0.09 m input distribution C1-D60-S50*

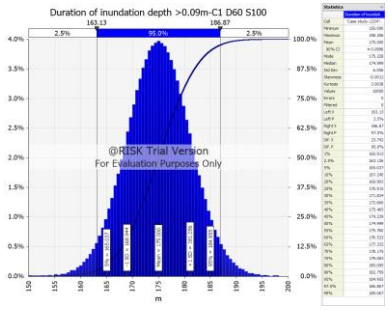



Figure A-D1. 135. Chamber "1234" duration of inundation depth >0.09 m input distribution C1-D60-S100

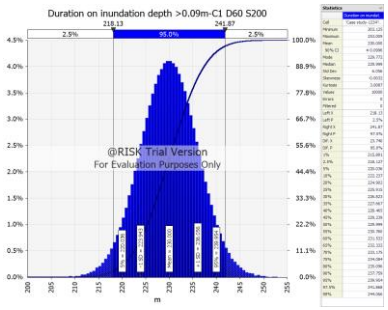



*Figure A-D1. 136. Chamber "1234" duration of inundation depth >0.09 m input distribution C1-D60-S200*

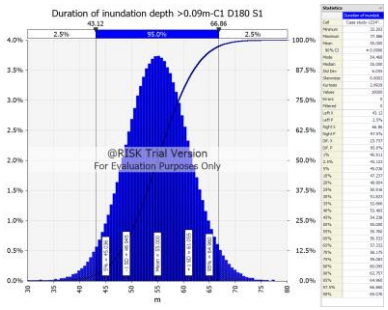



*Figure A-D1. 137. Chamber "1234" duration of inundation depth >0.09 m input distribution C1-D180-S1*

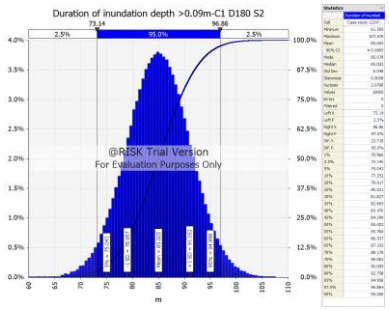



Figure A-D1. 138. Chamber "1234" duration of inundation depth >0.09 m input distribution C1-D180-S2

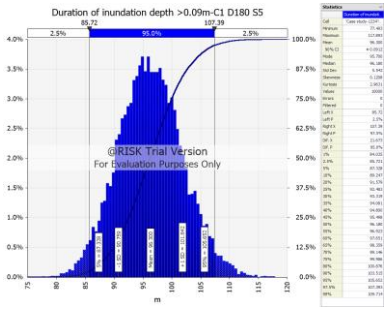



*Figure A-D1. 139. Chamber "1234" duration of inundation depth >0.09 m input distribution C1-D180-S5*

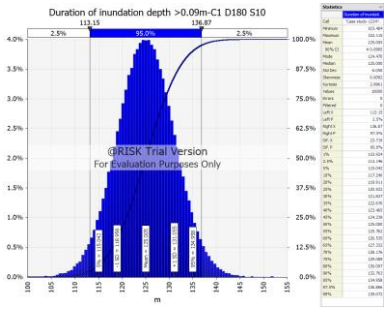



*Figure A-D1. 140. Chamber "1234" duration of inundation depth >0.09 m input distribution C1-D180-S10*

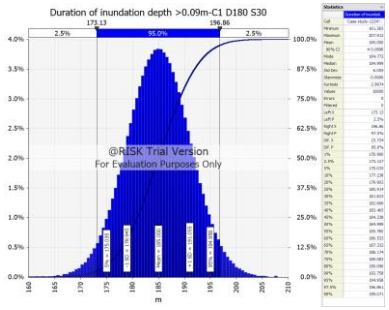



Figure A-D1. 141. Chamber "1234" duration of inundation depth >0.09 m input distribution C1-D180-S30

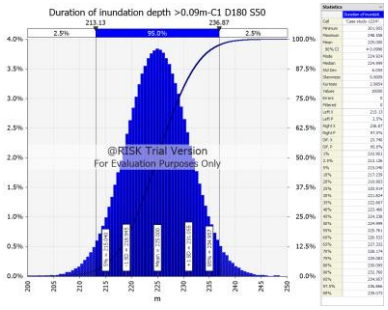



*Figure A-D1. 142. Chamber "1234" duration of inundation depth >0.09 m input distribution C1-D180-S50*

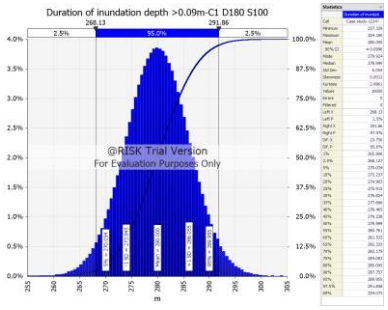



*Figure A-D1. 143. Chamber "1234" duration of inundation depth >0.09 m input distribution C1-D180-S100*

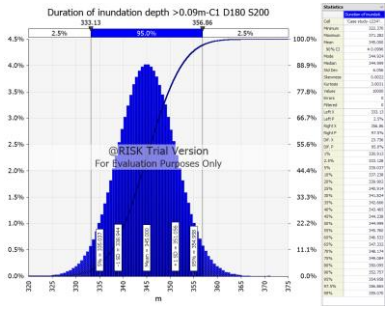



Figure A-D1. 144. Chamber "1234" duration of inundation depth >0.09 m input distribution C1-D180-S200

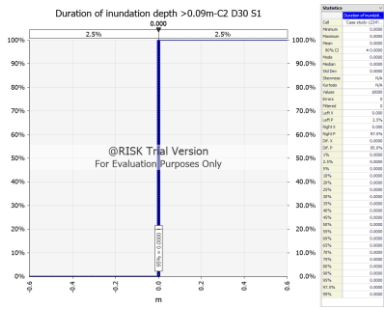



*Figure A-D1. 145. Chamber "1234" duration of inundation depth >0.09 m input distribution C2-D30-S1*

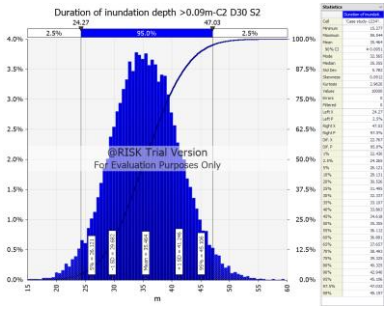



*Figure A-D1. 146. Chamber "1234" duration of inundation depth >0.09 m input distribution C2-D30-S2*

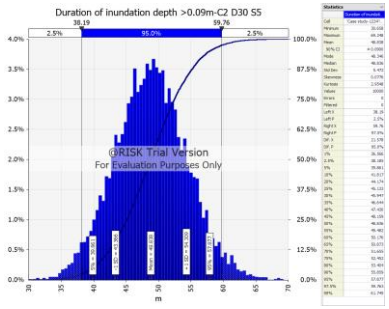



Figure A-D1. 147. Chamber "1234" duration of inundation depth >0.09 m input distribution C2-D30-S5

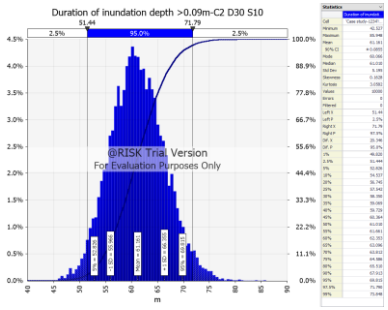



*Figure A-D1. 148. Chamber "1234" duration of inundation depth >0.09 m input distribution C2-D30-S10*

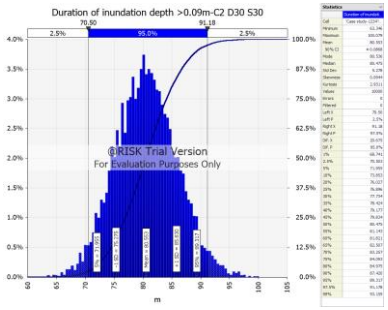



*Figure A-D1. 149. Chamber "1234" duration of inundation depth >0.09 m input distribution C2-D30-S30*

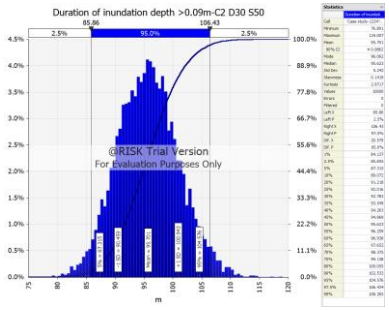



Figure A-D1. 150. Chamber "1234" duration of inundation depth >0.09 m input distribution C2-D30-S50

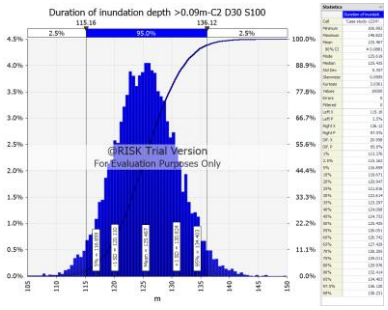



*Figure A-D1. 151. Chamber "1234" duration of inundation depth >0.09 m input distribution C2-D30-S100*

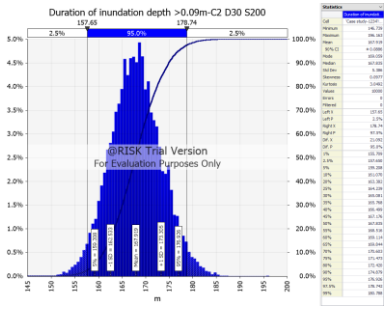



*Figure A-D1. 152. Chamber "1234" duration of inundation depth >0.09 m input distribution C2-D30-S200*

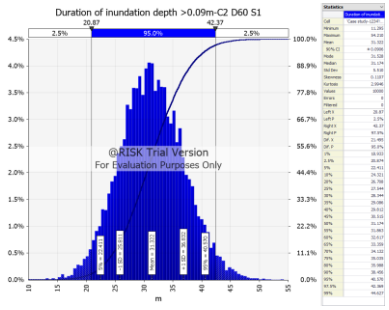



Figure A-D1. 153. Chamber "1234" duration of inundation depth >0.09 m input distribution C2-D60-S1

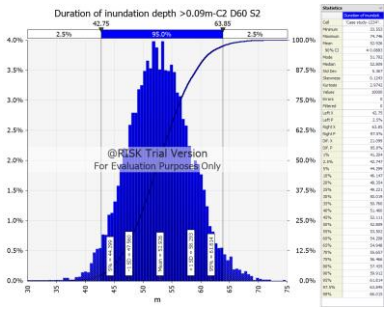



*Figure A-D1. 154. Chamber "1234" duration of inundation depth >0.09 m input distribution C2-D60-S2*

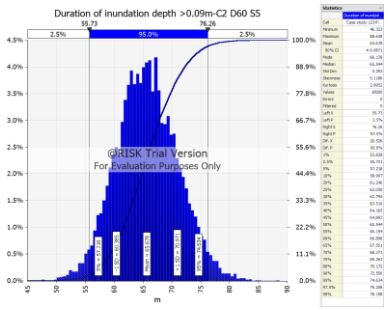



*Figure A-D1. 155. Chamber "1234" duration of inundation depth >0.09 m input distribution C2-D60-S5*

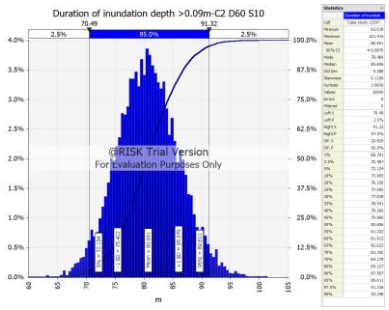



Figure A-D1. 156. Chamber "1234" duration of inundation depth >0.09 m input distribution C2-D60-S10

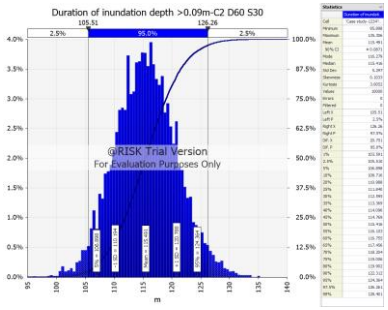



*Figure A-D1. 157. Chamber "1234" duration of inundation depth >0.09 m input distribution C2-D60-S30*

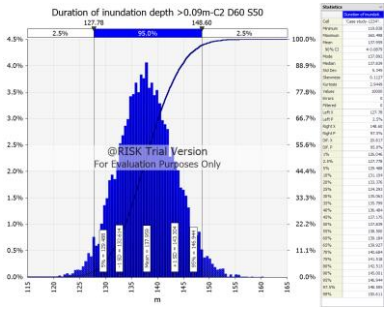



*Figure A-D1. 158. Chamber "1234" duration of inundation depth >0.09 m input distribution C2-D60-S50*

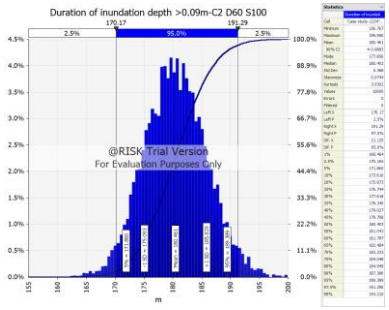



Figure A-D1. 159. Chamber "1234" duration of inundation depth >0.09 m input distribution C2-D60-S100

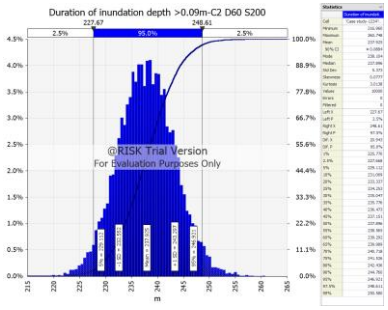



*Figure A-D1. 160. Chamber "1234" duration of inundation depth >0.09 m input distribution C2-D60-S200*

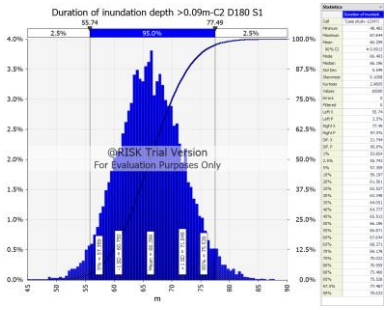



*Figure A-D1. 161. Chamber "1234" duration of inundation depth >0.09 m input distribution C2-D180-S1*

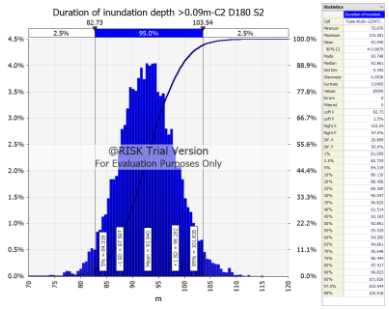



Figure A-D1. 162. Chamber "1234" duration of inundation depth >0.09 m input distribution C2-D180-S2

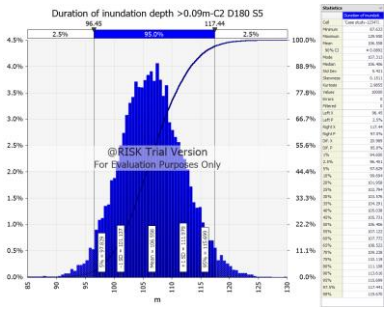



*Figure A-D1. 163. Chamber "1234" duration of inundation depth >0.09 m input distribution C2-D180-S5*

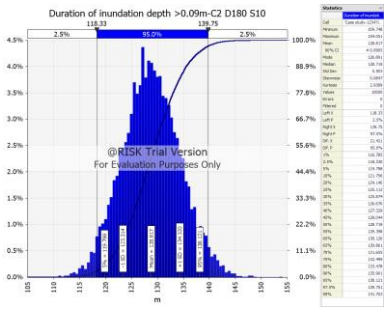



*Figure A-D1. 164. Chamber "1234" duration of inundation depth >0.09 m input distribution C2-D180-S10*

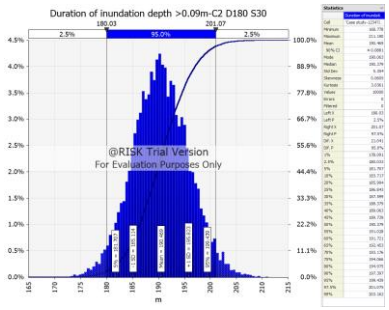



Figure A-D1. 165. Chamber "1234" duration of inundation depth >0.09 m input distribution C2-D180-S30

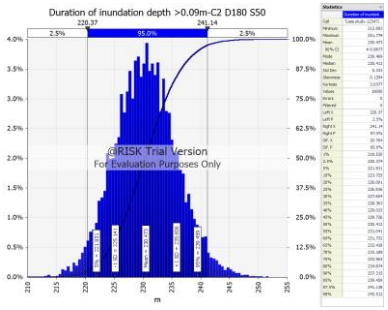



*Figure A-D1. 166. Chamber "1234" duration of inundation depth >0.09 m input distribution C2-D180-S50*

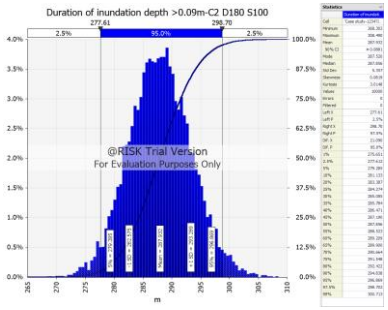



*Figure A-D1. 167. Chamber "1234" duration of inundation depth >0.09 m input distribution C2-D180-S100*

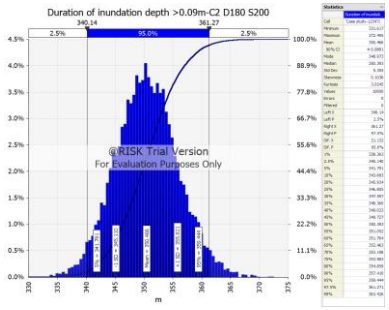



Figure A-D1. 168. Chamber "1234" duration of inundation depth >0.09 m input distribution C2-D180-S200

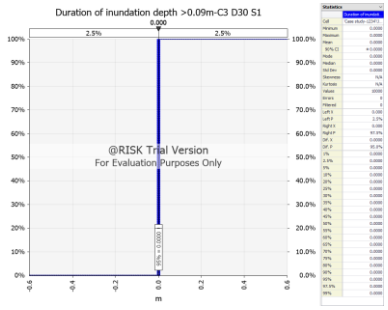



*Figure A-D1. 169. Chamber "1234" duration of inundation depth >0.09 m input distribution C3-D30-S1*

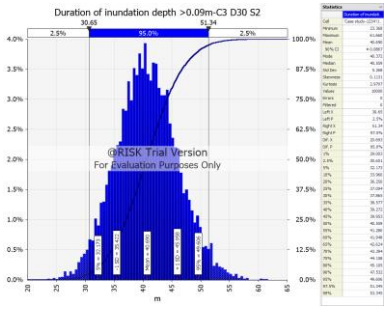



*Figure A-D1. 170. Chamber "1234" duration of inundation depth >0.09 m input distribution C3-D30-S2*

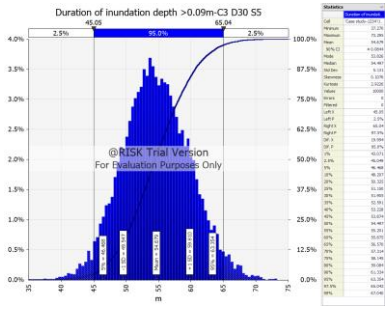



Figure A-D1. 171. Chamber "1234" duration of inundation depth >0.09 m input distribution C3-D30-S5

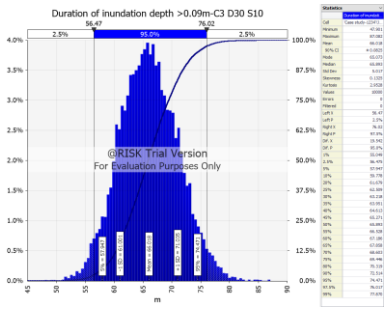



*Figure A-D1. 172. Chamber "1234" duration of inundation depth >0.09 m input distribution C3-D30-S10*

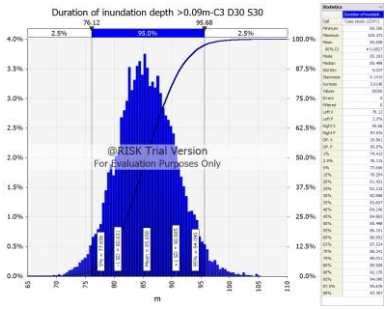



*Figure A-D1. 173. Chamber "1234" duration of inundation depth >0.09 m input distribution C3-D30-S30*

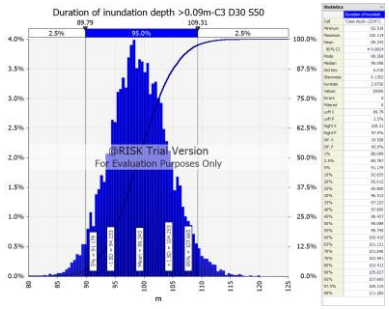



Figure A-D1. 174. Chamber "1234" duration of inundation depth >0.09 m input distribution C3-D30-S50

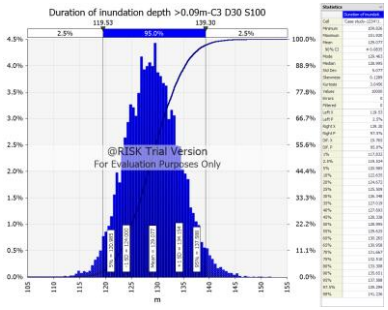



*Figure A-D1. 175. Chamber "1234" duration of inundation depth >0.09 m input distribution C3-D30-S100*

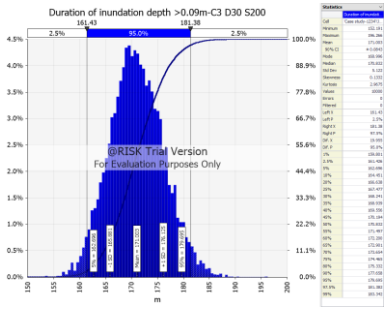



*Figure A-D1. 176. Chamber "1234" duration of inundation depth >0.09 m input distribution C3-D30-S200*

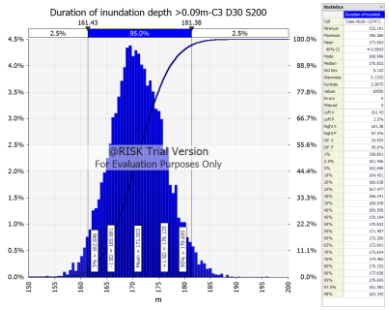



Figure A-D1. 177. Chamber "1234" duration of inundation depth >0.09 m input distribution C3-D30-S200

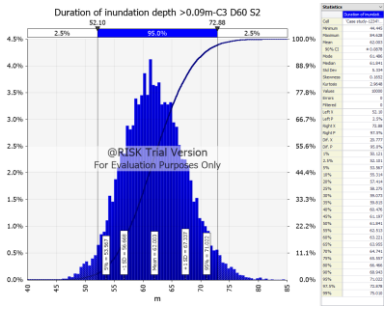



*Figure A-D1. 178. Chamber "1234" duration of inundation depth >0.09 m input distribution C3-D60-S2*

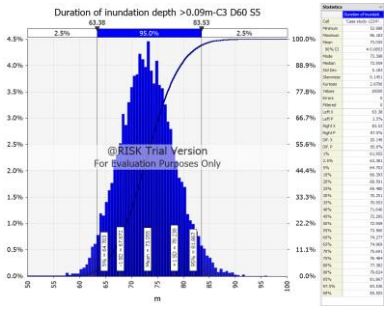



*Figure A-D1. 179. Chamber "1234" duration of inundation depth >0.09 m input distribution C3-D60-S5*

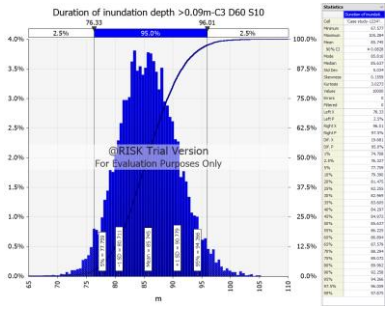



Figure A-D1. 180. Chamber "1234" duration of inundation depth >0.09 m input distribution C3-D60-S10

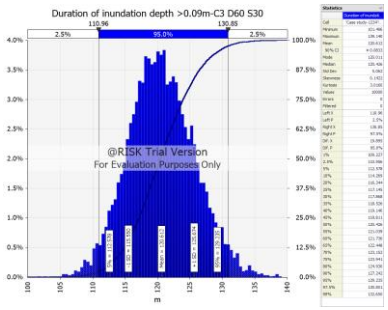



*Figure A-D1. 181. Chamber "1234" duration of inundation depth >0.09 m input distribution C3-D60-S30*

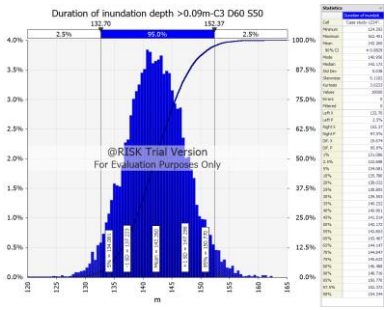



*Figure A-D1. 182. Chamber "1234" duration of inundation depth >0.09 m input distribution C3-D60-S50*

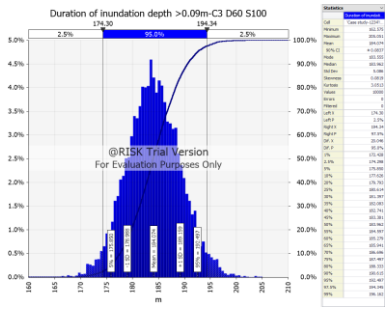



Figure A-D1. 183. Chamber "1234" duration of inundation depth >0.09 m input distribution C3-D60-S100

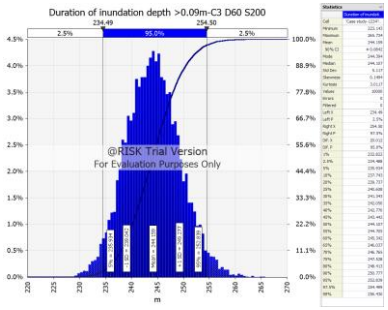



*Figure A-D1. 184. Chamber "1234" duration of inundation depth >0.09 m input distribution C3-D60-S200*

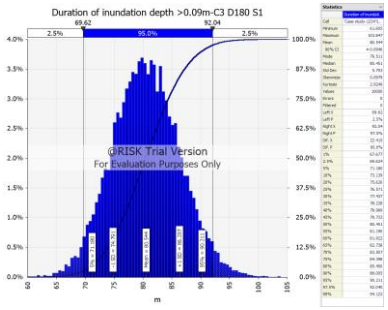



*Figure A-D1. 185. Chamber "1234" duration of inundation depth >0.09 m input distribution C3-D180-S1*

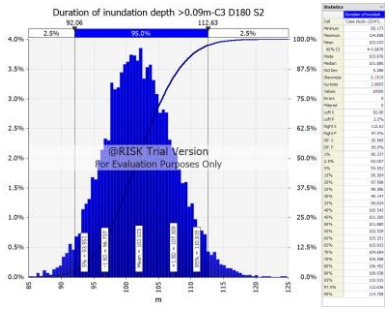



Figure A-D1. 186. Chamber "1234" duration of inundation depth >0.09 m input distribution C3-D180-S2

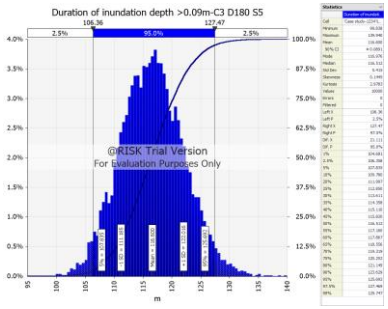



*Figure A-D1. 187. Chamber "1234" duration of inundation depth >0.09 m input distribution C3-D180-S5*

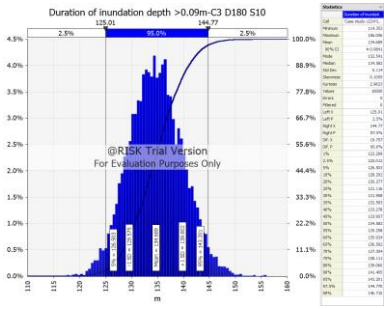



*Figure A-D1. 188. Chamber "1234" duration of inundation depth >0.09 m input distribution C3-D180-S10*

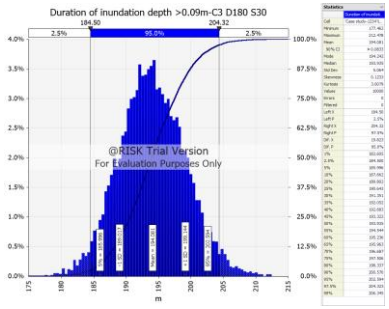



Figure A-D1. 189. Chamber "1234" duration of inundation depth >0.09 m input distribution C3-D180-S30

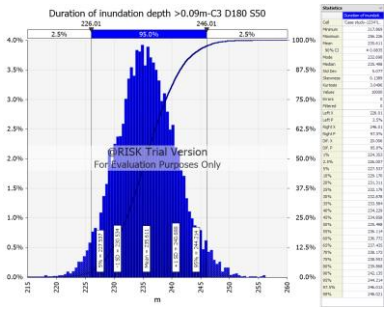



*Figure A-D1. 190. Chamber "1234" duration of inundation depth >0.09 m input distribution C3-D180-S50*

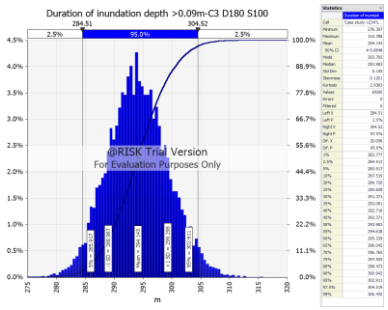



*Figure A-D1. 191. Chamber "1234" duration of inundation depth >0.09 m input distribution C3-D180-S100*

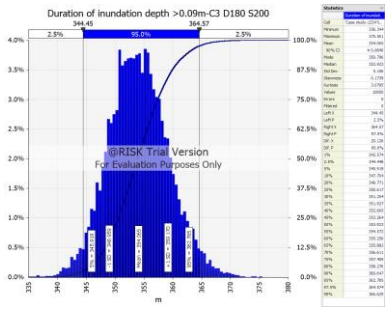



Figure A-D1. 192. Chamber "1234" duration of inundation depth >0.09 m input distribution C3-D180-S200

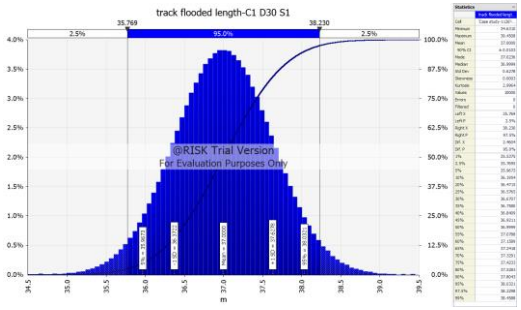



*Figure A-D1. 193. Chamber "1126" track flooded length input distribution C1-D30-S1*

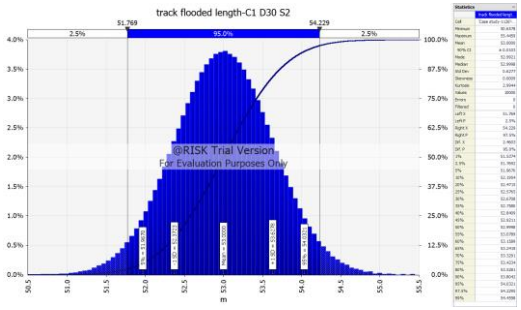



*Figure A-D1. 194. Chamber "1126" track flooded length input distribution C1-D30-S2*

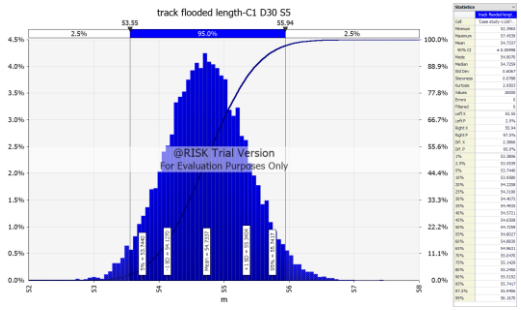



Figure A-D1. 195. Chamber "1126" track flooded length input distribution C1-D30-S5

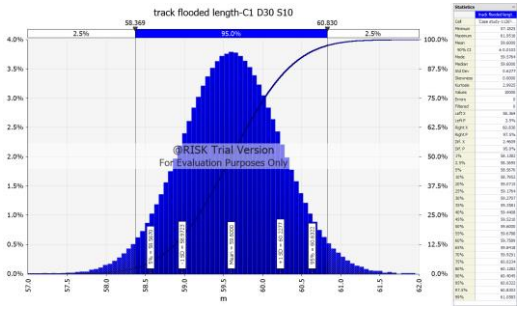



*Figure A-D1. 196. Chamber "1126" track flooded length input distribution C1-D30-S10*

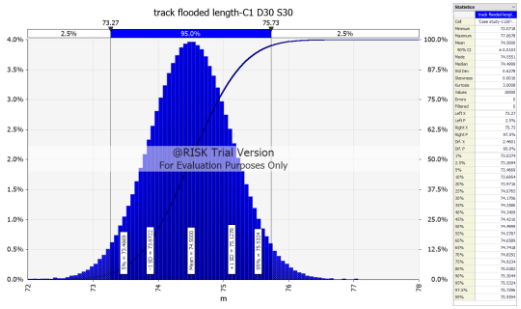



*Figure A-D1. 197. Chamber "1126" track flooded length input distribution C1-D30-S30*

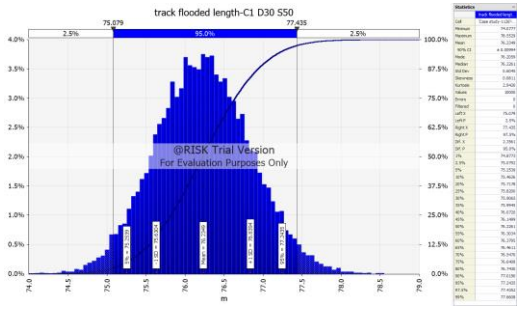



Figure A-D1. 198. Chamber "1126" track flooded length input distribution C1-D30-S50

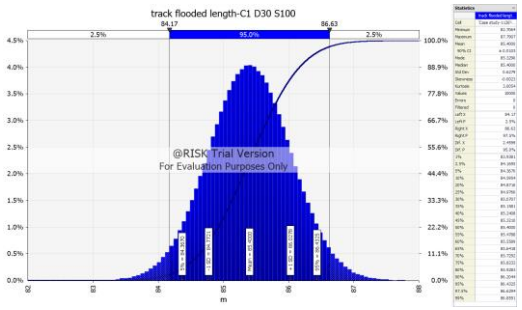



*Figure A-D1. 199. Chamber "1126" track flooded length input distribution C1-D30-S100*

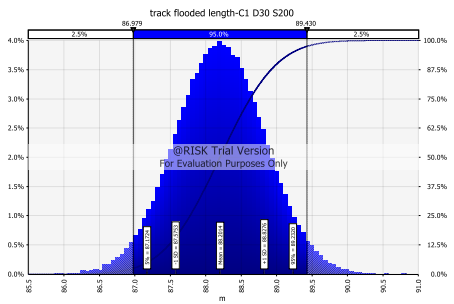



*Figure A-D1. 200. Chamber "1126" track flooded length input distribution C1-D30-S200*

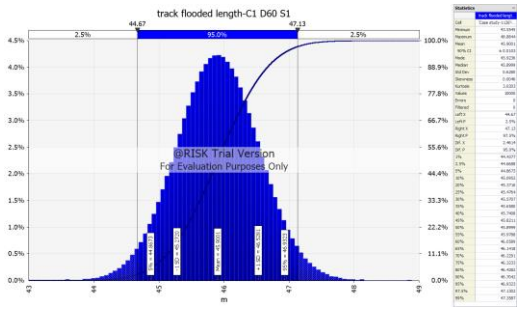



Figure A-D1. 201. Chamber "1126" track flooded length input distribution C1-D60-S1

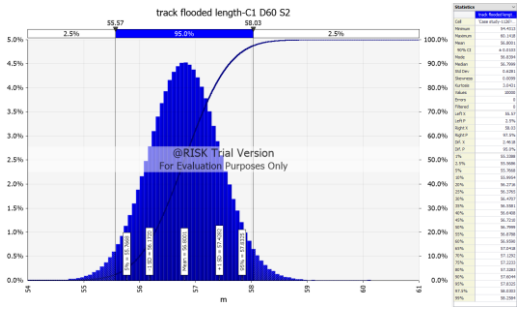



*Figure A-D1. 202. Chamber "1126" track flooded length input distribution C1-D60-S2*

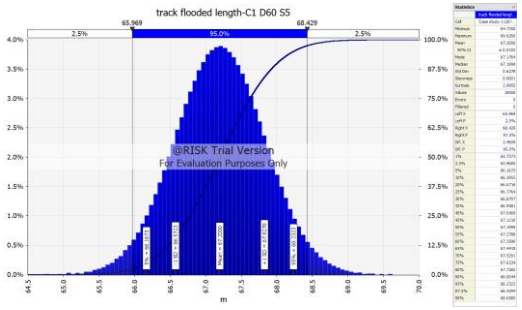



*Figure A-D1. 203. Chamber "1126" track flooded length input distribution C1-D60-S5.*

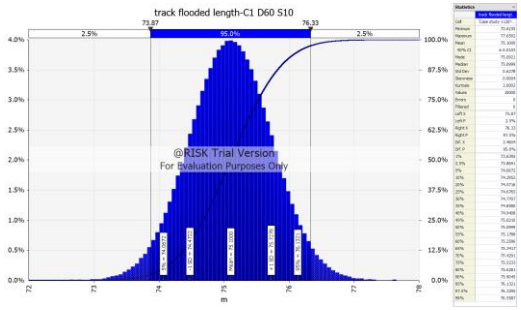



Figure A-D1. 204. Chamber "1126" track flooded length input distribution C1-D60-S10

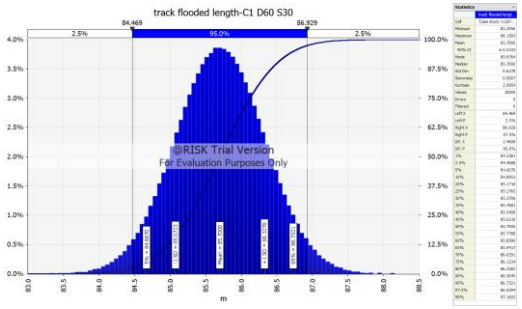



*Figure A-D1. 205. Chamber "1126" track flooded length input distribution C1-D60-S30*

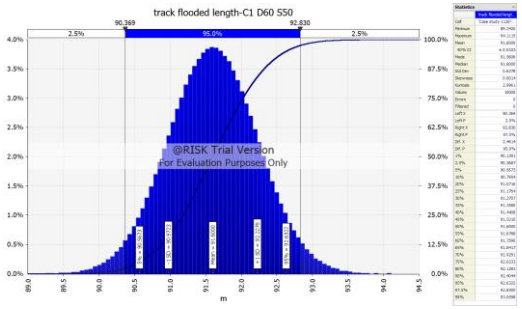



*Figure A-D1. 206. Chamber "1126" track flooded length input distribution C1-D60-S50*

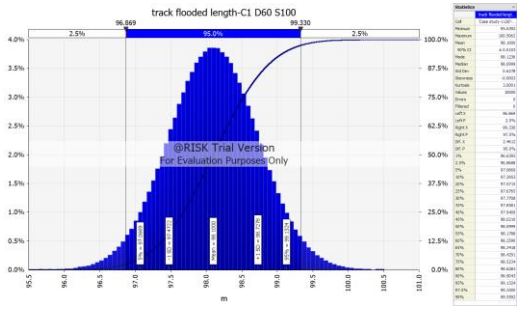



Figure A-D1. 207. Chamber "1126" track flooded length input distribution C1-D60-S100

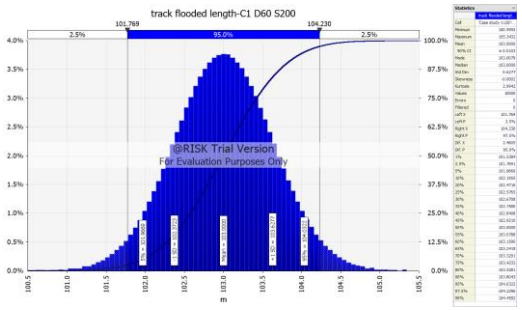



*Figure A-D1. 208. Chamber "1126" track flooded length input distribution C1-D60-S200*

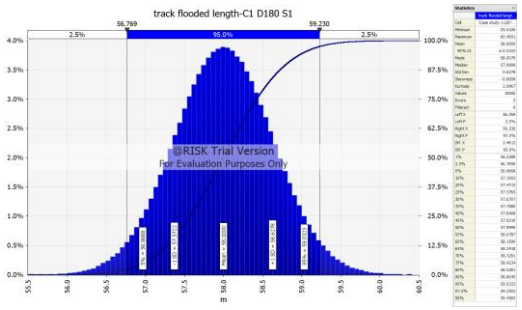



*Figure A-D1. 209. Chamber "1126" track flooded length input distribution C1-D180-S1*

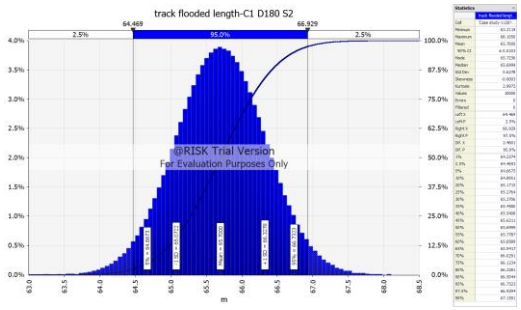



Figure A-D1. 210. Chamber "1126" track flooded length input distribution C1-D180-S2

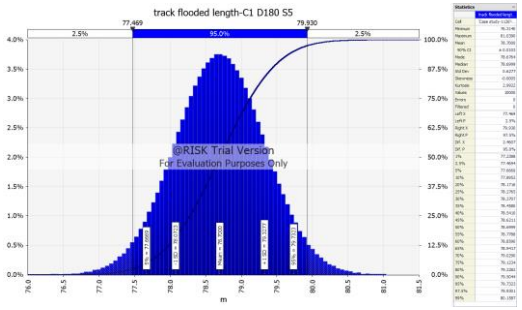



*Figure A-D1. 211. Chamber "1126" track flooded length input distribution C1-D180-S5*

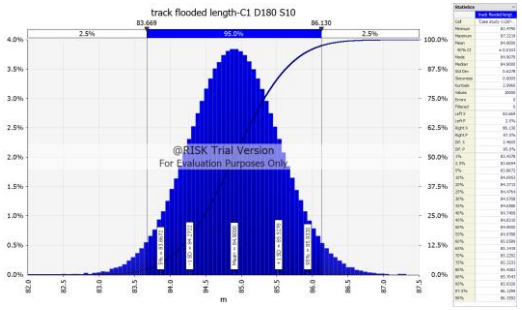



*Figure A-D1. 212. Chamber "1126" track flooded length input distribution C1-D180-S10*

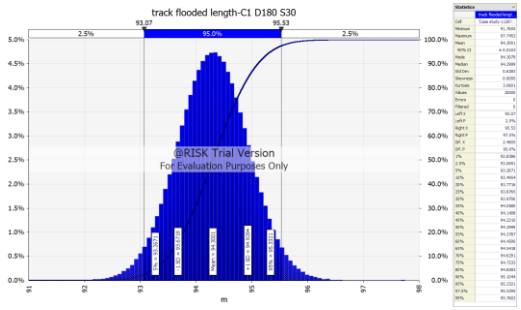



Figure A-D1. 213. Chamber "1126" track flooded length input distribution C1-D180-S30

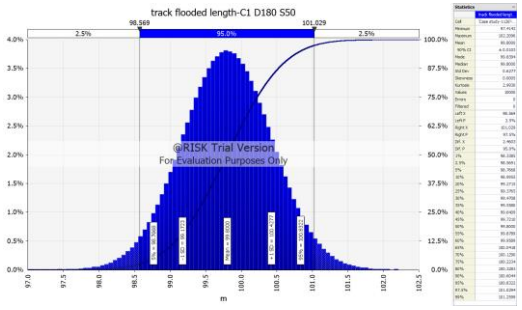



*Figure A-D1. 214. Chamber "1126" track flooded length input distribution C1-D180-S50*

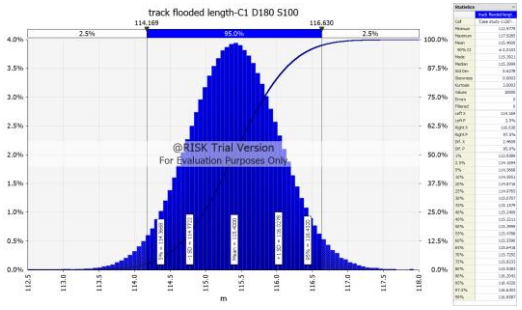



*Figure A-D1. 215. Chamber "1126" track flooded length input distribution C1-D180-S100*

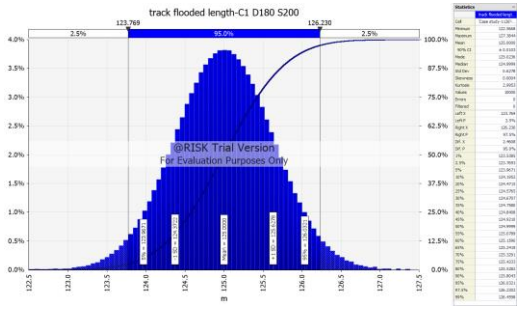



Figure A-D1. 216. Chamber "1126" track flooded length input distribution C1-D180-S200

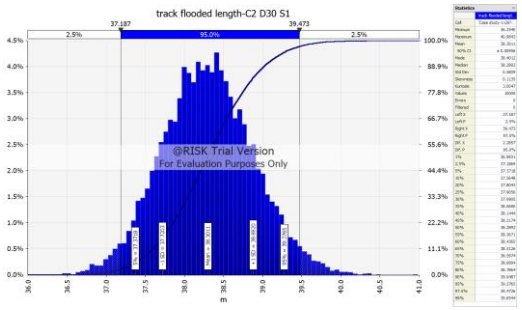



*Figure A-D1. 217. Chamber "1126" track flooded length input distribution C2-D30-S1*

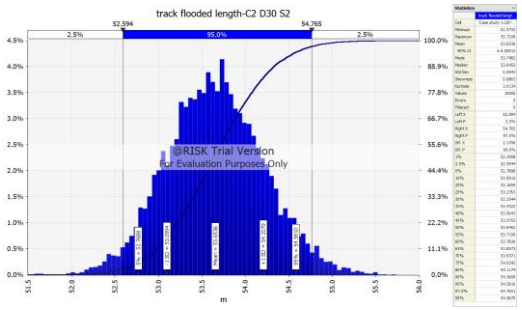



*Figure A-D1. 218. Chamber "1126" track flooded length input distribution C2-D30-S2*

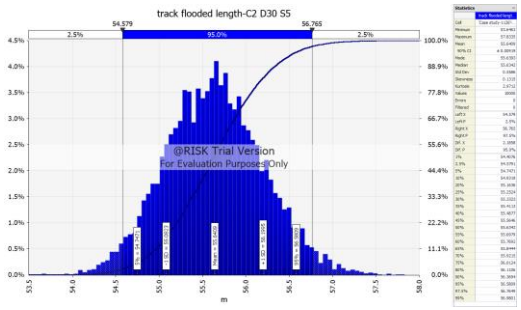



Figure A-D1. 219. Chamber "1126" track flooded length input distribution C2-D30-S5

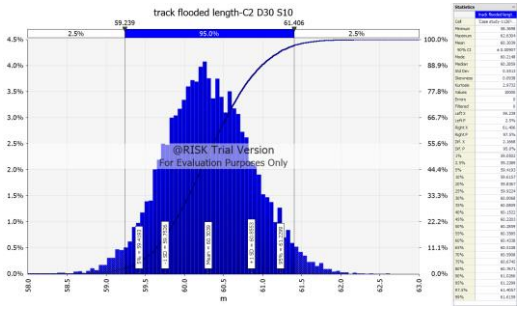



*Figure A-D1. 220. Chamber "1126" track flooded length input distribution C2-D30-S10*

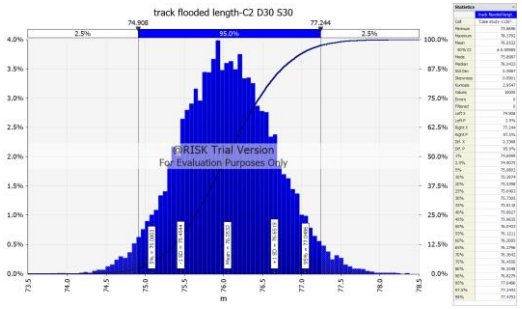



*Figure A-D1. 221. Chamber "1126" track flooded length input distribution C2-D30-S30*

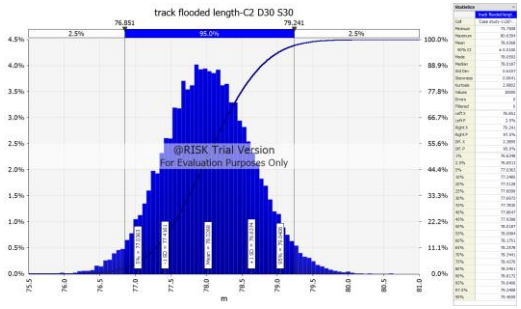



Figure A-D1. 222. Chamber "1126" track flooded length input distribution C2-D30-S50

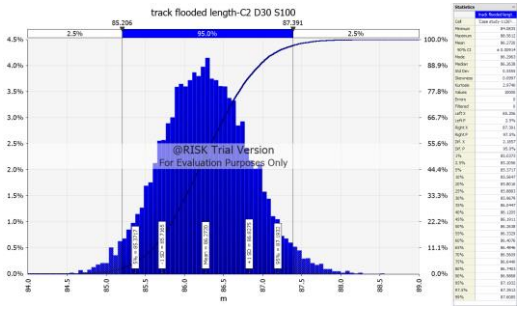



*Figure A-D1. 223. Chamber "1126" track flooded length input distribution C2-D30-S100*

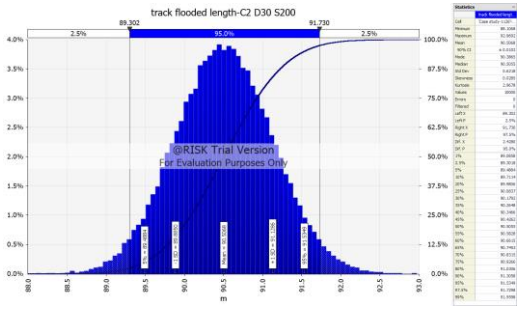



*Figure A-D1. 224. Chamber "1126" track flooded length input distribution C2-D30-S200*

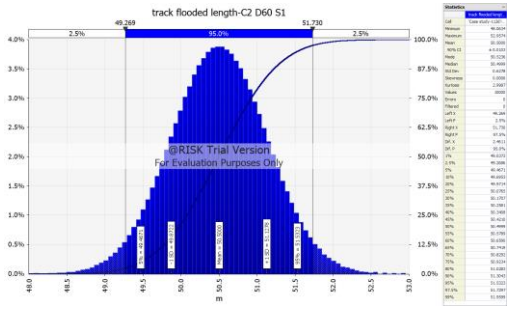



Figure A-D1. 225. Chamber "1126" track flooded length input distribution C2-D60-S1

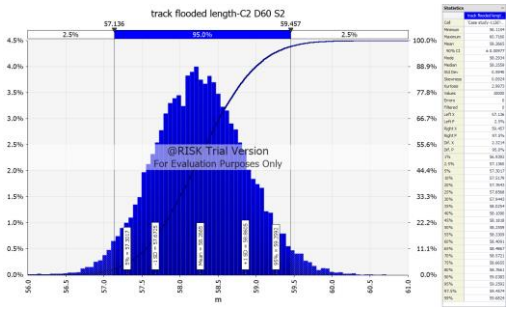



*Figure A-D1. 226. Chamber "1126" track flooded length input distribution C2-D60-S2*

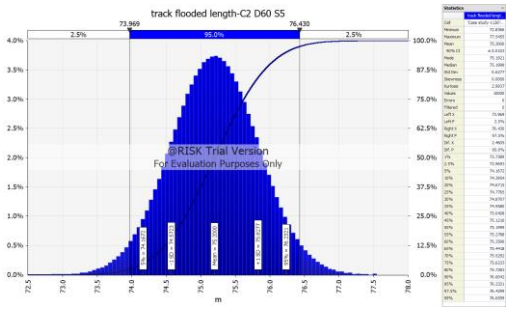



*Figure A-D1. 227. Chamber "1126" track flooded length input distribution C2-D60-S5*

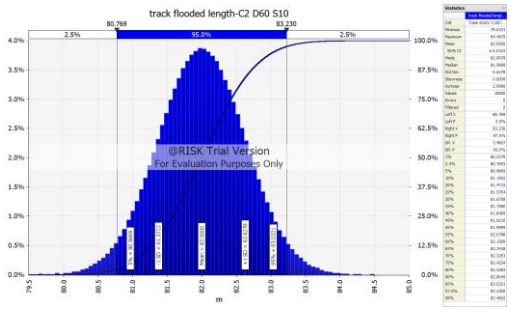



Figure A-D1. 228. Chamber "1126" track flooded length input distribution C2-D60-S10

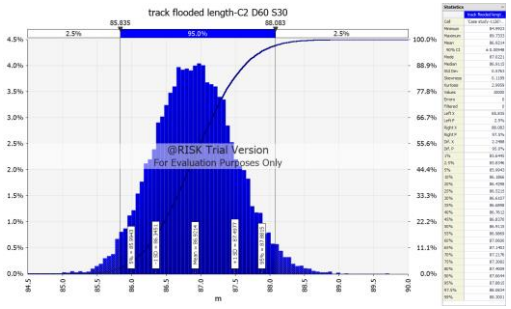



*Figure A-D1. 229. Chamber "1126" track flooded length input distribution C2-D60-S30*

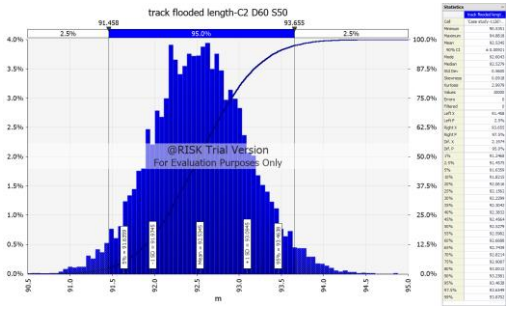



*Figure A-D1. 230. Chamber "1126" track flooded length input distribution C2-D60-S50*

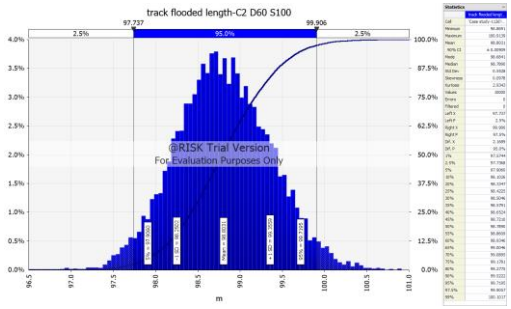



Figure A-D1. 231. Chamber "1126" track flooded length input distribution C2-D60-S100

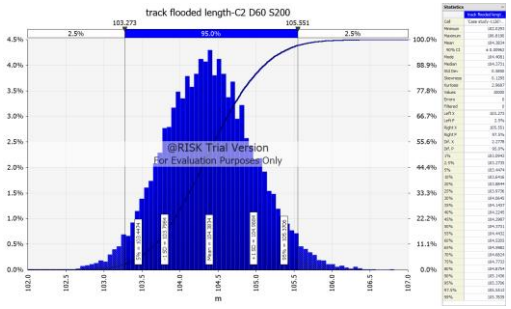



*Figure A-D1. 232. Chamber "1126" track flooded length input distribution C2-D60-S200*

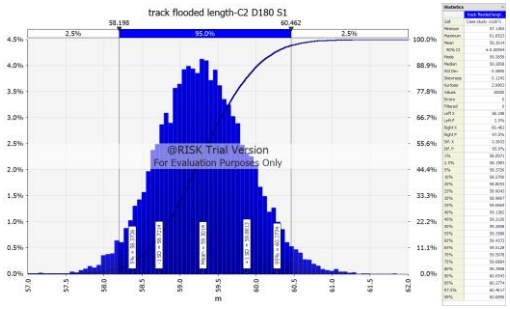



*Figure A-D1. 233. Chamber "1126" track flooded length input distribution C2-D180-S1*

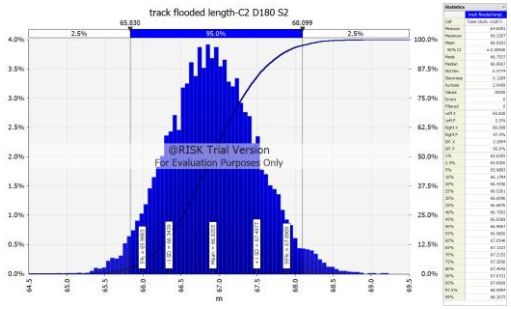



Figure A-D1. 234. Chamber "1126" track flooded length input distribution C2-D180-S2

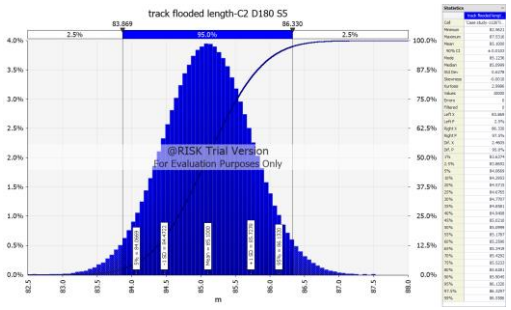



*Figure A-D1. 235. Chamber "1126" track flooded length input distribution C2-D180-S5*

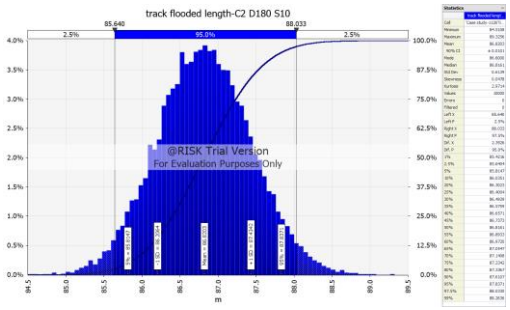



*Figure A-D1. 236. Chamber "1126" track flooded length input distribution C2-D180-S10*

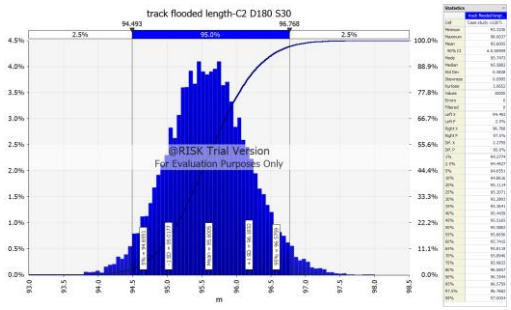
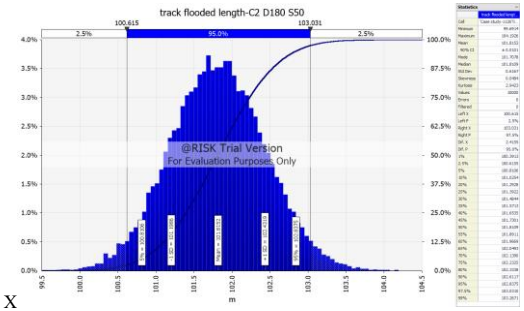



Figure A-D1. 237. Chamber "1126" track flooded length input distribution C2-D180-S30




X

*Figure A-D1. 238. Chamber "1126" track flooded length input distribution C2-D180-S50*

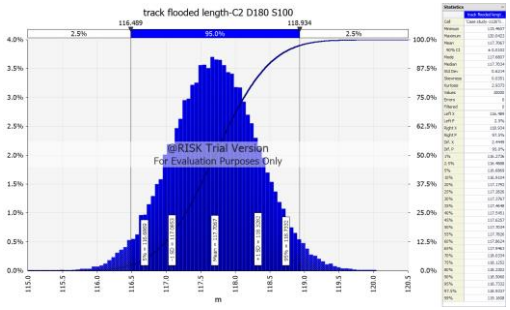



*Figure A-D1. 239. Chamber "1126" track flooded length input distribution C2-D180-S100*

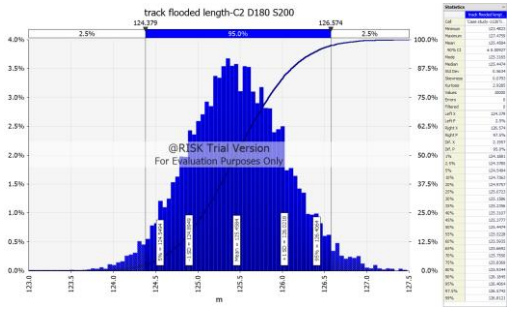



Figure A-D1. 240. Chamber "1126" track flooded length input distribution C2-D180-S200

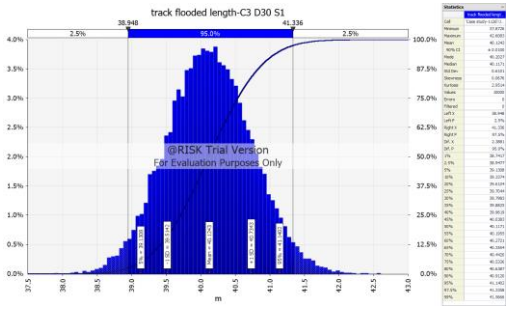



*Figure A-D1. 241. Chamber "1126" track flooded length input distribution C3-D30-S1*

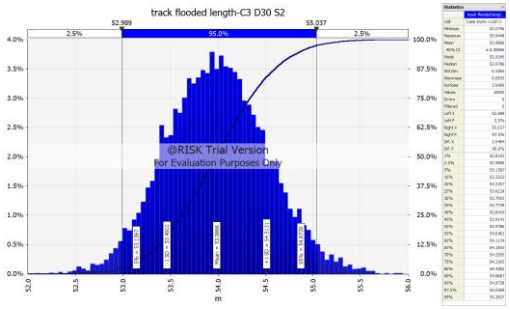



*Figure A-D1. 242. Chamber "1126" track flooded length input distribution C3-D30-S2*

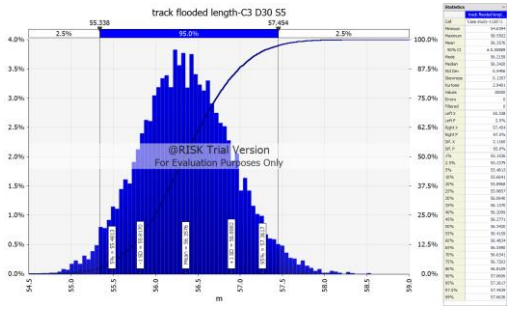



Figure A-D1. 243. Chamber "1126" track flooded length input distribution C3-D30-S5

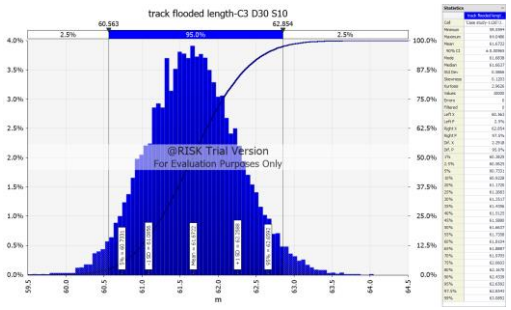



*Figure A-D1. 244. Chamber "1126" track flooded length input distribution C3-D30-S10*

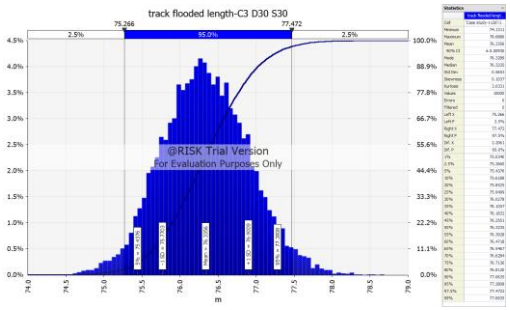



*Figure A-D1. 245. Chamber "1126" track flooded length input distribution C3-D30-S30*

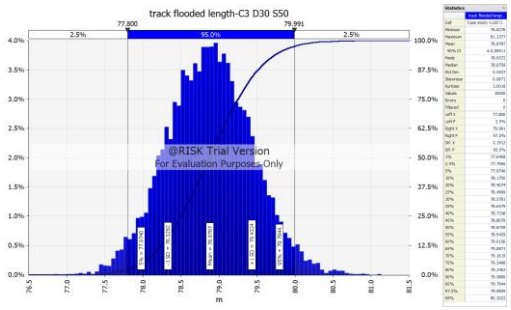



Figure A-D1. 246. Chamber "1126" track flooded length input distribution C3-D30-S50

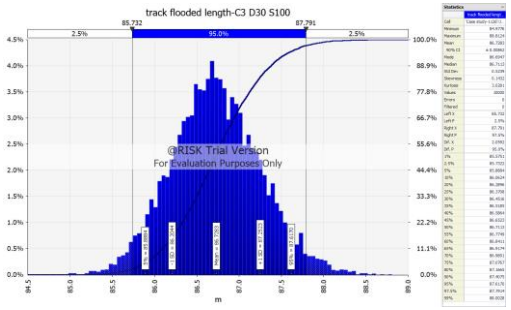



*Figure A-D1. 247. Chamber "1126" track flooded length input distribution C3-D30-S100*

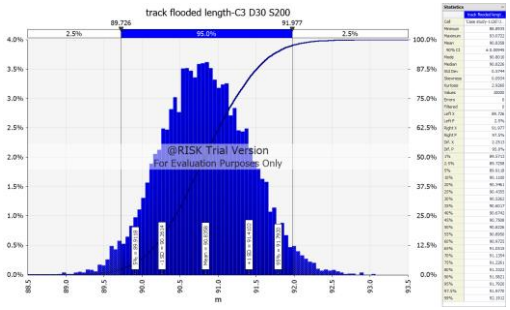



*Figure A-D1. 248. Chamber "1126" track flooded length input distribution C3-D30-S200*

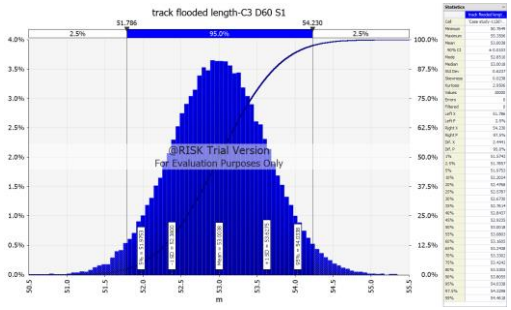



Figure A-D1. 249. Chamber "1126" track flooded length input distribution C3-D60-S1

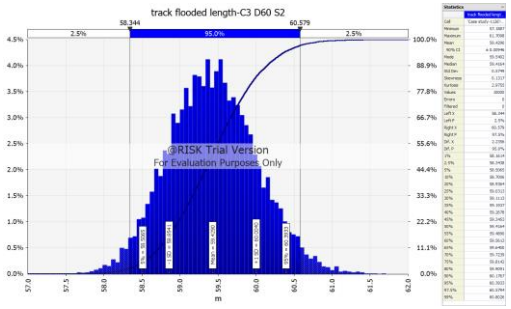



*Figure A-D1. 250. Chamber "1126" track flooded length input distribution C3-D60-S2*

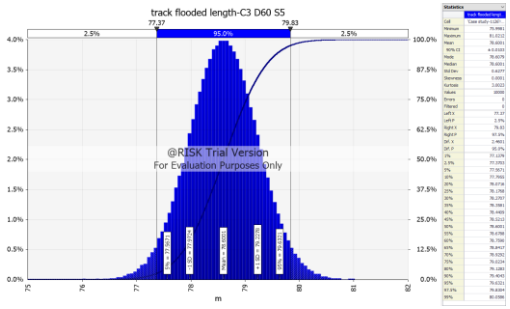



*Figure A-D1. 251. Chamber "1126" track flooded length input distribution C3-D60-S5*

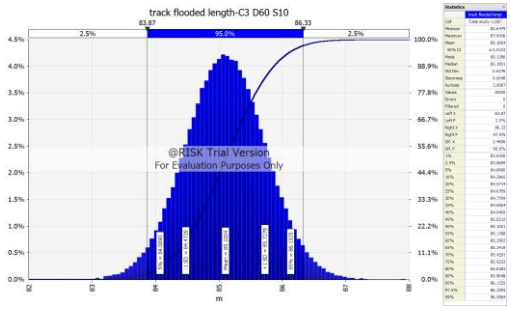



Figure A-D1. 252. Chamber "1126" track flooded length input distribution C3-D60-S10

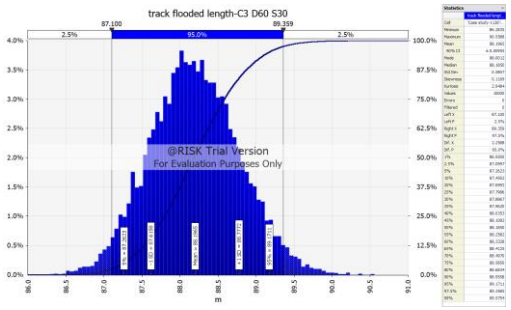



*Figure A-D1. 253. Chamber "1126" track flooded length input distribution C3-D60-S30*

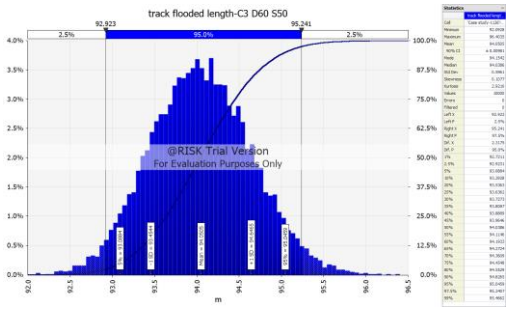



*Figure A-D1. 254. Chamber "1126" track flooded length input distribution C3-D60-S50*

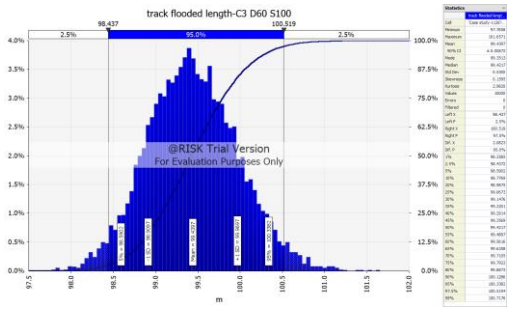



Figure A-D1. 255. Chamber "1126" track flooded length input distribution C3-D60-S100

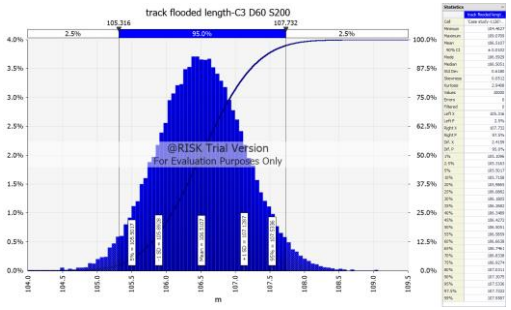



*Figure A-D1. 256. Chamber "1126" track flooded length input distribution C3-D60-S200*

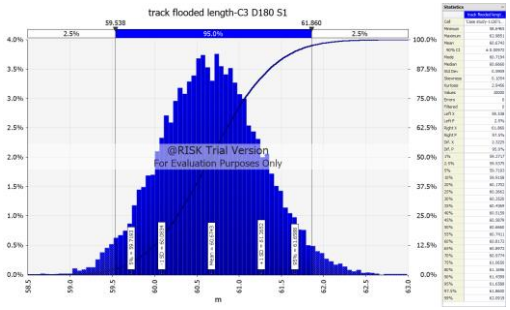



*Figure A-D1. 257. Chamber "1126" track flooded length input distribution C3-D180-S1*

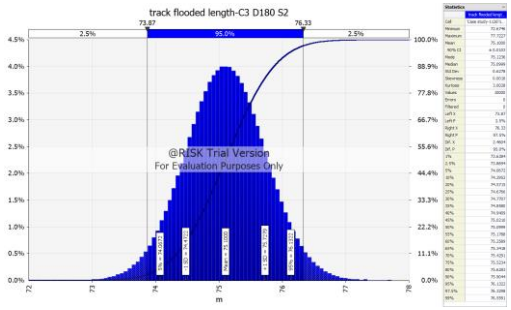



Figure A-D1. 258. Chamber "1126" track flooded length input distribution C3-D180-S2

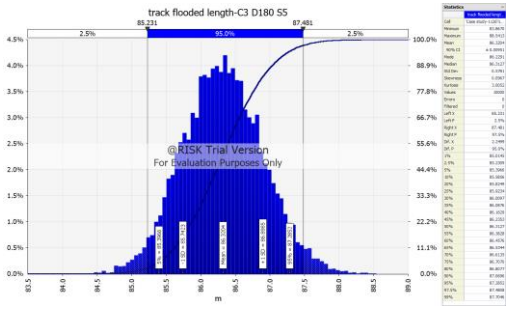



*Figure A-D1. 259. Chamber "1126" track flooded length input distribution C3-D180-S5*

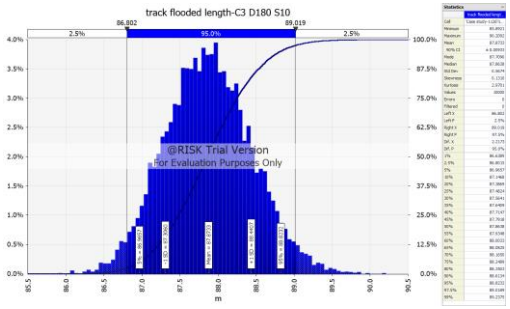



*Figure A-D1. 260. Chamber "1126" track flooded length input distribution C3-D180-S10*

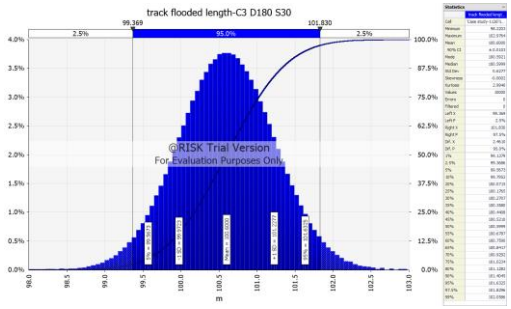



Figure A-D1. 261. Chamber "1126" track flooded length input distribution C3-D180-S30

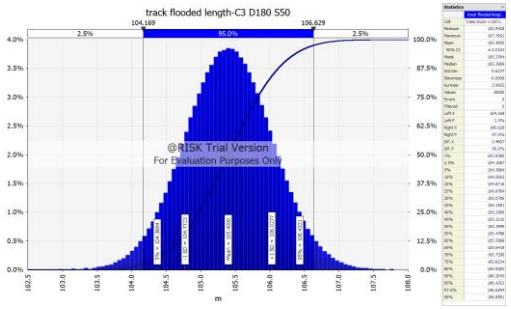



*Figure A-D1. 262. Chamber "1126" track flooded length input distribution C3-D180-S50*

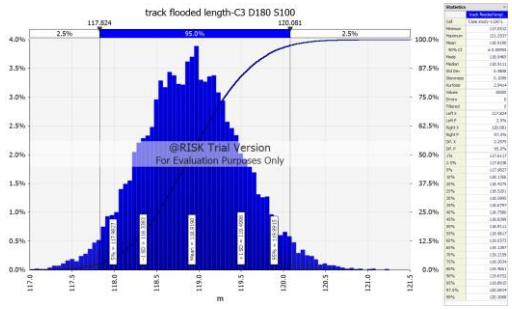



*Figure A-D1. 263. Chamber "1126" track flooded length input distribution C3-D180-S100*

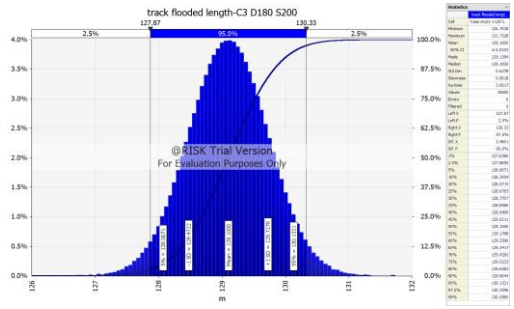



Figure A-D1. 264. Chamber "1126" track flooded length input distribution C3-D180-S200

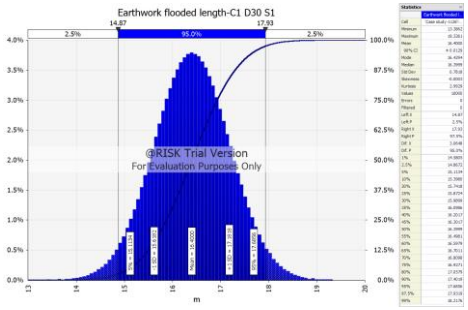



*Figure A-D1. 265. Chamber "1126" Earthwork flooded length input distribution C1-D30-S1*

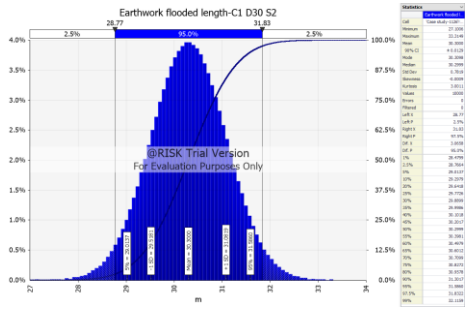



*Figure A-D1. 266. Chamber "1126" Earthwork flooded length input distribution C1-D30-S2*

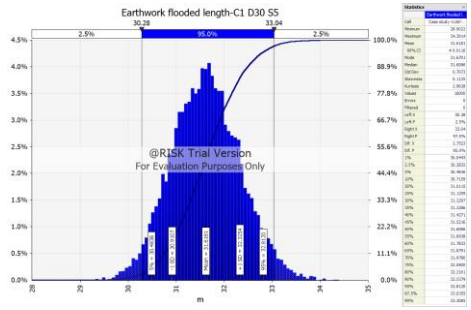



Figure A-D1. 267. Chamber "1126" Earthwork flooded length input distribution C1-D30-S5

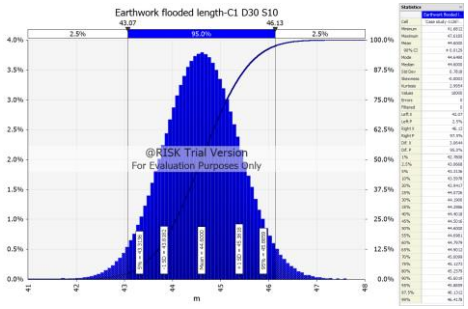



*Figure A-D1. 268. Chamber "1126" Earthwork flooded length input distribution C1-D30-S10*

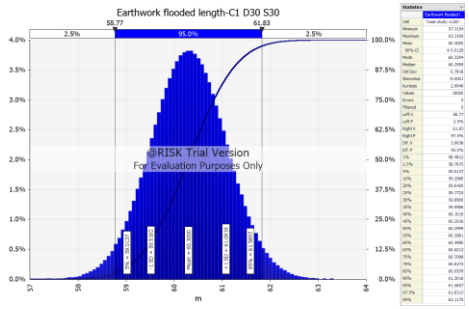



*Figure A-D1. 269. Chamber "1126" Earthwork flooded length input distribution C1-D30-S30*

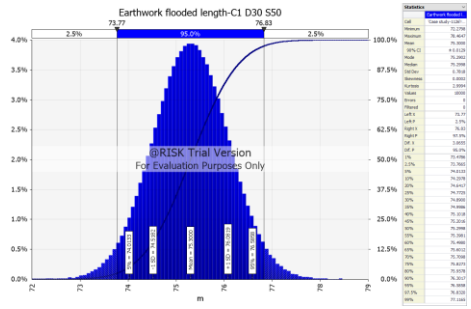



Figure A-D1. 270. Chamber "1126" Earthwork flooded length input distribution C1-D30-S50

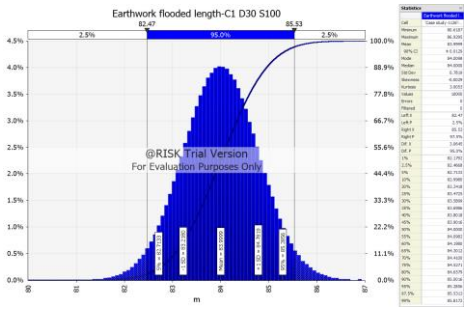



*Figure A-D1. 271. Chamber "1126" Earthwork flooded length input distribution C1-D30-S100*

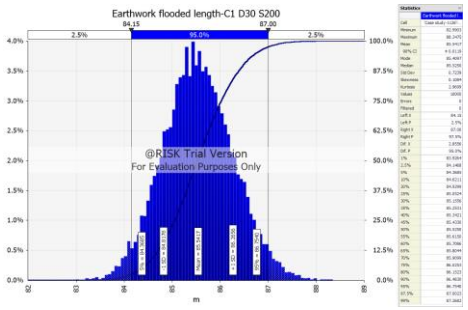



*Figure A-D1. 272. Chamber "1126" Earthwork flooded length input distribution C1-D30-S200*

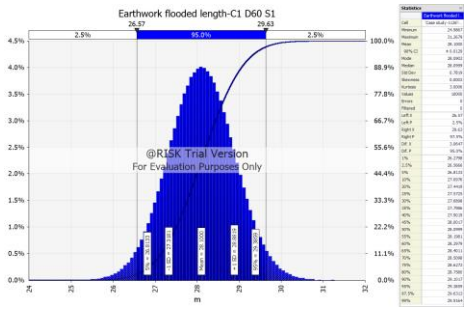



Figure A-D1. 273. Chamber "1126" Earthwork flooded length input distribution C1-D60-S1

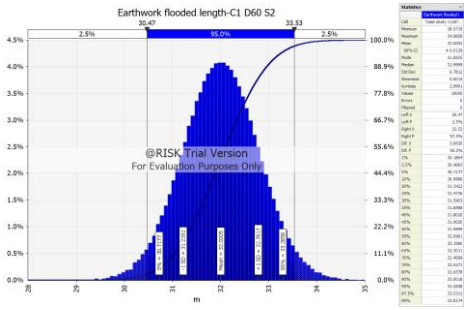



*Figure A-D1. 274. Chamber "1126" Earthwork flooded length input distribution C1-D60-S2*

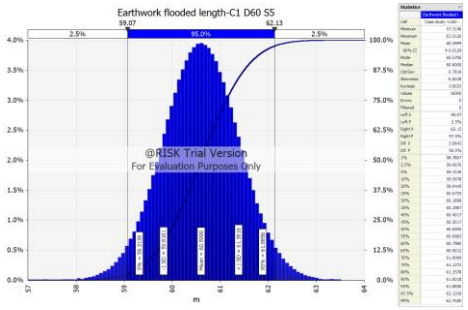



*Figure A-D1. 275. Chamber "1126" Earthwork flooded length input distribution C1-D60-S5*

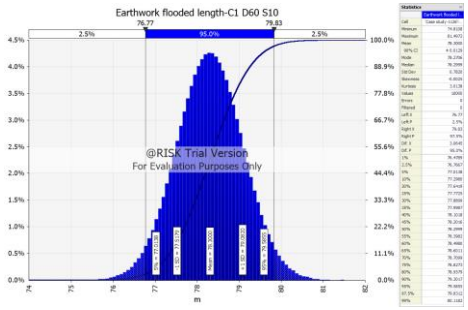



Figure A-D1. 276. Chamber "1126" Earthwork flooded length input distribution C1-D60-S10

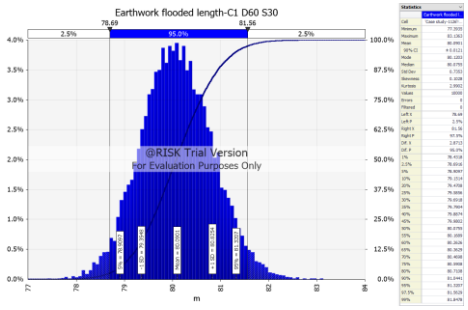



*Figure A-D1. 277. Chamber "1126" Earthwork flooded length input distribution C1-D60-S30*

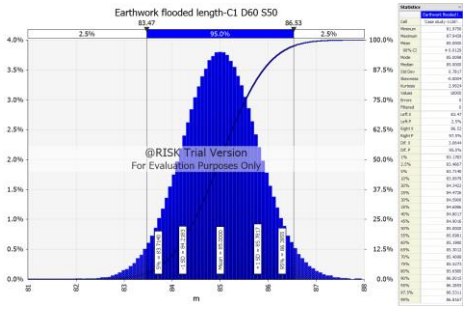



*Figure A-D1. 278. Chamber "1126" Earthwork flooded length input distribution C1-D60-S50*

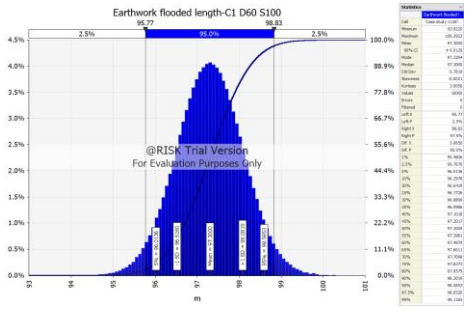



Figure A-D1. 279. Chamber "1126" Earthwork flooded length input distribution C1-D60-S100

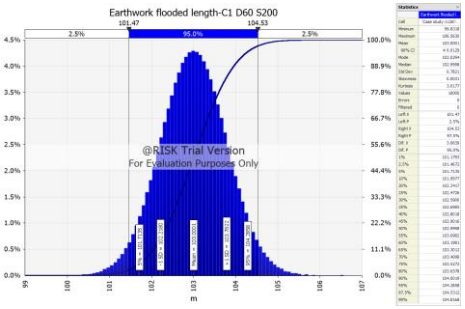



*Figure A-D1. 280. Chamber "1126" Earthwork flooded length input distribution C1-D60-S200*

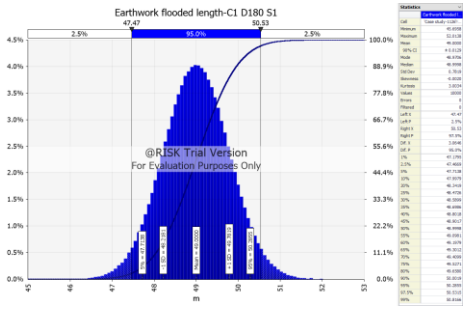



*Figure A-D1. 281. Chamber "1126" Earthwork flooded length input distribution C1-D180-S1*

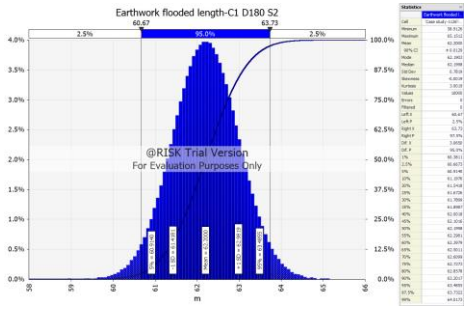



Figure A-D1. 282. Chamber "1126" Earthwork flooded length input distribution C1-D180-S2

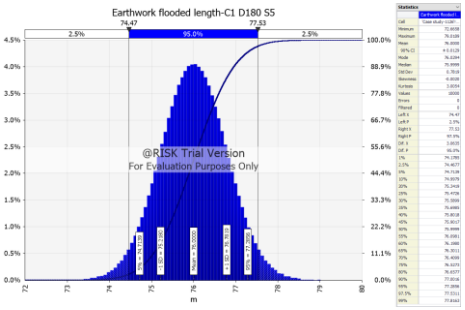



*Figure A-D1. 283. Chamber "1126" Earthwork flooded length input distribution C1-D180-S5*

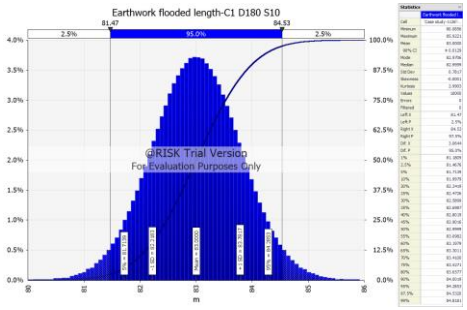



*Figure A-D1. 284. Chamber "1126" Earthwork flooded length input distribution C1-D180-S10*

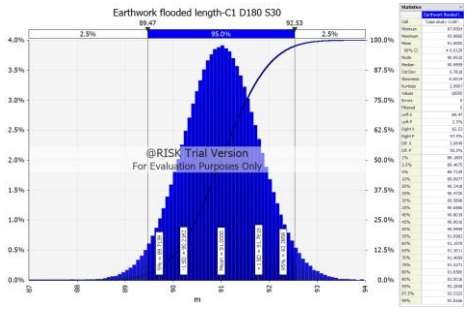



Figure A-D1. 285. Chamber "1126" Earthwork flooded length input distribution C1-D180-S30

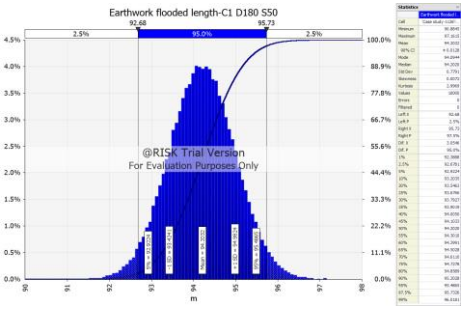



*Figure A-D1. 286. Chamber "1126" Earthwork flooded length input distribution C1-D180-S50*

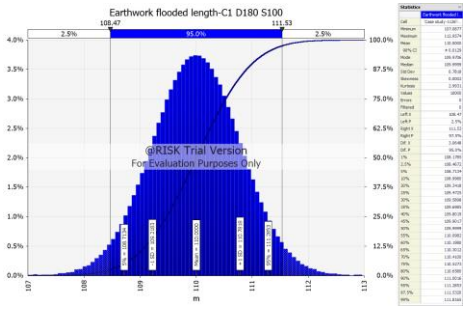



*Figure A-D1. 287. Chamber "1126" Earthwork flooded length input distribution C1-D180-S100*

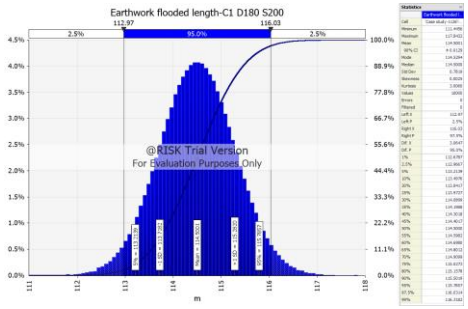



Figure A-D1. 288. Chamber "1126" Earthwork flooded length input distribution C1-D180-S200

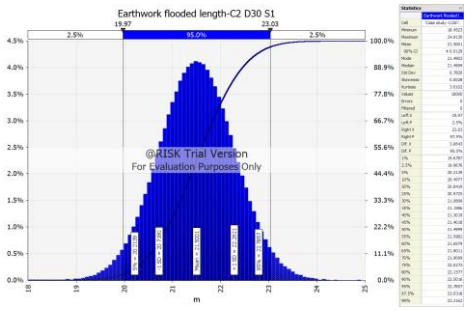



*Figure A-D1. 289. Chamber "1126" Earthwork flooded length input distribution C2-D30-S1*

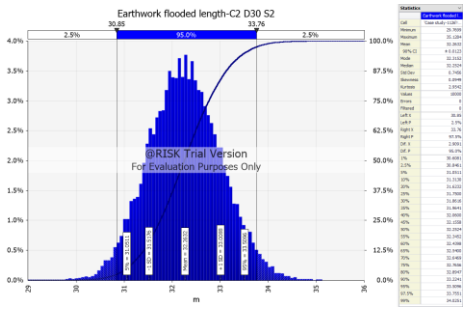



*Figure A-D1. 290. Chamber "1126" Earthwork flooded length input distribution C2-D30-S2*

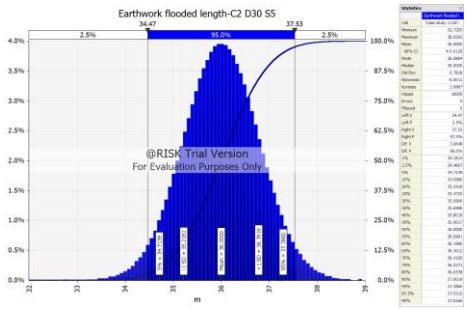



Figure A-D1. 291. Chamber "1126" Earthwork flooded length input distribution C2-D30-S5

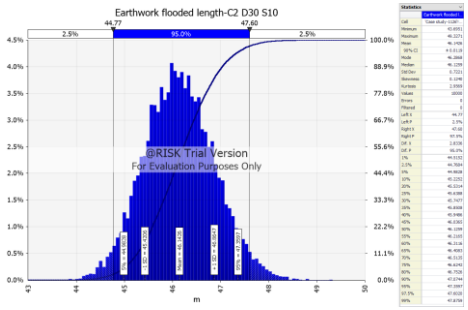



*Figure A-D1. 292. Chamber "1126" Earthwork flooded length input distribution C2-D30-S10*

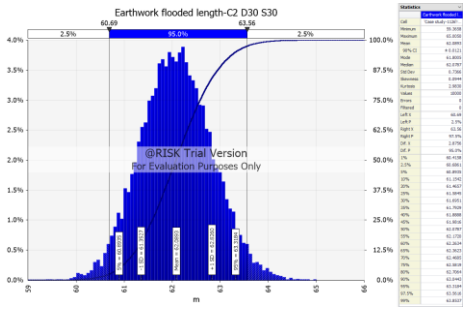



*Figure A-D1. 293. Chamber "1126" Earthwork flooded length input distribution C2-D30-S30*

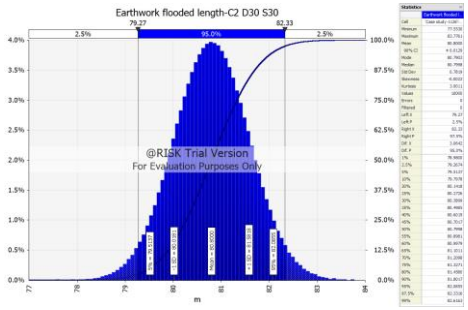



Figure A-D1. 294. Chamber "1126" Earthwork flooded length input distribution C2-D30-S50

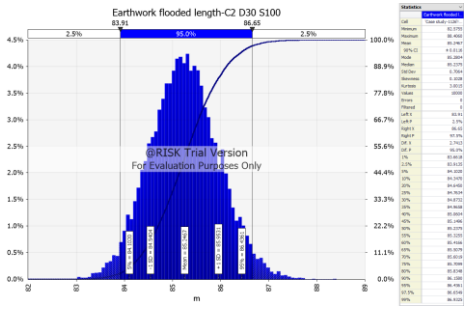



*Figure A-D1. 295. Chamber "1126" Earthwork flooded length input distribution C2-D30-S100*

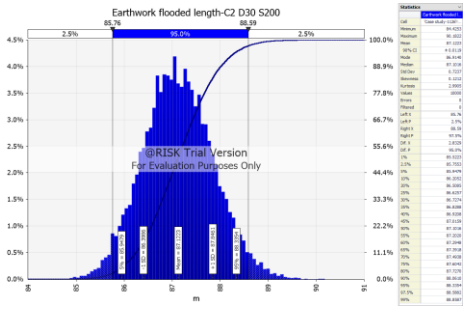



*Figure A-D1. 296. Chamber "1126" Earthwork flooded length input distribution C2-D30-S200*

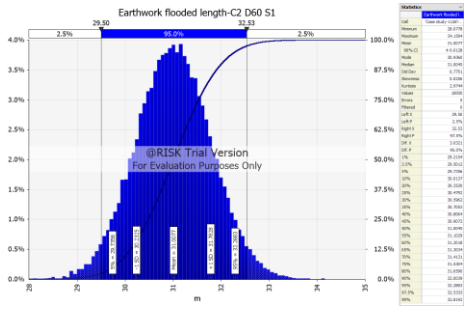



Figure A-D1. 297. Chamber "1126" Earthwork flooded length input distribution C2-D60-S1

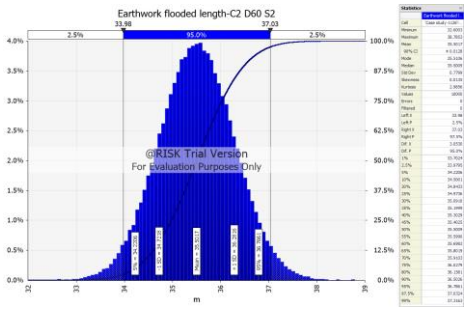



*Figure A-D1. 298. Chamber "1126" Earthwork flooded length input distribution C2-D60-S2*

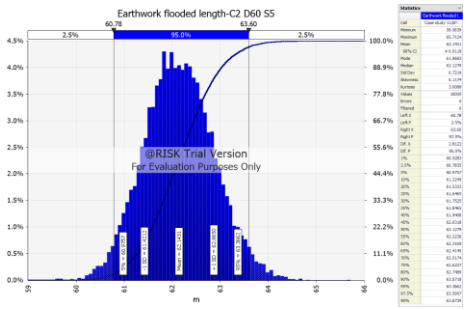



*Figure A-D1. 299. Chamber "1126" Earthwork flooded length input distribution C2-D60-S5*

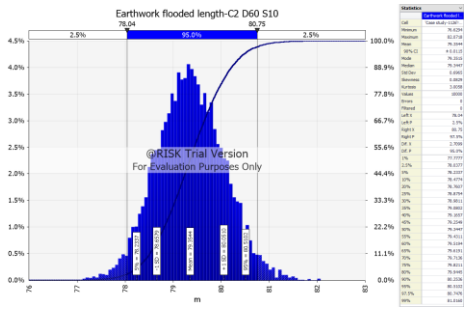



Figure A-D1. 300. Chamber "1126" Earthwork flooded length input distribution C2-D60-S10

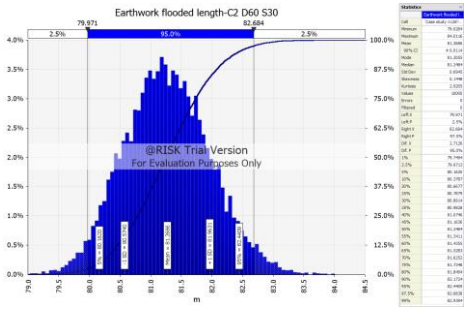



*Figure A-D1. 301. Chamber "1126" Earthwork flooded length input distribution C2-D60-S30*

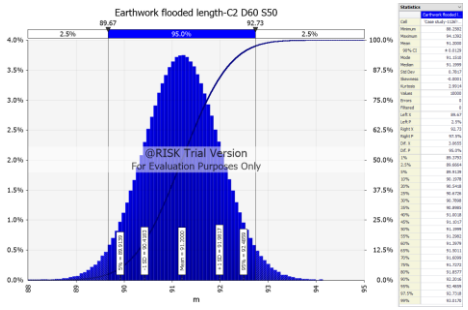



*Figure A-D1. 302. Chamber "1126" Earthwork flooded length input distribution C2-D60-S50*

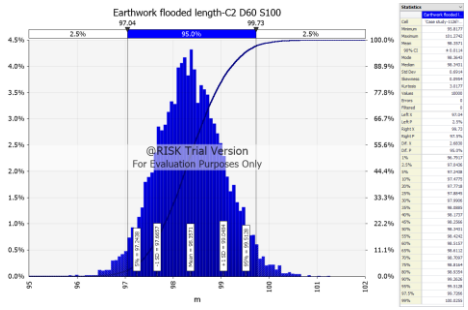



Figure A-D1. 303. Chamber "1126" Earthwork flooded length input distribution C2-D60-S100

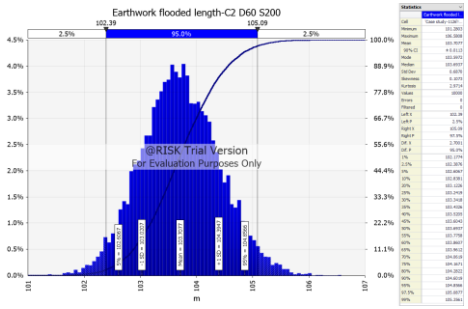



*Figure A-D1. 304. Chamber "1126" Earthwork flooded length input distribution C2-D60-S200*

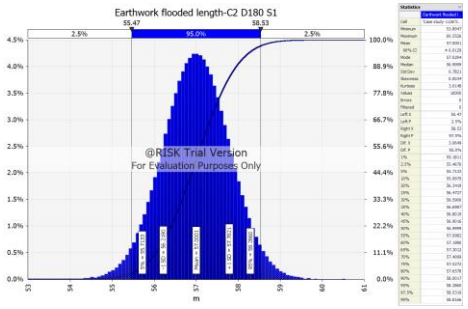



*Figure A-D1. 305. Chamber "1126" Earthwork flooded length input distribution C2-D180-S1*

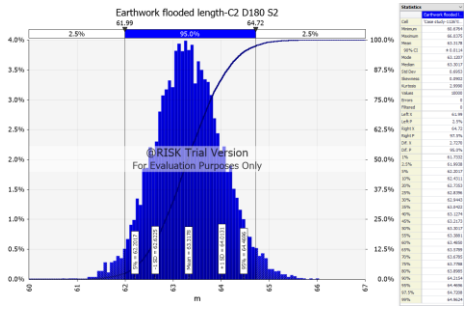



Figure A-D1. 306. Chamber "1126" Earthwork flooded length input distribution C2-D180-S2

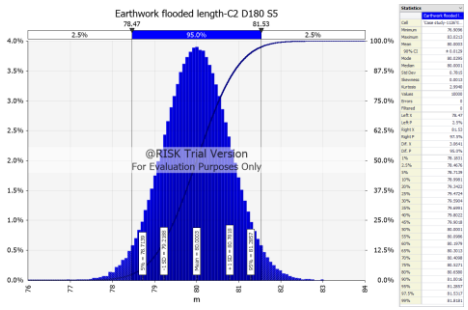



*Figure A-D1. 307. Chamber "1126" Earthwork flooded length input distribution C2-D180-S5*

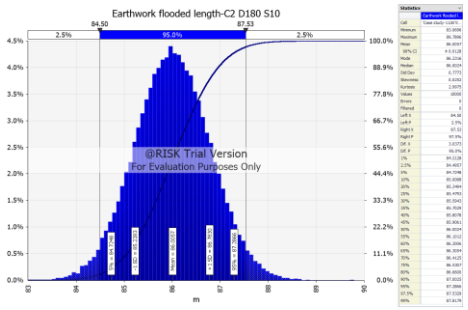



*Figure A-D1. 308. Chamber "1126" Earthwork flooded length input distribution C2-D180-S10*

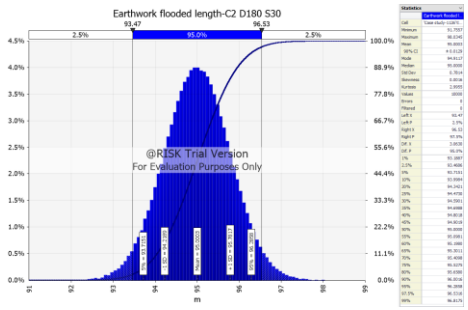



Figure A-D1. 309. Chamber "1126" Earthwork flooded length input distribution C2-D180-S30

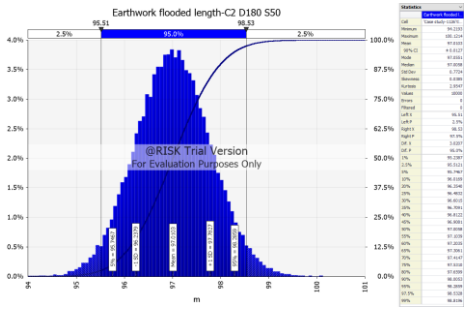



*Figure A-D1. 310. Chamber "1126" Earthwork flooded length input distribution C2-D180-S50*

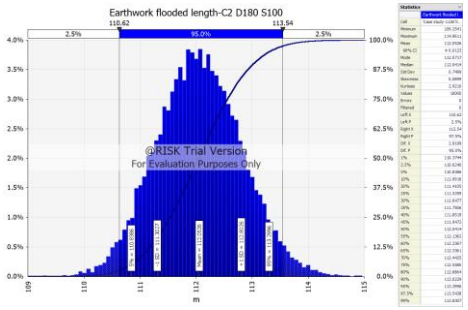



*Figure A-D1. 311. Chamber "1126" Earthwork flooded length input distribution C2-D180-S100*

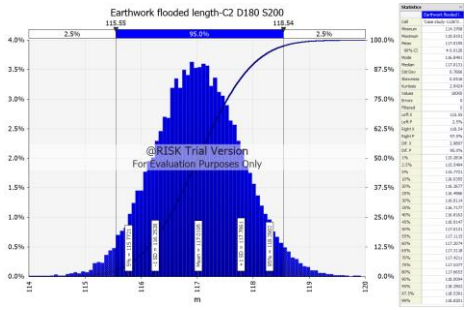



Figure A-D1. 312. Chamber "1126" Earthwork flooded length input distribution C2-D180-S200

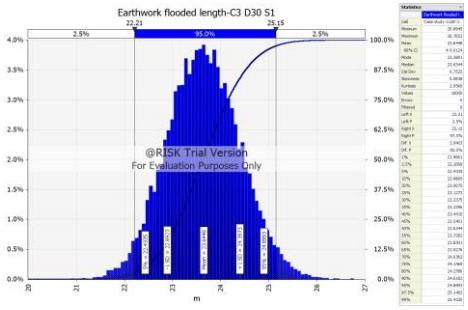



*Figure A-D1. 313. Chamber "1126" Earthwork flooded length input distribution C3-D30-S1*

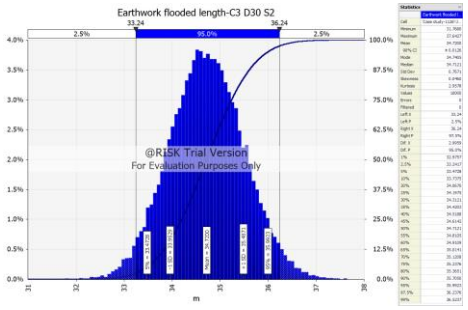



*Figure A-D1. 314. Chamber "1126" Earthwork flooded length input distribution C3-D30-S2*

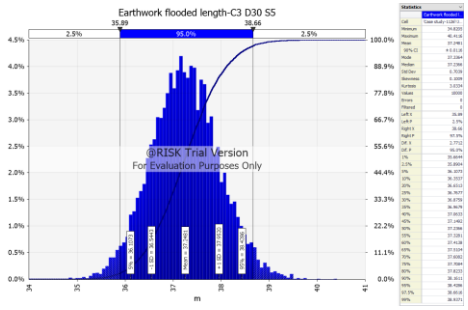



Figure A-D1. 315. Chamber "1126" Earthwork flooded length input distribution C3-D30-S5

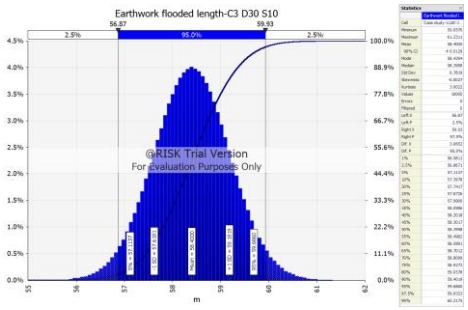



*Figure A-D1. 316. Chamber "1126" Earthwork flooded length input distribution C3-D30-S10*

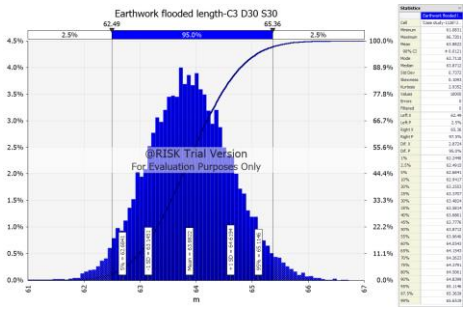



*Figure A-D1. 317. Chamber "1126" Earthwork flooded length input distribution C3-D30-S30*

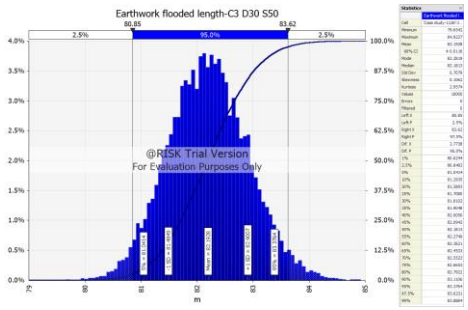



Figure A-D1. 318. Chamber "1126" Earthwork flooded length input distribution C3-D30-S50

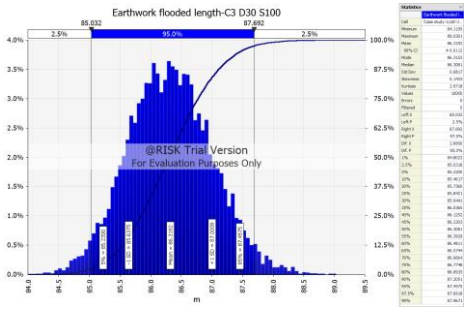



*Figure A-D1. 319. Chamber "1126" Earthwork flooded length input distribution C3-D30-S100*

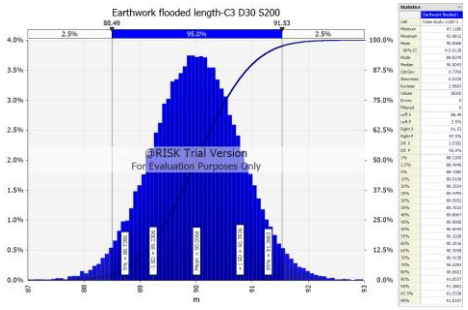



*Figure A-D1. 320. Chamber "1126" Earthwork flooded length input distribution C3-D30-S200*

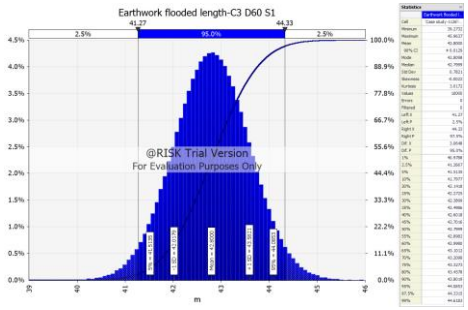



Figure A-D1. 321. Chamber "1126" Earthwork flooded length input distribution C3-D60-S1

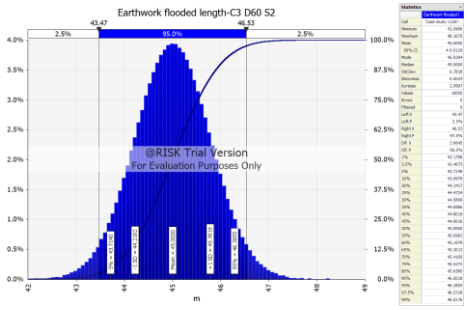



*Figure A-D1. 322. Chamber "1126" Earthwork flooded length input distribution C3-D60-S2*

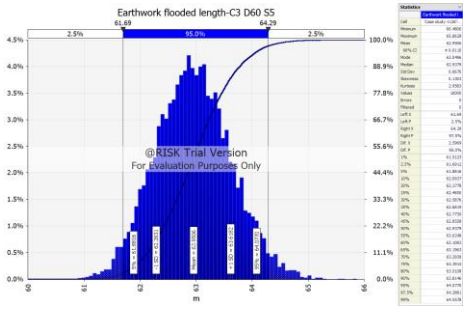



*Figure A-D1. 323. Chamber "1126" Earthwork flooded length input distribution C3-D60-S5*

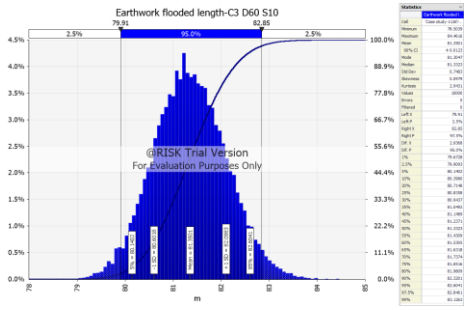



Figure A-D1. 324. Chamber "1126" Earthwork flooded length input distribution C3-D60-S10

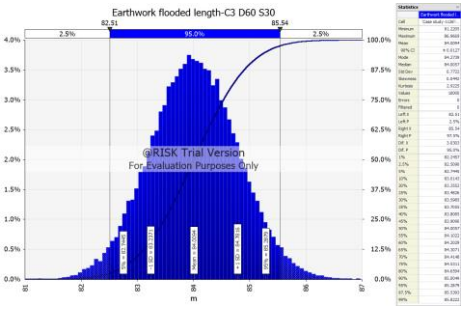



*Figure A-D1. 325. Chamber "1126" Earthwork flooded length input distribution C3-D60-S30*

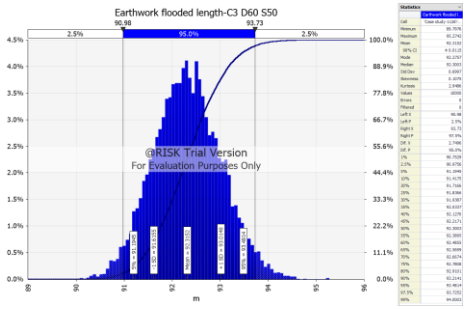



*Figure A-D1. 326. Chamber "1126" Earthwork flooded length input distribution C3-D60-S50*

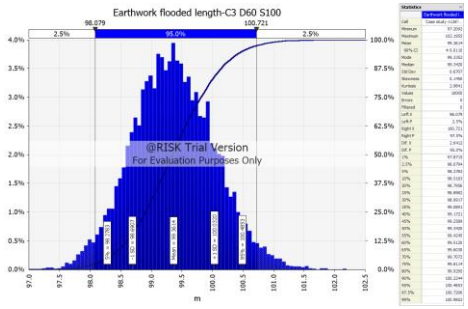



Figure A-D1. 327. Chamber "1126" Earthwork flooded length input distribution C3-D60-S100

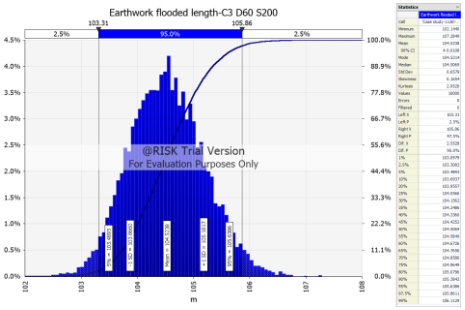



*Figure A-D1. 328. Chamber "1126" Earthwork flooded length input distribution C3-D60-S200*

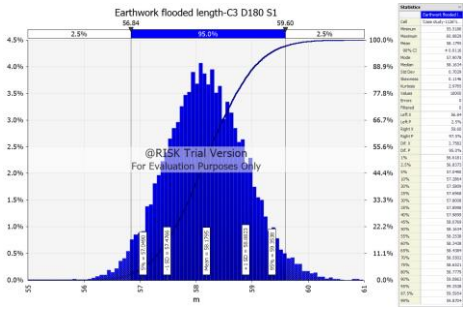



*Figure A-D1. 329. Chamber "1126" Earthwork flooded length input distribution C3-D180-S1*

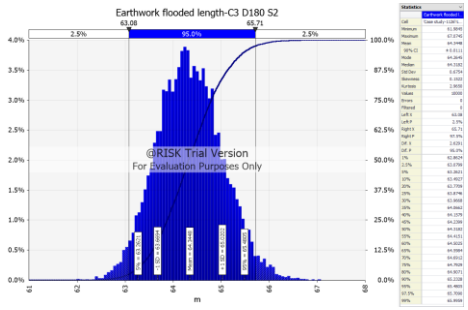



Figure A-D1. 330. Chamber "1126" Earthwork flooded length input distribution C3-D180-S2

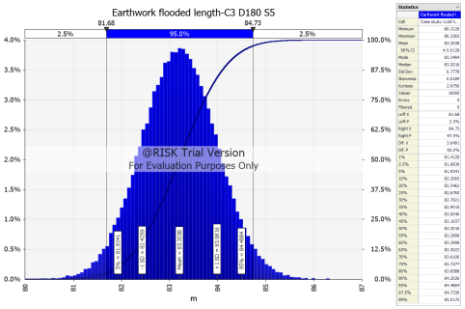



*Figure A-D1. 331. Chamber "1126" Earthwork flooded length input distribution C3-D180-S5*

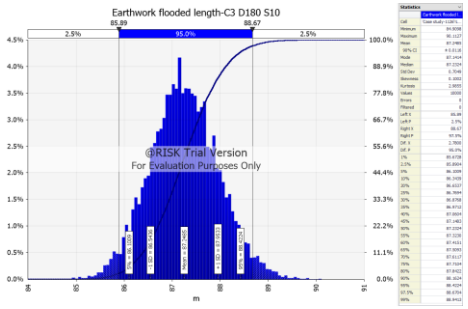



*Figure A-D1. 332. Chamber "1126" Earthwork flooded length input distribution C3-D180-S10*

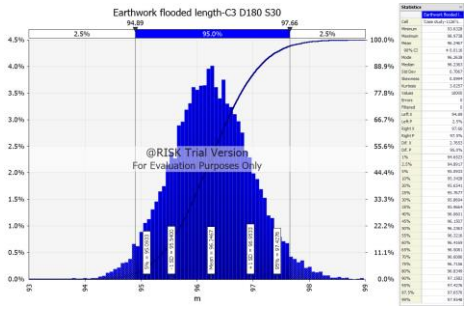



Figure A-D1. 333. Chamber "1126" Earthwork flooded length input distribution C3-D180-S30

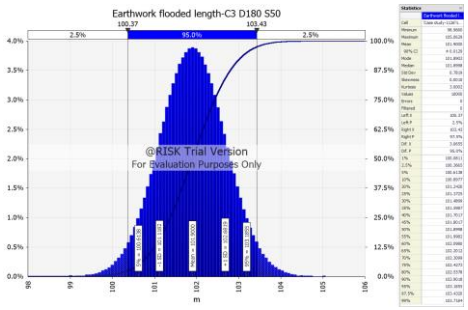



*Figure A-D1. 334. Chamber "1126" Earthwork flooded length input distribution C3-D180-S50*

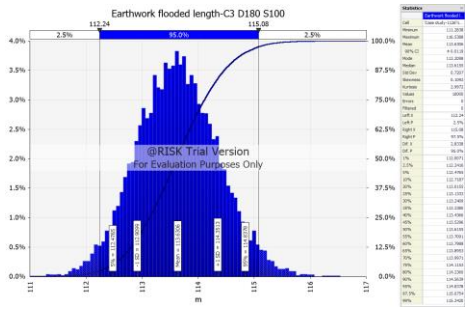



*Figure A-D1. 335. Chamber "1126" Earthwork flooded length input distribution C3-D180-S100*

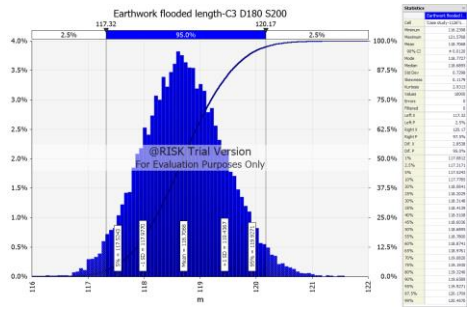



Figure A-D1. 336. Chamber "1126" Earthwork flooded length input distribution C3-D180-S200

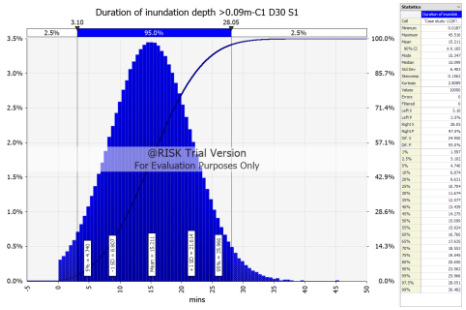



*Figure A-D1. 337. Chamber "1126" Duration of inundation >0.09m input distribution C1-D30-S1*

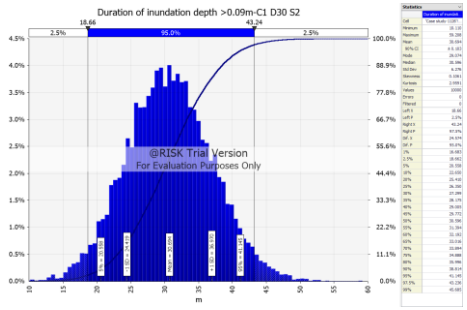



*Figure A-D1. 338. Chamber "1126" Duration of inundation >0.09m input distribution C1-D30-S2*

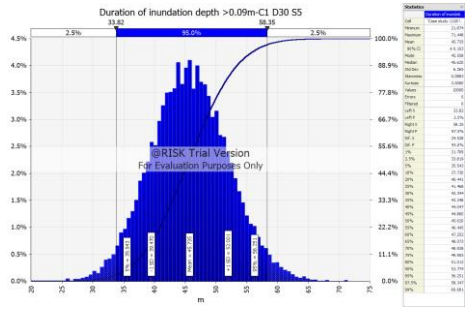



Figure A-D1. 339. Chamber "1126" Duration of inundation >0.09m input distribution C1-D30-S5

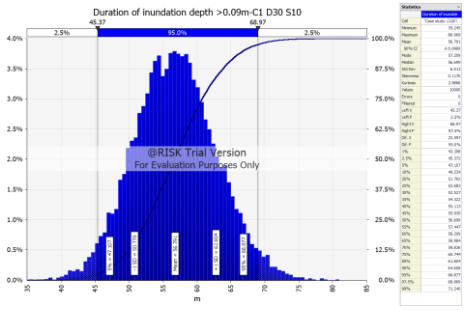



*Figure A-D1. 340. Chamber "1126" Duration of inundation >0.09m input distribution C1-D30-S10*

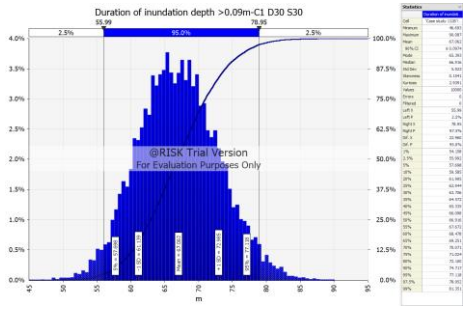



*Figure A-D1. 341. Chamber "1126" Duration of inundation >0.09m input distribution C1-D30-S30*

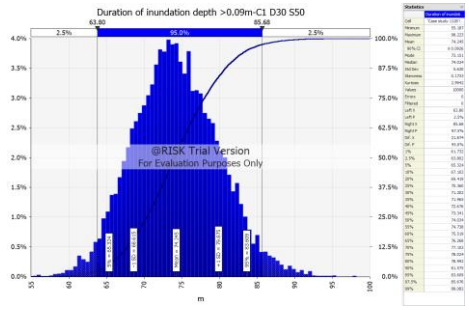



Figure A-D1. 342. Chamber "1126" Duration of inundation >0.09m input distribution C1-D30-S50

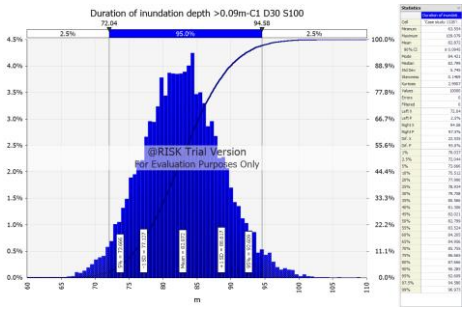



*Figure A-D1. 343. Chamber "1126" Duration of inundation >0.09m input distribution C1-D30-S100*

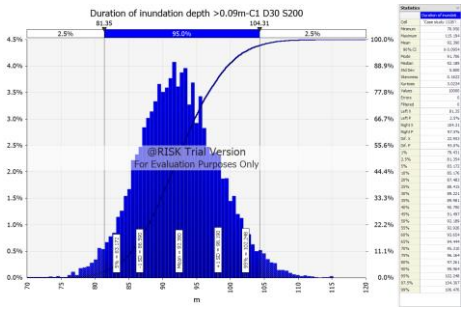



*Figure A-D1. 344. Chamber "1126" Duration of inundation >0.09m input distribution C1-D30-S200*

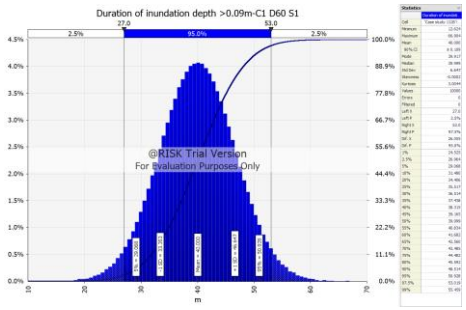



Figure A-D1. 345. Chamber "1126" Duration of inundation >0.09m input distribution C1-D60-S1

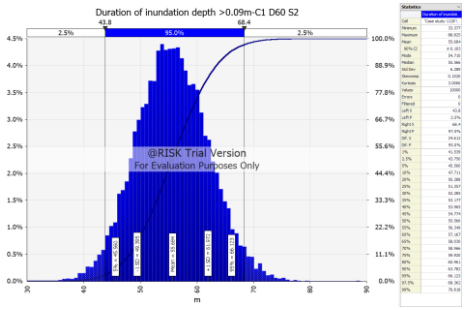



*Figure A-D1. 346. Chamber "1126" Duration of inundation >0.09m input distribution C1-D60-S2*

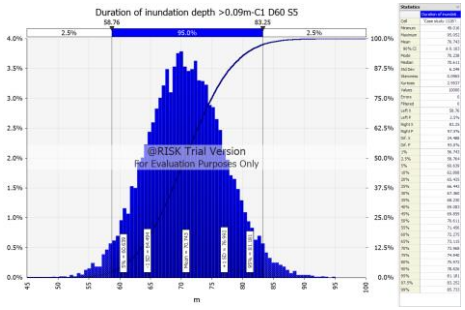



*Figure A-D1. 347. Chamber "1126" Duration of inundation >0.09m input distribution C1-D60-S5*

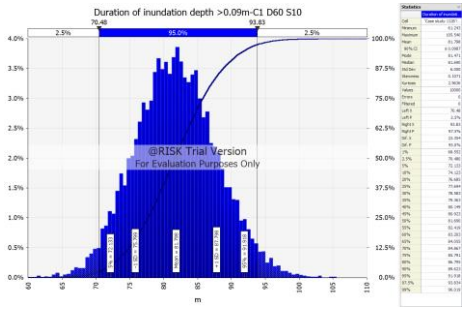



Figure A-D1. 348. Chamber "1126" Duration of inundation >0.09m input distribution C1-D60-S10

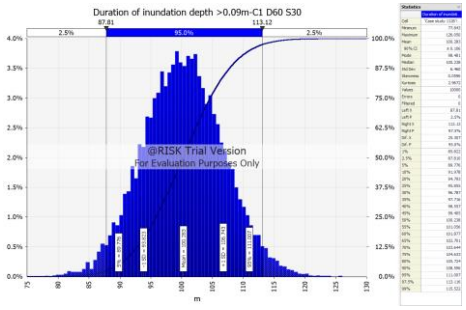



*Figure A-D1. 349. Chamber "1126" Duration of inundation >0.09m input distribution C1-D60-S30*

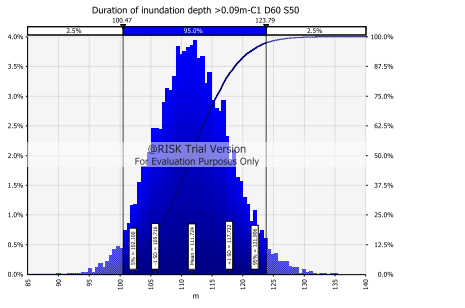



*Figure A-D1. 350. Chamber "1126" Duration of inundation >0.09m input distribution C1-D60-S50*

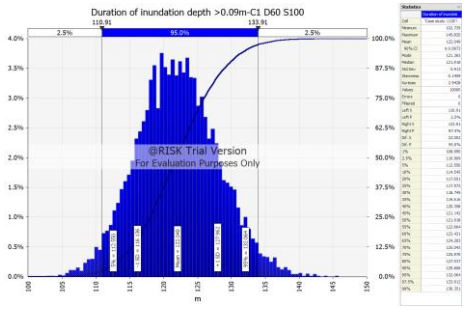



Figure A-D1. 351. Chamber "1126" Duration of inundation >0.09m input distribution C1-D60-S100

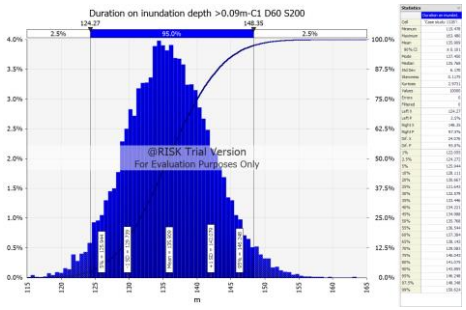



*Figure A-D1. 352. Chamber "1126" Duration of inundation >0.09m input distribution C1-D60-S200*

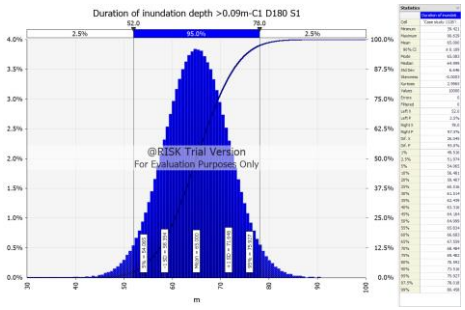



*Figure A-D1. 353. Chamber "1126" Duration of inundation >0.09m input distribution C1-D180-S1*

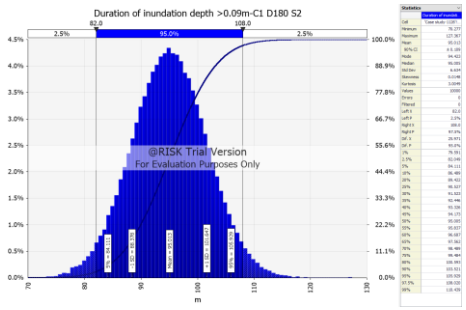



Figure A-D1. 354. Chamber "1126" Duration of inundation >0.09m input distribution C1-D180-S2

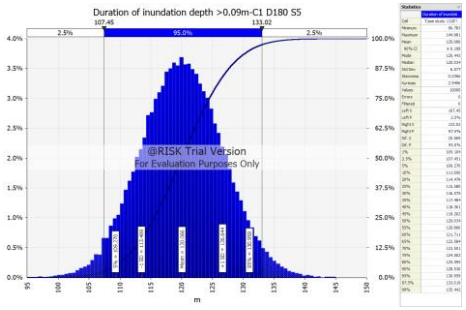



*Figure A-D1. 355. Chamber "1126" Duration of inundation >0.09m input distribution C1-D180-S5*

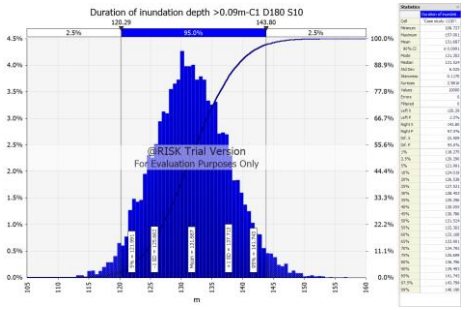



*Figure A-D1. 356. Chamber "1126" Duration of inundation >0.09m input distribution C1-D180-S10*

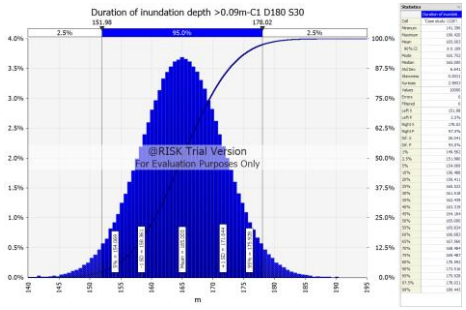



Figure A-D1. 357. Chamber "1126" Duration of inundation >0.09m input distribution C1-D180-S30

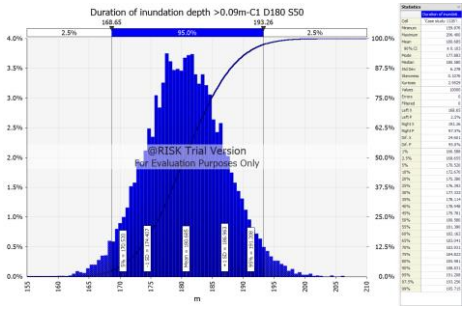



*Figure A-D1. 358. Chamber "1126" Duration of inundation >0.09m input distribution C1-D180-S50*

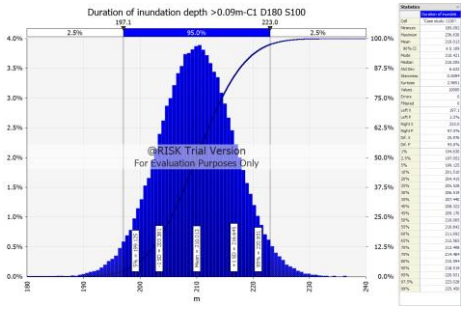



*Figure A-D1. 359. Chamber "1126" Duration of inundation >0.09m input distribution C1-D180-S100*

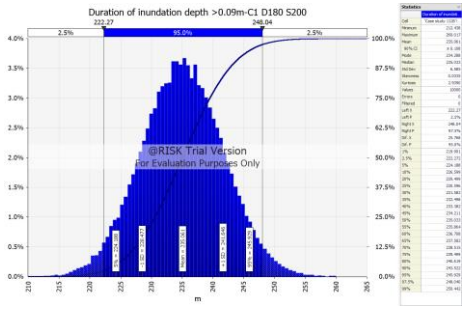



Figure A-D1. 360. Chamber "1126" Duration of inundation >0.09m input distribution C1-D180-S200

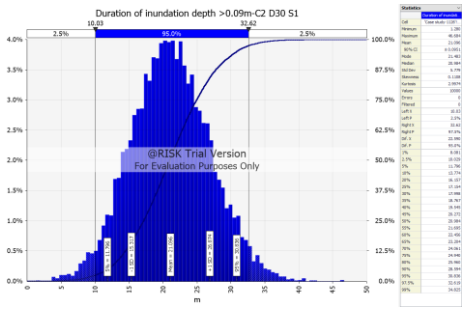



*Figure A-D1. 361. Chamber "1126" Duration of inundation >0.09m input distribution C2-D30-S1*

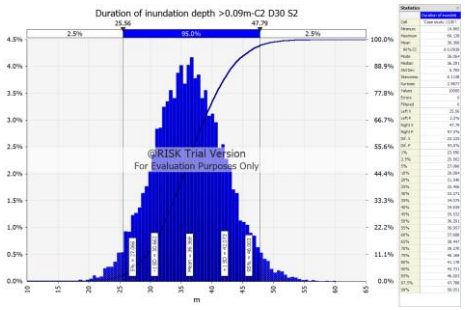



*Figure A-D1. 362. Chamber "1126" Duration of inundation >0.09m input distribution C2-D30-S2*

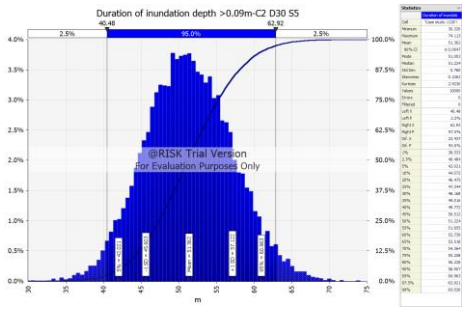



Figure A-D1. 363. Chamber "1126" Duration of inundation >0.09m input distribution C2-D30-S5

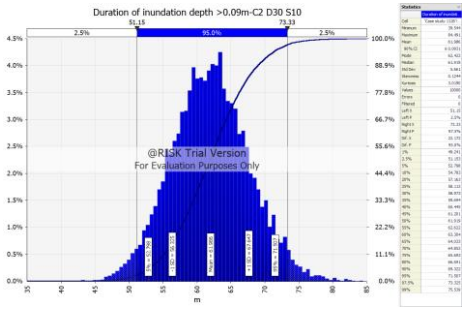



*Figure A-D1. 364. Chamber "1126" Duration of inundation >0.09m input distribution C2-D30-S10*

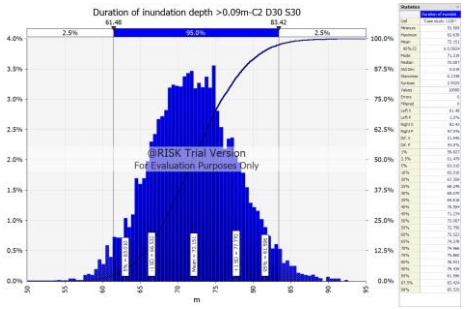



*Figure A-D1. 365. Chamber "1126" Duration of inundation >0.09m input distribution C2-D30-S30*

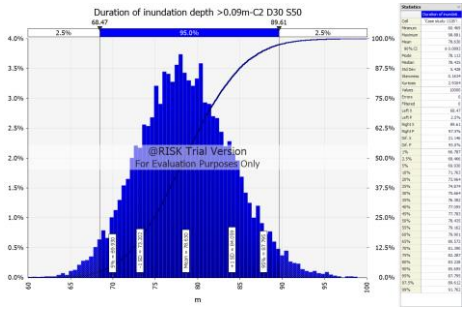



Figure A-D1. 366. Chamber "1126" Duration of inundation >0.09m input distribution C2-D30-S50

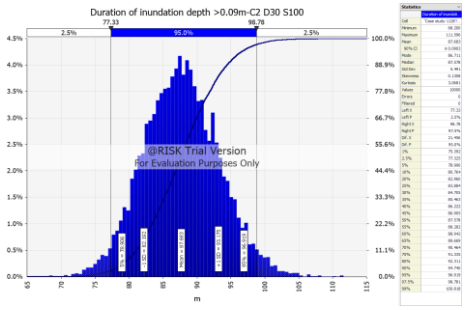



*Figure A-D1. 367. Chamber "1126" Duration of inundation >0.09m input distribution C2-D30-S100*

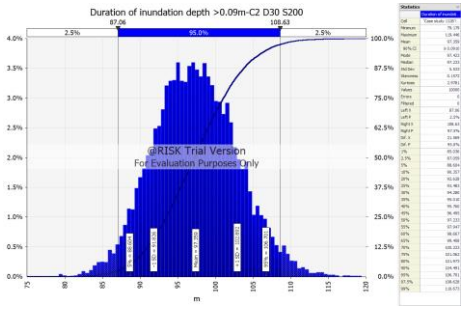



*Figure A-D1. 368. Chamber "1126" Duration of inundation >0.09m input distribution C2-D30-S200*

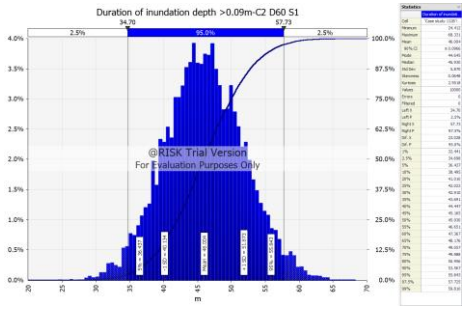



Figure A-D1. 369. Chamber "1126" Duration of inundation >0.09m input distribution C2-D60-S1

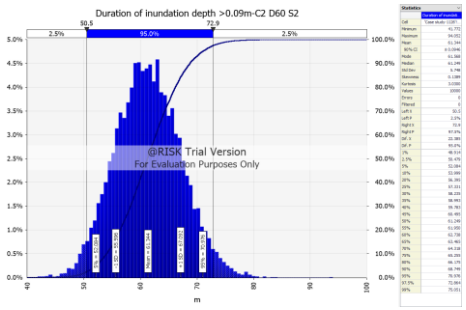



*Figure A-D1. 370. Chamber "1126" Duration of inundation >0.09m input distribution C2-D60-S2*

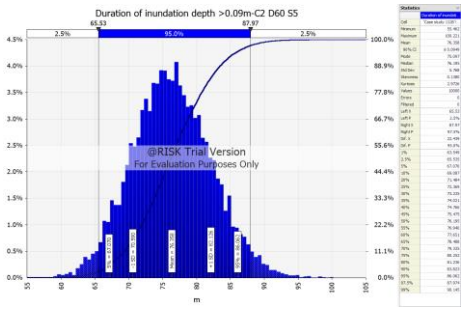



*Figure A-D1. 371. Chamber "1126" Duration of inundation >0.09m input distribution C2-D60-S5*

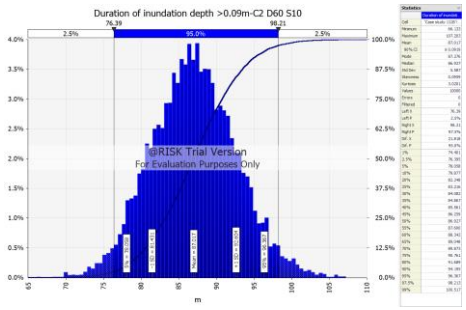



Figure A-D1. 372. Chamber "1126" Duration of inundation >0.09m input distribution C2-D60-S10

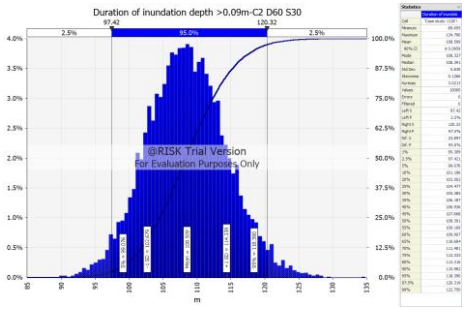



*Figure A-D1. 373. Chamber "1126" Duration of inundation >0.09m input distribution C2-D60-S30*

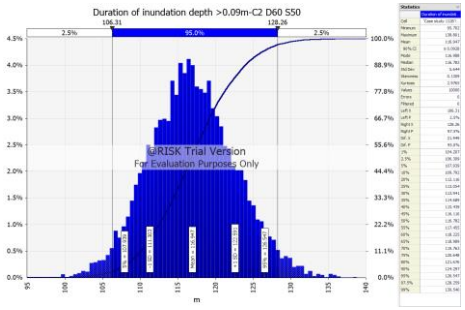



*Figure A-D1. 374. Chamber "1126" Duration of inundation >0.09m input distribution C2-D60-S50*

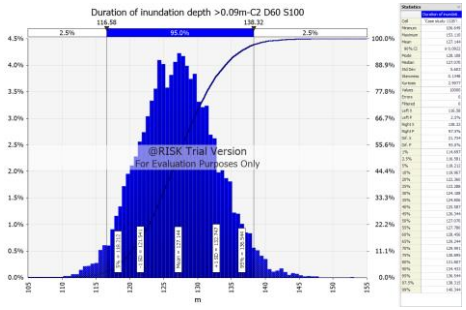



Figure A-D1. 375. Chamber "1126" Duration of inundation >0.09m input distribution C2-D60-S100

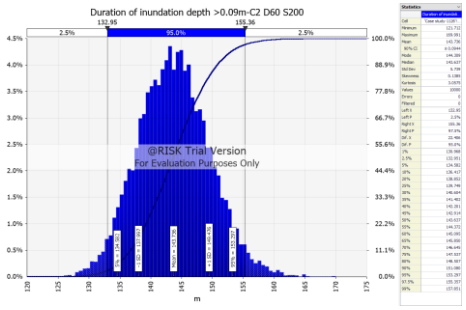



*Figure A-D1. 376. Chamber "1126" Duration of inundation >0.09m input distribution C2-D60-S200*

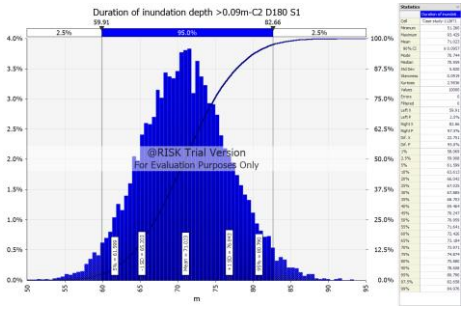



*Figure A-D1. 377. Chamber "1126" Duration of inundation >0.09m input distribution C2-D180-S1*

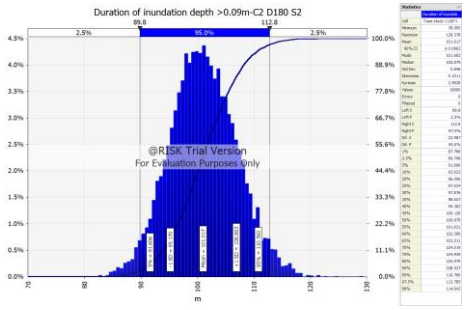



Figure A-D1. 378. Chamber "1126" Duration of inundation >0.09m input distribution C2-D180-S2

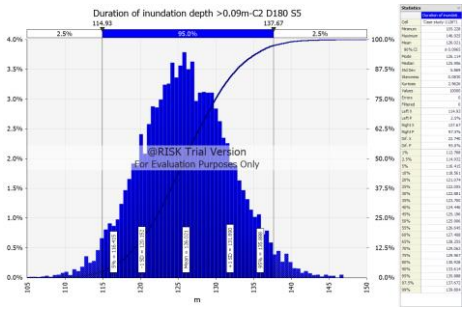



*Figure A-D1. 379. Chamber "1126" Duration of inundation >0.09m input distribution C2-D180-S5*

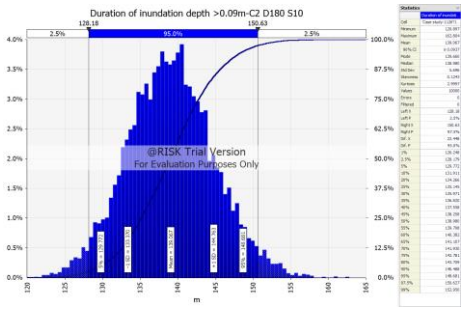



*Figure A-D1. 380. Chamber "1126" Duration of inundation >0.09m input distribution C2-D180-S10*

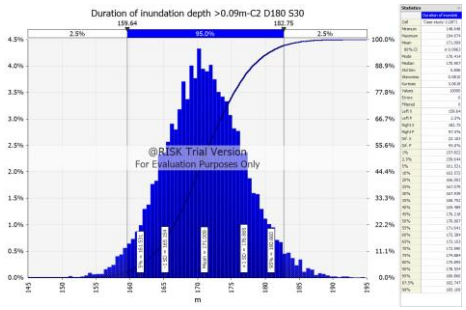



Figure A-D1. 381. Chamber "1126" Duration of inundation >0.09m input distribution C2-D180-S30

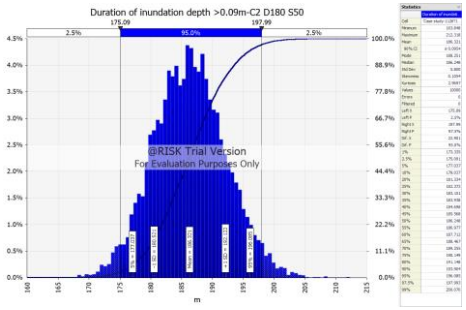



*Figure A-D1. 382. Chamber "1126" Duration of inundation >0.09m input distribution C2-D180-S50*

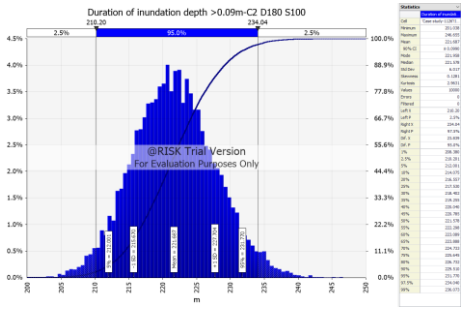



*Figure A-D1. 383. Chamber "1126" Duration of inundation >0.09m input distribution C2-D180-S100*

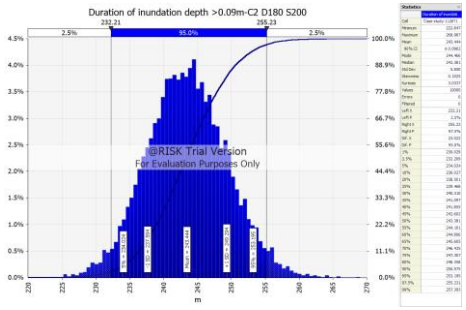



Figure A-D1. 384. Chamber "1126" Duration of inundation >0.09m input distribution C2-D180-S200

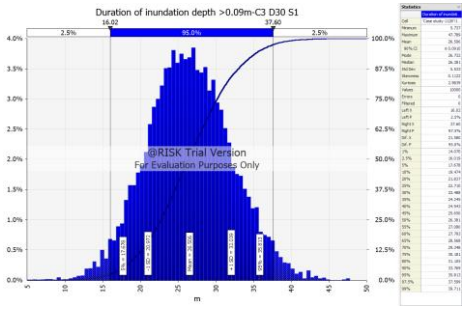



*Figure A-D1. 385. Chamber "1126" Duration of inundation >0.09m input distribution C3-D30-S1*

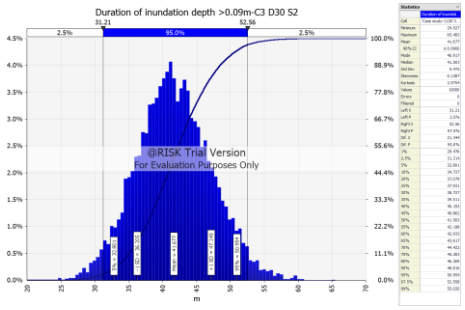



*Figure A-D1. 386. Chamber "1126" Duration of inundation >0.09m input distribution C3-D30-S2*

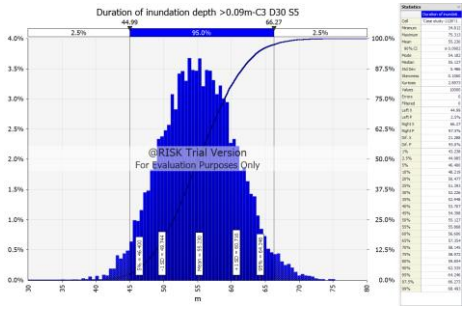



Figure A-D1. 387. Chamber "1126" Duration of inundation >0.09m input distribution C3-D30-S5

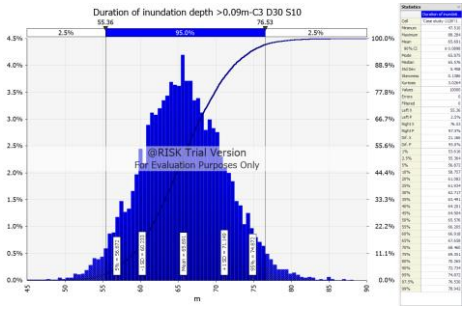



*Figure A-D1. 388. Chamber "1126" Duration of inundation >0.09m input distribution C3-D30-S10*

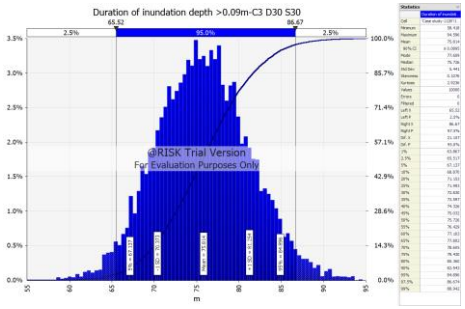



*Figure A-D1. 389. Chamber "1126" Duration of inundation >0.09m input distribution C3-D30-S30*

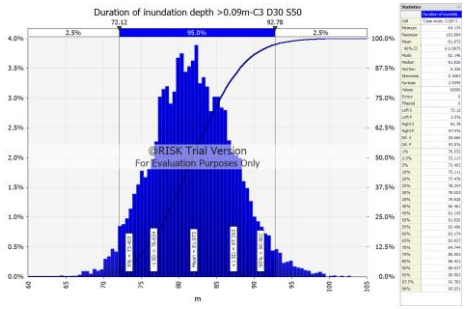



Figure A-D1. 390. Chamber "1126" Duration of inundation >0.09m input distribution C3-D30-S50

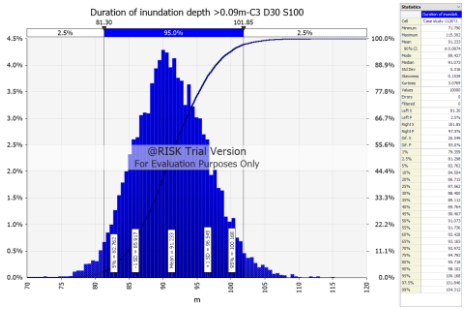



*Figure A-D1. 391. Chamber "1126" Duration of inundation >0.09m input distribution C3-D30-S100*

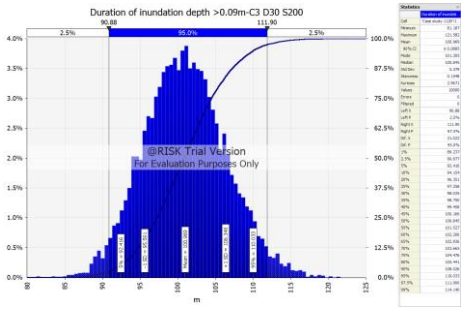



*Figure A-D1. 392. Chamber "1126" Duration of inundation >0.09m input distribution C3-D30-S200*

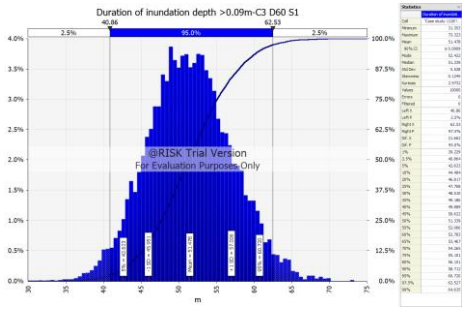



Figure A-D1. 393. Chamber "1126" Duration of inundation >0.09m input distribution C3-D60-S1

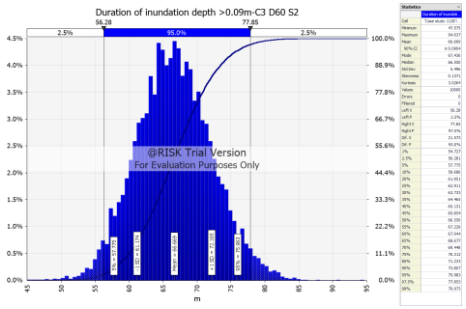



*Figure A-D1. 394. Chamber "1126" Duration of inundation >0.09m input distribution C3-D60-S2*

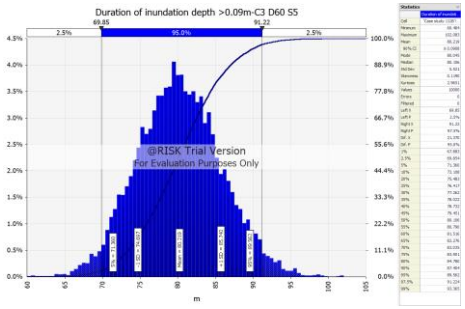



*Figure A-D1. 395. Chamber "1126" Duration of inundation >0.09m input distribution C3-D60-S5*

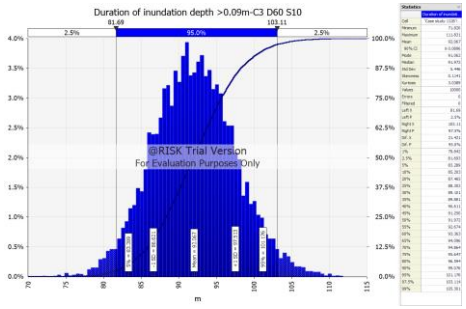



Figure A-D1. 396. Chamber "1126" Duration of inundation >0.09m input distribution C3-D60-S10

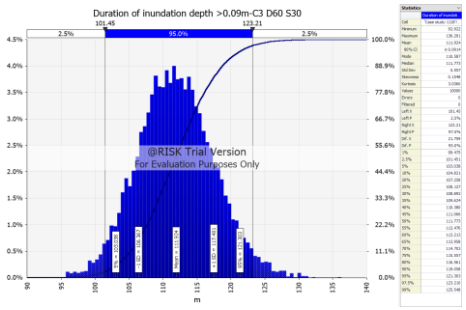



*Figure A-D1. 397. Chamber "1126" Duration of inundation >0.09m input distribution C3-D60-S30*

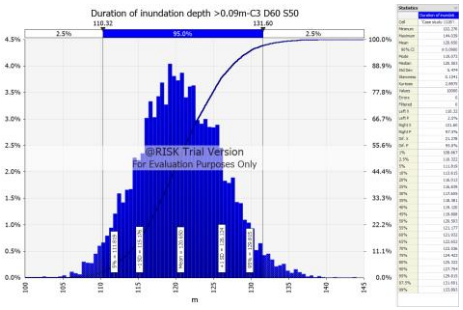



*Figure A-D1. 398. Chamber "1126" Duration of inundation >0.09m input distribution C3-D60-S50*

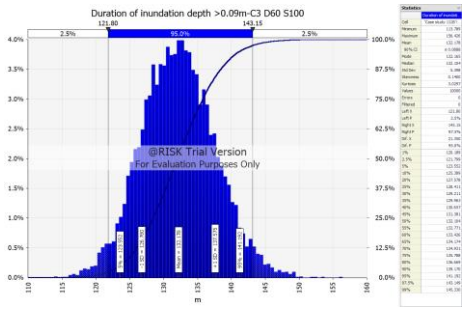



Figure A-D1. 399. Chamber "1126" Duration of inundation >0.09m input distribution C3-D60-S100

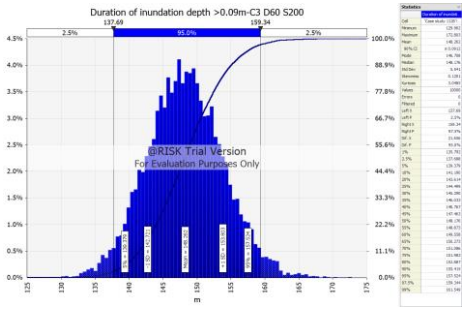



*Figure A-D1. 400. Chamber "1126" Duration of inundation >0.09m input distribution C3-D60-S200*

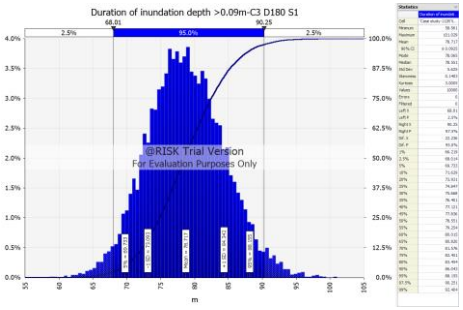



*Figure A-D1. 401. Chamber "1126" Duration of inundation >0.09m input distribution C3-D180-S1*

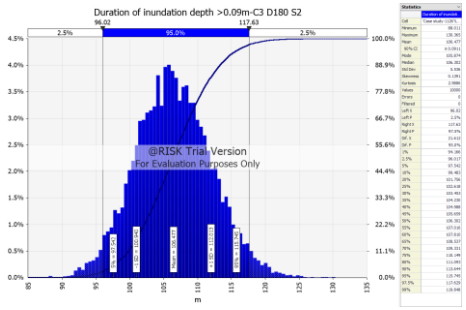



Figure A-D1. 402. Chamber "1126" Duration of inundation >0.09m input distribution C3-D180-S2

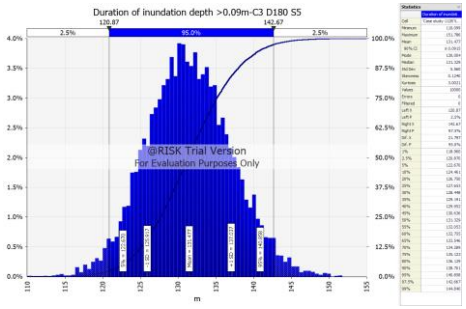



*Figure A-D1. 403. Chamber "1126" Duration of inundation >0.09m input distribution C3-D180-S5*

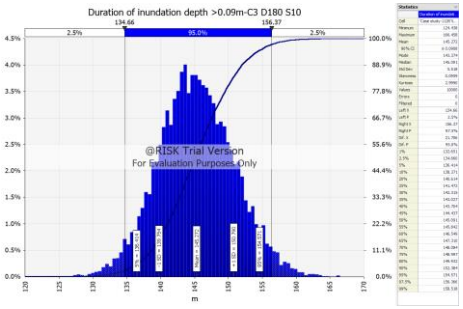



*Figure A-D1. 404. Chamber "1126" Duration of inundation >0.09m input distribution C3-D180-S10*

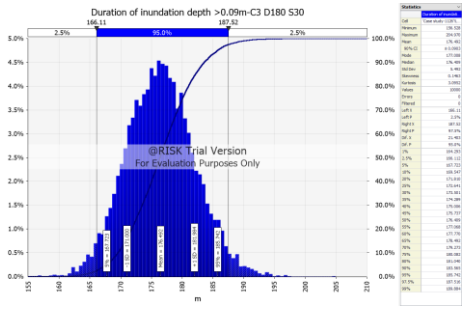



Figure A-D1. 405. Chamber "1126" Duration of inundation >0.09m input distribution C3-D180-S30

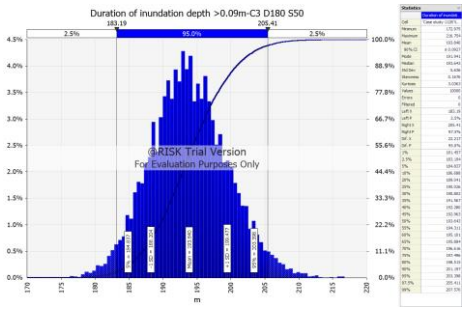



*Figure A-D1. 406. Chamber "1126" Duration of inundation >0.09m input distribution C3-D180-S50*

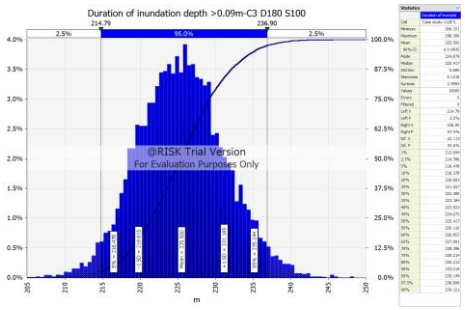



*Figure A-D1. 407. Chamber "1126" Duration of inundation >0.09m input distribution C3-D180-S100*

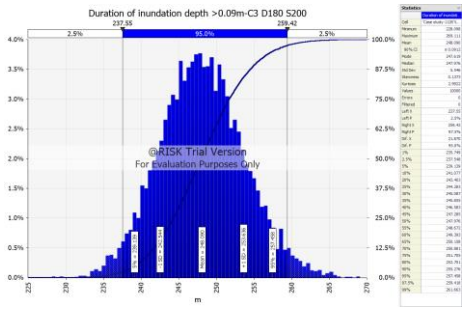



Figure A-D1. 408. Chamber "1126" Duration of inundation >0.09m input distribution C3-D180-S200

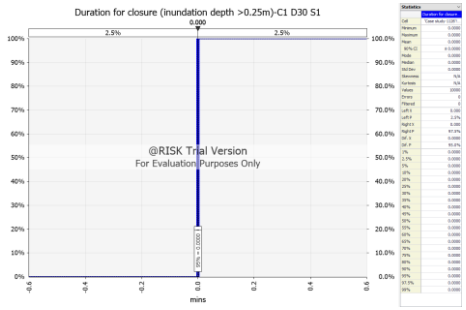



*Figure A-D1. 409. Chamber "1126" Closure duration input distribution C1-D30-S1*

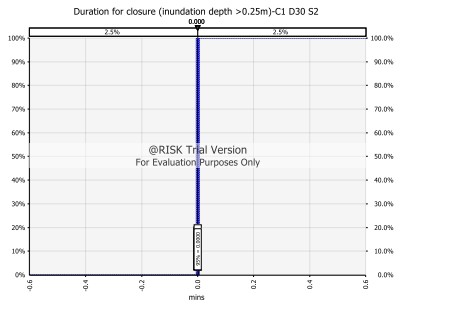



*Figure A-D1. 410. Chamber "1126" Closure duration input distribution C1-D30-S2*

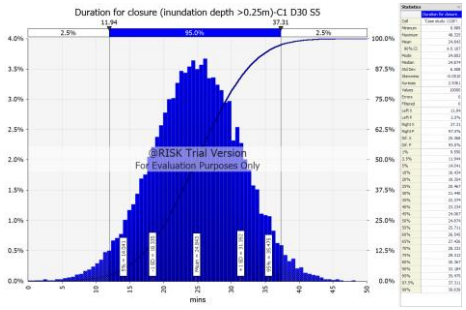



Figure A-D1. 411. Chamber "1126" Closure duration input distribution C1-D30-S5

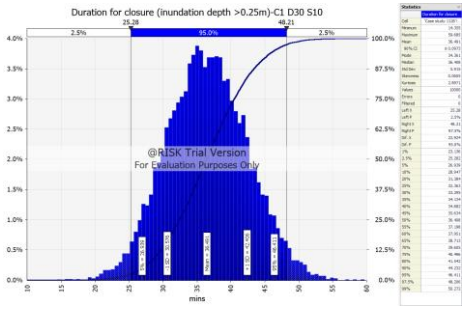



*Figure A-D1. 412. Chamber "1126" Closure duration input distribution C1-D30-S10*

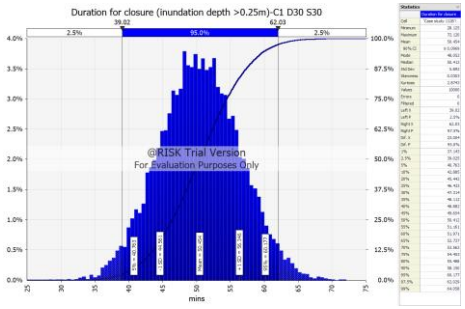



*Figure A-D1. 413. Chamber "1126" Closure duration input distribution C1-D30-S30*

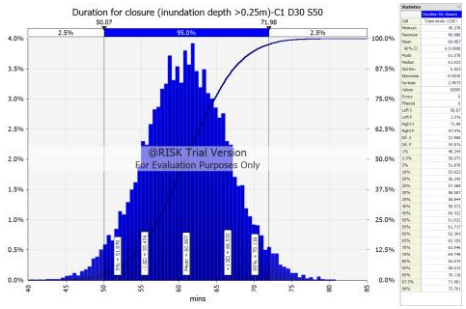



Figure A-D1. 414. Chamber "1126" Closure duration input distribution C1-D30-S50

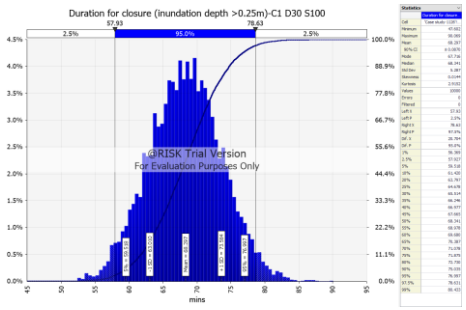



*Figure A-D1. 415. Chamber "1126" Closure duration input distribution C1-D30-S100*

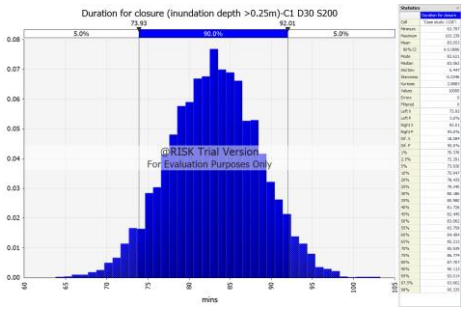



*Figure A-D1. 416. Chamber "1126" Closure duration input distribution C1-D30-S200*

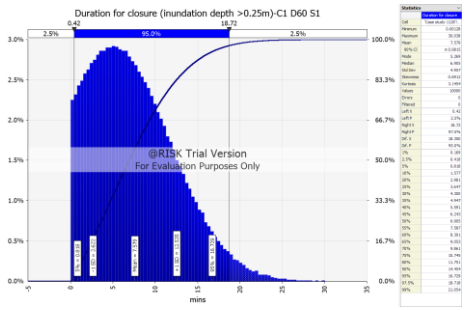



Figure A-D1. 417. Chamber "1126" Closure duration input distribution C1-D60-S1

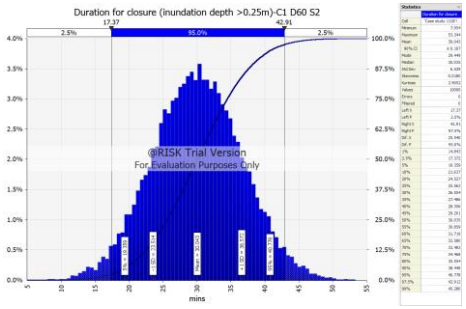



*Figure A-D1. 418. Chamber "1126" Closure duration input distribution C1-D60-S2*

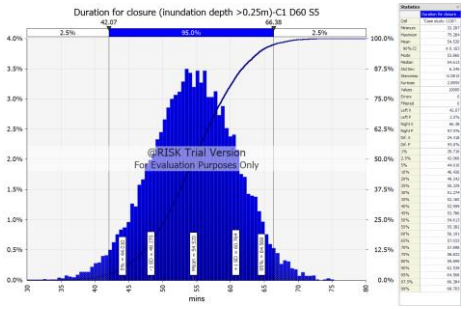



*Figure A-D1. 419. Chamber "1126" Closure duration input distribution C1-D60-S5*

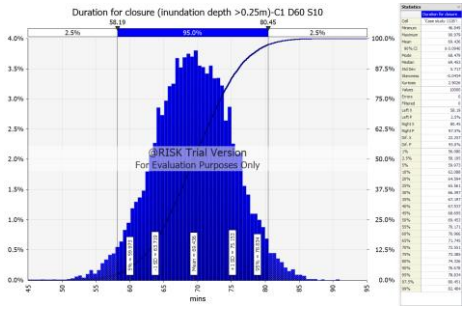



Figure A-D1. 420. Chamber "1126" Closure duration input distribution C1-D60-S10

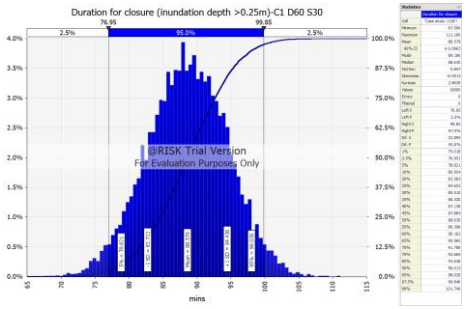



*Figure A-D1. 421. Chamber "1126" Closure duration input distribution C1-D60-S30*

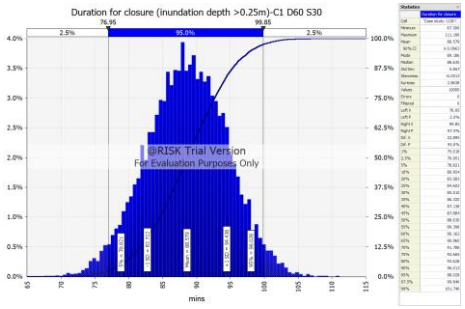



*Figure A-D1. 422. Chamber "1126" Closure duration input distribution C1-D60-S30*

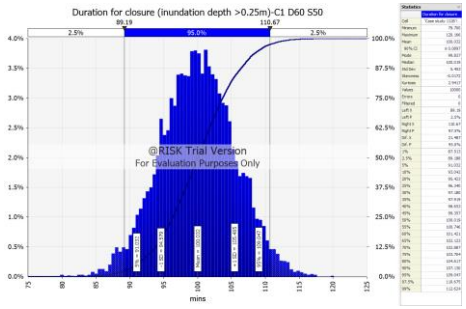



Figure A-D1. 423. Chamber "1126" Closure duration input distribution C1-D60-S50

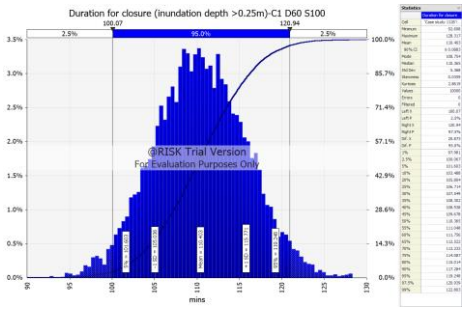



*Figure A-D1. 424. Chamber "1126" Closure duration input distribution C1-D60-S100*

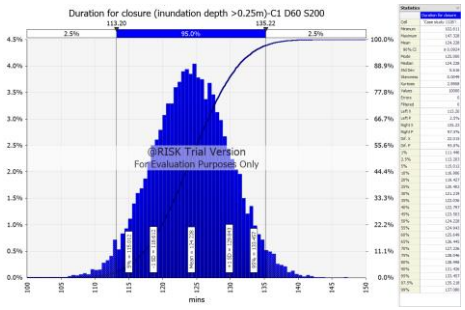



*Figure A-D1. 425. Chamber "1126" Closure duration input distribution C1-D60-S200*

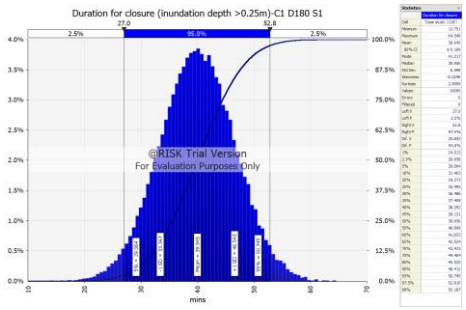



Figure A-D1. 426. Chamber "1126" Closure duration input distribution C1-D180-S1

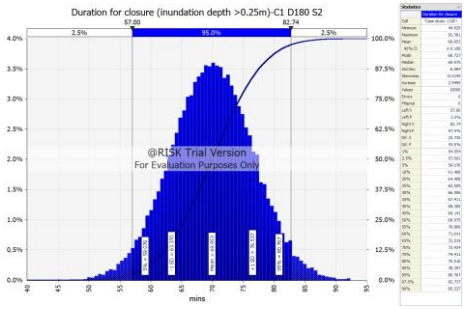



*Figure A-D1. 427. Chamber "1126" Closure duration input distribution C1-D180-S2*

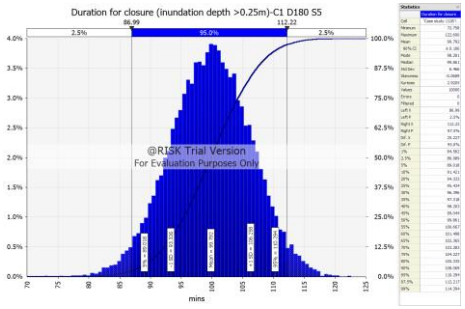



*Figure A-D1. 428. Chamber "1126" Closure duration input distribution C1-D180-S5*

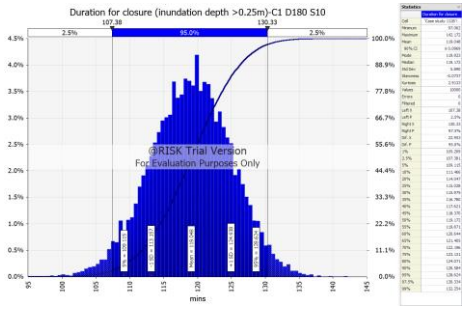



Figure A-D1. 429. Chamber "1126" Closure duration input distribution C1-D180-S10

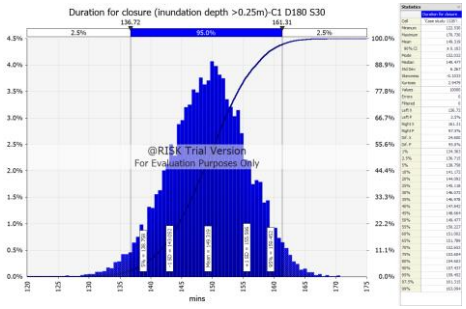



*Figure A-D1. 430. Chamber "1126" Closure duration input distribution C1-D180-S30*

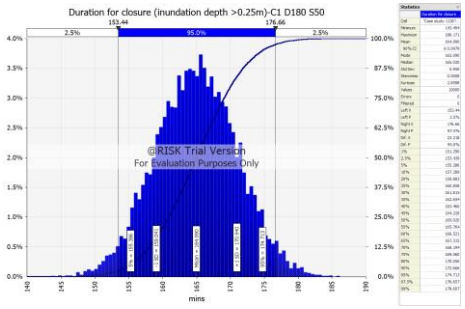



*Figure A-D1. 431. Chamber "1126" Closure duration input distribution C1-D180-S50*

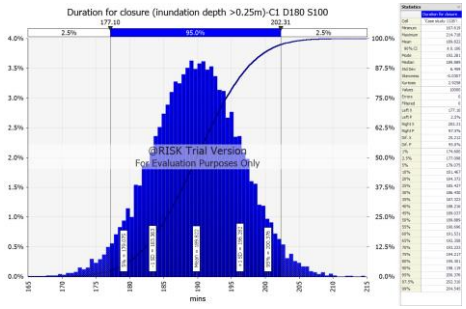



Figure A-D1. 432. Chamber "1126" Closure duration input distribution C1-D180-S100

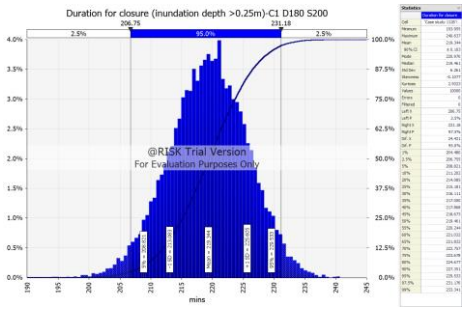



*Figure A-D1. 433. Chamber "1126" Closure duration input distribution C1-D180-S200*

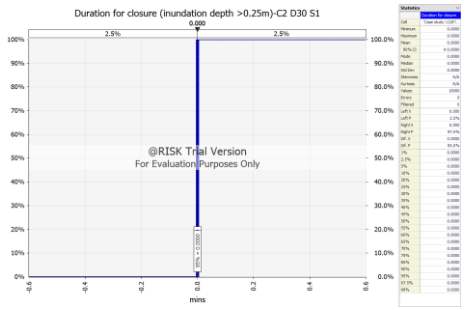



*Figure A-D1. 434. Chamber "1126" Closure duration input distribution C2-D30-S1*

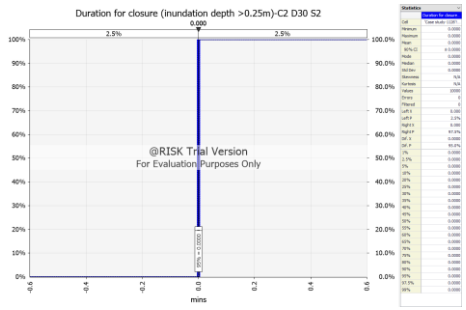



Figure A-D1. 435. Chamber "1126" Closure duration input distribution C2-D30-S2

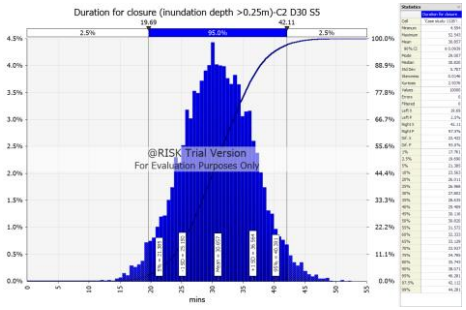



*Figure A-D1. 436. Chamber "1126" Closure duration input distribution C2-D30-S5*

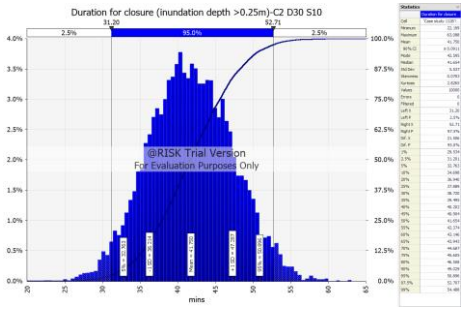



*Figure A-D1. 437. Chamber "1126" Closure duration input distribution C2-D30-S10*

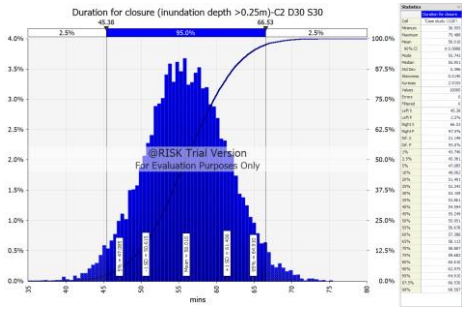



Figure A-D1. 438. Chamber "1126" Closure duration input distribution C2-D30-S30

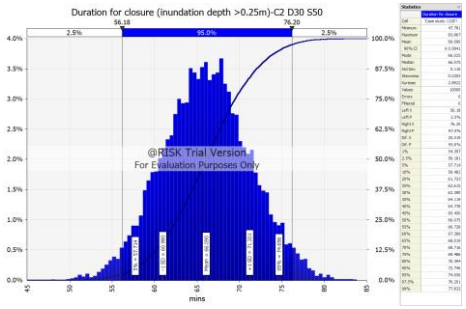



*Figure A-D1. 439. Chamber "1126" Closure duration input distribution C2-D30-S50*

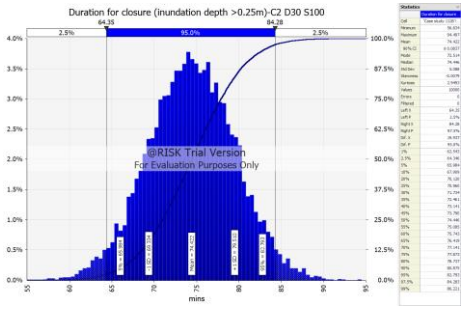



*Figure A-D1. 440. Chamber "1126" Closure duration input distribution C2-D30-S100*

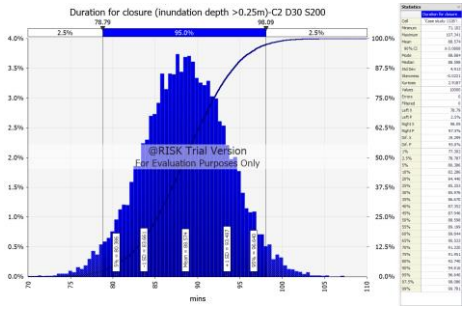



Figure A-D1. 441. Chamber "1126" Closure duration input distribution C2-D30-S200

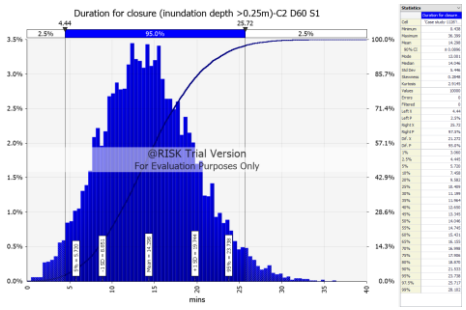



*Figure A-D1. 442. Chamber "1126" Closure duration input distribution C2-D60-S1*

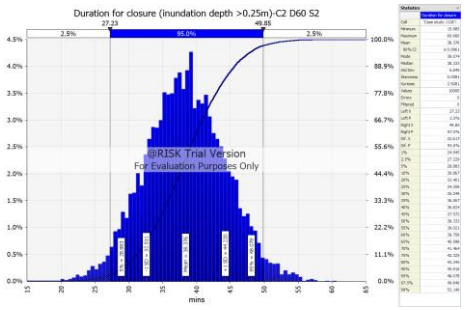



*Figure A-D1. 443. Chamber "1126" Closure duration input distribution C2-D60-S2*

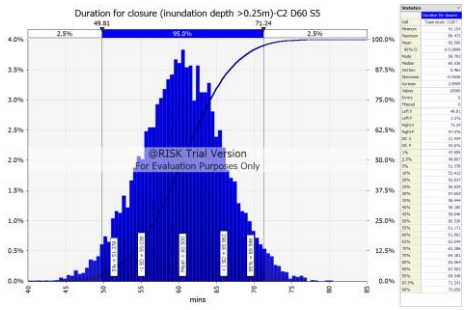



Figure A-D1. 444. Chamber "1126" Closure duration input distribution C2-D60-S5

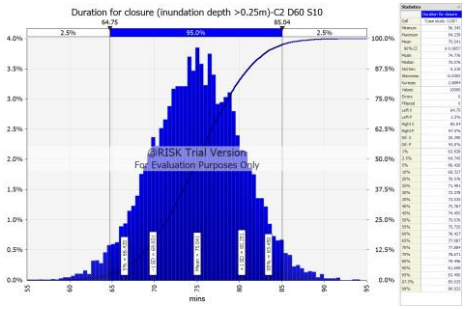



*Figure A-D1. 445. Chamber "1126" Closure duration input distribution C2-D60-S10*

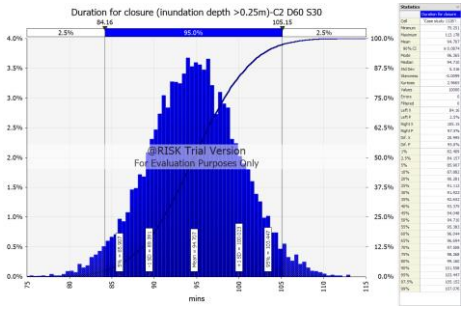



*Figure A-D1. 446. Chamber "1126" Closure duration input distribution C2-D60-S30*

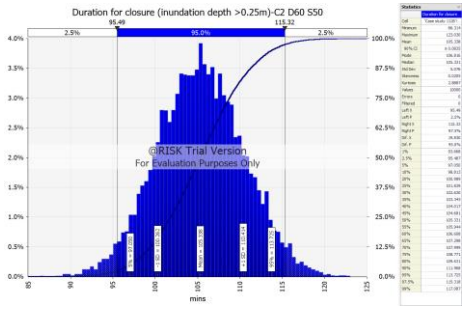



Figure A-D1. 447. Chamber "1126" Closure duration input distribution C2-D60-S50

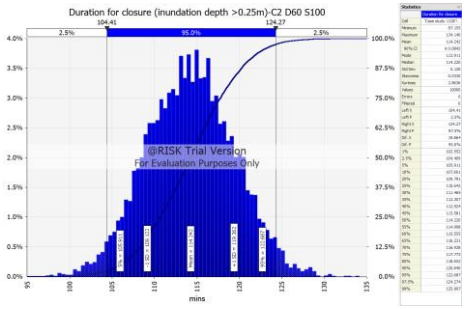



*Figure A-D1. 448. Chamber "1126" Closure duration input distribution C2-D60-S100*

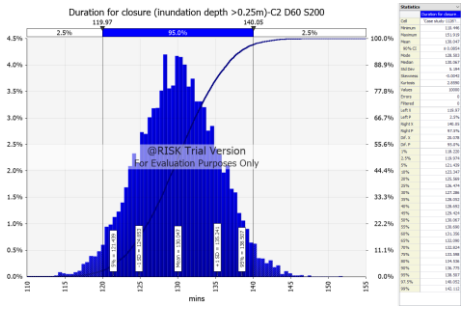



*Figure A-D1. 449. Chamber "1126" Closure duration input distribution C2-D60-S200*

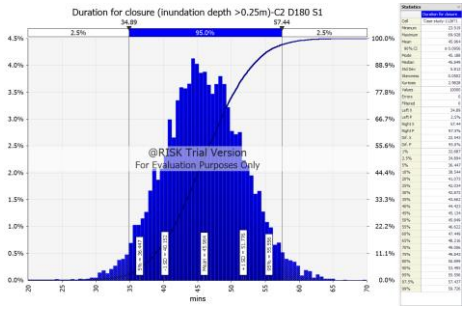



Figure A-D1. 450. Chamber "1126" Closure duration input distribution C2-D180-S1

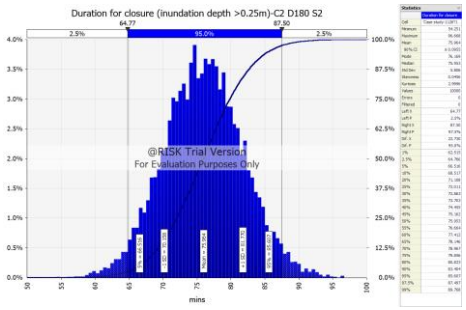



*Figure A-D1. 451. Chamber "1126" Closure duration input distribution C2-D180-S2*

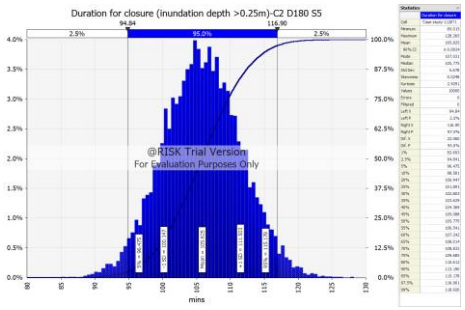



*Figure A-D1. 452. Chamber "1126" Closure duration input distribution C2-D180-S5*

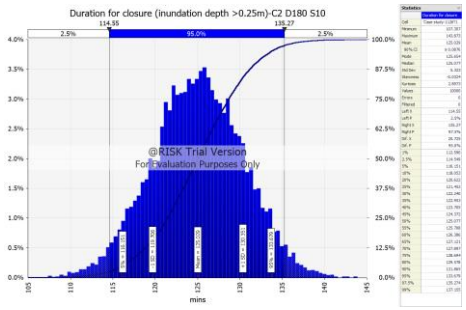



Figure A-D1. 453. Chamber "1126" Closure duration input distribution C2-D180-S10

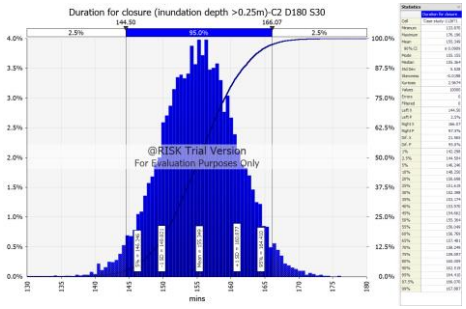



*Figure A-D1. 454. Chamber "1126" Closure duration input distribution C2-D180-S30*

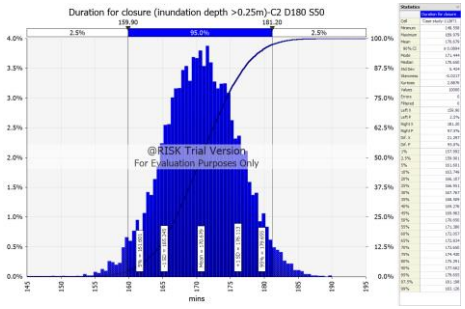



*Figure A-D1. 455. Chamber "1126" Closure duration input distribution C2-D180-S50*

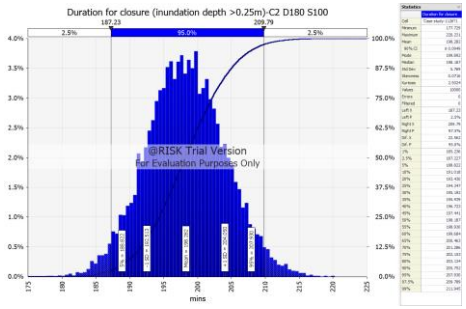



Figure A-D1. 456. Chamber "1126" Closure duration input distribution C2-D180-S100

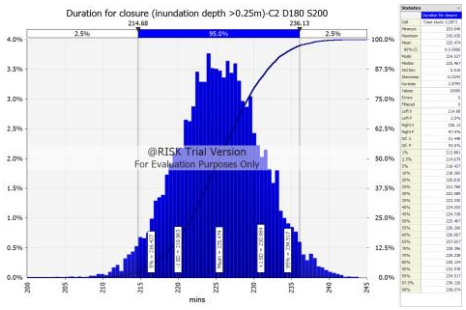



*Figure A-D1. 457. Chamber "1126" Closure duration input distribution C2-D180-S200*

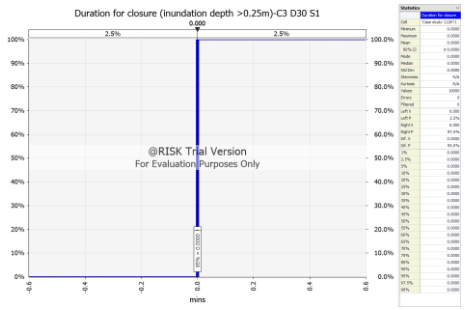



*Figure A-D1. 458. Chamber "1126" Closure duration input distribution C3-D30-S1*

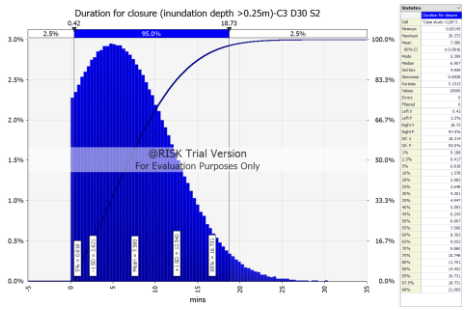



Figure A-D1. 459. Chamber "1126" Closure duration input distribution C3-D30-S2

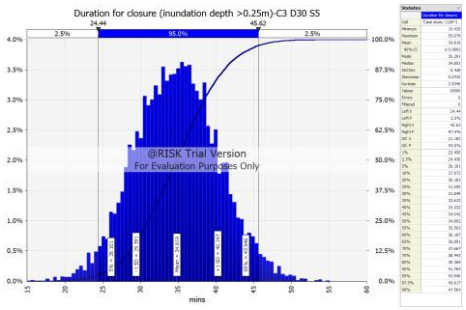



*Figure A-D1. 460. Chamber "1126" Closure duration input distribution C3-D30-S5*

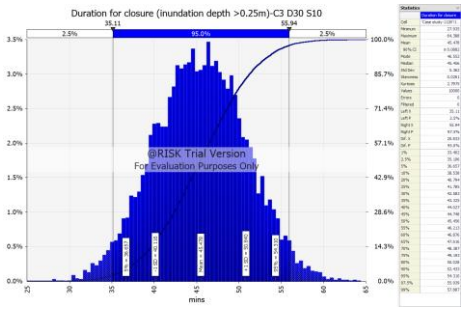



*Figure A-D1. 461. Chamber "1126" Closure duration input distribution C3-D30-S10*

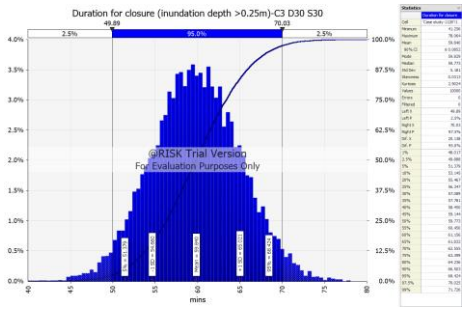



Figure A-D1. 462. Chamber "1126" Closure duration input distribution C3-D30-S30

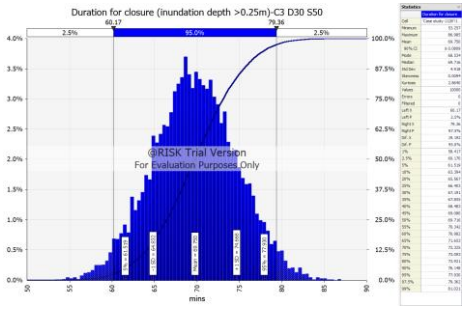



*Figure A-D1. 463. Chamber "1126" Closure duration input distribution C3-D30-S50*

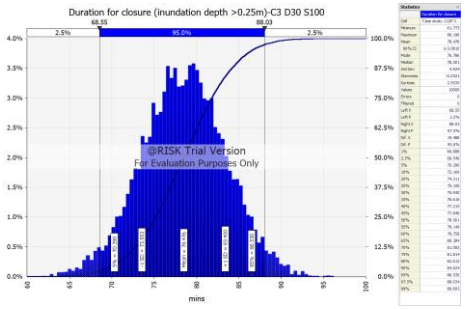



*Figure A-D1. 464. Chamber "1126" Closure duration input distribution C3-D30-S100*

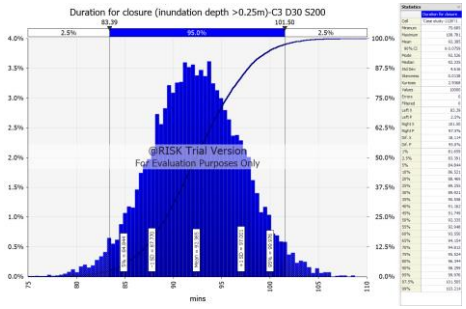



Figure A-D1. 465. Chamber "1126" Closure duration input distribution C3-D30-S200

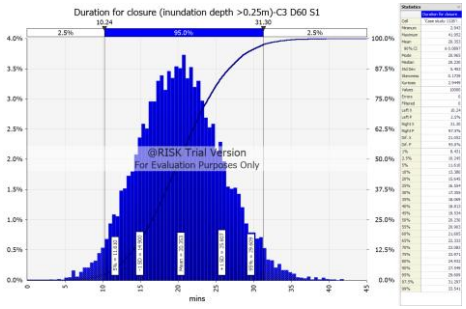



*Figure A-D1. 466. Chamber "1126" Closure duration input distribution C3-D60-S1*

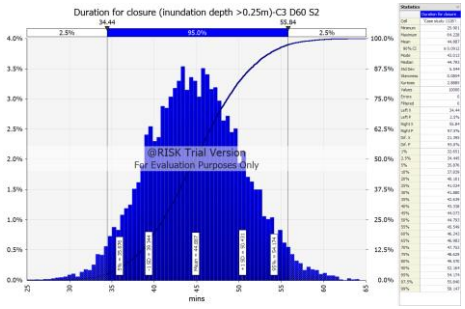



*Figure A-D1. 467. Chamber "1126" Closure duration input distribution C3-D60-S2*

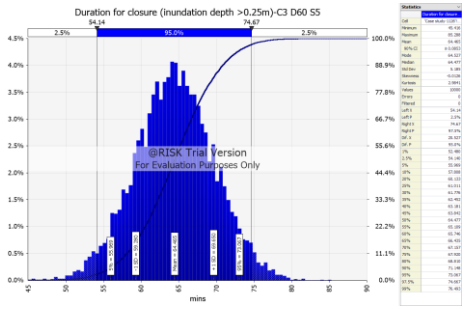



Figure A-D1. 468. Chamber "1126" Closure duration input distribution C3-D60-S5

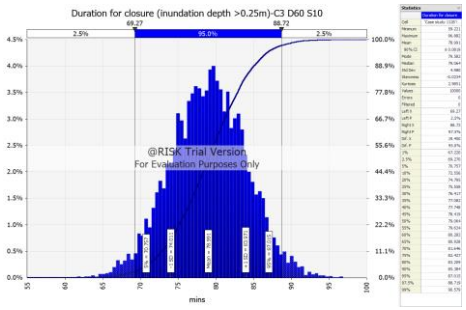



*Figure A-D1. 469. Chamber "1126" Closure duration input distribution C3-D60-S10*

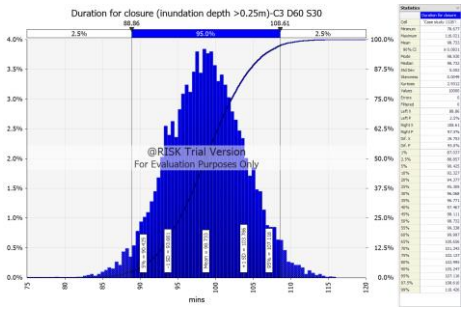



*Figure A-D1. 470. Chamber "1126" Closure duration input distribution C3-D60-S30*

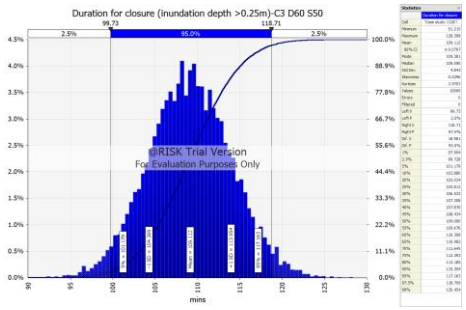



Figure A-D1. 471. Chamber "1126" Closure duration input distribution C3-D60-S50

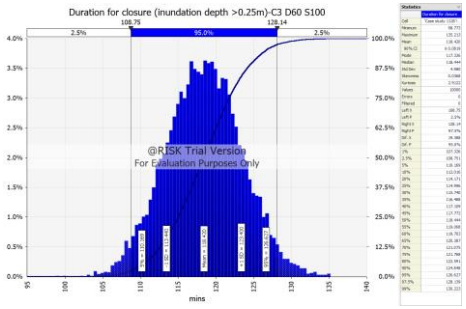



*Figure A-D1. 472. Chamber "1126" Closure duration input distribution C3-D60-S100*

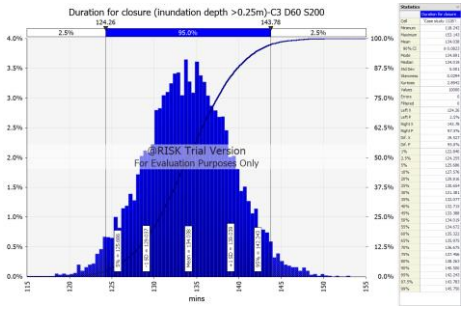



*Figure A-D1. 473. Chamber "1126" Closure duration input distribution C3-D60-S200*

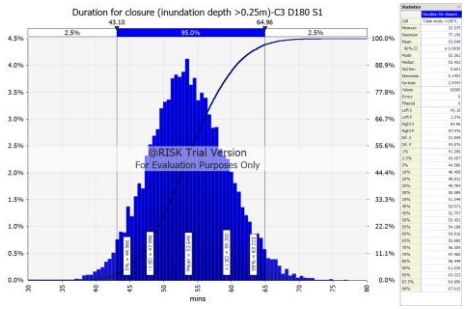



Figure A-D1. 474. Chamber "1126" Closure duration input distribution C3-D180-S1

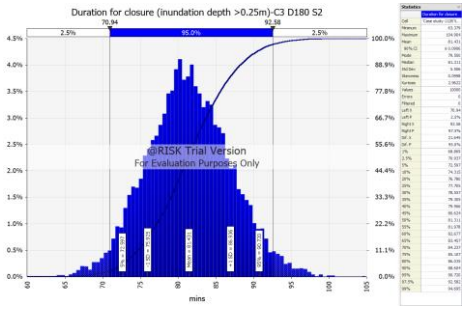



*Figure A-D1. 475. Chamber "1126" Closure duration input distribution C3-D180-S2*

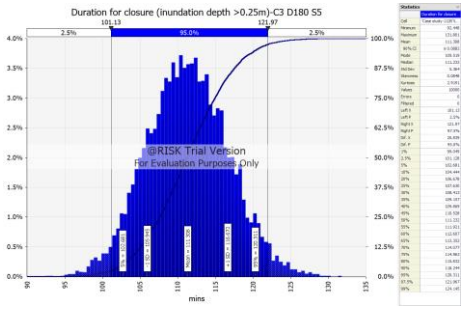



*Figure A-D1. 476. Chamber "1126" Closure duration input distribution C3-D180-S5*

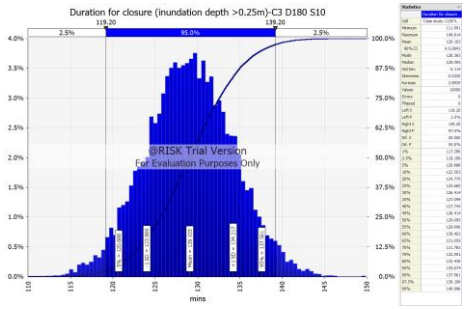



Figure A-D1. 477. Chamber "1126" Closure duration input distribution C3-D180-S10

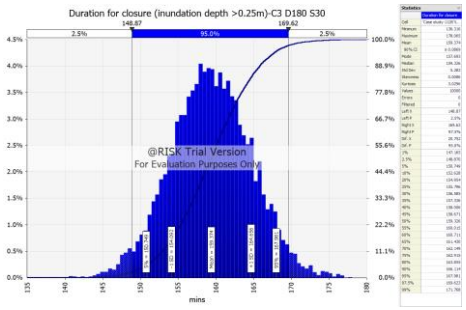



*Figure A-D1. 478. Chamber "1126" Closure duration input distribution C3-D180-S30*

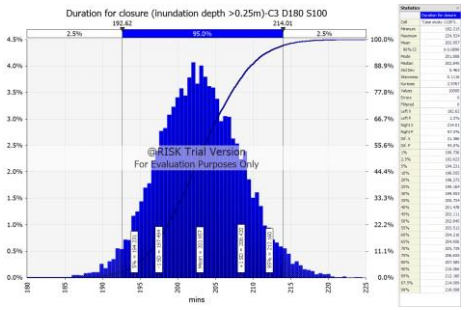



*Figure A-D1. 479. Chamber "1126" Closure duration input distribution C3-D180-S100*

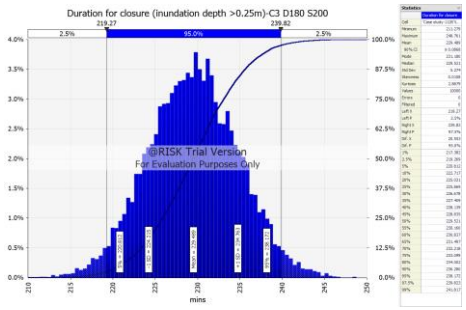



Figure A-D1. 480. Chamber "1126" Closure duration input distribution C3-D180-S200

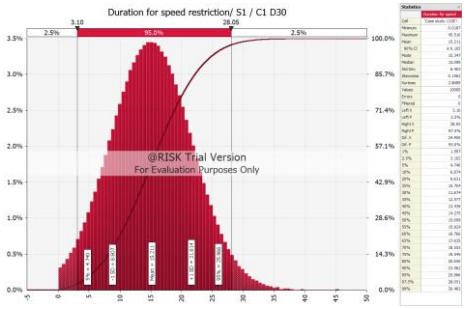



*Figure A-D1. 481. Chamber "1126" duration for speed restriction intermediate output distribution C1-D30-S1*

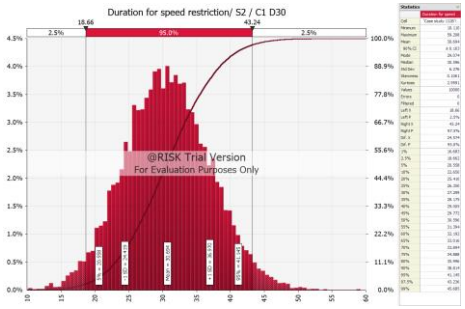



*Figure A-D1. 482. Chamber "1126" duration for speed restriction intermediate output distribution C1-D30-S2*

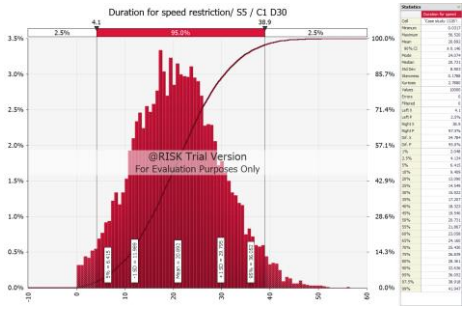



Figure A-D1. 483. Chamber "1126" duration for speed restriction intermediate output distribution C1-D30-S5

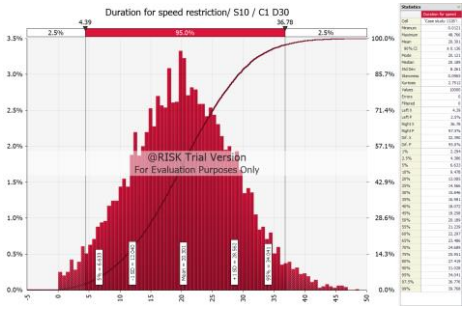



*Figure A-D1. 484. Chamber "1126" duration for speed restriction intermediate output distribution C1-D30-S10*

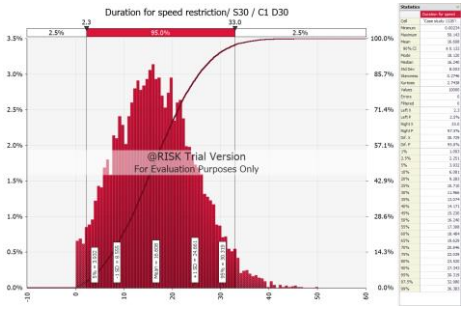



*Figure A-D1. 485. Chamber "1126" duration for speed restriction intermediate output distribution C1-D30-S30*

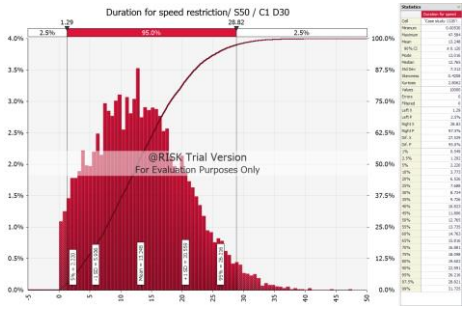



Figure A-D1. 486. Chamber "1126" duration for speed restriction intermediate output distribution C1-D30-S50

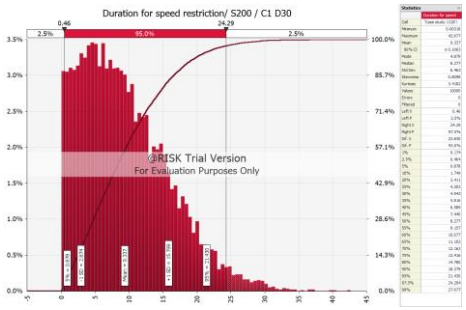



*Figure A-D1. 487. Chamber "1126" duration for speed restriction intermediate output distribution C1-D30-S200*

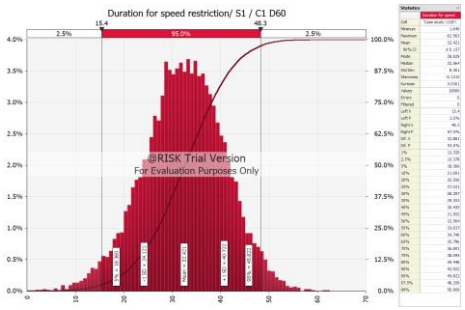



*Figure A-D1. 488. Chamber "1126" duration for speed restriction intermediate output distribution C1-D60-S1*

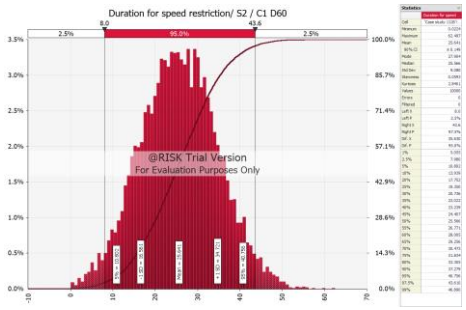



Figure A-D1. 489. Chamber "1126" duration for speed restriction intermediate output distribution C1-D60-S2

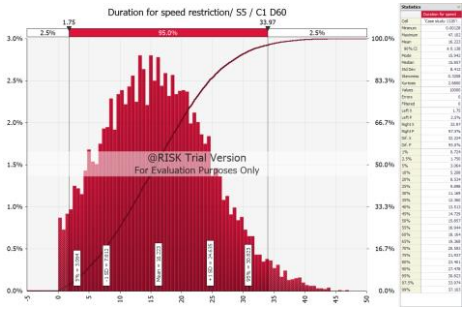



*Figure A-D1. 490. Chamber "1126" duration for speed restriction intermediate output distribution C1-D60-S5*

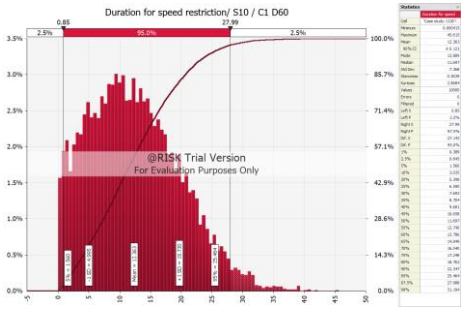



*Figure A-D1. 491. Chamber "1126" duration for speed restriction intermediate output distribution C1-D60-S10*

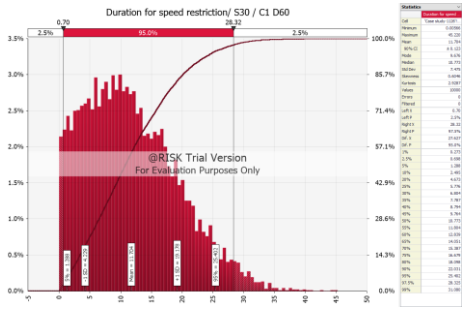



Figure A-D1. 492. Chamber "1126" duration for speed restriction intermediate output distribution C1-D60-S30

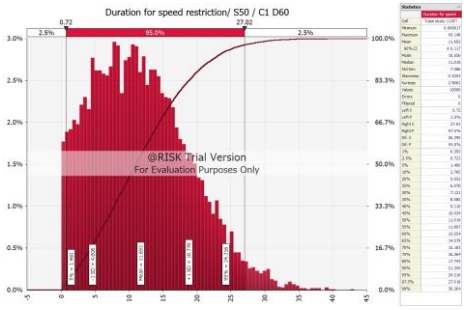



*Figure A-D1. 493. Chamber "1126" duration for speed restriction intermediate output distribution C1-D60-S50*

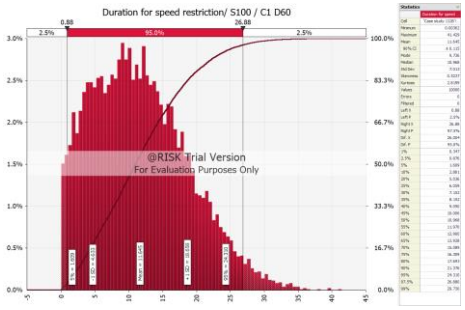



*Figure A-D1. 494. Chamber "1126" duration for speed restriction intermediate output distribution C1-D60-S100*

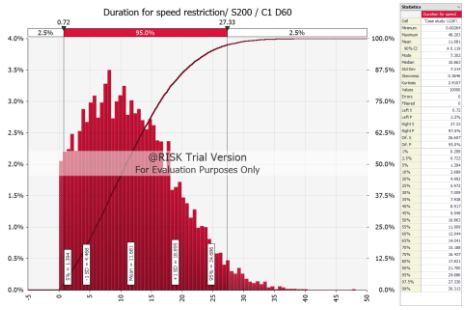



Figure A-D1. 495. Chamber "1126" duration for speed restriction intermediate output distribution C1-D60-S200

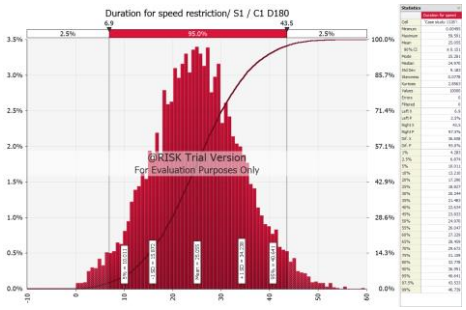



*Figure A-D1. 496. Chamber "1126" duration for speed restriction intermediate output distribution C1-D180-S1*

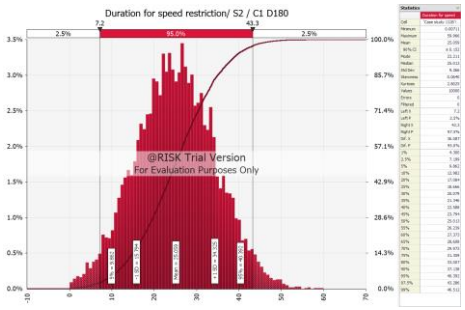



*Figure A-D1. 497. Chamber "1126" duration for speed restriction intermediate output distribution C1-D180-S2*

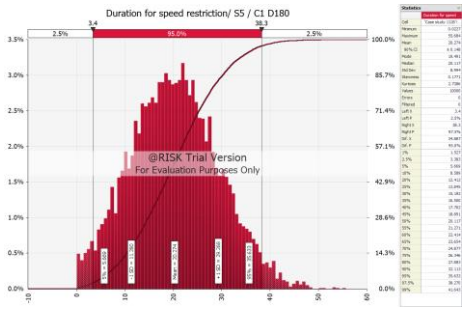



Figure A-D1. 498. Chamber "1126" duration for speed restriction intermediate output distribution C1-D180-S5

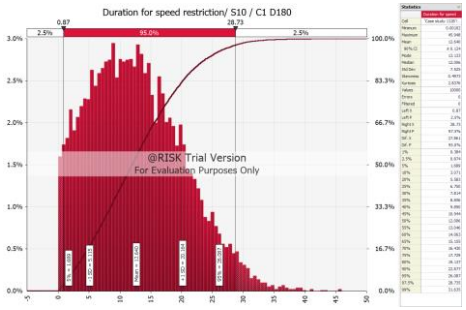



*Figure A-D1. 499. Chamber "1126" duration for speed restriction intermediate output distribution C1-D180-S10*

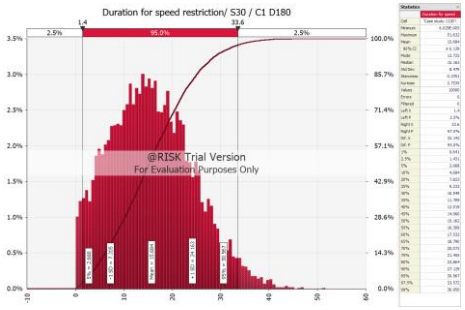



*Figure A-D1. 500. Chamber "1126" duration for speed restriction intermediate output distribution C1-D180-S30*

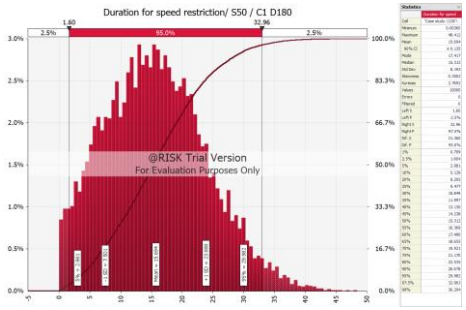



Figure A-D1. 501. Chamber "1126" duration for speed restriction intermediate output distribution C1-D180-S50

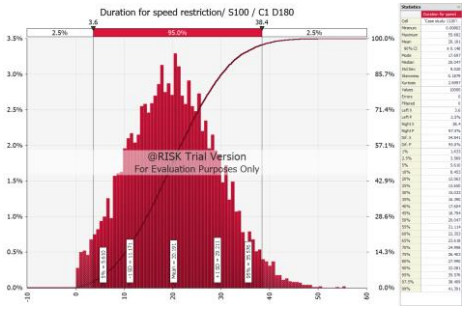



*Figure A-D1. 502. Chamber "1126" duration for speed restriction intermediate output distribution C1-D180-S100*

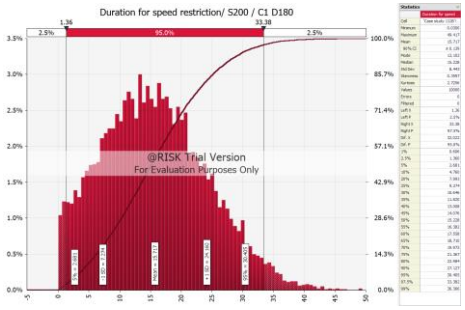



*Figure A-D1. 503. Chamber "1126" duration for speed restriction intermediate output distribution C1-D180-S200*

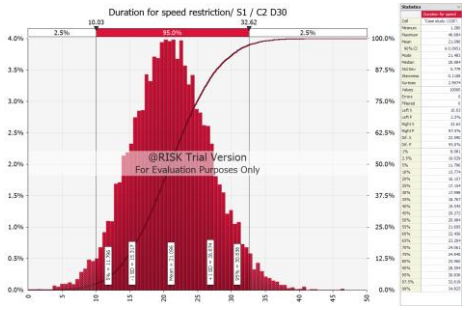



Figure A-D1. 504. Chamber "1126" duration for speed restriction intermediate output distribution C2-D30-S1

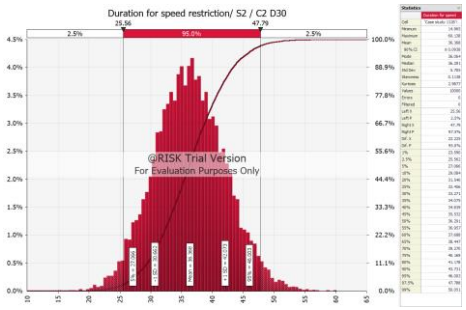



*Figure A-D1. 505. Chamber "1126" duration for speed restriction intermediate output distribution C2-D30-S2*

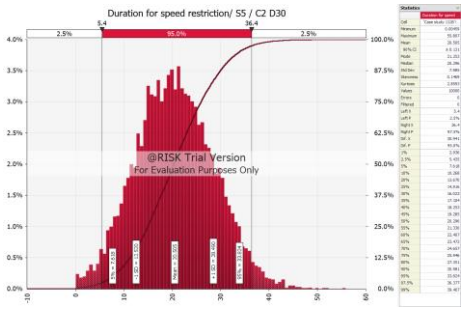



*Figure A-D1. 506. Chamber "1126" duration for speed restriction intermediate output distribution C2-D30-S5*

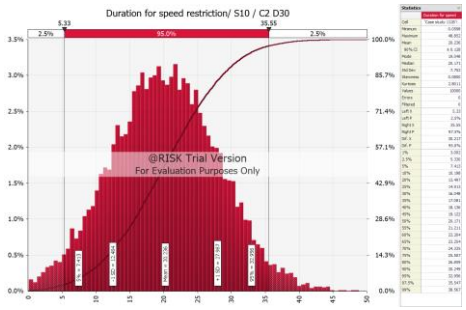



Figure A-D1. 507. Chamber "1126" duration for speed restriction intermediate output distribution C2-D30-S10

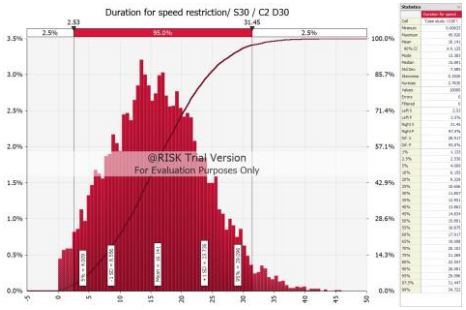



*Figure A-D1. 508. Chamber "1126" duration for speed restriction intermediate output distribution C2-D30-S30*

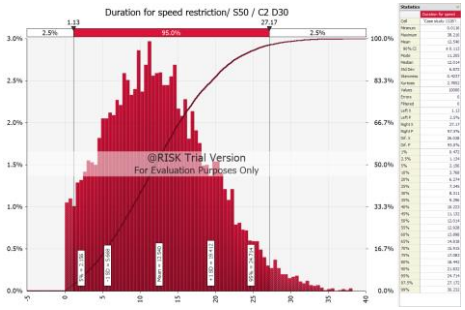



*Figure A-D1. 509. Chamber "1126" duration for speed restriction intermediate output distribution C2-D30-S50*

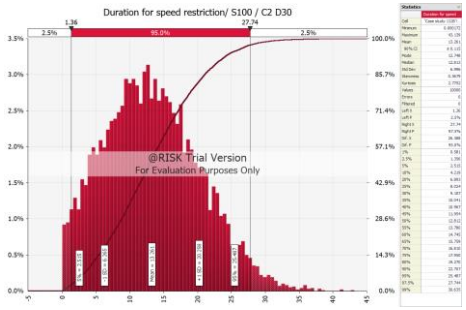



Figure A-D1. 510. Chamber "1126" duration for speed restriction intermediate output distribution C2-D30-S100

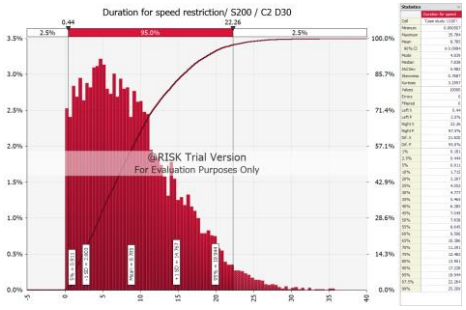



*Figure A-D1. 511. Chamber "1126" duration for speed restriction intermediate output distribution C2-D30-S200*

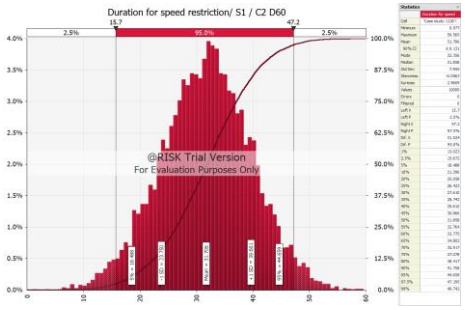



*Figure A-D1. 512. Chamber "1126" duration for speed restriction intermediate output distribution C2-D60-S1*

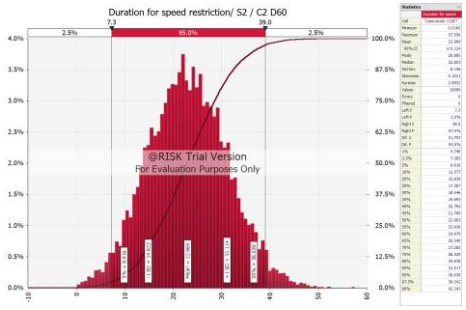



Figure A-D1. 513. Chamber "1126" duration for speed restriction intermediate output distribution C2-D60-S2

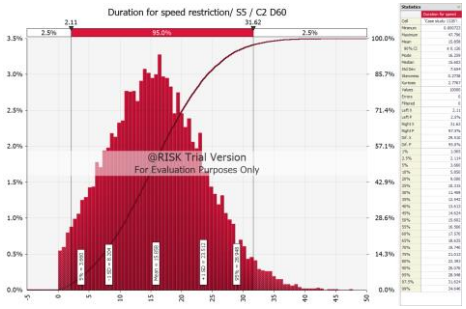



*Figure A-D1. 514. Chamber "1126" duration for speed restriction intermediate output distribution C2-D60-S5*

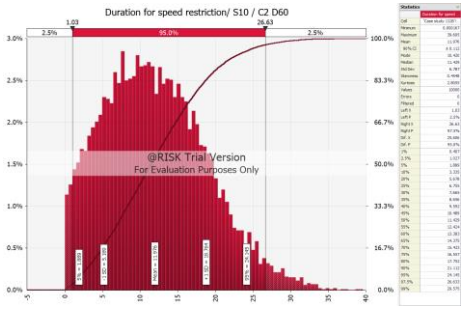



*Figure A-D1. 515. Chamber "1126" duration for speed restriction intermediate output distribution C2-D60-S10*

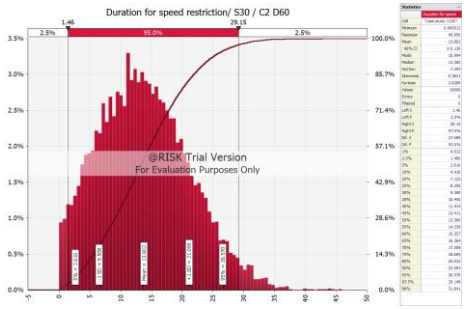



Figure A-D1. 516. Chamber "1126" duration for speed restriction intermediate output distribution C2-D60-S30

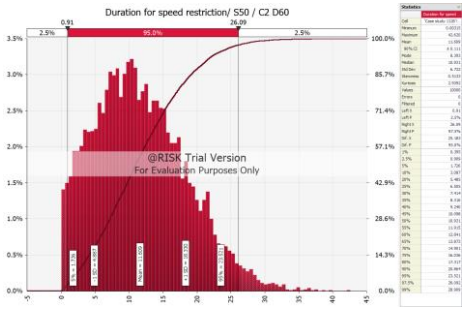



*Figure A-D1. 517. Chamber "1126" duration for speed restriction intermediate output distribution C2-D60-S50*

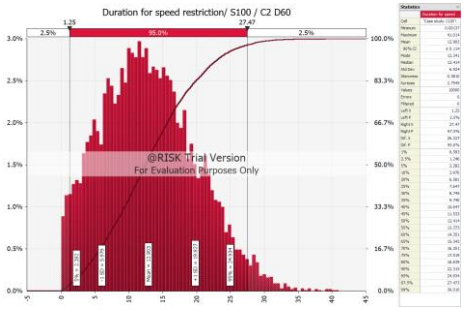



*Figure A-D1. 518. Chamber "1126" duration for speed restriction intermediate output distribution C2-D60-S100*

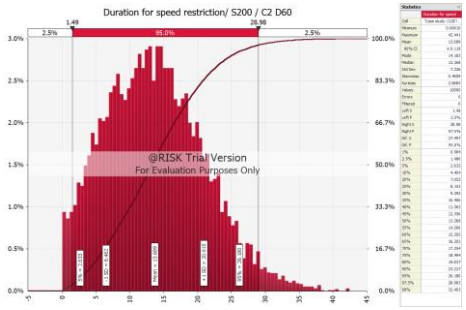



Figure A-D1. 519. Chamber "1126" duration for speed restriction intermediate output distribution C2-D60-S200

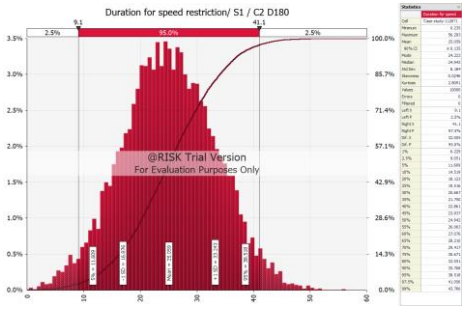



*Figure A-D1. 520. Chamber "1126" duration for speed restriction intermediate output distribution C2-180-S1*

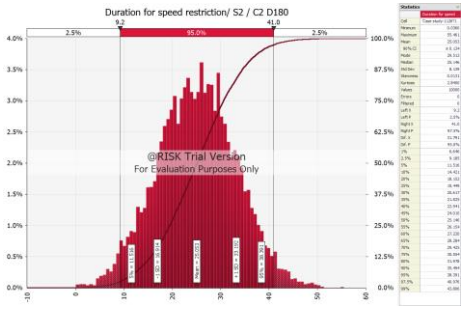



*Figure A-D1. 521. Chamber "1126" duration for speed restriction intermediate output distribution C2-180-S2*

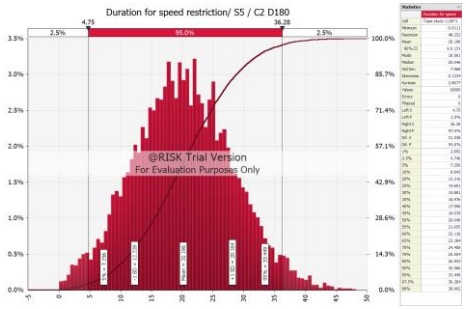



Figure A-D1. 522. Chamber "1126" duration for speed restriction intermediate output distribution C2-180-S5

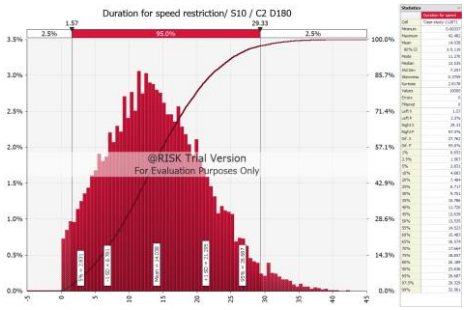



*Figure A-D1. 523. Chamber "1126" duration for speed restriction intermediate output distribution C2-180-S10*

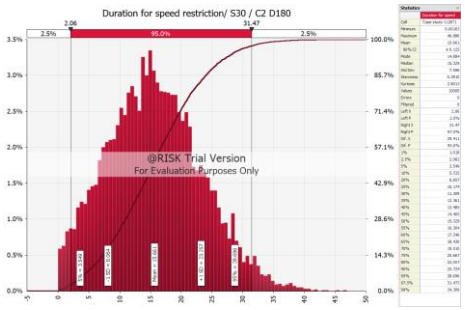



*Figure A-D1. 524. Chamber "1126" duration for speed restriction intermediate output distribution C2-180-S30*

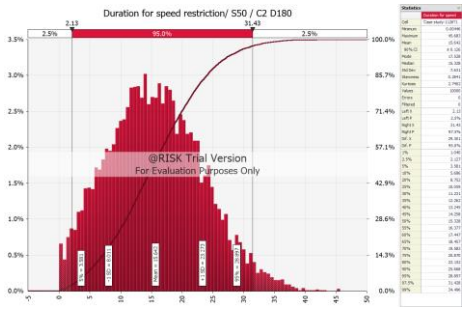



Figure A-D1. 525. Chamber "1126" duration for speed restriction intermediate output distribution C2-180-S50

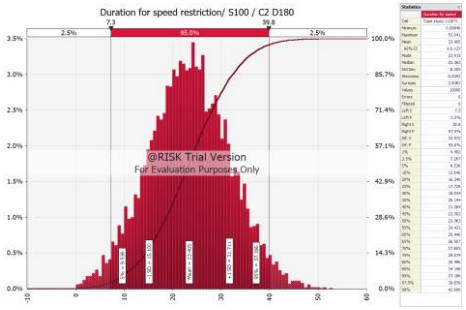



*Figure A-D1. 526. Chamber "1126" duration for speed restriction intermediate output distribution C2-180-S100*

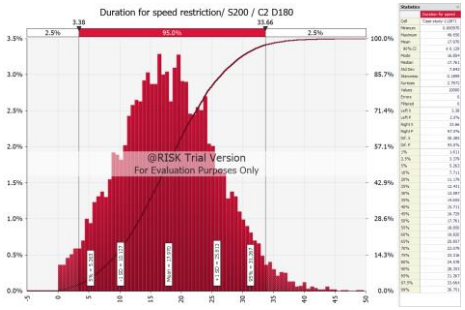



*Figure A-D1. 527. Chamber "1126" duration for speed restriction intermediate output distribution C2-180-S200*

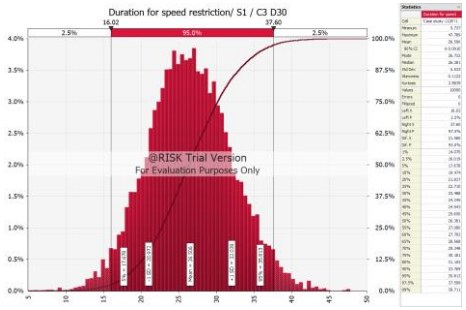



Figure A-D1. 528. Chamber "1126" duration for speed restriction intermediate output distribution C3-30-S1

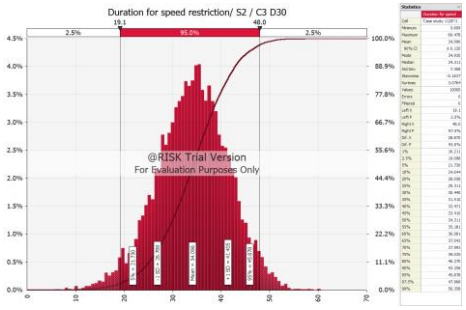



*Figure A-D1. 529. Chamber "1126" duration for speed restriction intermediate output distribution C3-30-S2*

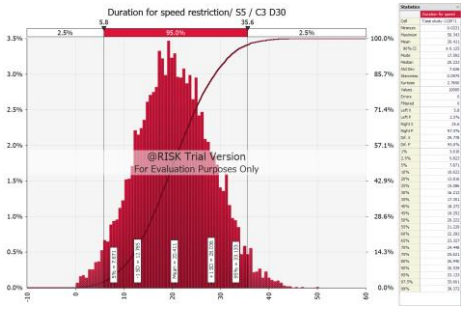



*Figure A-D1. 530. Chamber "1126" duration for speed restriction intermediate output distribution C3-30-S5*

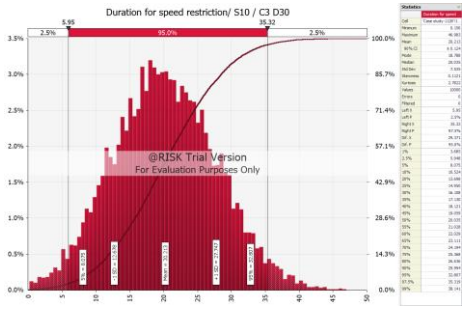



Figure A-D1. 531. Chamber "1126" duration for speed restriction intermediate output distribution C3-30-S10

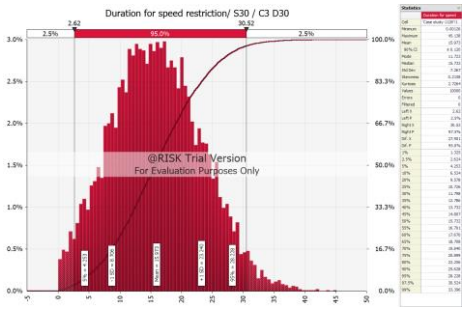



*Figure A-D1. 532. Chamber "1126" duration for speed restriction intermediate output distribution C3-30-S30*

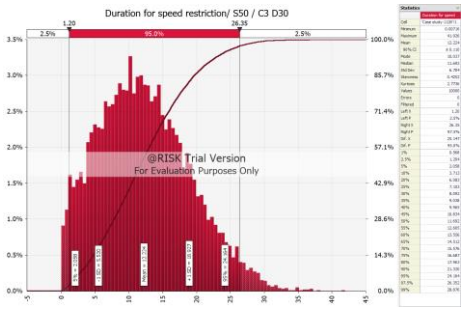



*Figure A-D1. 533. Chamber "1126" duration for speed restriction intermediate output distribution C3-30-S50*

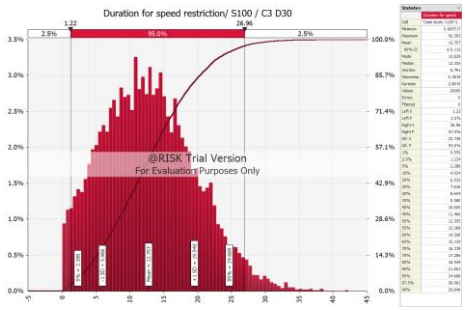



Figure A-D1. 534. Chamber "1126" duration for speed restriction intermediate output distribution C3-30-S100

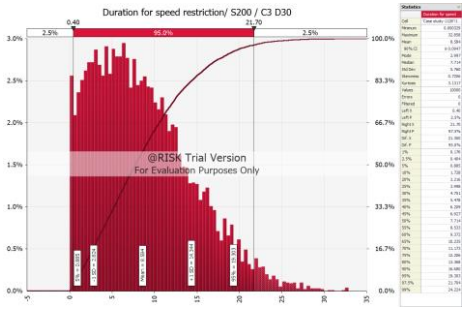



*Figure A-D1. 535. Chamber "1126" duration for speed restriction intermediate output distribution C3-30-S200*

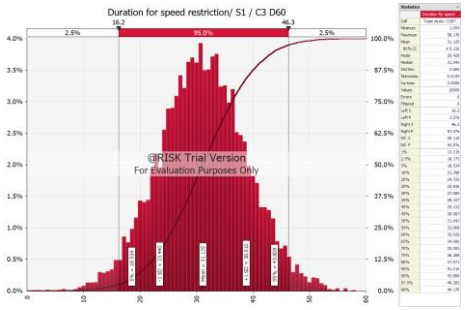



*Figure A-D1. 536. Chamber "1126" duration for speed restriction intermediate output distribution C3-60-S1*

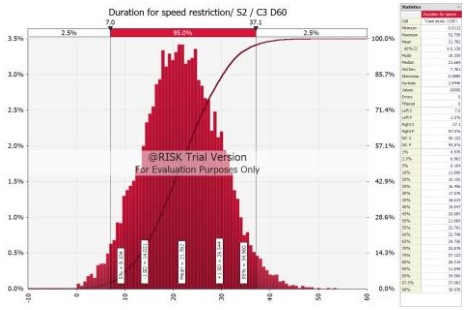



Figure A-D1. 537. Chamber "1126" duration for speed restriction intermediate output distribution C3-60-S2

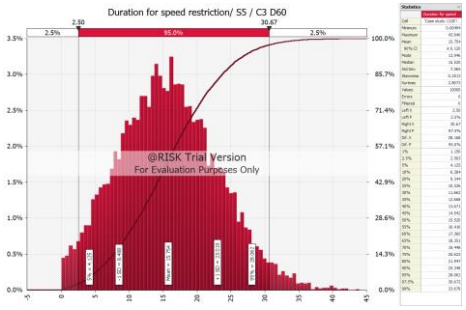



*Figure A-D1. 538. Chamber "1126" duration for speed restriction intermediate output distribution C3-60-S5*

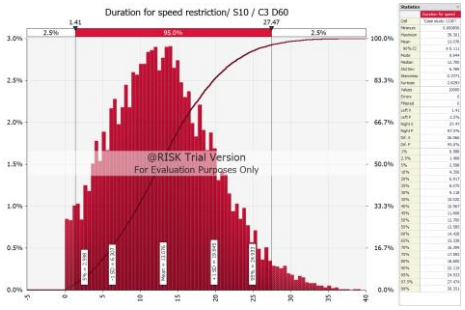



*Figure A-D1. 539. Chamber "1126" duration for speed restriction intermediate output distribution C3-60-S10*

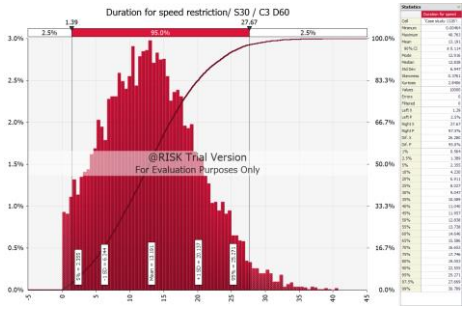



Figure A-D1. 540. Chamber "1126" duration for speed restriction intermediate output distribution C3-60-S30

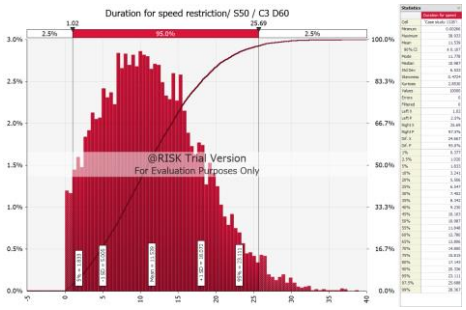



*Figure A-D1. 541. Chamber "1126" duration for speed restriction intermediate output distribution C3-60-S50*

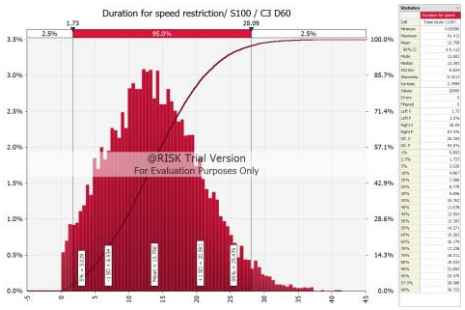



*Figure A-D1. 542. Chamber "1126" duration for speed restriction intermediate output distribution C3-60-S100*

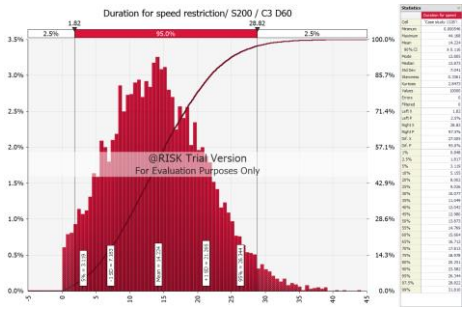



Figure A-D1. 543. Chamber "1126" duration for speed restriction intermediate output distribution C3-60-S200

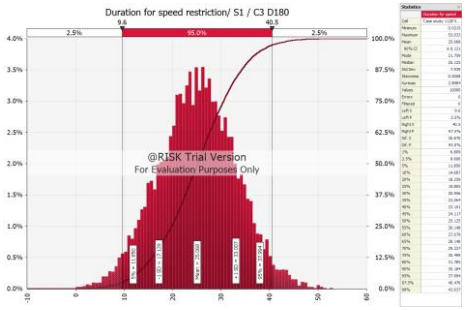



*Figure A-D1. 544. Chamber "1126" duration for speed restriction intermediate output distribution C3-180-S1*

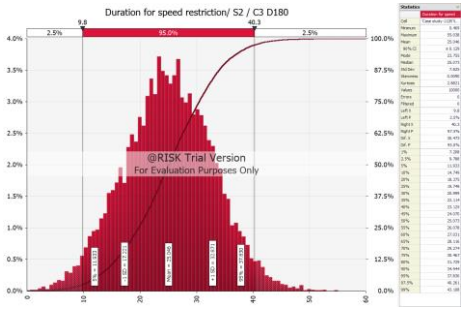



*Figure A-D1. 545. Chamber "1126" duration for speed restriction intermediate output distribution C3-180-S2*

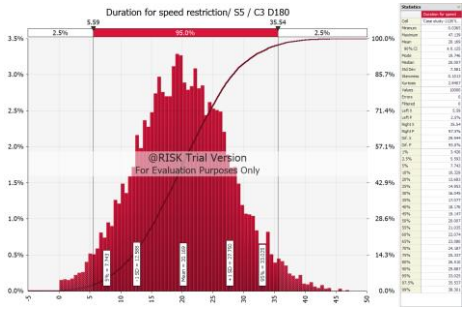



Figure A-D1. 546. Chamber "1126" duration for speed restriction intermediate output distribution C3-180-S5

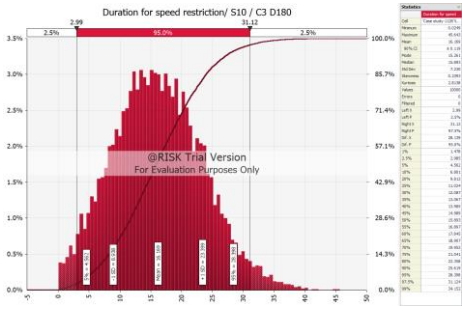



*Figure A-D1. 547. Chamber "1126" duration for speed restriction intermediate output distribution C3-180-S10*

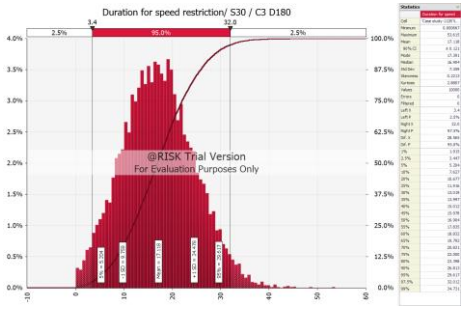



*Figure A-D1. 548. Chamber "1126" duration for speed restriction intermediate output distribution C3-180-S30*

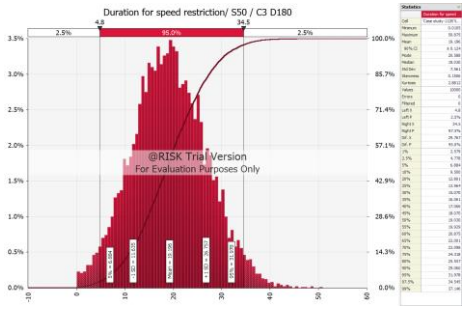



Figure A-D1. 549. Chamber "1126" duration for speed restriction intermediate output distribution C3-180-S50

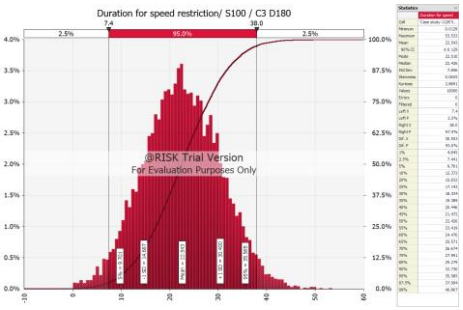



*Figure A-D1. 550. Chamber "1126" duration for speed restriction intermediate output distribution C3-180-S100*

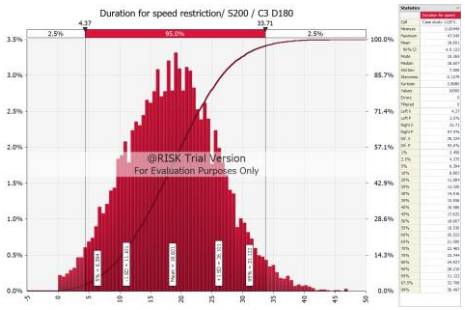



*Figure A-D1. 551. Chamber "1126" duration for speed restriction intermediate output distribution C3-180-S200*

# Appendix D.2: Damage quantification output distribution

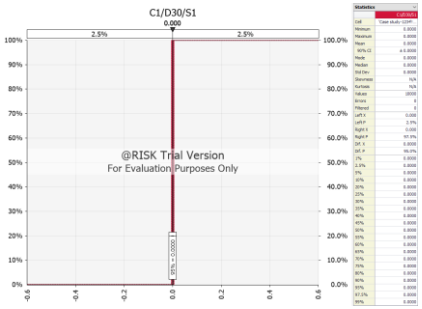



*Figure A-D2. 1. Chamber "1234" Damage cost output distribution C1-D30-S1*

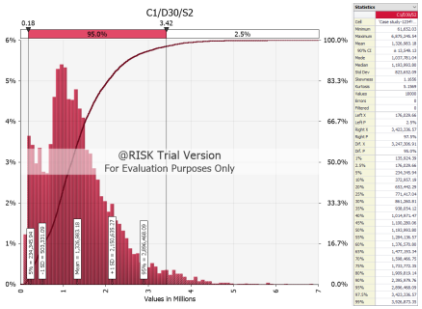



*Figure A-D2. 2. Chamber "1234" Damage cost output distribution C1-D30-S2*

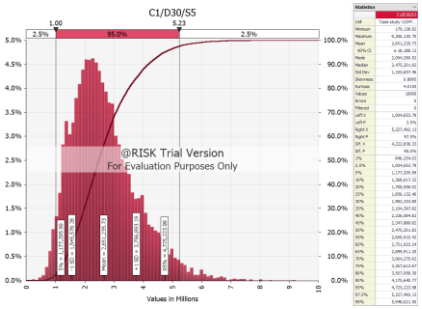



*Figure A-D2. 3.Chamber "1234" Damage cost output distribution C1-D30-S5*

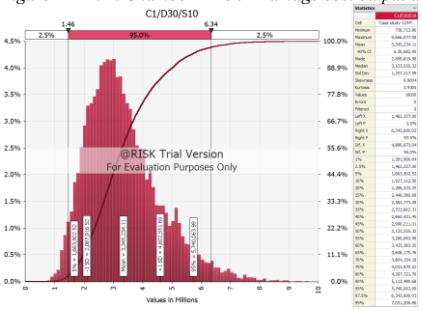



*Figure A-D2. 4. Chamber "1234" Damage cost output distribution C1-D30-S10*

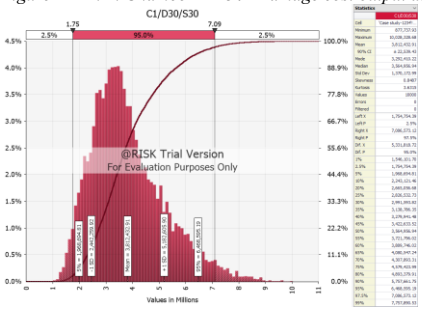



*Figure A-D2. 5. Chamber "1234" Damage cost output distribution C1-D30-S30*

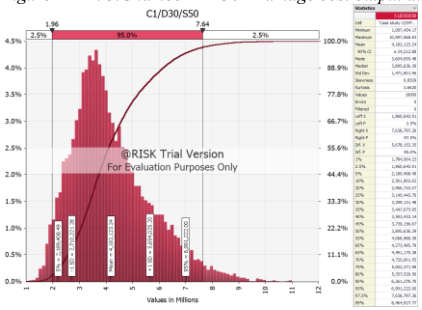



*Figure A-D2. 6. Chamber "1234" Damage cost output distribution C1-D30-S50*

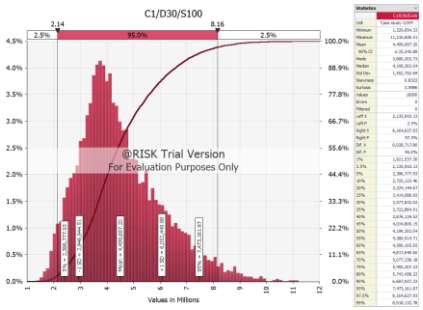



*Figure A-D2. 7. Chamber "1234" Damage cost output distribution C1-D30-S100*

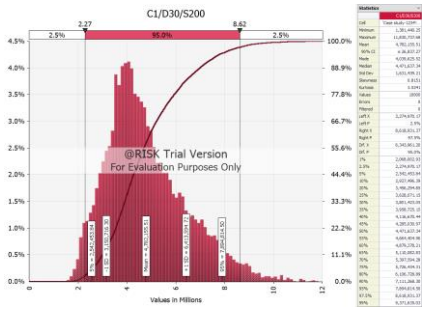



*Figure A-D2. 8. Chamber "1234" Damage cost output distribution C1-D30-S200*

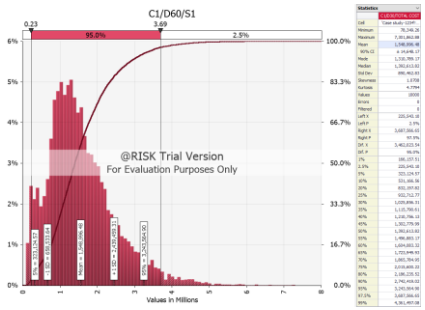



Figure A-D2. 9. Chamber "1234" Damage cost output distribution C1-D60-S1

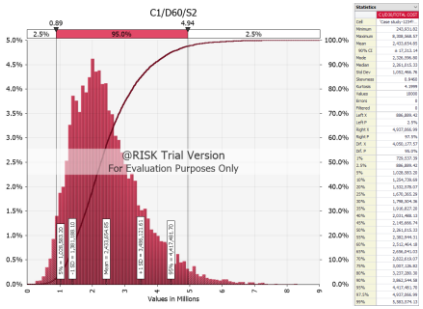



*Figure A-D2. 10. Chamber "1234" Damage cost output distribution C1-D60-S2*

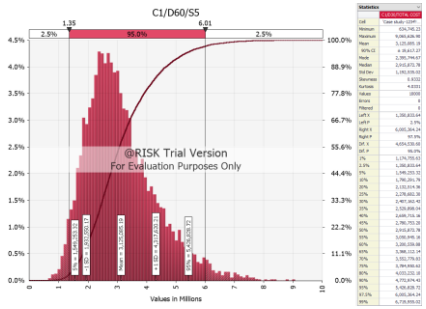



*Figure A-D2. 11. Chamber "1234" Damage cost output distribution C1-D60-S5*

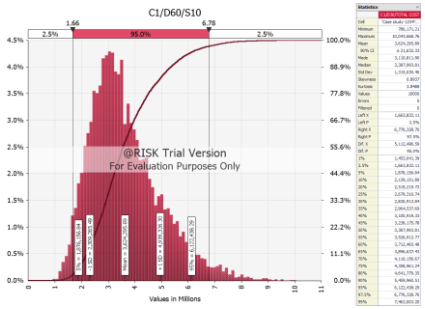



Figure A-D2. 12. Chamber "1234" Damage cost output distribution C1-D60-S10

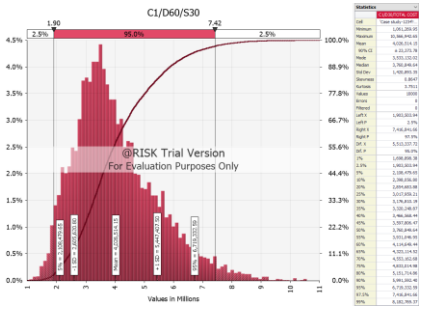



*Figure A-D2. 13. Chamber "1234" Damage cost output distribution C1-D60-S30*

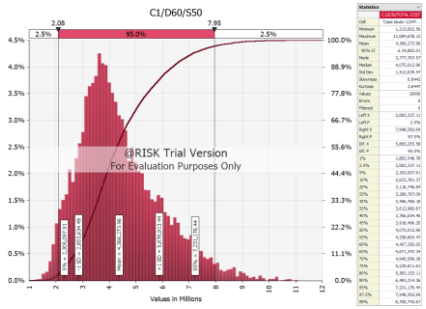



*Figure A-D2. 14. Chamber "1234" Damage cost output distribution C1-D60-S50*

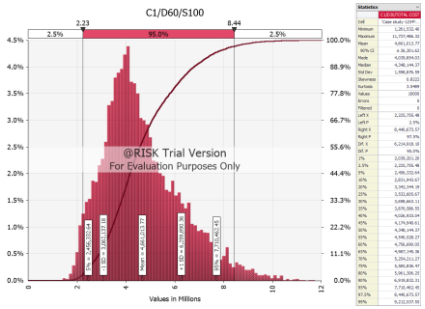



Figure A-D2. 15. Chamber "1234" Damage cost output distribution C1-D60-S100

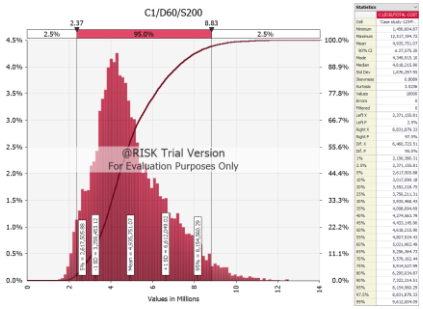



*Figure A-D2. 16. Chamber "1234" Damage cost output distribution C1-D60-S200*

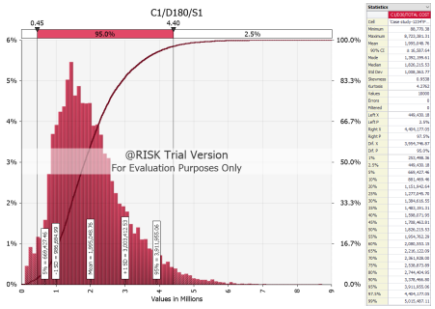



*Figure A-D2. 17. Chamber "1234" Damage cost output distribution C1-D180-S1*

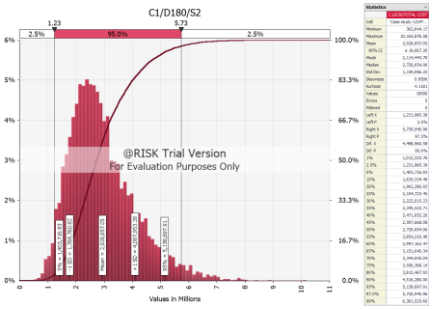



Figure A-D2. 18. Chamber "1234" Damage cost output distribution C1-D180-S2

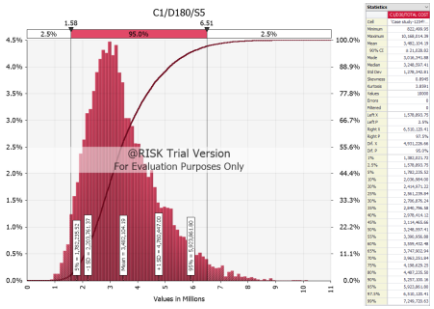



*Figure A-D2. 19. Chamber "1234" Damage cost output distribution C1-D180-S5*

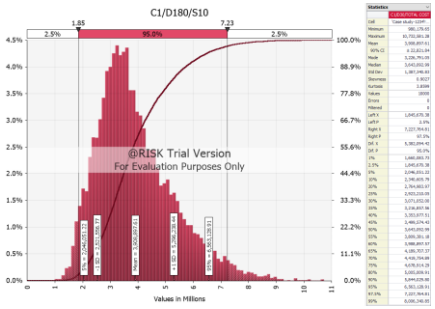



*Figure A-D2. 20. Chamber "1234" Damage cost output distribution C1-D180-S10*

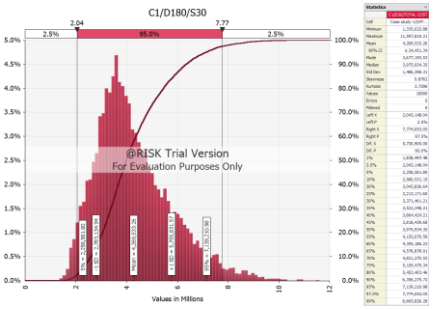



Figure A-D2. 21. Chamber "1234" Damage cost output distribution C1-D180-S30

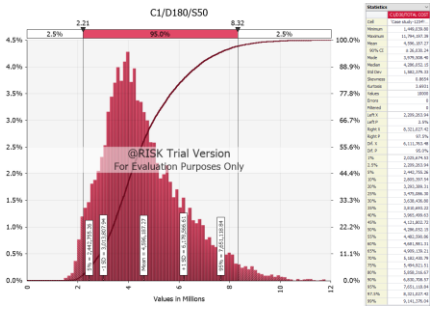



*Figure A-D2. 22. Chamber "1234" Damage cost output distribution C1-D180-S50*

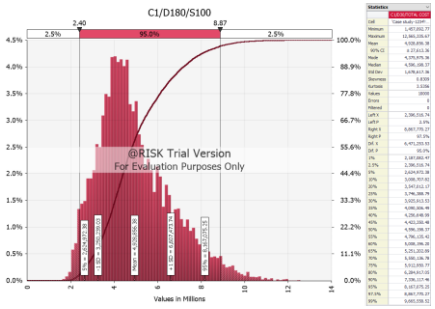



*Figure A-D2. 23. Chamber "1234" Damage cost output distribution C1-D180-S100*

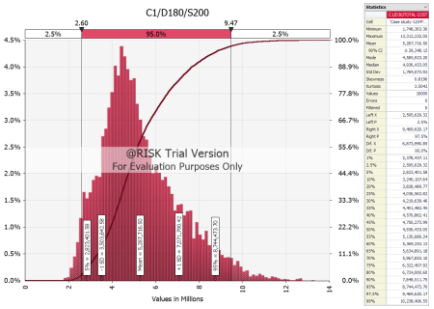



Figure A-D2. 24. Chamber "1234" Damage cost output distribution C1-D180-S200

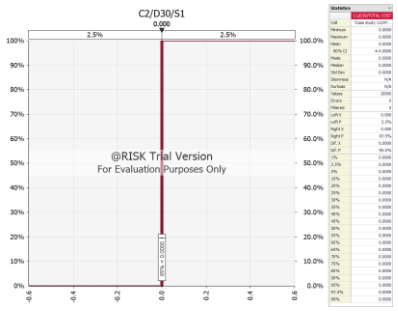



*Figure A-D2. 25. Chamber "1234" Damage cost output distribution C2-D30-S1*

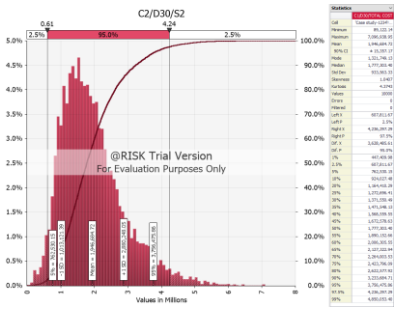



*Figure A-D2. 26. Chamber "1234" Damage cost output distribution C2-D30-S2*

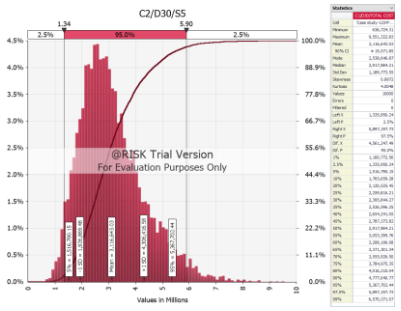



Figure A2. 27. Chamber "1234" Damage cost output distribution C2-D30-S5

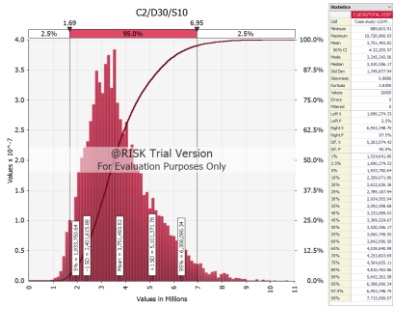



*Figure A-D2. 28. Chamber "1234" Damage cost output distribution C2-D30-S10*

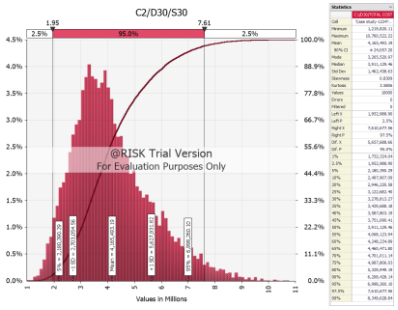



*Figure A-D2. 29. Chamber "1234" Damage cost output distribution C2-D30-S30*

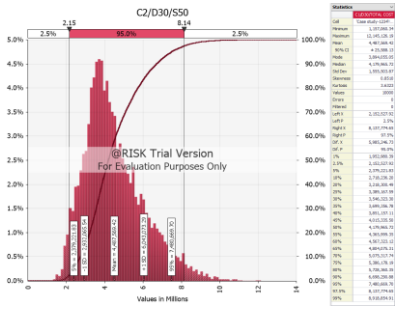



Figure A-D2. 30. Chamber "1234" Damage cost output distribution C2-D30-S50

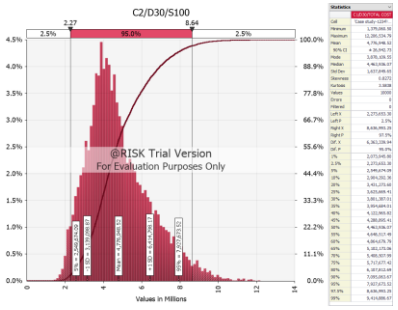



*Figure A-D2. 31. Chamber "1234" Damage cost output distribution C2-D30-S100*

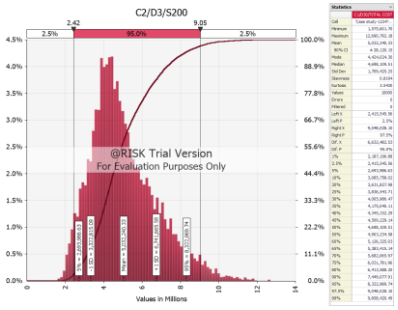



*Figure A-D2. 32. Chamber "1234" Damage cost output distribution C2-D30-S200*

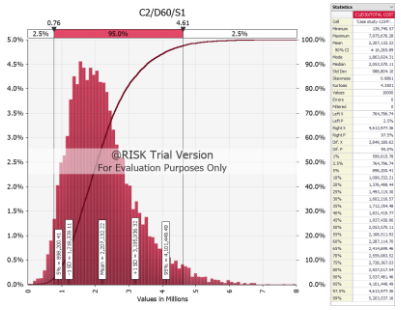



Figure A-D2. 33. Chamber "1234" Damage cost output distribution C2-D60-S1

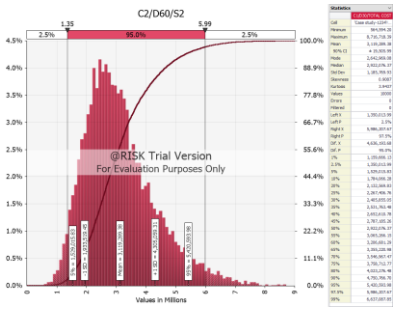



*Figure A-D2. 34. Chamber "1234" Damage cost output distribution C2-D60-S2*

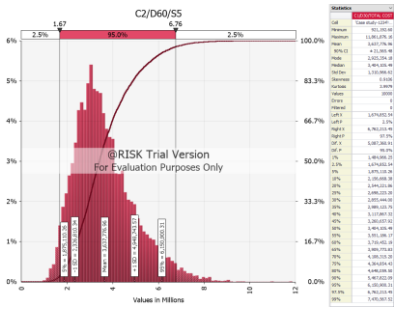



*Figure A-D2. 35. Chamber "1234" Damage cost output distribution C2-D60-S5*

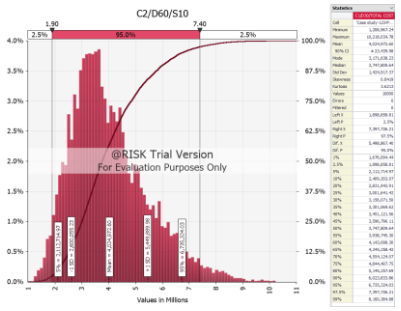



Figure A-D2. 36. Chamber "1234" Damage cost output distribution C2-D60-S10

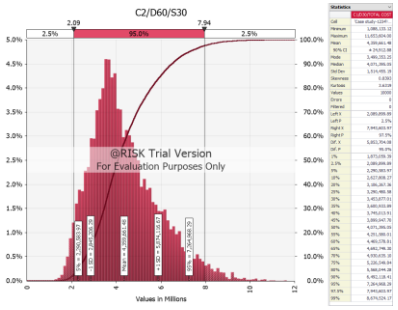



*Figure A-D2. 37. Chamber "1234" Damage cost output distribution C2-D60-S30*

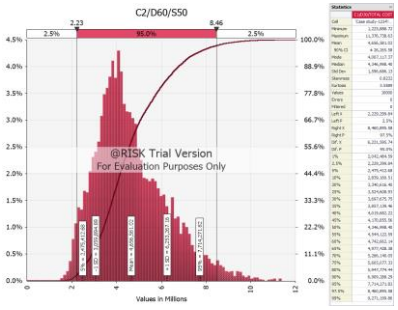



*Figure A-D2. 38. Chamber "1234" Damage cost output distribution C2-D60-S50*

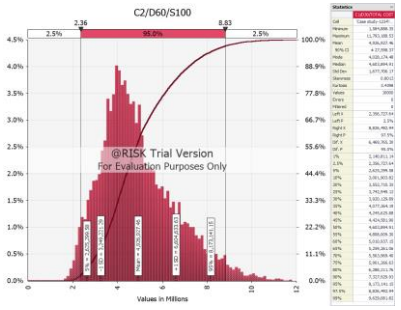



Figure A-D2. 39. Chamber "1234" Damage cost output distribution C2-D60-S100

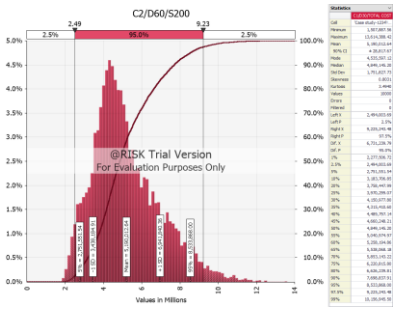



*Figure A-D2. 40. Chamber "1234" Damage cost output distribution C2-D60-S200*

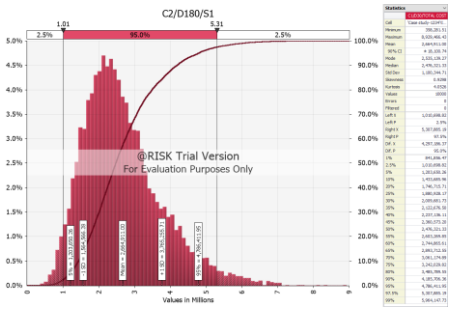



*Figure A-D2. 41. Chamber "1234" Damage cost output distribution C2-D180-S1*

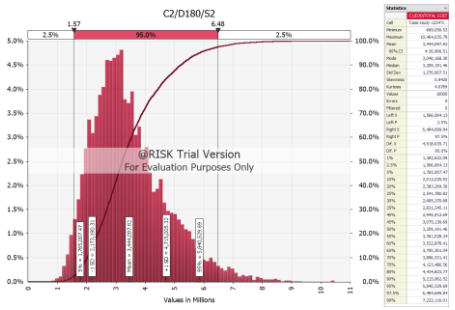



Figure A-D2. 42. Chamber "1234" Damage cost output distribution C2-D180-S2

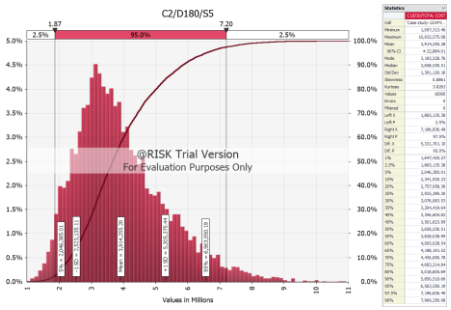



*Figure A-D2. 43. Chamber "1234" Damage cost output distribution C2-D180-S5*

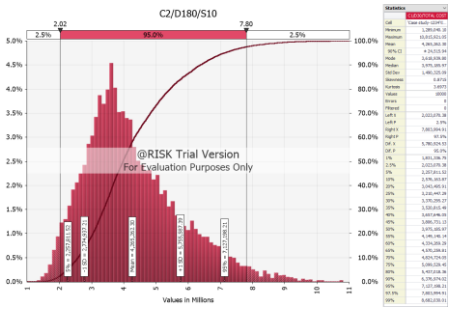



*Figure A-D2. 44. Chamber "1234" Damage cost output distribution C2-D180-S10*

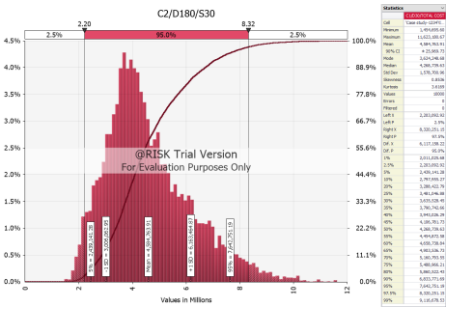



Figure A-D2. 45. Chamber "1234" Damage cost output distribution C2-D180-S30

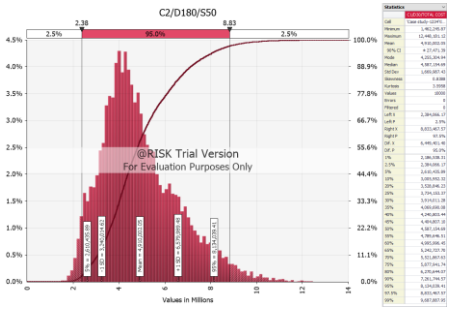



*Figure A-D2. 46. Chamber "1234" Damage cost output distribution C2-D180-S50*

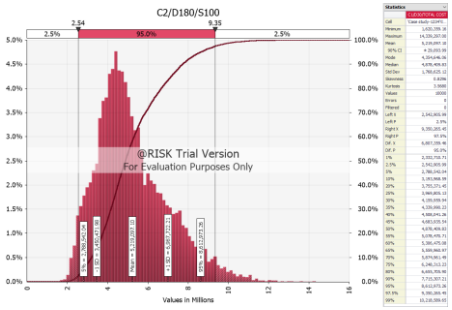



*Figure A-D2. 47. Chamber "1234" Damage cost output distribution C2-D180-S100*

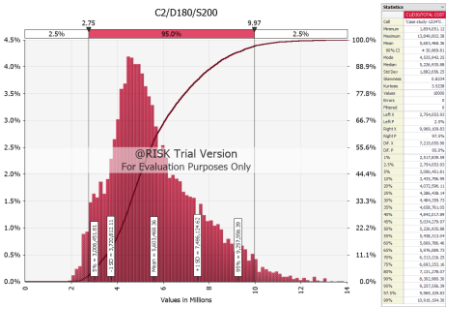



Figure A-D2. 48. Chamber "1234" Damage cost output distribution C2-D180-S200

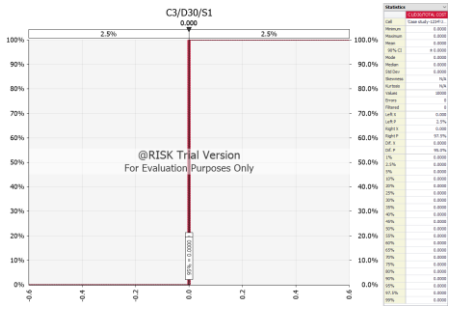



*Figure A-D2. 49. Chamber "1234" Damage cost output distribution C3-D30-S1*

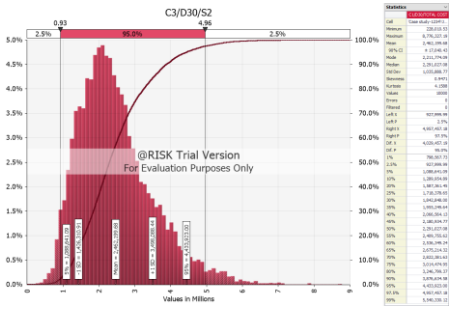



*Figure A-D2. 50. Chamber "1234" Damage cost output distribution C3-D30-S2*

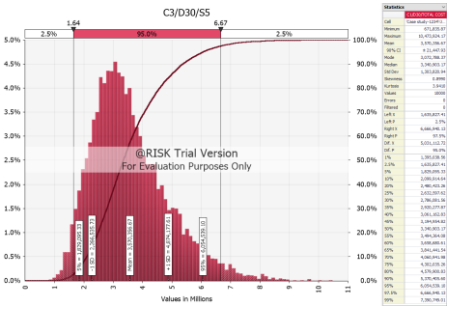



Figure A-D2. 51. Chamber "1234" Damage cost output distribution C3-D30-S5

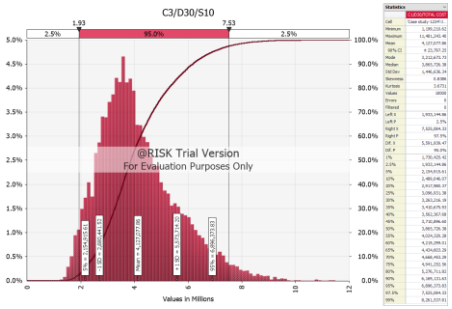



*Figure A-D2. 52. Chamber "1234" Damage cost output distribution C3-D30-S10*

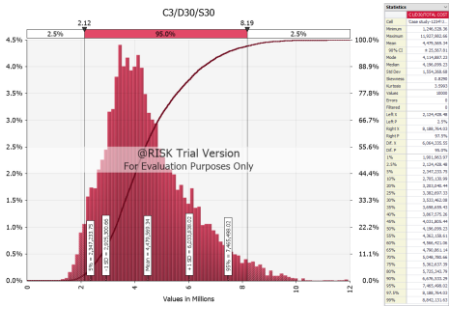



*Figure A-D2. 53. Chamber "1234" Damage cost output distribution C3-D30-S30*

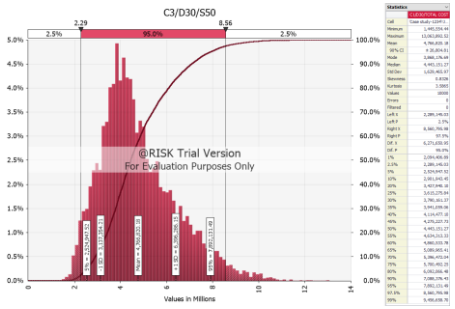



Figure A-D2. 54. Chamber "1234" Damage cost output distribution C3-D30-S50

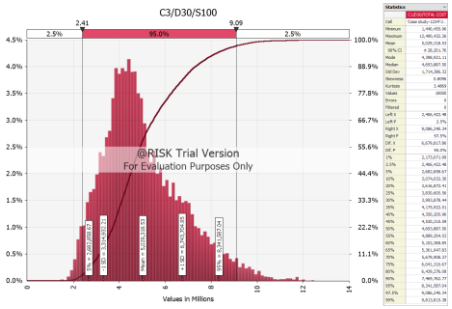



*Figure A-D2. 55. Chamber "1234" Damage cost output distribution C3-D30-S100*

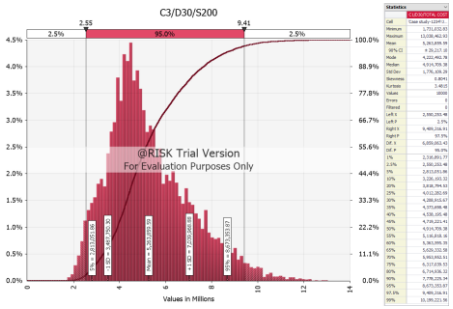



*Figure A-D2. 56. Chamber "1234" Damage cost output distribution C3-D30-S200*

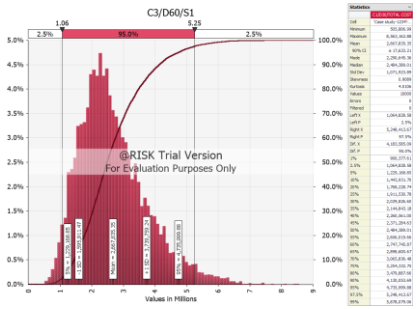



Figure A-D2. 57. Chamber "1234" Damage cost output distribution C3-D60-S1

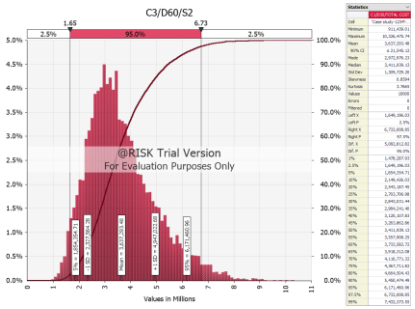



*Figure A-D2. 58. Chamber "1234" Damage cost output distribution C3-D60-S2*

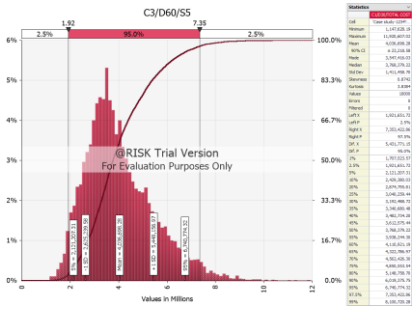



*Figure A-D2. 59. Chamber "1234" Damage cost output distribution C3-D60-S5*

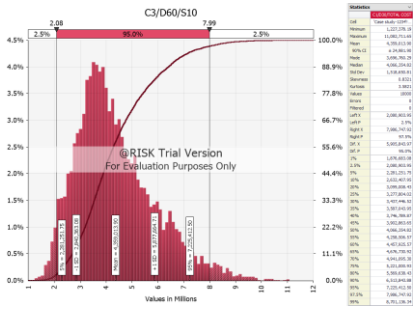



Figure A-D2. 60. Chamber "1234" Damage cost output distribution C3-D60-S10

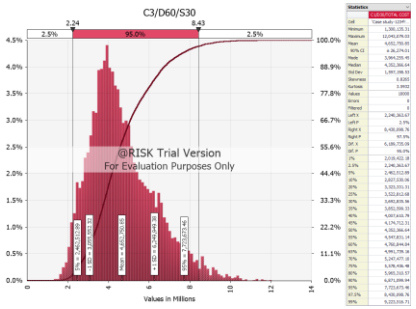



*Figure A-D2. 61. Chamber "1234" Damage cost output distribution C3-D60-S30*

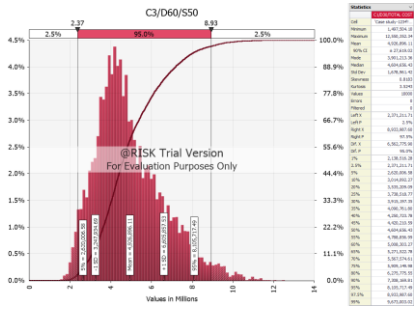



*Figure A-D2. 62. Chamber "1234" Damage cost output distribution C3-D60-S50*

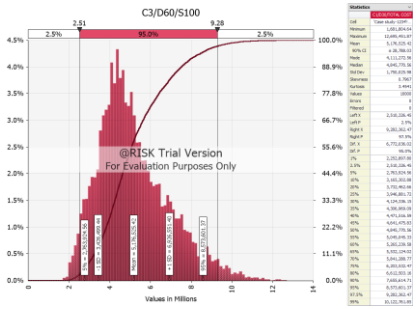



Figure A-D2. 63. Chamber "1234" Damage cost output distribution C3-D60-S100

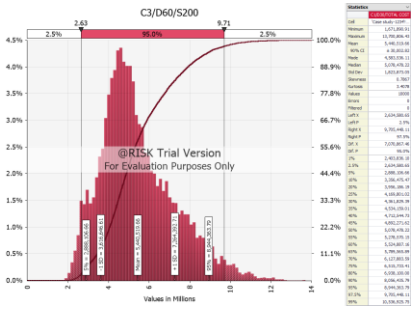



*Figure A-D2. 64. Chamber "1234" Damage cost output distribution C3-D60-S200*

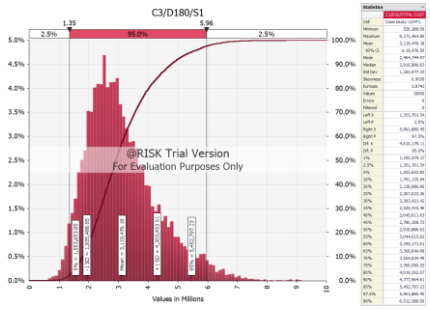



*Figure A-D2. 65. Chamber "1234" Damage cost output distribution C3-D180-S1*

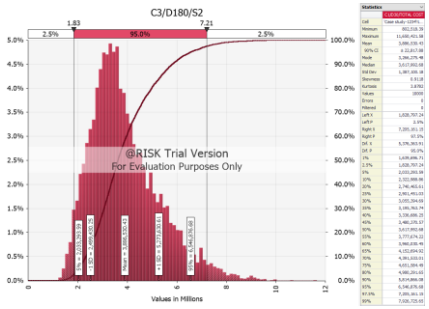



Figure A-D2. 66. Chamber "1234" Damage cost output distribution C3-D180-S2

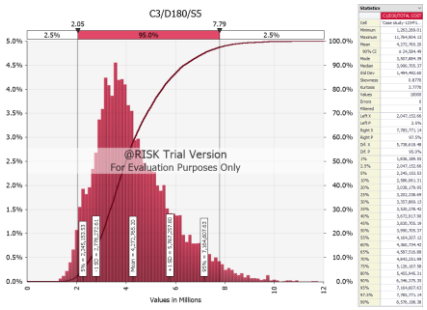



*Figure A-D2. 67. Chamber "1234" Damage cost output distribution C3-D180-S5*

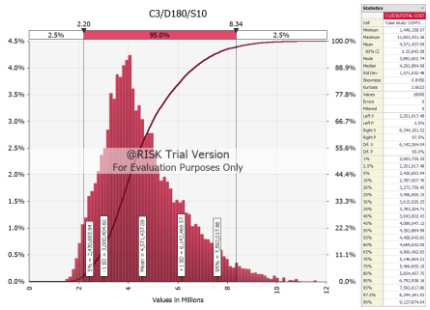



*Figure A-D2. 68. Chamber "1234" Damage cost output distribution C3-D180-S10*

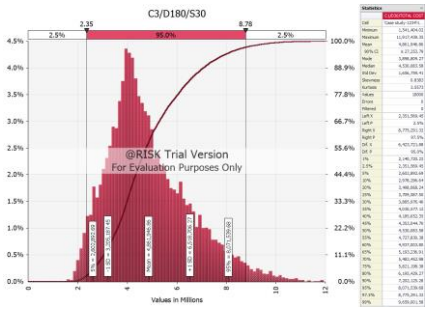



Figure A-D2. 69. Chamber "1234" Damage cost output distribution C3-D180-S30

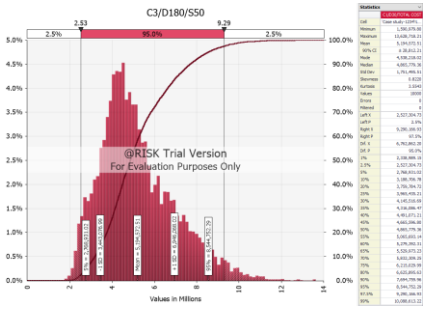



*Figure A-D2. 70. Chamber "1234" Damage cost output distribution C3-D180-S50*

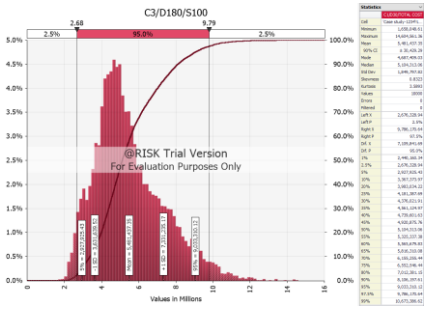



*Figure A-D2. 71. Chamber "1234" Damage cost output distribution C3-D180-S100*

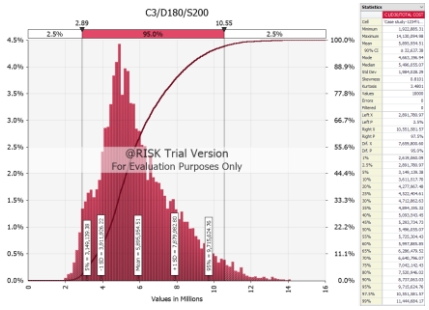



Figure A-D2. 72. Chamber "1234" Damage cost output distribution C3-D180-S200

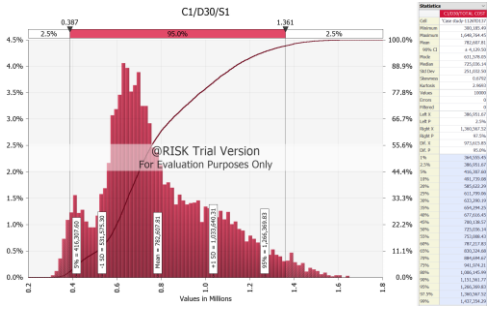



*Figure A-D2. 73. Chamber "1126" Damage cost output distribution C1-D30-S1*

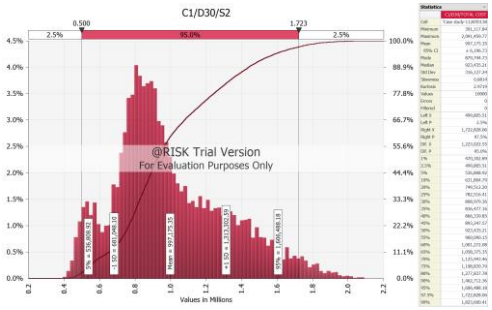



*Figure A-D2. 74. Chamber "1126" Damage cost output distribution C1-D30-S2*

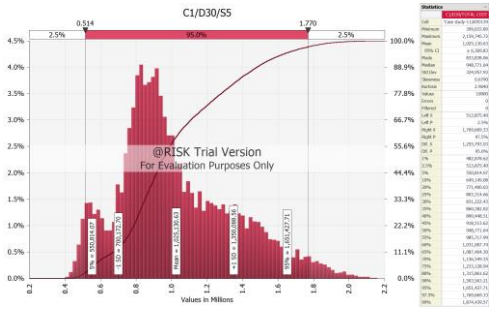



Figure A-D2. 75. Chamber "1126" Damage cost output distribution C1-D30-S5

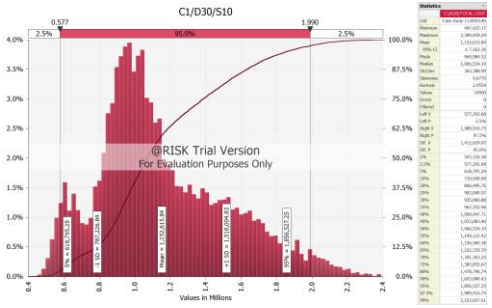



*Figure A-D2. 76. Chamber "1126" Damage cost output distribution C1-D30-S10*

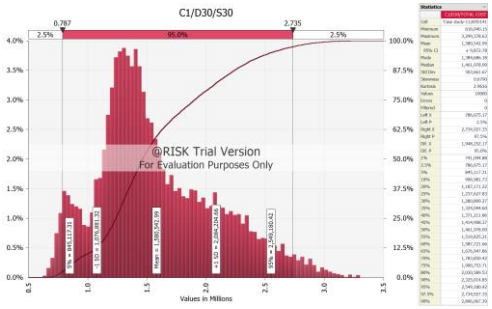



*Figure A-D2. 77. Chamber "1126" Damage cost output distribution C1-D30-S30*

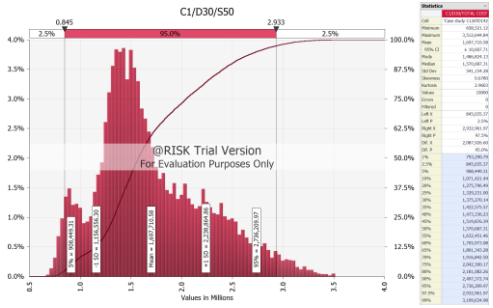



Figure A-D2. 78. Chamber "1126" Damage cost output distribution C1-D30-S50

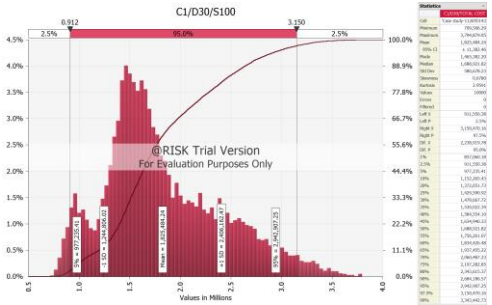



*Figure A-D2. 79. Chamber "1126" Damage cost output distribution C1-D30-S100*

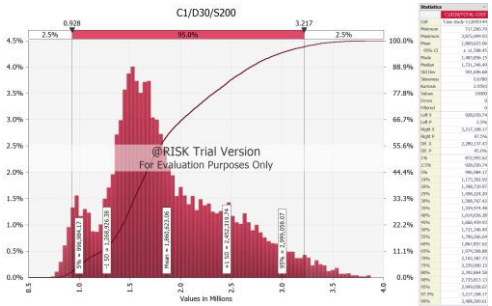



*Figure A-D2. 80. Chamber "1126" Damage cost output distribution C1-D30-S200*

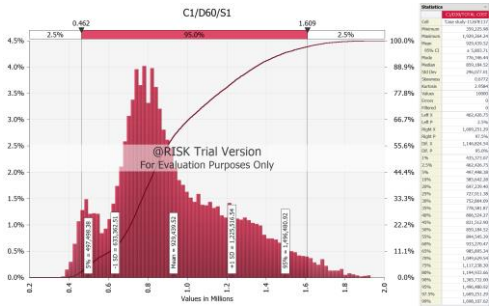



Figure A-D2. 81. Chamber "1126" Damage cost output distribution C1-D60-S1

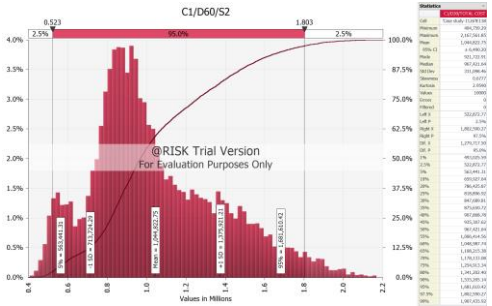



*Figure A-D2. 82. Chamber "1126" Damage cost output distribution C1-D60-S2*

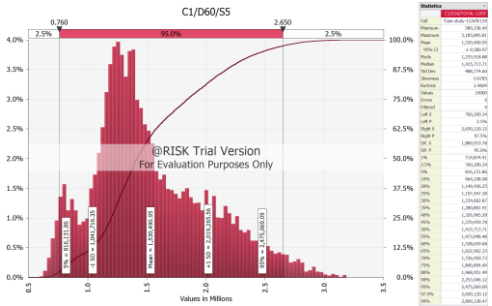



*Figure A-D2. 83. Chamber "1126" Damage cost output distribution C1-D60-S5*

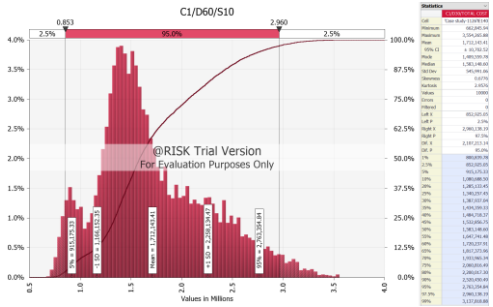



Figure A-D2. 84. Chamber "1126" Damage cost output distribution C1-D60-S10

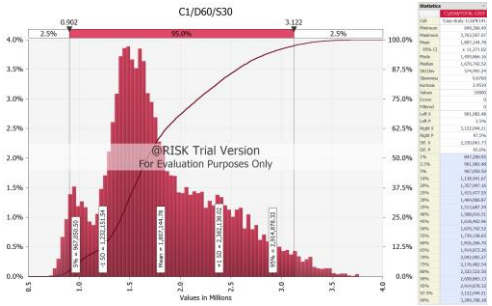



*Figure A-D2. 85. Chamber "1126" Damage cost output distribution C1-D60-S30*

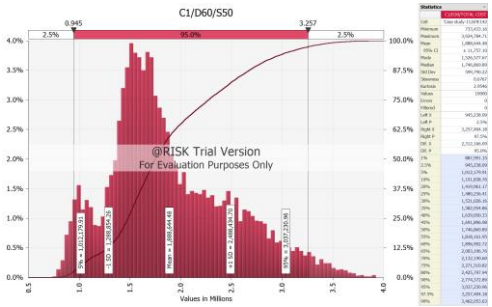



*Figure A-D2. 86. Chamber "1126" Damage cost output distribution C1-D60-S50*

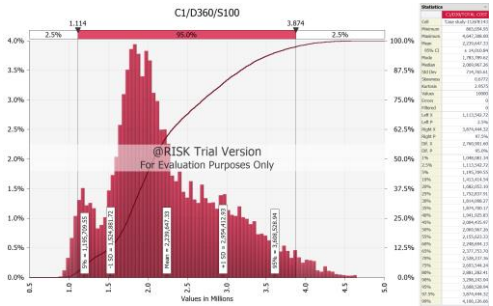



Figure A-D2. 87. Chamber "1126" Damage cost output distribution C1-D60-S100

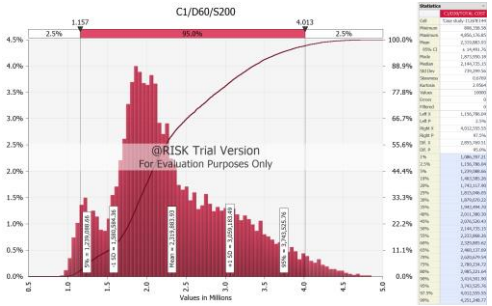



*Figure A-D2. 88. Chamber "1126" Damage cost output distribution C1-D60-S200*

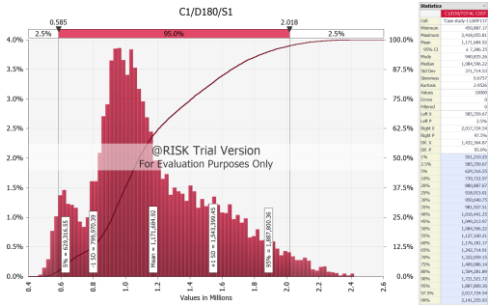



*Figure A-D2. 89. Chamber "1126" Damage cost output distribution C1-D180-S1*

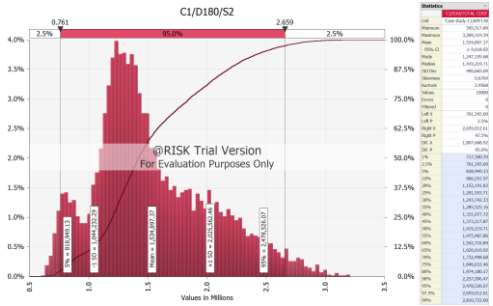



Figure A-D2. 90. Chamber "1126" Damage cost output distribution C1-D180-S2

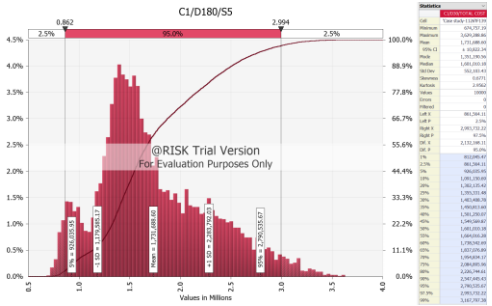



*Figure A-D2. 91. Chamber "1126" Damage cost output distribution C1-D180-S5*

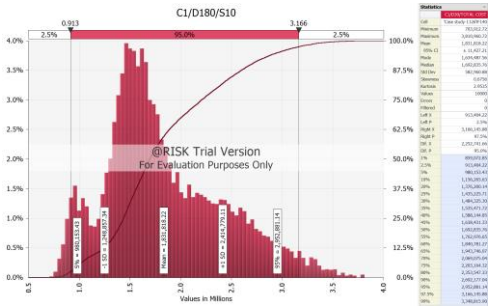



*Figure A-D2. 92. Chamber "1126" Damage cost output distribution C1-D180-S10*

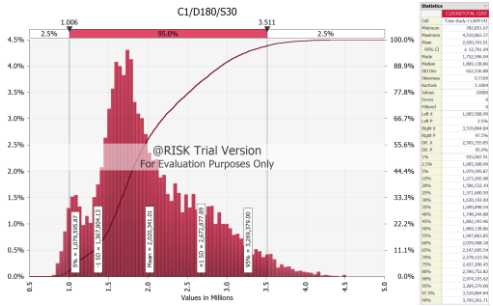



Figure A-D2. 93. Chamber "1126" Damage cost output distribution C1-D180-S30

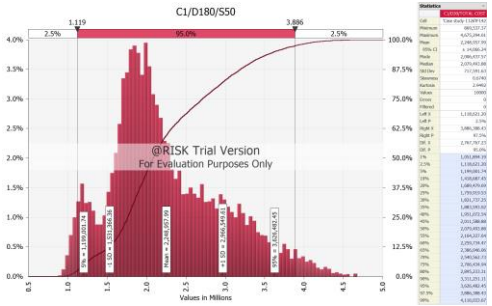



*Figure A-D2. 94. Chamber "1126" Damage cost output distribution C1-D180-S50*

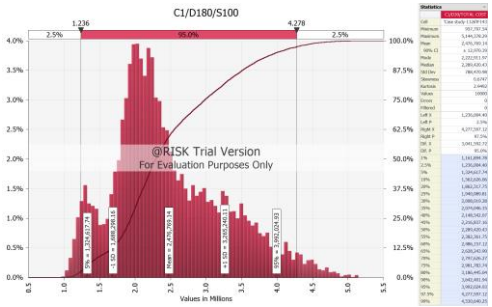



*Figure A-D2. 95. Chamber "1126" Damage cost output distribution C1-D180-S100*

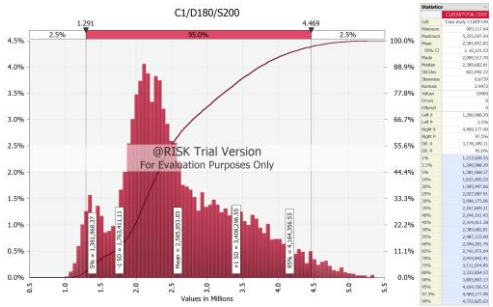



Figure A-D2. 96. Chamber "1126" Damage cost output distribution C1-D180-S200

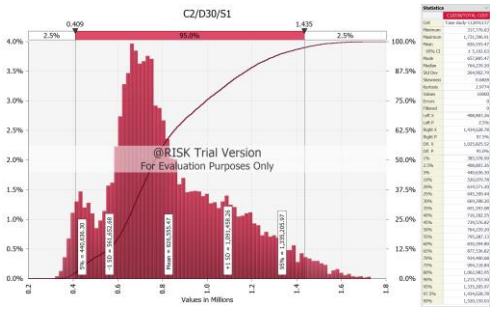



*Figure A-D2. 97. Chamber "1126" Damage cost output distribution C2-D30-S1*

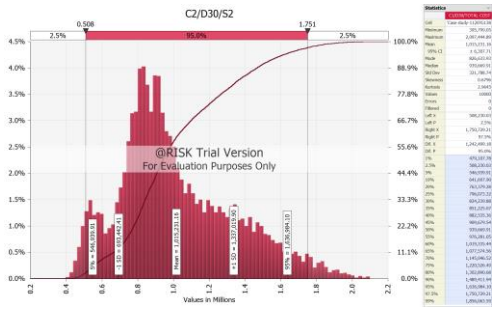



*Figure A-D2. 98. Chamber "1126" Damage cost output distribution C2-D30-S2*

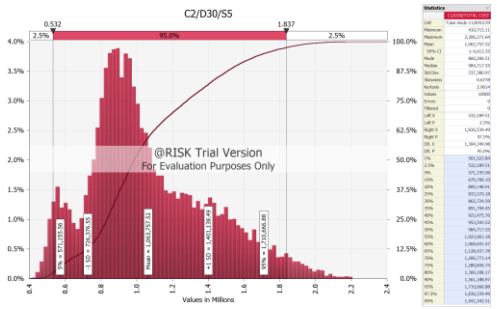



Figure A-D2. 99. Chamber "1126" Damage cost output distribution C2-D30-S5

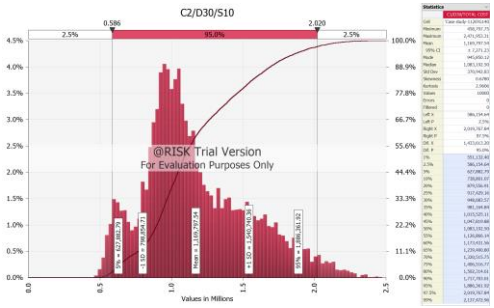



*Figure A-D2. 100. Chamber "1126" Damage cost output distribution C2-D30-S10*

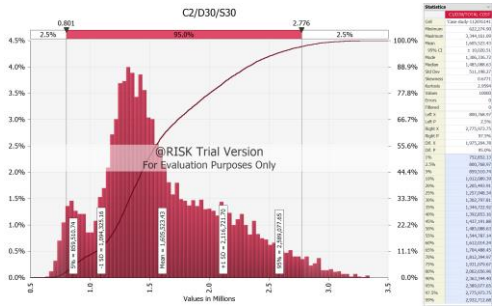



*Figure A-D2. 101. Chamber "1126" Damage cost output distribution C2-D30-S30*

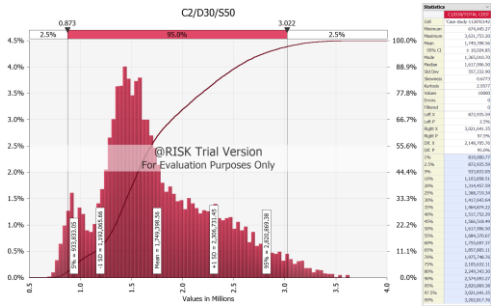



Figure A-D2. 102. Chamber "1126" Damage cost output distribution C2-D30-S50

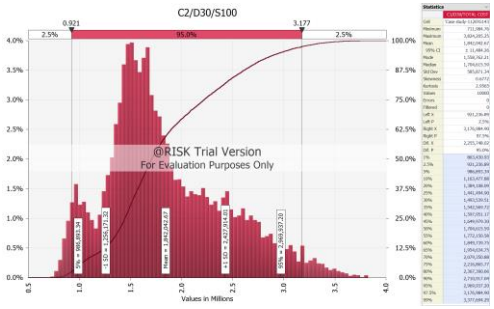



*Figure A-D2. 103. Chamber "1126" Damage cost output distribution C2-D30-S100*

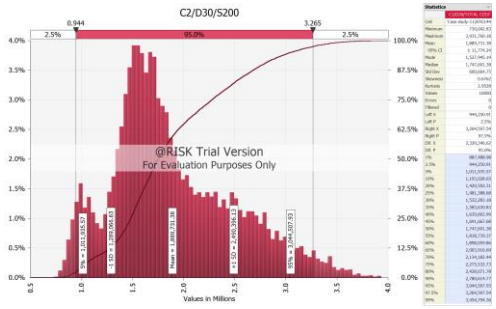



*Figure A-D2. 104. Chamber "1126" Damage cost output distribution C2-D30-S200*

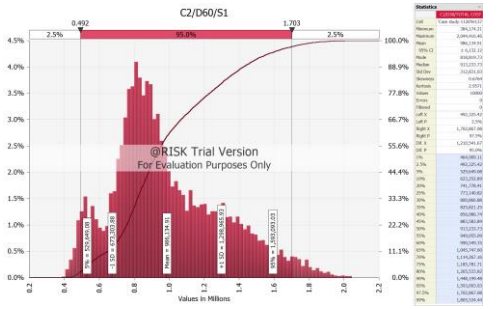



Figure A-D2. 105. Chamber "1126" Damage cost output distribution C2-D60-S1

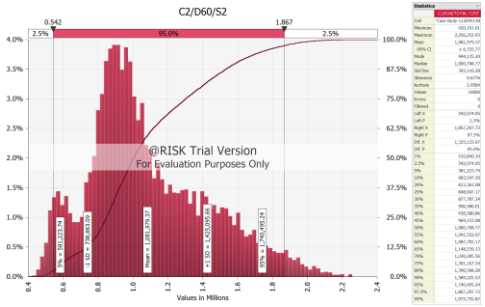



*Figure A-D2. 106. Chamber "1126" Damage cost output distribution C2-D60-S2*

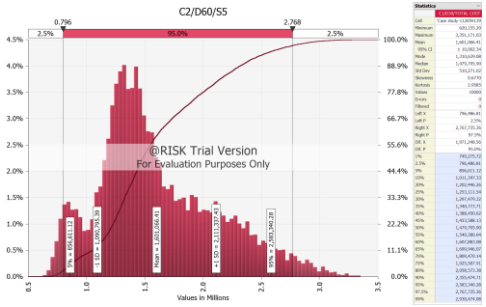



*Figure A-D2. 107. Chamber "1126" Damage cost output distribution C2-D60-S5*

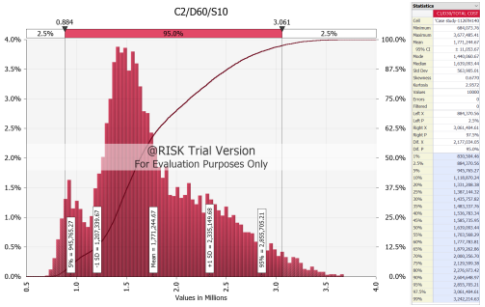



Figure A-D2. 108. Chamber "1126" Damage cost output distribution C2-D60-S10

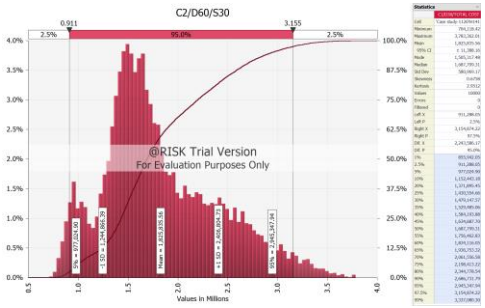



*Figure A-D2. 109. Chamber "1126" Damage cost output distribution C2-D60-S30*

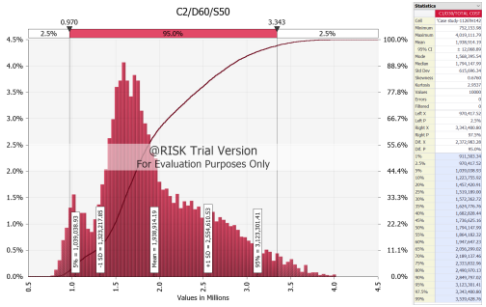



*Figure A-D2. 110. Chamber "1126" Damage cost output distribution C2-D60-S50*

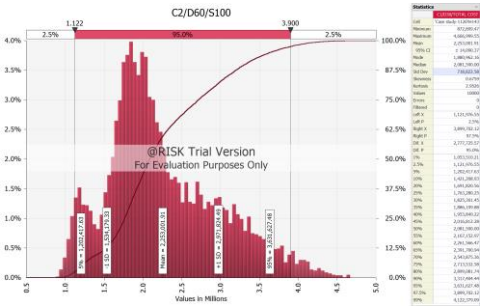



Figure A-D2. 111. Chamber "1126" Damage cost output distribution C2-D60-S100

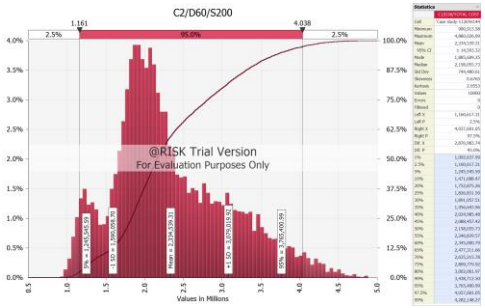



*Figure A-D2. 112. Chamber "1126" Damage cost output distribution C2-D60-S200*

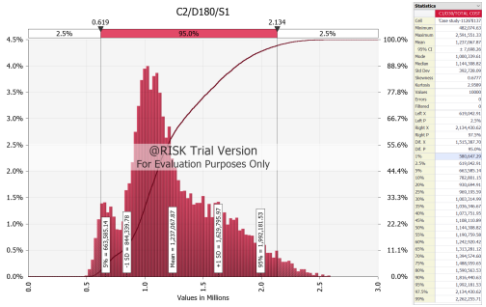



*Figure A-D2. 113. Chamber "1126" Damage cost output distribution C2-D180-S1*

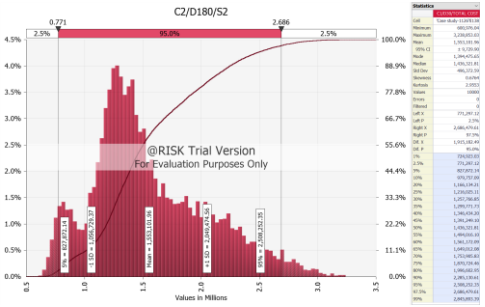



Figure A-D2. 114. Chamber "1126" Damage cost output distribution C2-D180-S2

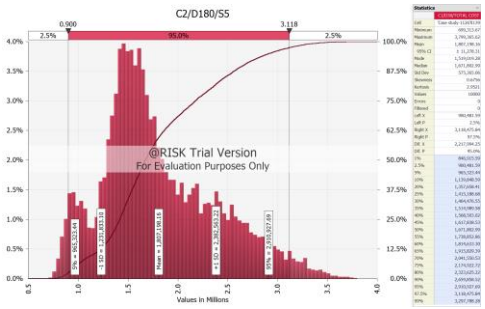



*Figure A-D2. 115. Chamber "1126" Damage cost output distribution C2-D180-S5*

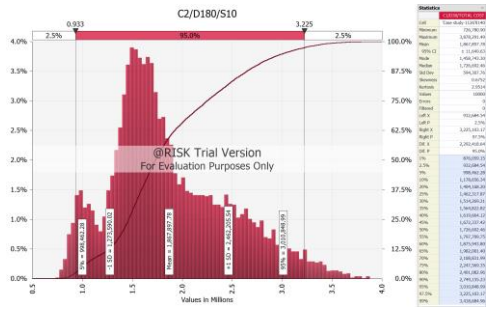



*Figure A-D2. 116. Chamber "1126" Damage cost output distribution C2-D180-S10*

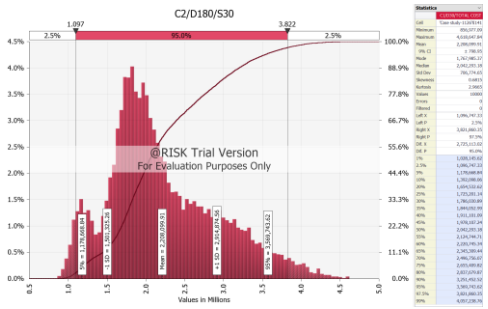



Figure A-D2. 117. Chamber "1126" Damage cost output distribution C2-D180-S30

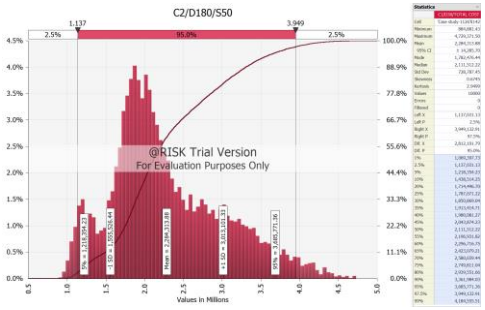



*Figure A-D2. 118. Chamber "1126" Damage cost output distribution C2-D180-S50*

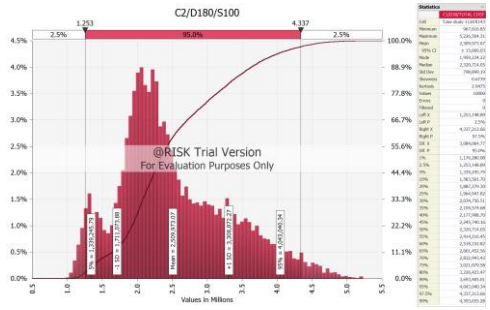



*Figure A-D2. 119. Chamber "1126" Damage cost output distribution C2-D180-S100*

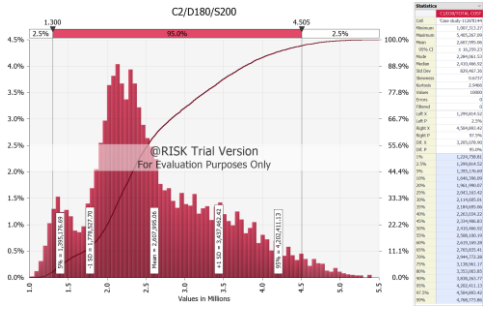



Figure A-D2. 120. Chamber "1126" Damage cost output distribution C2-D180-S200

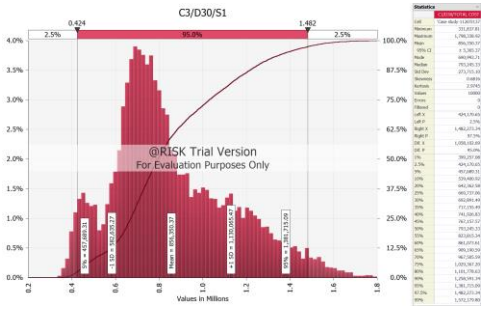



*Figure A-D2. 121. Chamber "1126" Damage cost output distribution C3-D30-S1*

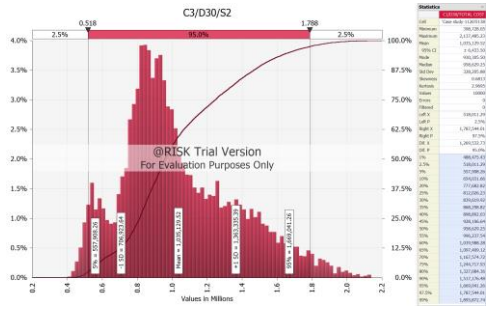



*Figure A-D2. 122. Chamber "1126" Damage cost output distribution C3-D30-S2*

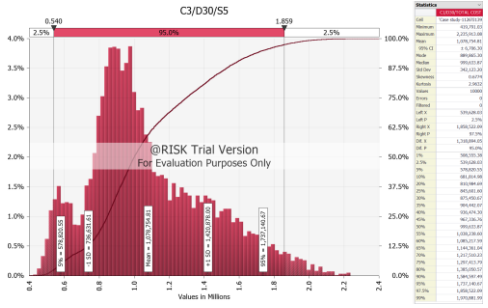



Figure A-D2. 123. Chamber "1126" Damage cost output distribution C3-D30-S5

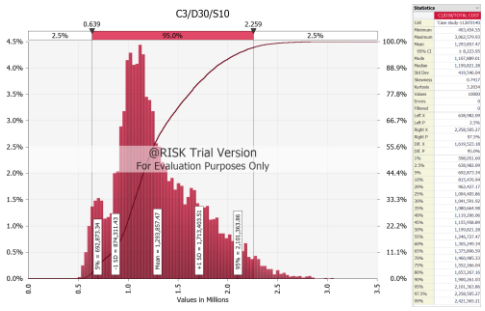



*Figure A-D2. 124. Chamber "1126" Damage cost output distribution C3-D30-S10*

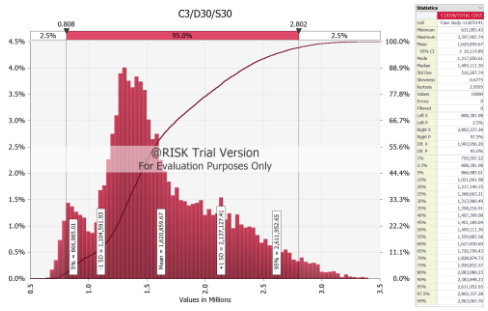



*Figure A-D2. 125. Chamber "1126" Damage cost output distribution C3-D30-S30*

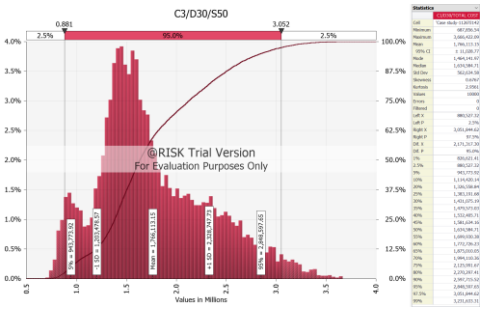



Figure A-D2. 126. Chamber "1126" Damage cost output distribution C3-D30-S50

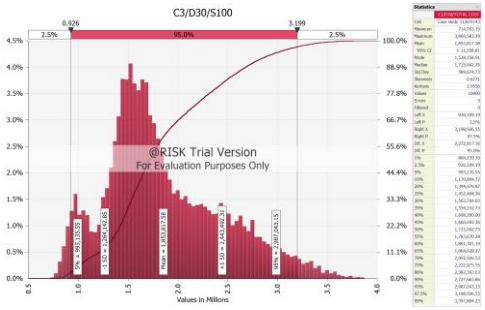



*Figure A-D2. 127. Chamber "1126" Damage cost output distribution C3-D30-S100*

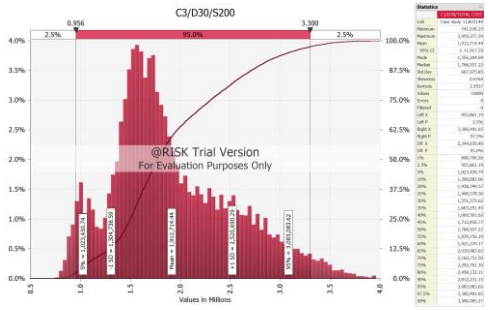



*Figure A-D2. 128. Chamber "1126" Damage cost output distribution C3-D30-S200*

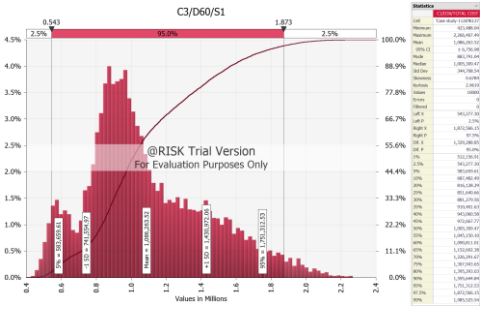



Figure A-D2. 129. Chamber "1126" Damage cost output distribution C3-D60-S1

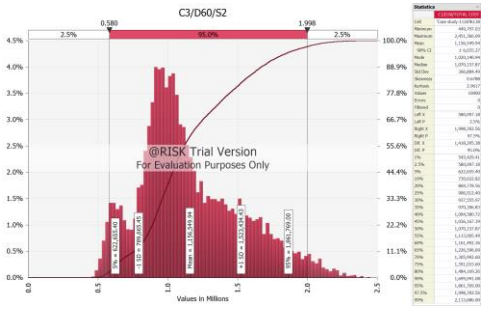



*Figure A-D2. 130. Chamber "1126" Damage cost output distribution C3-D60-S2*

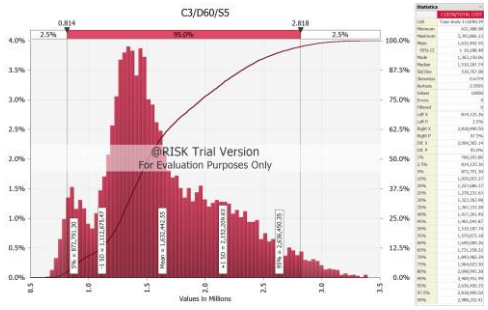



*Figure A-D2. 131. Chamber "1126" Damage cost output distribution C3-D60-S5*

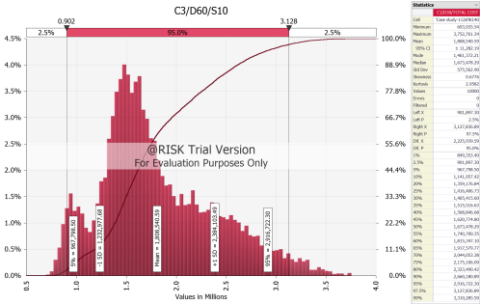



Figure A-D2. 132. Chamber "1126" Damage cost output distribution C3-D60-S10

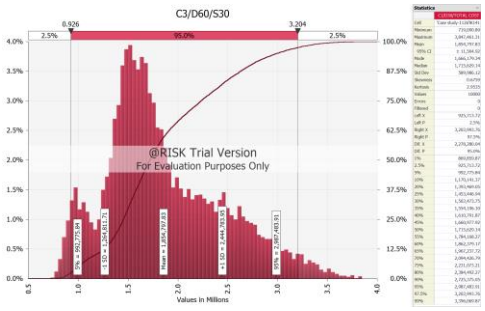



*Figure A-D2. 133. Chamber "1126" Damage cost output distribution C3-D60-S30*

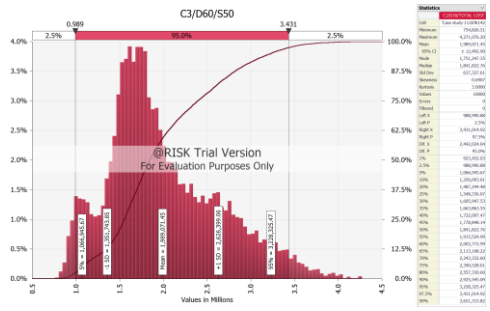



*Figure A-D2. 134. Chamber "1126" Damage cost output distribution C3-D60-S50*

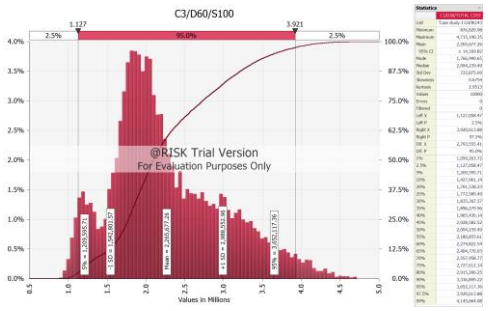



Figure A-D2. 135. Chamber "1126" Damage cost output distribution C3-D60-S100

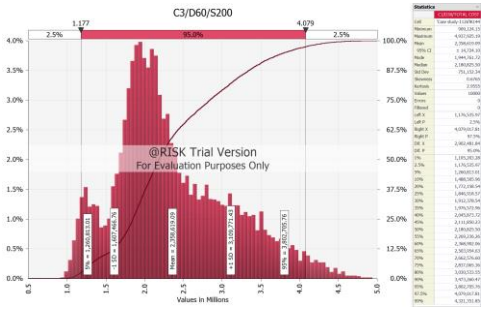



*Figure A-D2. 136. Chamber "1126" Damage cost output distribution C3-D60-S200*

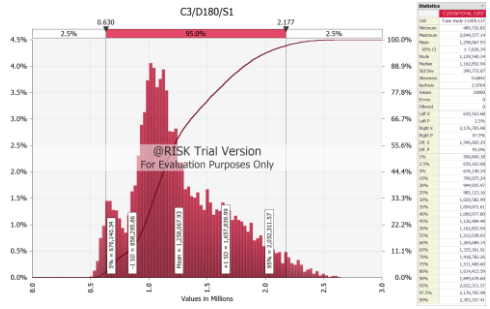



*Figure A-D2. 137. Chamber "1126" Damage cost output distribution C3-D180-S1*

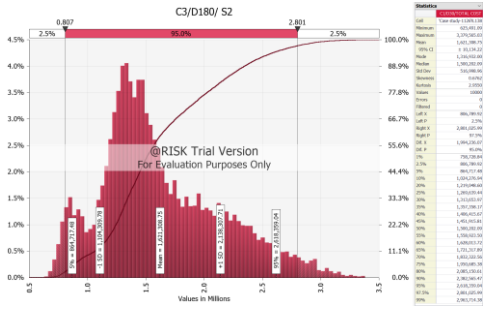



Figure A-D2. 138. Chamber "1126" Damage cost output distribution C3-D180-S2

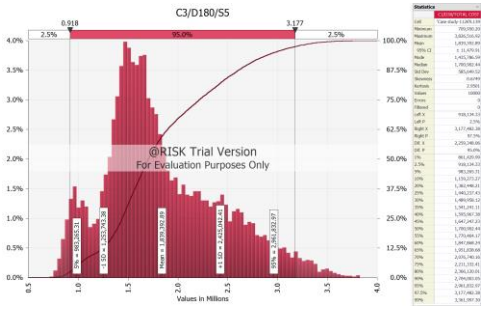



*Figure A-D2. 139. Chamber "1126" Damage cost output distribution C3-D180-S5*

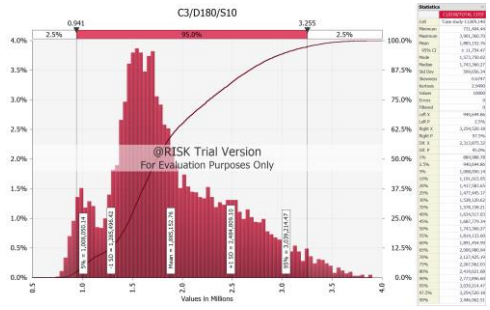



*Figure A-D2. 140. Chamber "1126" Damage cost output distribution C3-D180-S10*

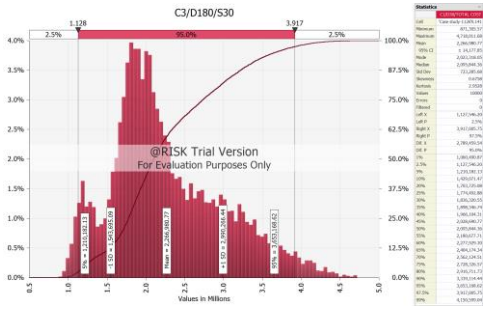



Figure A-D2. 141. Chamber "1126" Damage cost output distribution C3-D180-S30

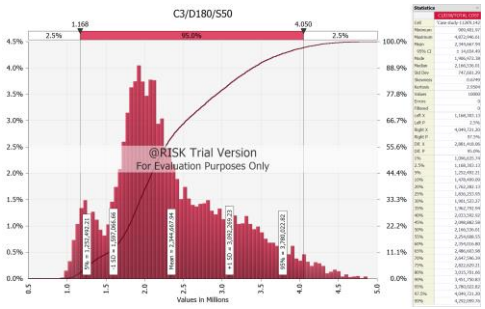



*Figure A-D2. 142. Chamber "1126" Damage cost output distribution C3-D180-S50*

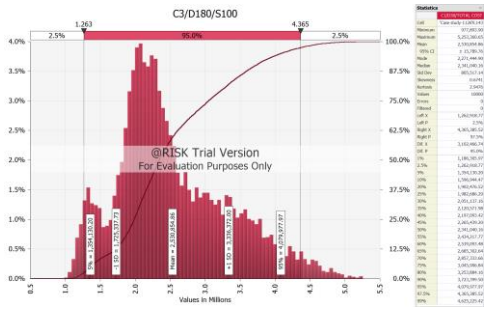



*Figure A-D2. 143. Chamber "1126" Damage cost output distribution C3-D180-S100*

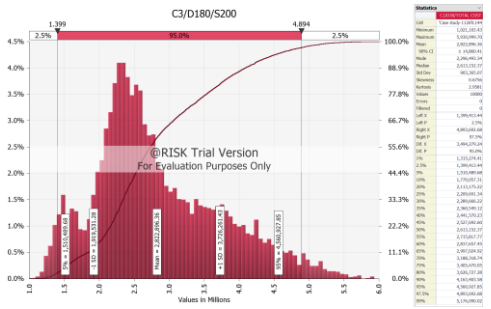



Figure A-D2. 144. Chamber "1126" Damage cost output distribution C3-D180-S200

# Appendix D.3: CDF statistics extracted from damage quantification output distributions

*Table A-D3. 1. Chamber "1234" Calculation of area under damage distribution charts using CDF percentiles*

| CDF percentiles | C-D scenario | **C1 D30** | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | P S | 1 | | 2 | | 5 | | 10 | | 30 | | 50 | | 100 | | 200 | |
| 1.0% | 1.0% | 0 | 0 | 135924 | 1359 | 846254 | 8463 | 1281907 | 12819 | 1546102 | 15461 | 1784564 | 17846 | 1921537 | 19215 | 2068003 | 20680 |
| 2.5% | 1.5% | 0 | 0 | 176030 | 2640 | 1004654 | 15070 | 1462327 | 21935 | 1754754 | 26321 | 1960644 | 29410 | 2135910 | 32039 | 2274970 | 34125 |
| 5.0% | 2.5% | 0 | 0 | 234346 | 5859 | 1177296 | 29432 | 1663503 | 41588 | 1968695 | 49217 | 2189408 | 54735 | 2386778 | 59669 | 2542454 | 63561 |
| 10.0% | 5.0% | 0 | 0 | 372957 | 18648 | 1368617 | 68431 | 1927113 | 96356 | 2243121 | 112156 | 2501903 | 125095 | 2725123 | 136256 | 2927496 | 146375 |
| 20.0% | 10.0% | 0 | 0 | 653442 | 65344 | 1708958 | 170896 | 2286533 | 228653 | 2665057 | 266506 | 2966710 | 296671 | 3224145 | 322414 | 3456295 | 345629 |
| 25.0% | 5.0% | 0 | 0 | 771417 | 38571 | 1856132 | 92807 | 2446381 | 122319 | 2826533 | 141327 | 3145444 | 157272 | 3414089 | 170704 | 3628071 | 181404 |
| 30.0% | 5.0% | 0 | 0 | 861261 | 43063 | 1982334 | 99117 | 2582773 | 129139 | 2991594 | 149580 | 3299131 | 164957 | 3577832 | 178892 | 3801423 | 190071 |
| 35.0% | 5.0% | 0 | 0 | 938054 | 46903 | 2104398 | 105220 | 2723862 | 136193 | 3138786 | 156939 | 3447074 | 172354 | 3722885 | 186144 | 3958725 | 197936 |
| 40.0% | 5.0% | 0 | 0 | 1014971 | 50749 | 2226085 | 111304 | 2860421 | 143021 | 3279941 | 163997 | 3593433 | 179672 | 3876135 | 193807 | 4116670 | 205834 |
| 45.0% | 5.0% | 0 | 0 | 1100280 | 55014 | 2347889 | 117394 | 2990211 | 149511 | 3422634 | 171132 | 3739157 | 186958 | 4034809 | 201740 | 4285031 | 214252 |
| 50.0% | 5.0% | 0 | 0 | 1193994 | 59700 | 2475202 | 123760 | 3133555 | 156678 | 3564957 | 178248 | 3895636 | 194782 | 4199303 | 209965 | 4471637 | 223582 |
| 55.0% | 5.0% | 0 | 0 | 1284137 | 64207 | 2609910 | 130496 | 3280064 | 164003 | 3721796 | 186090 | 4068968 | 203448 | 4380915 | 219046 | 4664405 | 233220 |
| 60.0% | 5.0% | 0 | 0 | 1376571 | 68829 | 2751922 | 137596 | 3435383 | 171769 | 3889746 | 194487 | 4273496 | 213675 | 4590106 | 229505 | 4879378 | 243969 |
| 65.0% | 5.0% | 0 | 0 | 1477193 | 73860 | 2899911 | 144996 | 3608176 | 180409 | 4080547 | 204027 | 4491175 | 224559 | 4817641 | 240882 | 5110083 | 255504 |
| 70.0% | 5.0% | 0 | 0 | 1598467 | 79923 | 3064276 | 153214 | 3804154 | 190208 | 4307893 | 215395 | 4725002 | 236250 | 5077338 | 253867 | 5397594 | 269880 |
| 75.0% | 5.0% | 0 | 0 | 1733772 | 86689 | 3267614 | 163381 | 4031970 | 201599 | 4579424 | 228971 | 5002372 | 250119 | 5400207 | 270010 | 5726434 | 286322 |
| 80.0% | 5.0% | 0 | 0 | 1909819 | 95491 | 3507958 | 175398 | 4297722 | 214886 | 4893380 | 244669 | 5357530 | 267876 | 5743458 | 287173 | 6106729 | 305336 |
| 90.0% | 10.0% | 0 | 0 | 2395980 | 239598 | 4175641 | 417564 | 5113500 | 511350 | 5757662 | 575766 | 6261279 | 626128 | 6687927 | 668793 | 7111268 | 711127 |
| 95.0% | 5.0% | 0 | 0 | 2896468 | 144823 | 4725224 | 236261 | 5740064 | 287003 | 6468595 | 323430 | 6991222 | 349561 | 7473162 | 373658 | 7894815 | 394741 |
| 97.5% | 2.5% | 0 | 0 | 3423337 | 85583 | 5227492 | 130687 | 6343000 | 158575 | 7086573 | 177164 | 7638797 | 190970 | 8164628 | 204116 | 8618931 | 215473 |
| 99.0% | 1.5% | 0 | 0 | 3926873 | 58903 | 5948622 | 89229 | 7051207 | 105768 | 7757891 | 116368 | 8464928 | 126974 | 8918133 | 133772 | 9371635 | 140575 |
| Area under distribution chart | | 0 | | 1385755 | | 2720715 | | 3423780 | | 3897252 | | 4269310 | | 4591668 | | 4879595 | |

| CDF percentiles | C-D scenario | **C1 D60** | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | P \ S | 1 | | 2 | | 5 | | 10 | | 30 | | 50 | | 100 | | 200 | |
| 1.0% | 1.0% | 166158 | 1662 | 729537 | 7295 | 1174756 | 11748 | 1453041 | 14530 | 1698898 | 16989 | 1882549 | 18825 | 2039201 | 20392 | 2156380 | 21564 |
| 2.5% | 1.5% | 225543 | 3383 | 886889 | 13303 | 1350834 | 20263 | 1663832 | 24957 | 1903504 | 28553 | 2083337 | 31250 | 2225755 | 33386 | 2371156 | 35567 |
| 5.0% | 2.5% | 323125 | 8078 | 1028583 | 25715 | 1549253 | 38731 | 1876157 | 46904 | 2108480 | 52712 | 2305098 | 57627 | 2456333 | 61408 | 2617506 | 65438 |
| 10.0% | 5.0% | 531167 | 26558 | 1254740 | 62737 | 1790292 | 89515 | 2139152 | 106958 | 2398057 | 119903 | 2633781 | 131689 | 2831944 | 141597 | 3017099 | 150855 |
| 20.0% | 10.0% | 832198 | 83220 | 1532578 | 153258 | 2132514 | 213251 | 2519220 | 251922 | 2854684 | 285468 | 3116747 | 311675 | 3342344 | 334234 | 3552219 | 355222 |
| 25.0% | 5.0% | 932713 | 46636 | 1670365 | 83518 | 2278682 | 113934 | 2679311 | 133966 | 3017959 | 150898 | 3289707 | 164485 | 3532606 | 176630 | 3756211 | 187811 |
| 30.0% | 5.0% | 1025856 | 51293 | 1798504 | 89925 | 2407162 | 120358 | 2830914 | 141546 | 3176810 | 158841 | 3456766 | 172838 | 3698663 | 184933 | 3935468 | 196773 |
| 35.0% | 5.0% | 1115791 | 55790 | 1916827 | 95841 | 2529898 | 126495 | 2964538 | 148227 | 3320249 | 166012 | 3612981 | 180649 | 3870587 | 193529 | 4098095 | 204905 |
| 40.0% | 5.0% | 1210756 | 60538 | 2031488 | 101574 | 2659715 | 132986 | 3100919 | 155046 | 3466568 | 173328 | 3766054 | 188303 | 4026933 | 201347 | 4274564 | 213728 |
| 45.0% | 5.0% | 1302780 | 65139 | 2145667 | 107283 | 2780753 | 139038 | 3238176 | 161909 | 3597806 | 179890 | 3916496 | 195825 | 4174941 | 208747 | 4433146 | 221657 |
| 50.0% | 5.0% | 1392614 | 69631 | 2261015 | 113051 | 2915873 | 145794 | 3387994 | 169400 | 3760850 | 188042 | 4075013 | 203751 | 4348144 | 217407 | 4618216 | 230911 |
| 55.0% | 5.0% | 1496883 | 74844 | 2382944 | 119147 | 3050945 | 152547 | 3526913 | 176346 | 3931047 | 196552 | 4258665 | 212933 | 4540528 | 227026 | 4807924 | 240396 |
| 60.0% | 5.0% | 1604083 | 80204 | 2512464 | 125623 | 3200560 | 160028 | 3712493 | 185625 | 4114649 | 205732 | 4457250 | 222863 | 4756690 | 237835 | 5021963 | 251098 |
| 65.0% | 5.0% | 1723950 | 86197 | 2656041 | 132802 | 3368112 | 168406 | 3896637 | 194832 | 4323115 | 216156 | 4671347 | 233567 | 4987145 | 249357 | 5256365 | 262818 |
| 70.0% | 5.0% | 1865785 | 93289 | 2822619 | 141131 | 3552780 | 177639 | 4110157 | 205508 | 4553163 | 227658 | 4940599 | 247030 | 5254211 | 262711 | 5579162 | 278958 |
| 75.0% | 5.0% | 2015600 | 100780 | 3007127 | 150356 | 3784951 | 189248 | 4358961 | 217948 | 4833015 | 241651 | 5229812 | 261491 | 5585836 | 279292 | 5914528 | 295726 |
| 80.0% | 5.0% | 2186236 | 109312 | 3237280 | 161864 | 4033232 | 201662 | 4641779 | 232089 | 5151715 | 257586 | 5583153 | 279158 | 5961306 | 298065 | 6295035 | 314752 |
| 90.0% | 10.0% | 2742419 | 274242 | 3862545 | 386254 | 4772974 | 477297 | 5459961 | 545996 | 5991592 | 599159 | 6493314 | 649331 | 6919832 | 691983 | 7322315 | 732231 |
| 95.0% | 5.0% | 3243565 | 162178 | 4417482 | 220874 | 5426829 | 271341 | 6122438 | 306122 | 6719333 | 335967 | 7231176 | 361559 | 7710462 | 385523 | 8154560 | 407728 |
| 97.5% | 2.5% | 3687567 | 92189 | 4937067 | 123427 | 6005364 | 150134 | 6776329 | 169408 | 7416842 | 185421 | 7948593 | 198715 | 8440674 | 211017 | 8831879 | 220797 |
| 99.0% | 1.5% | 4361497 | 65422 | 5583574 | 83754 | 6719955 | 100799 | 7463003 | 111945 | 8182769 | 122742 | 8708744 | 130631 | 9212538 | 138188 | 9612004 | 144180 |
| Area under distribution chart | | 1610585 | | 2498734 | | 3201213 | | 3701182 | | 4109261 | | 4454195 | | 4754609 | | 5033116 | |
| CDF percentiles | C-D scenario | **C1 D180** | | | | | | | | | | | | | | | |
| | P \ S | 1 | | 2 | | 5 | | 10 | | 30 | | 50 | | 100 | | 200 | |
| 1.0% | 1.0% | 253498 | 2535 | 1012334 | 10123 | 1382022 | 13820 | 1660084 | 16601 | 1838497 | 18385 | 2025675 | 20257 | 2187082 | 21871 | 2378437 | 23784 |
| 2.5% | 1.5% | 449430 | 6741 | 1231985 | 18480 | 1578894 | 23683 | 1845670 | 27685 | 2043148 | 30647 | 2209264 | 33139 | 2396517 | 35948 | 2595629 | 38934 |

| | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 5.0% | 2.5% | 669427 | 16736 | 1403717 | 35093 | 1782236 | 44556 | 2046051 | 51151 | 2258582 | 56465 | 2442755 | 61069 | 2624972 | 65624 | 2823402 | 70585 |
| 10.0% | 5.0% | 881469 | 44073 | 1635334 | 81767 | 2036984 | 101849 | 2340606 | 117030 | 2580531 | 129027 | 2805398 | 140270 | 3008708 | 150435 | 3240108 | 162005 |
| 20.0% | 10.0% | 1151943 | 115194 | 1962291 | 196229 | 2414971 | 241497 | 2764984 | 276498 | 3043827 | 304383 | 3293389 | 329339 | 3547012 | 354701 | 3828490 | 382849 |
| 25.0% | 5.0% | 1277046 | 63852 | 2104723 | 105236 | 2561240 | 128062 | 2923210 | 146161 | 3213172 | 160659 | 3475086 | 173754 | 3746389 | 187319 | 4036564 | 201828 |
| 30.0% | 5.0% | 1384617 | 69231 | 2222015 | 111101 | 2706876 | 135344 | 3071052 | 153553 | 3371461 | 168573 | 3638437 | 181922 | 3925914 | 196296 | 4219639 | 210982 |
| 35.0% | 5.0% | 1483191 | 74160 | 2345533 | 117277 | 2840797 | 142040 | 3216858 | 160843 | 3522348 | 176117 | 3810693 | 190535 | 4090506 | 204525 | 4401482 | 220074 |
| 40.0% | 5.0% | 1598072 | 79904 | 2471052 | 123553 | 2978414 | 148921 | 3353978 | 167699 | 3664424 | 183221 | 3965500 | 198275 | 4256649 | 212832 | 4570862 | 228543 |
| 45.0% | 5.0% | 1708464 | 85423 | 2597668 | 129883 | 3114466 | 155723 | 3499574 | 174979 | 3818440 | 190922 | 4121803 | 206090 | 4423350 | 221168 | 4750274 | 237514 |
| 50.0% | 5.0% | 1826216 | 91311 | 2726654 | 136333 | 3248597 | 162430 | 3643093 | 182155 | 3975934 | 198797 | 4286052 | 214303 | 4596198 | 229810 | 4936433 | 246822 |
| 55.0% | 5.0% | 1954762 | 97738 | 2854210 | 142711 | 3390957 | 169548 | 3809381 | 190469 | 4155071 | 207754 | 4482591 | 224130 | 4796135 | 239807 | 5130689 | 256534 |
| 60.0% | 5.0% | 2080553 | 104028 | 2997162 | 149858 | 3559432 | 177972 | 3988898 | 199445 | 4355186 | 217759 | 4681981 | 234099 | 5008196 | 250410 | 5369253 | 268463 |
| 65.0% | 5.0% | 2216122 | 110806 | 3151640 | 157582 | 3747903 | 187395 | 4189707 | 209485 | 4576879 | 228844 | 4909139 | 245457 | 5251203 | 262560 | 5634891 | 281745 |
| 70.0% | 5.0% | 2361928 | 118096 | 3344942 | 167247 | 3963252 | 198163 | 4419755 | 220988 | 4821271 | 241064 | 5182431 | 259122 | 5550137 | 277507 | 5967853 | 298393 |
| 75.0% | 5.0% | 2538874 | 126944 | 3556368 | 177818 | 4198629 | 209931 | 4678914 | 233946 | 5109475 | 255474 | 5494922 | 274746 | 5912951 | 295648 | 6322408 | 316120 |
| 80.0% | 5.0% | 2744405 | 137220 | 3815468 | 190773 | 4487236 | 224362 | 5005010 | 250250 | 5453403 | 272670 | 5858317 | 292916 | 6284917 | 314246 | 6724001 | 336200 |
| 90.0% | 10.0% | 3378467 | 337847 | 4516280 | 451628 | 5257100 | 525710 | 5844030 | 584403 | 6356276 | 635628 | 6830709 | 683071 | 7336117 | 733612 | 7848512 | 784851 |
| 95.0% | 5.0% | 3911955 | 195598 | 5730946 | 286547 | 5923862 | 296193 | 6563129 | 328156 | 7139211 | 356961 | 7651119 | 382556 | 8167075 | 408354 | 8744474 | 437224 |
| 97.5% | 2.5% | 4404177 | 110104 | 6381526 | 159538 | 6510120 | 162753 | 7227765 | 180694 | 7774053 | 194351 | 8321027 | 208026 | 8867770 | 221694 | 9469620 | 236741 |
| 99.0% | 1.5% | 5015487 | 75232 | 6306783 | 94602 | 7249721 | 108746 | 8006341 | 120095 | 8665826 | 129987 | 9141376 | 137121 | 9665559 | 144983 | 10238407 | 153576 |
| Area under distribution chart | | 2062773 | | 3043379 | | 3558698 | | 3992286 | | 4357686 | | 4690194 | | 5029350 | | 5393767 | |
| CDF percentiles | C-D scenario | **C2 D30** | | | | | | | | | | | | | | | |
| | P \ S | 1 | | 2 | | 5 | | 10 | | 30 | | 50 | | 100 | | 200 | |
| 1.0% | 1.0% | 0 | 0 | 447410 | 4474 | 1160773 | 11608 | 1524642 | 15246 | 1732324 | 17323 | 1952980 | 19530 | 2073946 | 20739 | 2187197 | 21872 |
| 2.5% | 1.5% | 0 | 0 | 607812 | 9117 | 1335950 | 20039 | 1690274 | 25354 | 1952989 | 29295 | 2152528 | 32288 | 2273653 | 34105 | 2415546 | 36233 |
| 5.0% | 2.5% | 0 | 0 | 762530 | 19063 | 1516790 | 37920 | 1933751 | 48344 | 2180390 | 54510 | 2379222 | 59481 | 2549674 | 63742 | 2693987 | 67350 |
| 10.0% | 5.0% | 0 | 0 | 924027 | 46201 | 1765659 | 88283 | 2209072 | 110454 | 2497907 | 124895 | 2718236 | 135912 | 2904292 | 145215 | 3085758 | 154288 |
| 20.0% | 10.0% | 0 | 0 | 1164410 | 116441 | 2120525 | 212053 | 2622626 | 262263 | 2946221 | 294622 | 3218300 | 321830 | 3431274 | 343127 | 3631828 | 363183 |
| 25.0% | 5.0% | 0 | 0 | 1272696 | 63635 | 2259816 | 112991 | 2789188 | 139459 | 3122682 | 156134 | 3389168 | 169458 | 3625669 | 181283 | 3836544 | 191827 |

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|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 30.0% | 5.0% | 0 | 0 | 1371550 | 68578 | 2395844 | 119792 | 2934506 | 146725 | 3278813 | 163941 | 3546323 | 177316 | 3801387 | 190069 | 4005986 | 200299 |
| 35.0% | 5.0% | 0 | 0 | 1471548 | 73577 | 2526596 | 126330 | 3092599 | 154630 | 3429688 | 171484 | 3699357 | 184968 | 3954684 | 197734 | 4175040 | 208752 |
| 40.0% | 5.0% | 0 | 0 | 1568560 | 78428 | 2654241 | 132712 | 3233089 | 161654 | 3587803 | 179390 | 3851157 | 192558 | 4122966 | 206148 | 4345332 | 217267 |
| 45.0% | 5.0% | 0 | 0 | 1672579 | 83629 | 2787374 | 139369 | 3369525 | 168476 | 3751090 | 187555 | 4015336 | 200767 | 4288895 | 214445 | 4509229 | 225461 |
| 50.0% | 5.0% | 0 | 0 | 1777303 | 88865 | 2917984 | 145899 | 3520556 | 176028 | 3911129 | 195556 | 4179966 | 208998 | 4463936 | 223197 | 4698110 | 234905 |
| 55.0% | 5.0% | 0 | 0 | 1890153 | 94508 | 3053400 | 152670 | 3660750 | 183037 | 4068124 | 203406 | 4365999 | 218300 | 4648517 | 232426 | 4903235 | 245162 |
| 60.0% | 5.0% | 0 | 0 | 2006306 | 100315 | 3208196 | 160410 | 3842097 | 192105 | 4248235 | 212412 | 4567323 | 228366 | 4864680 | 243234 | 5126325 | 256316 |
| 65.0% | 5.0% | 0 | 0 | 2127323 | 106366 | 3371301 | 168565 | 4039841 | 201992 | 4460472 | 223024 | 4804075 | 240204 | 5102173 | 255109 | 5383415 | 269171 |
| 70.0% | 5.0% | 0 | 0 | 2264004 | 113200 | 3555927 | 177796 | 4253604 | 212680 | 4701011 | 235051 | 5075318 | 253766 | 5408508 | 270425 | 5682066 | 284103 |
| 75.0% | 5.0% | 0 | 0 | 2423796 | 121190 | 3784975 | 189249 | 4504655 | 225233 | 4987806 | 249390 | 5386178 | 269309 | 5717677 | 285884 | 6031782 | 301589 |
| 80.0% | 5.0% | 0 | 0 | 2622578 | 131129 | 4016210 | 200811 | 4810454 | 240523 | 5329949 | 266497 | 5728360 | 286418 | 6107813 | 305391 | 6413588 | 320679 |
| 90.0% | 10.0% | 0 | 0 | 3233685 | 323368 | 4777041 | 477704 | 5642263 | 564226 | 6208428 | 620843 | 6698291 | 669829 | 7095064 | 709506 | 7449078 | 744908 |
| 95.0% | 5.0% | 0 | 0 | 3756476 | 187824 | 5367702 | 268385 | 6308090 | 315405 | 6998260 | 349913 | 7480670 | 374033 | 7927674 | 396384 | 8322990 | 416149 |
| 97.5% | 2.5% | 0 | 0 | 4236297 | 105907 | 5897198 | 147430 | 6953349 | 173834 | 7610678 | 190267 | 8137775 | 203444 | 8636993 | 215925 | 9048028 | 226201 |
| 99.0% | 1.5% | 0 | 0 | 4850053 | 72751 | 6570371 | 98556 | 7715090 | 115726 | 8349629 | 125244 | 8918855 | 133783 | 9414887 | 141223 | 9858420 | 147876 |
| Area under distribution chart | | 0 | | 2008567 | | 3188570 | | 3833394 | | 4250753 | | 4580558 | | 4875312 | | 5133592 | |
| CDF percentiles | C-D scenario | **C2 D60** | | | | | | | | | | | | | | | |
| | P \ S | 1 | | 2 | | 5 | | 10 | | 30 | | 50 | | 100 | | 200 | |
| 1.0% | 1.0% | 599916 | 5999 | 1159666 | 11597 | 1484966 | 14850 | 1676094 | 16761 | 1873059 | 18731 | 2042485 | 20425 | 2140811 | 21408 | 2277507 | 22775 |
| 2.5% | 1.5% | 764797 | 11472 | 1350014 | 20250 | 1674853 | 25123 | 1898859 | 28483 | 2089900 | 31348 | 2229300 | 33439 | 2356728 | 35351 | 2494004 | 37410 |
| 5.0% | 2.5% | 898200 | 22455 | 1529016 | 38225 | 1875110 | 46878 | 2112715 | 52818 | 2290584 | 57265 | 2475413 | 61885 | 2625300 | 65632 | 2751552 | 68789 |
| 10.0% | 5.0% | 1099332 | 54967 | 1784066 | 89203 | 2156668 | 107833 | 2409202 | 120460 | 2627808 | 131390 | 2839161 | 141958 | 3001904 | 150095 | 3183707 | 159185 |
| 20.0% | 10.0% | 1376498 | 137650 | 2132570 | 213257 | 2544222 | 254422 | 2831944 | 283194 | 3106267 | 310627 | 3340616 | 334062 | 3552710 | 355271 | 3758448 | 375845 |
| 25.0% | 5.0% | 1493115 | 74656 | 2267407 | 113370 | 2698223 | 134911 | 3001641 | 150082 | 3290481 | 164524 | 3524609 | 176230 | 3742949 | 187147 | 3970299 | 198515 |
| 30.0% | 5.0% | 1602217 | 80111 | 2405855 | 120293 | 2855444 | 142772 | 3156072 | 157804 | 3453877 | 172694 | 3697676 | 184884 | 3920130 | 196006 | 4150978 | 207549 |
| 35.0% | 5.0% | 1712354 | 85618 | 2531763 | 126588 | 2989124 | 149456 | 3301070 | 165053 | 3600934 | 180047 | 3857139 | 192857 | 4077264 | 203863 | 4315411 | 215771 |
| 40.0% | 5.0% | 1831420 | 91571 | 2652611 | 132631 | 3117867 | 155893 | 3451122 | 172556 | 3745014 | 187251 | 4019682 | 200984 | 4245626 | 212281 | 4489797 | 224490 |
| 45.0% | 5.0% | 1937431 | 96872 | 2787185 | 139359 | 3260658 | 163033 | 3596796 | 179840 | 3899948 | 194997 | 4170856 | 208543 | 4424582 | 221229 | 4660248 | 233012 |

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|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 50.0% | 5.0% | 2053570 | 102679 | 2922076 | 146104 | 3404105 | 170205 | 3747810 | 187390 | 4071395 | 203570 | 4346998 | 217350 | 4603895 | 230195 | 4849145 | 242457 |
| 55.0% | 5.0% | 2168512 | 108426 | 3065266 | 153263 | 3551186 | 177559 | 3938745 | 196937 | 4251580 | 212579 | 4544123 | 227206 | 4808009 | 240400 | 5040975 | 252049 |
| 60.0% | 5.0% | 2287115 | 114356 | 3206681 | 160334 | 3719452 | 185973 | 4143098 | 207155 | 4469579 | 223479 | 4742662 | 237133 | 5010937 | 250547 | 5258195 | 262910 |
| 65.0% | 5.0% | 2414699 | 120735 | 3355221 | 167761 | 3909774 | 195489 | 4345258 | 217263 | 4692749 | 234637 | 4977428 | 248871 | 5259261 | 262963 | 5538068 | 276903 |
| 70.0% | 5.0% | 2559084 | 127954 | 3546967 | 177348 | 4108315 | 205416 | 4554124 | 227706 | 4930635 | 246532 | 5266140 | 263307 | 5563969 | 278198 | 5853143 | 292657 |
| 75.0% | 5.0% | 2728367 | 136418 | 3758713 | 187936 | 4364854 | 218243 | 4844408 | 242220 | 5226550 | 261327 | 5605077 | 280254 | 5901267 | 295063 | 6220816 | 311041 |
| 80.0% | 5.0% | 2927018 | 146351 | 4023276 | 201164 | 4648060 | 232403 | 5145258 | 257263 | 5568044 | 278402 | 5947774 | 297389 | 6288212 | 314411 | 6626240 | 331312 |
| 90.0% | 10.0% | 3537481 | 353748 | 4750767 | 475077 | 5467822 | 546782 | 6023834 | 602383 | 6492118 | 649212 | 6909288 | 690929 | 7327930 | 732793 | 7698838 | 769884 |
| 95.0% | 5.0% | 4101449 | 205072 | 5420594 | 271030 | 6150900 | 307545 | 6735324 | 336766 | 7264968 | 363248 | 7714272 | 385714 | 8173141 | 408657 | 8533868 | 426693 |
| 97.5% | 2.5% | 4613977 | 115349 | 5986208 | 149655 | 6762213 | 169055 | 7397726 | 184943 | 7943604 | 198590 | 8460896 | 211522 | 8826493 | 220662 | 9225243 | 230631 |
| 99.0% | 1.5% | 5203537 | 78053 | 6637088 | 99556 | 7470568 | 112059 | 8160385 | 122406 | 8674524 | 130118 | 9271200 | 139068 | 9629082 | 144436 | 10156946 | 152354 |
| Area under distribution chart | | 2270511 | | 3194002 | | 3715900 | | 4109485 | | 4450568 | | 4754010 | | 5026611 | | 5292232 | |
| CDF percentiles | C-D scenario | **C2 D180** | | | | | | | | | | | | | | | |
| | P S | 1 | | 2 | | 5 | | 10 | | 30 | | 50 | | 100 | | 200 | |
| 1.0% | 1.0% | 841856 | 8419 | 1382622 | 13826 | 1647425 | 16474 | 1831337 | 18313 | 2011026 | 20110 | 2186538 | 21865 | 2332711 | 23327 | 2517840 | 25178 |
| 2.5% | 1.5% | 1010699 | 15160 | 1566064 | 23491 | 1865135 | 27977 | 2023070 | 30346 | 2203093 | 33046 | 2384066 | 35761 | 2542906 | 38144 | 2754054 | 41311 |
| 5.0% | 2.5% | 1203650 | 30091 | 1765007 | 44125 | 2046385 | 51160 | 2257812 | 56445 | 2439141 | 60979 | 2610436 | 65261 | 2788542 | 69714 | 3006452 | 75161 |
| 10.0% | 5.0% | 1433686 | 71684 | 2013021 | 100651 | 2341920 | 117096 | 2576164 | 128808 | 2797955 | 139898 | 3005952 | 150298 | 3193969 | 159698 | 3435797 | 171790 |
| 20.0% | 10.0% | 1746716 | 174672 | 2383269 | 238327 | 2757958 | 275796 | 3043496 | 304350 | 3288423 | 328842 | 3528846 | 352885 | 3755371 | 375537 | 4072596 | 407260 |
| 25.0% | 5.0% | 1880928 | 94046 | 2541781 | 127089 | 2925390 | 146270 | 3210447 | 160522 | 3481047 | 174052 | 3734153 | 186708 | 3969805 | 198490 | 4286438 | 214322 |
| 30.0% | 5.0% | 2009682 | 100484 | 2685371 | 134269 | 3076084 | 153804 | 3370295 | 168515 | 3635528 | 181776 | 3914011 | 195701 | 4159960 | 207998 | 4484360 | 224218 |
| 35.0% | 5.0% | 2122677 | 106134 | 2821245 | 141062 | 3204420 | 160221 | 3520815 | 176041 | 3790743 | 189537 | 4069690 | 203485 | 4339990 | 217000 | 4658761 | 232938 |
| 40.0% | 5.0% | 2237136 | 111857 | 2945914 | 147296 | 3356606 | 167830 | 3657646 | 182882 | 3943026 | 197151 | 4240803 | 212040 | 4508041 | 225402 | 4842018 | 242101 |
| 45.0% | 5.0% | 2360573 | 118029 | 3075131 | 153757 | 3501824 | 175091 | 3806731 | 190337 | 4106782 | 205339 | 4404807 | 220240 | 4683936 | 234197 | 5034280 | 251714 |
| 50.0% | 5.0% | 2476321 | 123816 | 3209191 | 160460 | 3658531 | 182927 | 3975186 | 198759 | 4268740 | 213437 | 4587155 | 229358 | 4878410 | 243920 | 5226936 | 261347 |
| 55.0% | 5.0% | 2603270 | 130163 | 3361028 | 168051 | 3828039 | 191402 | 4149140 | 207457 | 4454873 | 222744 | 4789647 | 239482 | 5078471 | 253924 | 5438313 | 271916 |
| 60.0% | 5.0% | 2744866 | 137243 | 3522878 | 176144 | 4005029 | 200251 | 4334269 | 216713 | 4658739 | 232937 | 4995996 | 249800 | 5306475 | 265324 | 5669786 | 283489 |
| 65.0% | 5.0% | 2893713 | 144686 | 3700201 | 185010 | 4198192 | 209910 | 4570260 | 228513 | 4903537 | 245177 | 5242728 | 262136 | 5559961 | 277998 | 5976090 | 298804 |

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|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 70.0% | 5.0% | 3061175 | 153059 | 3896531 | 194827 | 4436691 | 221835 | 4824724 | 241236 | 5160794 | 258040 | 5521868 | 276093 | 5874961 | 293748 | 6313216 | 315661 |
| 75.0% | 5.0% | 3242030 | 162101 | 4123487 | 206174 | 4683215 | 234161 | 5099529 | 254976 | 5488966 | 274448 | 5877942 | 293897 | 6248313 | 312416 | 6693253 | 334663 |
| 80.0% | 5.0% | 3485790 | 174289 | 4434824 | 221741 | 5018606 | 250930 | 5437018 | 271851 | 5860522 | 293026 | 6270644 | 313532 | 6655706 | 332785 | 7131278 | 356564 |
| 90.0% | 10.0% | 4185706 | 418571 | 5215063 | 521506 | 5850511 | 585051 | 6376974 | 637697 | 6833772 | 683377 | 7261745 | 726174 | 7715307 | 771531 | 8302980 | 830298 |
| 95.0% | 5.0% | 4786412 | 239321 | 5840530 | 292026 | 6563550 | 328178 | 7127198 | 356360 | 7642751 | 382138 | 8134039 | 406702 | 8612973 | 430649 | 9257556 | 462878 |
| 97.5% | 2.5% | 5307885 | 132697 | 6484700 | 162117 | 7196836 | 179921 | 7803995 | 195100 | 8320251 | 208006 | 8833468 | 220837 | 9350265 | 233757 | 9969110 | 249228 |
| 99.0% | 1.5% | 5964148 | 89462 | 7222116 | 108332 | 7969251 | 119539 | 8682030 | 130230 | 9116679 | 136750 | 9687888 | 145318 | 10218590 | 153279 | 10916194 | 163743 |
| Area under distribution chart | | 2735985 | | 3520281 | | 3995822 | | 4355453 | | 4680811 | | 5007573 | | 5318836 | | 5714583 | |
| CDF percentiles | C-D scenario | **C3 D30** | | | | | | | | | | | | | | | |
| | P S | 1 | | 2 | | 5 | | 10 | | 30 | | 50 | | 100 | | 200 | |
| 1.0% | 1.0% | 0 | 0 | 798568 | 7986 | 1395039 | 13950 | 1730425 | 17304 | 1901964 | 19020 | 2094407 | 20944 | 2173072 | 21731 | 2316892 | 23169 |
| 2.5% | 1.5% | 0 | 0 | 928000 | 13920 | 1635827 | 24537 | 1933145 | 28997 | 2124428 | 31866 | 2289145 | 34337 | 2406422 | 36096 | 2550253 | 38254 |
| 5.0% | 2.5% | 0 | 0 | 1088641 | 27216 | 1829095 | 45727 | 2154916 | 53873 | 2347234 | 58681 | 2524948 | 63124 | 2682859 | 67071 | 2813052 | 70326 |
| 10.0% | 5.0% | 0 | 0 | 1289955 | 64498 | 2099915 | 104996 | 2489046 | 124452 | 2705131 | 135257 | 2901943 | 145097 | 3074032 | 153702 | 3226193 | 161310 |
| 20.0% | 10.0% | 0 | 0 | 1587361 | 158736 | 2480423 | 248042 | 2917980 | 291798 | 3203040 | 320304 | 3427940 | 342794 | 3616872 | 361687 | 3818795 | 381879 |
| 25.0% | 5.0% | 0 | 0 | 1718379 | 85919 | 2632598 | 131630 | 3096931 | 154847 | 3382697 | 169135 | 3615276 | 180764 | 3830606 | 191530 | 4012283 | 200614 |
| 30.0% | 5.0% | 0 | 0 | 1842848 | 92142 | 2786082 | 139304 | 3263216 | 163161 | 3533462 | 176673 | 3790161 | 189508 | 3993878 | 199694 | 4208916 | 210446 |
| 35.0% | 5.0% | 0 | 0 | 1955250 | 97762 | 2920278 | 146014 | 3410676 | 170534 | 3698659 | 184933 | 3941059 | 197053 | 4175923 | 208796 | 4373698 | 218685 |
| 40.0% | 5.0% | 0 | 0 | 2066564 | 103328 | 3061163 | 153058 | 3562368 | 178118 | 3867575 | 193379 | 4114477 | 205724 | 4350206 | 217510 | 4538195 | 226910 |
| 45.0% | 5.0% | 0 | 0 | 2180935 | 109047 | 3194955 | 159748 | 3710897 | 185545 | 4031805 | 201590 | 4275228 | 213761 | 4520216 | 226011 | 4719221 | 235961 |
| 50.0% | 5.0% | 0 | 0 | 2291027 | 114551 | 3340903 | 167045 | 3865726 | 193286 | 4196099 | 209805 | 4443151 | 222158 | 4693888 | 234694 | 4914709 | 245735 |
| 55.0% | 5.0% | 0 | 0 | 2409756 | 120488 | 3494364 | 174718 | 4024320 | 201216 | 4362159 | 218108 | 4634313 | 231716 | 4889205 | 244460 | 5116818 | 255841 |
| 60.0% | 5.0% | 0 | 0 | 2536349 | 126817 | 3658681 | 182934 | 4219299 | 210965 | 4566421 | 228321 | 4860534 | 243027 | 5102369 | 255118 | 5363595 | 268180 |
| 65.0% | 5.0% | 0 | 0 | 2675214 | 133761 | 3841442 | 192072 | 4434603 | 221730 | 4790861 | 239543 | 5089965 | 254498 | 5361948 | 268097 | 5629333 | 281467 |
| 70.0% | 5.0% | 0 | 0 | 2822382 | 141119 | 4060942 | 203047 | 4668453 | 233423 | 5048781 | 252439 | 5396472 | 269824 | 5679908 | 283995 | 5953953 | 297698 |
| 75.0% | 5.0% | 0 | 0 | 3014475 | 150724 | 4302035 | 215102 | 4941253 | 247063 | 5362637 | 268132 | 5700492 | 285025 | 6041311 | 302066 | 6317040 | 315852 |
| 80.0% | 5.0% | 0 | 0 | 3246799 | 162340 | 4579901 | 228995 | 5276712 | 263836 | 5725344 | 286267 | 6092066 | 304603 | 6439276 | 321964 | 6714936 | 335747 |
| 90.0% | 10.0% | 0 | 0 | 3876635 | 387663 | 5370406 | 537041 | 6169132 | 616913 | 6676533 | 667653 | 7088376 | 708838 | 7469763 | 746976 | 7778225 | 777823 |

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|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 95.0% | 5.0% | 0 | 0 | 4433923 | 221696 | 6054539 | 302727 | 6896374 | 344819 | 7465498 | 373275 | 7892131 | 394607 | 8341587 | 417079 | 8673354 | 433668 |
| 97.5% | 2.5% | 0 | 0 | 4957457 | 123936 | 6666940 | 166674 | 7525084 | 188127 | 8188764 | 204719 | 8560796 | 214020 | 9086240 | 227156 | 9409317 | 235233 |
| 99.0% | 1.5% | 0 | 0 | 5540330 | 83105 | 7390749 | 110861 | 8261538 | 123923 | 8842132 | 132632 | 9456659 | 141850 | 9813815 | 147207 | 10199222 | 152988 |
| Area under distribution chart | | 0 | | 2526755 | | 3648223 | | 4213929 | | 4571732 | | 4863270 | | 5132643 | | 5367784 | |
| CDF percentiles | C-D scenario | **C3 D60** | | | | | | | | | | | | | | | |
| | P S | 1 | | 2 | | 5 | | 10 | | 30 | | 50 | | 100 | | 200 | |
| 1.0% | 1.0% | 900378 | 9004 | 1478288 | 14783 | 1707524 | 17075 | 1876683 | 18767 | 2019422 | 20194 | 2138516 | 21385 | 2252898 | 22529 | 2403836 | 24038 |
| 2.5% | 1.5% | 1064829 | 15972 | 1649196 | 24738 | 1921652 | 28825 | 2080904 | 31214 | 2240364 | 33605 | 2371212 | 35568 | 2510326 | 37655 | 2634581 | 39519 |
| 5.0% | 2.5% | 1229169 | 30729 | 1854355 | 46359 | 2121207 | 53030 | 2281252 | 57031 | 2462513 | 61563 | 2620007 | 65500 | 2763925 | 69098 | 2888107 | 72203 |
| 10.0% | 5.0% | 1443932 | 72197 | 2149426 | 107471 | 2429380 | 121469 | 2632408 | 131620 | 2827530 | 141377 | 3014092 | 150705 | 3165303 | 158265 | 3356475 | 167824 |
| 20.0% | 10.0% | 1768229 | 176823 | 2543187 | 254319 | 2874796 | 287480 | 3099008 | 309901 | 3323331 | 332333 | 3535209 | 353521 | 3732463 | 373246 | 3956186 | 395619 |
| 25.0% | 5.0% | 1911531 | 95577 | 2703707 | 135185 | 3040259 | 152013 | 3277804 | 163890 | 3522813 | 176141 | 3738519 | 186926 | 3946882 | 197344 | 4169801 | 208490 |
| 30.0% | 5.0% | 2029827 | 101491 | 2843031 | 142152 | 3192489 | 159624 | 3437447 | 171872 | 3692836 | 184642 | 3915197 | 195760 | 4124336 | 206217 | 4361829 | 218091 |
| 35.0% | 5.0% | 2144843 | 107242 | 2984241 | 149212 | 3340680 | 167034 | 3587044 | 179352 | 3852599 | 192630 | 4090762 | 204538 | 4306969 | 215348 | 4534159 | 226708 |
| 40.0% | 5.0% | 2260561 | 113028 | 3120108 | 156005 | 3482734 | 174137 | 3746790 | 187339 | 4007611 | 200381 | 4250724 | 212536 | 4471517 | 223576 | 4712545 | 235627 |
| 45.0% | 5.0% | 2371285 | 118564 | 3263863 | 163193 | 3612575 | 180629 | 3902864 | 195143 | 4174712 | 208736 | 4420211 | 221011 | 4641476 | 232074 | 4892272 | 244614 |
| 50.0% | 5.0% | 2484389 | 124219 | 3411939 | 170597 | 3768379 | 188419 | 4066355 | 203318 | 4352367 | 217618 | 4604656 | 230233 | 4845771 | 242289 | 5078478 | 253924 |
| 55.0% | 5.0% | 2606020 | 130301 | 3557908 | 177895 | 3938244 | 196912 | 4258507 | 212925 | 4547831 | 227392 | 4788857 | 239443 | 5045045 | 252252 | 5278570 | 263929 |
| 60.0% | 5.0% | 2747746 | 137387 | 3733583 | 186679 | 4110921 | 205546 | 4457926 | 222896 | 4760845 | 238042 | 5008303 | 250415 | 5265240 | 263262 | 5524887 | 276244 |
| 65.0% | 5.0% | 2898601 | 144930 | 3918312 | 195916 | 4322787 | 216139 | 4676731 | 233837 | 4991739 | 249587 | 5271523 | 263576 | 5532124 | 276606 | 5789566 | 289478 |
| 70.0% | 5.0% | 3065836 | 153292 | 4116771 | 205839 | 4562426 | 228121 | 4941095 | 247055 | 5247477 | 262374 | 5567575 | 278379 | 5841289 | 292064 | 6127884 | 306394 |
| 75.0% | 5.0% | 3254333 | 162717 | 4367712 | 218386 | 4850554 | 242528 | 5221001 | 261050 | 5578436 | 278922 | 5909150 | 295457 | 6203532 | 310177 | 6515733 | 325787 |
| 80.0% | 5.0% | 3479888 | 173994 | 4664504 | 233225 | 5148759 | 257438 | 5569638 | 278482 | 5965311 | 298266 | 6275776 | 313789 | 6612503 | 330625 | 6938100 | 346905 |
| 90.0% | 10.0% | 4130054 | 413005 | 5450474 | 545047 | 6019376 | 601938 | 6513844 | 651384 | 6871100 | 687110 | 7308170 | 730817 | 7655615 | 765561 | 8056436 | 805644 |
| 95.0% | 5.0% | 4736000 | 236800 | 6171461 | 308573 | 6740774 | 337039 | 7225413 | 361271 | 7723673 | 386184 | 8105717 | 405286 | 8573601 | 428680 | 8944364 | 447218 |
| 97.5% | 2.5% | 5248414 | 131210 | 6732009 | 168300 | 7353423 | 183836 | 7986748 | 199669 | 8430099 | 210752 | 8933988 | 223350 | 9282362 | 232059 | 9705448 | 242636 |
| 99.0% | 1.5% | 5878079 | 88171 | 7432374 | 111486 | 8100720 | 121511 | 8701136 | 130517 | 9223517 | 138353 | 9673003 | 145095 | 10122762 | 151841 | 10536926 | 158054 |
| Area under distribution chart | | 2736655 | | 3715360 | | 4120742 | | 4448534 | | 4746200 | | 5023289 | | 5280770 | | 5548945 | |

| CDF percentiles | C-D scenario | **C3 D180** | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | P \ S | 1 | | 2 | | 5 | | 10 | | 30 | | 50 | | 100 | | 200 | |
| 1.0% | 1.0% | 1192574 | 11926 | 1639697 | 16397 | 1836190 | 18362 | 2003735 | 20037 | 2140720 | 21407 | 2338989 | 23390 | 2440160 | 24402 | 2619060 | 26191 |
| 2.5% | 1.5% | 1351701 | 20276 | 1828797 | 27432 | 2047153 | 30707 | 2201917 | 33029 | 2351569 | 35274 | 2527305 | 37910 | 2676329 | 40145 | 2891781 | 43377 |
| 5.0% | 2.5% | 1553654 | 38841 | 2033294 | 50832 | 2245154 | 56129 | 2430694 | 60767 | 2602893 | 65072 | 2768931 | 69223 | 2927925 | 73198 | 3149139 | 78728 |
| 10.0% | 5.0% | 1791126 | 89556 | 2322989 | 116149 | 2586061 | 129303 | 2787008 | 139350 | 2978297 | 148915 | 3188707 | 159435 | 3367374 | 168369 | 3611518 | 180576 |
| 20.0% | 10.0% | 2128987 | 212899 | 2740466 | 274047 | 3038180 | 303818 | 3273759 | 327376 | 3498068 | 349807 | 3759785 | 375978 | 3983034 | 398303 | 4277967 | 427797 |
| 25.0% | 5.0% | 2267023 | 113351 | 2901451 | 145073 | 3202339 | 160117 | 3456000 | 172800 | 3709588 | 185479 | 3965435 | 198272 | 4181388 | 209069 | 4522405 | 226120 |
| 30.0% | 5.0% | 2393421 | 119671 | 3055395 | 152770 | 3357869 | 167893 | 3615920 | 180796 | 3885976 | 194299 | 4145517 | 207276 | 4376022 | 218801 | 4712863 | 235643 |
| 35.0% | 5.0% | 2520415 | 126021 | 3195764 | 159788 | 3520278 | 176014 | 3783305 | 189165 | 4030577 | 201529 | 4316086 | 215804 | 4561125 | 228056 | 4894195 | 244710 |
| 40.0% | 5.0% | 2645012 | 132251 | 3336686 | 166834 | 3672918 | 183646 | 3943002 | 197150 | 4185652 | 209283 | 4491071 | 224554 | 4739602 | 236980 | 5093543 | 254677 |
| 45.0% | 5.0% | 2780309 | 139015 | 3480371 | 174019 | 3830705 | 191535 | 4089047 | 204452 | 4353045 | 217652 | 4665597 | 233280 | 4920876 | 246044 | 5293735 | 264687 |
| 50.0% | 5.0% | 2910887 | 145544 | 3617993 | 180900 | 3990705 | 199535 | 4262885 | 213144 | 4530084 | 226504 | 4865779 | 243289 | 5104313 | 255216 | 5496055 | 274803 |
| 55.0% | 5.0% | 3044016 | 152201 | 3777674 | 188884 | 4164207 | 208210 | 4458044 | 222902 | 4727830 | 236392 | 5065693 | 253285 | 5325337 | 266267 | 5725304 | 286265 |
| 60.0% | 5.0% | 3195172 | 159759 | 3960030 | 198002 | 4360734 | 218037 | 4669632 | 233482 | 4937004 | 246850 | 5279392 | 263970 | 5565680 | 278284 | 5997886 | 299894 |
| 65.0% | 5.0% | 3368845 | 168442 | 4152695 | 207635 | 4587517 | 229376 | 4900493 | 245025 | 5193237 | 259662 | 5529973 | 276499 | 5816310 | 290816 | 6286480 | 314324 |
| 70.0% | 5.0% | 3554034 | 177702 | 4391533 | 219577 | 4843252 | 242163 | 5146064 | 257303 | 5483453 | 274173 | 5832309 | 291615 | 6155255 | 307763 | 6640796 | 332040 |
| 75.0% | 5.0% | 3769090 | 188455 | 4651584 | 232579 | 5126168 | 256308 | 5466855 | 273343 | 5821198 | 291060 | 6215030 | 310751 | 6552546 | 327627 | 7042142 | 352107 |
| 80.0% | 5.0% | 4019262 | 200963 | 4980292 | 249015 | 5455945 | 272797 | 5834458 | 291723 | 6195429 | 309771 | 6625896 | 331295 | 7012381 | 350619 | 7520946 | 376047 |
| 90.0% | 10.0% | 4777965 | 477796 | 5814866 | 581487 | 6346375 | 634638 | 6792938 | 679294 | 7202125 | 720213 | 7694760 | 769476 | 8106198 | 810620 | 8737063 | 873706 |
| 95.0% | 5.0% | 5452797 | 272640 | 6546877 | 327344 | 7164608 | 358230 | 7592018 | 379601 | 8071540 | 403577 | 8544752 | 427238 | 9033310 | 451666 | 9715625 | 485781 |
| 97.5% | 2.5% | 5961880 | 149047 | 7205161 | 180129 | 7785771 | 194644 | 8344182 | 208605 | 8775291 | 219382 | 9290167 | 232254 | 9786171 | 244654 | 10551582 | 263790 |
| 99.0% | 1.5% | 6512588 | 97689 | 7926726 | 118901 | 8576198 | 128643 | 9127875 | 136918 | 9659002 | 144885 | 10088613 | 151329 | 10673387 | 160101 | 11444684 | 171670 |
| Area under distribution chart | | 3194044 | | 3967791 | | 4360106 | | 4666262 | | 4961185 | | 5296122 | | 5586999 | | 6012933 | |

*Table A-D3. 2. Chamber "1126" Calculation of area under damage distribution charts using CDF percentiles*

| CDF percentiles | C-D scenario | **C1 D30** | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | P \ S | 1 | 2 | 5 | 10 | 30 | 50 | 100 | 200 |

| | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1.0% | 1.0% | 364555 | 3646 | 470303 | 4703 | 482879 | 4829 | 543150 | 5432 | 743008 | 7430 | 793291 | 7933 | 857060 | 8571 | 872994 | 8730 |
| 2.5% | 1.5% | 386952 | 5804 | 499806 | 7497 | 513875 | 7708 | 577293 | 8659 | 794467 | 11917 | 845035 | 12676 | 911550 | 13673 | 928031 | 13920 |
| 5.0% | 2.5% | 416308 | 10408 | 536809 | 13420 | 550814 | 13770 | 618795 | 15470 | 851393 | 21285 | 908449 | 22711 | 977235 | 24431 | 996984 | 24925 |
| 10.0% | 5.0% | 491739 | 24587 | 631805 | 31590 | 649149 | 32457 | 730041 | 36502 | 1003421 | 50171 | 1071421 | 53571 | 1152265 | 57613 | 1173303 | 58665 |
| 20.0% | 10.0% | 585622 | 58562 | 749512 | 74951 | 771400 | 77140 | 866446 | 86645 | 1187224 | 118722 | 1275796 | 127580 | 1372652 | 137265 | 1398740 | 139874 |
| 25.0% | 5.0% | 611799 | 30590 | 782516 | 39126 | 803315 | 40166 | 903091 | 45155 | 1236115 | 61806 | 1329231 | 66462 | 1429591 | 71480 | 1458224 | 72911 |
| 30.0% | 5.0% | 633290 | 31665 | 808979 | 40449 | 831222 | 41561 | 935067 | 46753 | 1282140 | 64107 | 1375270 | 68764 | 1478668 | 73933 | 1508767 | 75438 |
| 35.0% | 5.0% | 654294 | 32715 | 836477 | 41824 | 860382 | 43019 | 967353 | 48368 | 1322956 | 66148 | 1422576 | 71129 | 1530022 | 76501 | 1559974 | 77999 |
| 40.0% | 5.0% | 677616 | 33881 | 866340 | 43317 | 890449 | 44522 | 1000448 | 50022 | 1368014 | 68401 | 1473336 | 73667 | 1584554 | 79228 | 1614656 | 80733 |
| 45.0% | 5.0% | 700139 | 35007 | 893248 | 44662 | 918514 | 45926 | 1033083 | 51654 | 1411575 | 70579 | 1519876 | 75994 | 1634940 | 81747 | 1666460 | 83323 |
| 50.0% | 5.0% | 725036 | 36252 | 923435 | 46172 | 948772 | 47439 | 1066534 | 53327 | 1459634 | 72982 | 1570687 | 78534 | 1688922 | 84446 | 1721346 | 86067 |
| 55.0% | 5.0% | 753008 | 37650 | 960090 | 48005 | 985718 | 49286 | 1109121 | 55456 | 1516683 | 75834 | 1632451 | 81623 | 1756261 | 87813 | 1790266 | 89513 |
| 60.0% | 5.0% | 787218 | 39361 | 1001272 | 50064 | 1031008 | 51550 | 1156589 | 57829 | 1585937 | 79297 | 1705973 | 85299 | 1834426 | 91721 | 1867858 | 93393 |
| 65.0% | 5.0% | 830325 | 41516 | 1058375 | 52919 | 1087464 | 54373 | 1222359 | 61118 | 1675735 | 83787 | 1801343 | 90067 | 1937455 | 96873 | 1974569 | 98728 |
| 70.0% | 5.0% | 884695 | 44235 | 1125943 | 56297 | 1156549 | 57827 | 1301363 | 65068 | 1786097 | 89305 | 1916843 | 95842 | 2060487 | 103024 | 2102388 | 105119 |
| 75.0% | 5.0% | 941974 | 47099 | 1198840 | 59942 | 1233129 | 61656 | 1385856 | 69293 | 1902557 | 95128 | 2042300 | 102115 | 2197283 | 109864 | 2239000 | 111950 |
| 80.0% | 5.0% | 1006146 | 50307 | 1277838 | 63892 | 1315862 | 65793 | 1478797 | 73940 | 2023213 | 101161 | 2181082 | 109054 | 2343615 | 117181 | 2392865 | 119643 |
| 90.0% | 10.0% | 1151562 | 115156 | 1462712 | 146271 | 1503563 | 150356 | 1693080 | 169308 | 2324849 | 232485 | 2497373 | 249737 | 2684187 | 268419 | 2735813 | 273581 |
| 95.0% | 5.0% | 1266370 | 63318 | 1606488 | 80324 | 1651428 | 82571 | 1856527 | 92826 | 2541642 | 127082 | 2736210 | 136810 | 2942907 | 147145 | 2999058 | 149953 |
| 97.5% | 2.5% | 1360568 | 34014 | 1722828 | 43071 | 1769669 | 44242 | 1989917 | 49748 | 2720061 | 68002 | 2932962 | 73324 | 3150470 | 78762 | 3217168 | 80429 |
| 99.0% | 1.5% | 1437354 | 21560 | 1823600 | 27354 | 1874440 | 28117 | 2103628 | 31554 | 2903277 | 43549 | 3109635 | 46645 | 3343443 | 50152 | 3408270 | 51124 |
| Area under distribution chart | | 797333 | | 1015850 | | 1044310 | | 1174127 | | 1609176 | | 1729535 | | 1859842 | | 1896020 | |
| CDF percentiles | C-D scenario P \ S | **C1 D60** | | | | | | | | | | | | | | | |
| | | 1 | | 2 | | 5 | | 10 | | 30 | | 50 | | 100 | | 200 | |
| 1.0% | 1.0% | 435373 | 4354 | 493026 | 4930 | 714874 | 7149 | 800840 | 8008 | 847201 | 8472 | 887991 | 8880 | 1048081 | 10481 | 1086397 | 10864 |
| 2.5% | 1.5% | 462427 | 6936 | 522873 | 7843 | 760200 | 11403 | 852925 | 12794 | 901982 | 13530 | 945238 | 14179 | 1113543 | 16703 | 1156786 | 17352 |
| 5.0% | 2.5% | 497498 | 12437 | 563441 | 14086 | 816132 | 20403 | 915175 | 22879 | 967051 | 24176 | 1012180 | 25304 | 1195710 | 29893 | 1239089 | 30977 |
| 10.0% | 5.0% | 585642 | 29282 | 659928 | 32996 | 964198 | 48210 | 1080689 | 54034 | 1138942 | 56947 | 1191839 | 59592 | 1413415 | 70671 | 1463585 | 73179 |

| | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 20.0% | 10.0% | 697239 | 69724 | 786426 | 78643 | 1149426 | 114943 | 1285133 | 128513 | 1357997 | 135800 | 1419961 | 141996 | 1682053 | 168205 | 1743118 | 174312 |
| 25.0% | 5.0% | 727911 | 36396 | 818897 | 40945 | 1197447 | 59872 | 1340257 | 67013 | 1415478 | 70774 | 1480236 | 74012 | 1752838 | 87642 | 1815046 | 90752 |
| 30.0% | 5.0% | 752864 | 37643 | 847690 | 42384 | 1239663 | 61983 | 1387937 | 69397 | 1464067 | 73203 | 1531026 | 76551 | 1814098 | 90705 | 1879670 | 93984 |
| 35.0% | 5.0% | 778582 | 38929 | 875651 | 43783 | 1280802 | 64040 | 1434359 | 71718 | 1513687 | 75684 | 1582955 | 79148 | 1874700 | 93735 | 1943495 | 97175 |
| 40.0% | 5.0% | 806524 | 40326 | 907869 | 45393 | 1326965 | 66348 | 1484718 | 74236 | 1568617 | 78431 | 1639050 | 81953 | 1941926 | 97096 | 2011380 | 100569 |
| 45.0% | 5.0% | 831513 | 41576 | 935308 | 46765 | 1370460 | 68523 | 1532857 | 76643 | 1618403 | 80920 | 1691897 | 84595 | 2004436 | 100222 | 2076520 | 103826 |
| 50.0% | 5.0% | 859185 | 42959 | 967422 | 48371 | 1415714 | 70786 | 1583149 | 79157 | 1670743 | 83537 | 1746870 | 87343 | 2069967 | 103498 | 2144735 | 107237 |
| 55.0% | 5.0% | 894545 | 44727 | 1006415 | 50321 | 1473046 | 73652 | 1647741 | 82387 | 1739159 | 86958 | 1818162 | 90908 | 2155623 | 107781 | 2233868 | 111693 |
| 60.0% | 5.0% | 933270 | 46664 | 1048988 | 52449 | 1538660 | 76933 | 1720238 | 86012 | 1816267 | 90813 | 1896903 | 94845 | 2248694 | 112435 | 2329806 | 116490 |
| 65.0% | 5.0% | 985895 | 49295 | 1108215 | 55411 | 1622962 | 81148 | 1817374 | 90869 | 1914872 | 95744 | 2003197 | 100160 | 2377754 | 118888 | 2460138 | 123007 |
| 70.0% | 5.0% | 1049630 | 52481 | 1178133 | 58907 | 1726451 | 86323 | 1933965 | 96698 | 2042005 | 102100 | 2132191 | 106610 | 2528237 | 126412 | 2620680 | 131034 |
| 75.0% | 5.0% | 1117238 | 55862 | 1254913 | 62746 | 1840894 | 92045 | 2060816 | 103041 | 2176483 | 108824 | 2271511 | 113576 | 2693544 | 134677 | 2789235 | 139462 |
| 80.0% | 5.0% | 1194934 | 59747 | 1341202 | 67060 | 1968951 | 98448 | 2200017 | 110001 | 2322523 | 116126 | 2425798 | 121290 | 2881282 | 144064 | 2985222 | 149261 |
| 90.0% | 10.0% | 1365732 | 136573 | 1535205 | 153521 | 2253046 | 225305 | 2520450 | 252045 | 2658865 | 265887 | 2774373 | 277437 | 3298243 | 329824 | 3414502 | 341450 |
| 95.0% | 5.0% | 1496481 | 74824 | 1681610 | 84081 | 2475069 | 123753 | 2763355 | 138168 | 2914878 | 145744 | 3037231 | 151862 | 3608529 | 180426 | 3743526 | 187176 |
| 97.5% | 2.5% | 1609251 | 40231 | 1802590 | 45065 | 2650120 | 66253 | 2960138 | 74003 | 3122044 | 78051 | 3257404 | 81435 | 3874444 | 96861 | 4012556 | 100314 |
| 99.0% | 1.5% | 1698108 | 25472 | 1907436 | 28612 | 2809128 | 42137 | 3137819 | 47067 | 3299708 | 49496 | 3462054 | 51931 | 4106127 | 61592 | 4251249 | 63769 |
| Area under distribution chart | | 946438 | | 1064311 | | 1559656 | | 1744684 | | 1841217 | | 1923606 | | 2281812 | | 2363883 | |
| CDF percentiles | C-D scenario | **C1 D180** | | | | | | | | | | | | | | | |
| | P \ S | 1 | | 2 | | 5 | | 10 | | 30 | | 50 | | 100 | | 200 | |
| 1.0% | 1.0% | 551210 | 5512 | 717301 | 7173 | 812045 | 8120 | 859073 | 8591 | 935008 | 9350 | 1051894 | 10519 | 1161895 | 11619 | 1213029 | 12130 |
| 2.5% | 1.5% | 585360 | 8780 | 761344 | 11420 | 861564 | 12923 | 913404 | 13701 | 1005509 | 15083 | 1118621 | 16779 | 1236004 | 18540 | 1290988 | 19365 |
| 5.0% | 2.5% | 629317 | 15733 | 818949 | 20474 | 926036 | 23151 | 980153 | 24504 | 1079596 | 26990 | 1199002 | 29975 | 1324618 | 33115 | 1381968 | 34549 |
| 10.0% | 5.0% | 739723 | 36986 | 966292 | 48315 | 1091151 | 54558 | 1156266 | 57813 | 1273205 | 63660 | 1418687 | 70934 | 1562626 | 78131 | 1631096 | 81555 |
| 20.0% | 10.0% | 880888 | 88089 | 1152192 | 115219 | 1302135 | 130214 | 1376200 | 137620 | 1506532 | 150653 | 1689480 | 168948 | 1862318 | 186232 | 1945947 | 194595 |
| 25.0% | 5.0% | 918915 | 45946 | 1201594 | 60080 | 1355331 | 67767 | 1435226 | 71761 | 1571601 | 78580 | 1759920 | 87996 | 1940090 | 97004 | 2027088 | 101354 |
| 30.0% | 5.0% | 950641 | 47532 | 1243742 | 62187 | 1403409 | 70170 | 1484325 | 74216 | 1630193 | 81510 | 1821737 | 91087 | 2008019 | 100401 | 2096175 | 104809 |
| 35.0% | 5.0% | 981928 | 49096 | 1285525 | 64276 | 1450814 | 72541 | 1535472 | 76774 | 1690849 | 84542 | 1883593 | 94180 | 2074046 | 103702 | 2167609 | 108380 |

| | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 40.0% | 5.0% | 1016441 | 50822 | 1331078 | 66554 | 1501250 | 75063 | 1588145 | 79407 | 1748245 | 87412 | 1951073 | 97554 | 2148542 | 107427 | 2244161 | 112208 |
| 45.0% | 5.0% | 1049214 | 52461 | 1373218 | 68661 | 1549570 | 77478 | 1638431 | 81922 | 1802194 | 90110 | 2011589 | 100579 | 2216837 | 110842 | 2314011 | 115701 |
| 50.0% | 5.0% | 1084596 | 54230 | 1419220 | 70961 | 1601010 | 80051 | 1692836 | 84642 | 1869139 | 93457 | 2079494 | 103975 | 2289420 | 114471 | 2389683 | 119484 |
| 55.0% | 5.0% | 1127160 | 56358 | 1475488 | 73774 | 1664016 | 83201 | 1762977 | 88149 | 1947864 | 97393 | 2164228 | 108211 | 2382362 | 119118 | 2487134 | 124357 |
| 60.0% | 5.0% | 1176181 | 58809 | 1542717 | 77136 | 1738543 | 86927 | 1840781 | 92039 | 2039908 | 101995 | 2259734 | 112987 | 2486157 | 124308 | 2596202 | 129810 |
| 65.0% | 5.0% | 1242715 | 62136 | 1626611 | 81331 | 1837077 | 91854 | 1943746 | 97187 | 2147696 | 107385 | 2386046 | 119302 | 2628244 | 131412 | 2741973 | 137099 |
| 70.0% | 5.0% | 1322059 | 66103 | 1732499 | 86625 | 1954834 | 97742 | 2069075 | 103454 | 2278124 | 113906 | 2540563 | 127028 | 2797626 | 139881 | 2919842 | 145992 |
| 75.0% | 5.0% | 1409086 | 70454 | 1846632 | 92332 | 2084896 | 104245 | 2203164 | 110158 | 2427206 | 121360 | 2706435 | 135322 | 2981784 | 149089 | 3111075 | 155554 |
| 80.0% | 5.0% | 1504282 | 75214 | 1974180 | 98709 | 2226745 | 111337 | 2353547 | 117677 | 2590753 | 129538 | 2895233 | 144762 | 3186445 | 159322 | 3322855 | 166143 |
| 90.0% | 10.0% | 1721522 | 172152 | 2257096 | 225710 | 2547445 | 254745 | 2692177 | 269218 | 2974194 | 297419 | 3311251 | 331125 | 3642402 | 364240 | 3803893 | 380389 |
| 95.0% | 5.0% | 1887800 | 94390 | 2478526 | 123926 | 2790536 | 139527 | 2952881 | 147644 | 3269379 | 163469 | 3626482 | 181324 | 3992025 | 199601 | 4164357 | 208218 |
| 97.5% | 2.5% | 2017725 | 50443 | 2659013 | 66475 | 2993732 | 74843 | 3166146 | 79154 | 3510865 | 87772 | 3886388 | 97160 | 4277597 | 106940 | 4469177 | 111729 |
| 99.0% | 1.5% | 2141256 | 32119 | 2810723 | 42161 | 3167797 | 47517 | 3348816 | 50232 | 3769262 | 56539 | 4116034 | 61741 | 4530640 | 67960 | 4722826 | 70842 |
| Area under distribution chart | | 1193365 | | 1563498 | | 1763972 | | 1865863 | | 2058123 | | 2291487 | | 2523357 | | 2634263 | |
| CDF percentiles | C-D scenario | **C2 D30** | | | | | | | | | | | | | | | |
| | P S | 1 | | 2 | | 5 | | 10 | | 30 | | 50 | | 100 | | 200 | |
| 1.0% | 1.0% | 385579 | 3856 | 479108 | 4791 | 501524 | 5015 | 551132 | 5511 | 757960 | 7580 | 819001 | 8190 | 863431 | 8634 | 887489 | 8875 |
| 2.5% | 1.5% | 408803 | 6132 | 508230 | 7623 | 532190 | 7983 | 586155 | 8792 | 805746 | 12086 | 872936 | 13094 | 921237 | 13819 | 944251 | 14164 |
| 5.0% | 2.5% | 440636 | 11016 | 546940 | 13673 | 571156 | 14279 | 627883 | 15697 | 865861 | 21647 | 933833 | 23346 | 986893 | 24672 | 1011936 | 25298 |
| 10.0% | 5.0% | 520080 | 26004 | 641698 | 32085 | 670706 | 33535 | 738801 | 36940 | 1017867 | 50893 | 1103859 | 55193 | 1163478 | 58174 | 1193029 | 59651 |
| 20.0% | 10.0% | 619571 | 61957 | 763379 | 76338 | 800149 | 80015 | 879557 | 87956 | 1205521 | 120552 | 1314458 | 131446 | 1384108 | 138411 | 1420592 | 142059 |
| 25.0% | 5.0% | 645399 | 32270 | 796073 | 39804 | 833570 | 41679 | 917429 | 45871 | 1255195 | 62760 | 1368719 | 68436 | 1441495 | 72075 | 1481389 | 74069 |
| 30.0% | 5.0% | 669208 | 33460 | 824240 | 41212 | 862725 | 43136 | 948684 | 47434 | 1301149 | 65057 | 1417644 | 70882 | 1493540 | 74677 | 1532283 | 76614 |
| 35.0% | 5.0% | 691593 | 34580 | 851225 | 42561 | 891704 | 44585 | 981165 | 49058 | 1345029 | 67251 | 1464874 | 73244 | 1542570 | 77128 | 1583631 | 79182 |
| 40.0% | 5.0% | 716183 | 35809 | 882535 | 44127 | 923476 | 46174 | 1015525 | 50776 | 1389770 | 69488 | 1517752 | 75888 | 1597951 | 79898 | 1639604 | 81980 |
| 45.0% | 5.0% | 739577 | 36979 | 909680 | 45484 | 953544 | 47677 | 1047820 | 52391 | 1432458 | 71623 | 1566518 | 78326 | 1649979 | 82499 | 1691668 | 84583 |
| 50.0% | 5.0% | 764239 | 38212 | 939670 | 46983 | 984718 | 49236 | 1083193 | 54160 | 1482153 | 74108 | 1617997 | 80900 | 1704616 | 85231 | 1747691 | 87385 |
| 55.0% | 5.0% | 795287 | 39764 | 976281 | 48814 | 1023063 | 51153 | 1126866 | 56343 | 1540981 | 77049 | 1684371 | 84219 | 1772151 | 88608 | 1818739 | 90937 |

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|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 60.0% | 5.0% | 830595 | 41530 | 1019335 | 50967 | 1068691 | 53435 | 1173432 | 58672 | 1610915 | 80546 | 1755697 | 87785 | 1849740 | 92487 | 1898060 | 94903 |
| 65.0% | 5.0% | 877537 | 43877 | 1077575 | 53879 | 1128438 | 56422 | 1239401 | 61970 | 1703563 | 85178 | 1857805 | 92890 | 1954635 | 97732 | 2003917 | 100196 |
| 70.0% | 5.0% | 934401 | 46720 | 1145047 | 57252 | 1200773 | 60039 | 1320516 | 66026 | 1814743 | 90737 | 1975749 | 98787 | 2079351 | 103968 | 2134182 | 106709 |
| 75.0% | 5.0% | 994119 | 49706 | 1220526 | 61026 | 1280845 | 64042 | 1406517 | 70326 | 1932176 | 96609 | 2105632 | 105282 | 2216866 | 110843 | 2275533 | 113777 |
| 80.0% | 5.0% | 1062984 | 53149 | 1302891 | 65145 | 1366108 | 68305 | 1502315 | 75116 | 2053943 | 102697 | 2249343 | 112467 | 2367301 | 118365 | 2428072 | 121404 |
| 90.0% | 10.0% | 1215754 | 121575 | 1489412 | 148941 | 1561189 | 156119 | 1717703 | 171770 | 2359601 | 235960 | 2574093 | 257409 | 2710917 | 271092 | 2780615 | 278061 |
| 95.0% | 5.0% | 1335206 | 66760 | 1636984 | 81849 | 1710667 | 85533 | 1886362 | 94318 | 2584140 | 129207 | 2820869 | 141043 | 2969937 | 148497 | 3044508 | 152225 |
| 97.5% | 2.5% | 1434629 | 35866 | 1750729 | 43768 | 1836539 | 45913 | 2019768 | 50494 | 2762052 | 69051 | 3021641 | 75541 | 3176985 | 79425 | 3264598 | 81615 |
| 99.0% | 1.5% | 1520159 | 22802 | 1856064 | 27841 | 1941543 | 29123 | 2137473 | 32062 | 2948174 | 44223 | 3202818 | 48042 | 3377694 | 50665 | 3454794 | 51822 |
| Area under distribution chart | | 842025 | | 1034164 | | 1083399 | | 1191684 | | 1634302 | | 1782410 | | 1876898 | | 1925510 | |
| CDF percentiles | C-D scenario | **C2 D60** | | | | | | | | | | | | | | | |
| | P S | 1 | | 2 | | 5 | | 10 | | 30 | | 50 | | 100 | | 200 | |
| 1.0% | 1.0% | 464909 | 4649 | 510849 | 5108 | 749276 | 7493 | 830504 | 8305 | 855942 | 8559 | 911503 | 9115 | 1053510 | 10535 | 1092638 | 10926 |
| 2.5% | 1.5% | 492325 | 7385 | 542074 | 8131 | 796487 | 11947 | 884371 | 13266 | 911288 | 13669 | 970418 | 14556 | 1121977 | 16830 | 1160617 | 17409 |
| 5.0% | 2.5% | 529649 | 13241 | 581224 | 14531 | 856611 | 21415 | 945765 | 23644 | 977025 | 24426 | 1039039 | 25976 | 1202418 | 30060 | 1245546 | 31139 |
| 10.0% | 5.0% | 623253 | 31163 | 683547 | 34177 | 1011347 | 50567 | 1118870 | 55944 | 1152443 | 57622 | 1223756 | 61188 | 1421209 | 71060 | 1471688 | 73584 |
| 20.0% | 10.0% | 741778 | 74178 | 813363 | 81336 | 1202446 | 120245 | 1331208 | 133121 | 1371895 | 137190 | 1457421 | 145742 | 1691821 | 169182 | 1752875 | 175288 |
| 25.0% | 5.0% | 773141 | 38657 | 848047 | 42402 | 1253112 | 62656 | 1387144 | 69357 | 1430555 | 71528 | 1519189 | 75959 | 1763280 | 88164 | 1826832 | 91342 |
| 30.0% | 5.0% | 800867 | 40043 | 877787 | 43889 | 1297479 | 64874 | 1435758 | 71788 | 1479148 | 73957 | 1572363 | 78618 | 1825301 | 91265 | 1891058 | 94553 |
| 35.0% | 5.0% | 825821 | 41291 | 906586 | 45329 | 1340774 | 67039 | 1483338 | 74167 | 1529485 | 76474 | 1624777 | 81239 | 1886110 | 94305 | 1956644 | 97832 |
| 40.0% | 5.0% | 856087 | 42804 | 938581 | 46929 | 1388451 | 69423 | 1536783 | 76839 | 1584194 | 79210 | 1682828 | 84141 | 1953849 | 97692 | 2024985 | 101249 |
| 45.0% | 5.0% | 883584 | 44179 | 969153 | 48458 | 1433588 | 71679 | 1585736 | 79287 | 1634688 | 81734 | 1736625 | 86831 | 2016812 | 100841 | 2088457 | 104423 |
| 50.0% | 5.0% | 913234 | 45662 | 1000709 | 50035 | 1479796 | 73990 | 1639093 | 81955 | 1687799 | 84390 | 1794148 | 89707 | 2081590 | 104080 | 2158056 | 107903 |
| 55.0% | 5.0% | 949055 | 47453 | 1041552 | 52078 | 1540380 | 77019 | 1703568 | 85178 | 1756463 | 87823 | 1864182 | 93209 | 2167153 | 108358 | 2246840 | 112342 |
| 60.0% | 5.0% | 990549 | 49527 | 1087783 | 54389 | 1607883 | 80394 | 1777784 | 88889 | 1834116 | 91706 | 1947647 | 97382 | 2261566 | 113078 | 2345001 | 117250 |
| 65.0% | 5.0% | 1045748 | 52287 | 1148539 | 57427 | 1699946 | 84997 | 1879263 | 93963 | 1936753 | 96838 | 2056299 | 102815 | 2391701 | 119585 | 2477312 | 123866 |
| 70.0% | 5.0% | 1114267 | 55713 | 1220286 | 61014 | 1809470 | 90474 | 2000357 | 100018 | 2061557 | 103078 | 2189137 | 109457 | 2543875 | 127194 | 2635216 | 131761 |
| 75.0% | 5.0% | 1185782 | 59289 | 1301168 | 65058 | 1925508 | 96275 | 2129599 | 106480 | 2198413 | 109921 | 2333833 | 116692 | 2713533 | 135677 | 2809780 | 140489 |

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|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 80.0% | 5.0% | 1265534 | 63277 | 1390508 | 69525 | 2058573 | 102929 | 2276973 | 113849 | 2344779 | 117239 | 2490970 | 124549 | 2899082 | 144954 | 3002062 | 150103 |
| 90.0% | 10.0% | 1448199 | 144820 | 1589226 | 158923 | 2355475 | 235547 | 2604649 | 260465 | 2686732 | 268673 | 2849797 | 284980 | 3317404 | 331740 | 3438713 | 343871 |
| 95.0% | 5.0% | 1593093 | 79655 | 1740495 | 87025 | 2583340 | 129167 | 2855705 | 142785 | 2945348 | 147267 | 3123301 | 156165 | 3631627 | 181581 | 3765401 | 188270 |
| 97.5% | 2.5% | 1702867 | 42572 | 1867208 | 46680 | 2767735 | 69193 | 3061405 | 76535 | 3154874 | 78872 | 3343401 | 83585 | 3899702 | 97493 | 4037601 | 100940 |
| 99.0% | 1.5% | 1805534 | 27083 | 1975756 | 29636 | 2930474 | 43957 | 3242215 | 48633 | 3337080 | 50056 | 3539429 | 53091 | 4122379 | 61836 | 4282148 | 64232 |
| Area under distribution chart | | 1004928 | | 1102083 | | 1631280 | | 1804467 | | 1860232 | | 1974998 | | 2295510 | | 2378772 | |
| CDF percentiles | C-D scenario | **C2 D180** | | | | | | | | | | | | | | | |
| | P S | 1 | | 2 | | 5 | | 10 | | 30 | | 50 | | 100 | | 200 | |
| 1.0% | 1.0% | 580647 | 5806 | 724923 | 7249 | 846916 | 8469 | 876059 | 8761 | 1028146 | 10281 | 1069398 | 10694 | 1176280 | 11763 | 1224759 | 12248 |
| 2.5% | 1.5% | 619043 | 9286 | 771297 | 11569 | 900482 | 13507 | 932685 | 13990 | 1096747 | 16451 | 1137031 | 17055 | 1253149 | 18797 | 1299815 | 19497 |
| 5.0% | 2.5% | 663585 | 16590 | 827872 | 20697 | 965323 | 24133 | 998462 | 24962 | 1178669 | 29467 | 1218354 | 30459 | 1339246 | 33481 | 1395177 | 34879 |
| 10.0% | 5.0% | 782801 | 39140 | 979757 | 48988 | 1139849 | 56992 | 1178656 | 58933 | 1392098 | 69605 | 1438514 | 71926 | 1583502 | 79175 | 1646396 | 82320 |
| 20.0% | 10.0% | 930695 | 93069 | 1166134 | 116613 | 1357658 | 135766 | 1404168 | 140417 | 1654533 | 165453 | 1714497 | 171450 | 1887279 | 188728 | 1961990 | 196199 |
| 25.0% | 5.0% | 969196 | 48460 | 1216025 | 60801 | 1415189 | 70759 | 1462318 | 73116 | 1725201 | 86260 | 1787071 | 89354 | 1964948 | 98247 | 2043163 | 102158 |
| 30.0% | 5.0% | 1003315 | 50166 | 1257767 | 62888 | 1464477 | 73224 | 1514269 | 75713 | 1786031 | 89302 | 1850869 | 92543 | 2034757 | 101738 | 2114605 | 105730 |
| 35.0% | 5.0% | 1036347 | 51817 | 1299772 | 64989 | 1514990 | 75749 | 1564823 | 78241 | 1844053 | 92203 | 1913415 | 95671 | 2104575 | 105229 | 2184695 | 109235 |
| 40.0% | 5.0% | 1073752 | 53688 | 1346434 | 67322 | 1568503 | 78425 | 1619664 | 80983 | 1911101 | 95555 | 1980081 | 99004 | 2177909 | 108895 | 2263034 | 113152 |
| 45.0% | 5.0% | 1108111 | 55406 | 1391249 | 69562 | 1617839 | 80892 | 1672337 | 83617 | 1978107 | 98905 | 2043874 | 102194 | 2245740 | 112287 | 2334907 | 116745 |
| 50.0% | 5.0% | 1144309 | 57215 | 1436322 | 71816 | 1671803 | 83590 | 1726692 | 86335 | 2042293 | 102115 | 2111512 | 105576 | 2320714 | 116036 | 2410467 | 120523 |
| 55.0% | 5.0% | 1190760 | 59538 | 1494016 | 74701 | 1738853 | 86943 | 1797710 | 89885 | 2124745 | 106237 | 2196932 | 109847 | 2414216 | 120711 | 2508100 | 125405 |
| 60.0% | 5.0% | 1242920 | 62146 | 1561172 | 78059 | 1814633 | 90732 | 1875944 | 93797 | 2220745 | 111037 | 2296717 | 114836 | 2518153 | 125908 | 2619169 | 130958 |
| 65.0% | 5.0% | 1313281 | 65664 | 1649012 | 82451 | 1915829 | 95791 | 1982001 | 99100 | 2345309 | 117265 | 2423079 | 121154 | 2661453 | 133073 | 2765835 | 138292 |
| 70.0% | 5.0% | 1394575 | 69729 | 1753906 | 87695 | 2041551 | 102078 | 2108832 | 105442 | 2496756 | 124838 | 2580659 | 129033 | 2832943 | 141647 | 2944772 | 147239 |
| 75.0% | 5.0% | 1488960 | 74448 | 1870724 | 93536 | 2174923 | 108746 | 2247569 | 112378 | 2655410 | 132770 | 2749811 | 137491 | 3021080 | 151054 | 3138961 | 156948 |
| 80.0% | 5.0% | 1590564 | 79528 | 1996603 | 99830 | 2323625 | 116181 | 2401083 | 120054 | 2837680 | 141884 | 2939552 | 146978 | 3226423 | 161321 | 3353004 | 167650 |
| 90.0% | 10.0% | 1816441 | 181644 | 2285131 | 228513 | 2659859 | 265986 | 2749155 | 274916 | 3251453 | 325145 | 3361984 | 336198 | 3693405 | 369341 | 3838264 | 383826 |
| 95.0% | 5.0% | 1992182 | 99609 | 2508252 | 125413 | 2910928 | 145546 | 3010849 | 150542 | 3569744 | 178487 | 3685771 | 184289 | 4043040 | 202152 | 4202411 | 210121 |
| 97.5% | 2.5% | 2134431 | 53361 | 2686480 | 67162 | 3118476 | 77962 | 3225103 | 80628 | 3821860 | 95547 | 3949133 | 98728 | 4337214 | 108430 | 4504893 | 112622 |

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|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 99.0% | 1.5% | 2262256 | 33934 | 2845893 | 42688 | 3297788 | 49467 | 3418685 | 51280 | 4057239 | 60859 | 4184556 | 62768 | 4593655 | 68905 | 4768774 | 71532 |
| Area under distribution chart | | 1260243 | | 1582543 | | 1840939 | | 1903090 | | 2249667 | | 2327246 | | 2556917 | | 2657280 | |
| CDF percentiles | C-D scenario | **C3 D30** | | | | | | | | | | | | | | | |
| | P S | 1 | | 2 | | 5 | | 10 | | 30 | | 50 | | 100 | | 200 | |
| 1.0% | 1.0% | 399257 | 3993 | 488475 | 4885 | 508555 | 5086 | 598052 | 5981 | 759597 | 7596 | 826621 | 8266 | 869240 | 8692 | 898700 | 8987 |
| 2.5% | 1.5% | 424171 | 6363 | 518011 | 7770 | 539628 | 8094 | 638982 | 9585 | 808381 | 12126 | 880527 | 13208 | 926109 | 13892 | 955861 | 14338 |
| 5.0% | 2.5% | 457689 | 11442 | 557908 | 13948 | 578821 | 14471 | 692873 | 17322 | 866985 | 21675 | 943774 | 23594 | 993136 | 24828 | 1023431 | 25586 |
| 10.0% | 5.0% | 539401 | 26970 | 654032 | 32702 | 681815 | 34091 | 815477 | 40774 | 1021662 | 51083 | 1114420 | 55721 | 1170895 | 58545 | 1208882 | 60444 |
| 20.0% | 10.0% | 642363 | 64236 | 777683 | 77768 | 810985 | 81098 | 962427 | 96243 | 1217140 | 121714 | 1326559 | 132656 | 1394080 | 139408 | 1438750 | 143875 |
| 25.0% | 5.0% | 669737 | 33487 | 812026 | 40601 | 845602 | 42280 | 1004406 | 50220 | 1268663 | 63433 | 1383192 | 69160 | 1452404 | 72620 | 1498578 | 74929 |
| 30.0% | 5.0% | 692891 | 34645 | 839620 | 41981 | 875451 | 43773 | 1041592 | 52080 | 1313960 | 65698 | 1431075 | 71554 | 1503769 | 75188 | 1551376 | 77569 |
| 35.0% | 5.0% | 717155 | 35858 | 868299 | 43415 | 904442 | 45222 | 1080665 | 54033 | 1358217 | 67911 | 1479573 | 73979 | 1554153 | 77708 | 1603291 | 80165 |
| 40.0% | 5.0% | 741927 | 37096 | 898892 | 44945 | 936474 | 46824 | 1119206 | 55960 | 1407399 | 70370 | 1532406 | 76620 | 1608290 | 80415 | 1660562 | 83028 |
| 45.0% | 5.0% | 767158 | 38358 | 928107 | 46405 | 967337 | 48367 | 1155959 | 57798 | 1451189 | 72559 | 1581634 | 79082 | 1660692 | 83035 | 1712837 | 85642 |
| 50.0% | 5.0% | 793245 | 39662 | 958629 | 47931 | 999634 | 49982 | 1199821 | 59991 | 1499111 | 74956 | 1634585 | 81729 | 1715043 | 85752 | 1768937 | 88447 |
| 55.0% | 5.0% | 823815 | 41191 | 996238 | 49812 | 1038239 | 51912 | 1246727 | 62336 | 1559884 | 77994 | 1699930 | 84997 | 1783670 | 89184 | 1839156 | 91958 |
| 60.0% | 5.0% | 861074 | 43054 | 1039988 | 51999 | 1085218 | 54261 | 1305249 | 65262 | 1627831 | 81392 | 1772726 | 88636 | 1861301 | 93065 | 1921270 | 96064 |
| 65.0% | 5.0% | 909191 | 45460 | 1097409 | 54870 | 1144361 | 57218 | 1375897 | 68795 | 1720799 | 86040 | 1875010 | 93751 | 1964628 | 98231 | 2030084 | 101504 |
| 70.0% | 5.0% | 967506 | 48375 | 1167575 | 58379 | 1217510 | 60876 | 1460985 | 73049 | 1828875 | 91444 | 1994110 | 99706 | 2092927 | 104646 | 2160754 | 108038 |
| 75.0% | 5.0% | 1029367 | 51468 | 1244718 | 62236 | 1297414 | 64871 | 1552266 | 77613 | 1950833 | 97542 | 2125992 | 106300 | 2232976 | 111649 | 2299701 | 114985 |
| 80.0% | 5.0% | 1101779 | 55089 | 1327084 | 66354 | 1385051 | 69253 | 1653267 | 82663 | 2083080 | 104154 | 2270297 | 113515 | 2382394 | 119120 | 2458132 | 122907 |
| 90.0% | 10.0% | 1258591 | 125859 | 1517176 | 151718 | 1584597 | 158460 | 1900261 | 190026 | 2383848 | 238385 | 2597716 | 259772 | 2727664 | 272766 | 2812231 | 281223 |
| 95.0% | 5.0% | 1381715 | 69086 | 1669041 | 83452 | 1737141 | 86857 | 2101364 | 105068 | 2611953 | 130598 | 2848598 | 142430 | 2987043 | 149352 | 3083084 | 154154 |
| 97.5% | 2.5% | 1482273 | 37057 | 1787544 | 44689 | 1858522 | 46463 | 2258505 | 56463 | 2802337 | 70058 | 3051845 | 76296 | 3198927 | 79973 | 3300492 | 82512 |
| 99.0% | 1.5% | 1572180 | 23583 | 1895873 | 28438 | 1970882 | 29563 | 2421565 | 36323 | 2963064 | 44446 | 3231633 | 48474 | 3397804 | 50967 | 3500985 | 52515 |
| Area under distribution chart | | 872330 | | 1054298 | | 1099019 | | 1317586 | | 1651172 | | 1799444 | | 1889036 | | 1948868 | |
| CDF percentiles | C-D scenario | **C3 D60** | | | | | | | | | | | | | | | |
| | P S | 1 | | 2 | | 5 | | 10 | | 30 | | 50 | | 100 | | 200 | |

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|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1.0% | 1.0% | 512157 | 5122 | 545429 | 5454 | 766294 | 7663 | 849353 | 8494 | 869860 | 8699 | 923452 | 9235 | 1059264 | 10593 | 1105203 | 11052 |
| 2.5% | 1.5% | 543277 | 8149 | 580097 | 8701 | 814125 | 12212 | 901897 | 13528 | 925714 | 13886 | 988991 | 14835 | 1127058 | 16906 | 1176536 | 17648 |
| 5.0% | 2.5% | 583660 | 14591 | 622655 | 15566 | 872791 | 21820 | 967799 | 24195 | 992776 | 24819 | 1066946 | 26674 | 1209596 | 30240 | 1260813 | 31520 |
| 10.0% | 5.0% | 687482 | 34374 | 730623 | 36531 | 1030053 | 51503 | 1141957 | 57098 | 1170141 | 58507 | 1256093 | 62805 | 1427961 | 71398 | 1488506 | 74425 |
| 20.0% | 10.0% | 816128 | 81613 | 869779 | 86978 | 1227686 | 122769 | 1359177 | 135918 | 1393469 | 139347 | 1487244 | 148724 | 1701538 | 170154 | 1772159 | 177216 |
| 25.0% | 5.0% | 851641 | 42582 | 906912 | 45346 | 1278232 | 63912 | 1416407 | 70820 | 1453447 | 72672 | 1548336 | 77417 | 1772589 | 88629 | 1846919 | 92346 |
| 30.0% | 5.0% | 881280 | 44064 | 937556 | 46878 | 1323364 | 66168 | 1465416 | 73271 | 1503474 | 75174 | 1605948 | 80297 | 1835308 | 91765 | 1912379 | 95619 |
| 35.0% | 5.0% | 910402 | 45520 | 970307 | 48515 | 1367153 | 68358 | 1515517 | 75776 | 1554106 | 77705 | 1663864 | 83193 | 1896280 | 94814 | 1976573 | 98829 |
| 40.0% | 5.0% | 943061 | 47153 | 1004581 | 50229 | 1417361 | 70868 | 1568847 | 78442 | 1610792 | 80540 | 1722097 | 86105 | 1965436 | 98272 | 2045874 | 102294 |
| 45.0% | 5.0% | 972668 | 48633 | 1036167 | 51808 | 1461042 | 73052 | 1620775 | 81039 | 1660978 | 83049 | 1778848 | 88942 | 2028583 | 101429 | 2111850 | 105593 |
| 50.0% | 5.0% | 1005309 | 50265 | 1070158 | 53508 | 1510188 | 75509 | 1673478 | 83674 | 1715629 | 85781 | 1841823 | 92091 | 2094239 | 104712 | 2180826 | 109041 |
| 55.0% | 5.0% | 1045150 | 52258 | 1113005 | 55650 | 1570872 | 78544 | 1740700 | 87035 | 1784168 | 89208 | 1915525 | 95776 | 2180856 | 109043 | 2269236 | 113462 |
| 60.0% | 5.0% | 1090811 | 54541 | 1161492 | 58075 | 1640000 | 82000 | 1815347 | 90767 | 1862379 | 93119 | 2003773 | 100189 | 2274823 | 113741 | 2368902 | 118445 |
| 65.0% | 5.0% | 1152692 | 57635 | 1226597 | 61330 | 1731258 | 86563 | 1917580 | 95879 | 1967238 | 98362 | 2113168 | 105658 | 2404771 | 120239 | 2503955 | 125198 |
| 70.0% | 5.0% | 1226292 | 61315 | 1305993 | 65300 | 1843982 | 92199 | 2044053 | 102203 | 2094427 | 104721 | 2243333 | 112167 | 2557959 | 127898 | 2662577 | 133129 |
| 75.0% | 5.0% | 1307944 | 65397 | 1391034 | 69552 | 1964024 | 98201 | 2175106 | 108755 | 2231073 | 111554 | 2390528 | 119526 | 2727612 | 136381 | 2837065 | 141853 |
| 80.0% | 5.0% | 1395293 | 69765 | 1484169 | 74208 | 2098995 | 104950 | 2323490 | 116175 | 2384492 | 119225 | 2557331 | 127867 | 2915206 | 145760 | 3030534 | 151527 |
| 90.0% | 10.0% | 1595645 | 159564 | 1699041 | 169904 | 2400452 | 240045 | 2660181 | 266018 | 2725375 | 272538 | 2925545 | 292555 | 3336809 | 333681 | 3473260 | 347326 |
| 95.0% | 5.0% | 1751313 | 87566 | 1861769 | 93088 | 2636450 | 131823 | 2916722 | 145836 | 2987484 | 149374 | 3228325 | 161416 | 3652117 | 182606 | 3802706 | 190135 |
| 97.5% | 2.5% | 1872566 | 46814 | 1998393 | 49960 | 2818491 | 70462 | 3127837 | 78196 | 3203994 | 80100 | 3431015 | 85775 | 3920614 | 98015 | 4079018 | 101975 |
| 99.0% | 1.5% | 1985526 | 29783 | 2113686 | 31705 | 2988252 | 44824 | 3310286 | 49654 | 3396070 | 50941 | 3651316 | 54770 | 4145664 | 62185 | 4321352 | 64820 |
| Area under distribution chart | | 1106703 | | 1178287 | | 1663443 | | 1842773 | | 1889320 | | 2026017 | | 2308460 | | 2403453 | |
| CDF percentiles | C-D scenario | **C3 D180** | | | | | | | | | | | | | | | |
| | P \ S | 1 | | 2 | | 5 | | 10 | | 30 | | 50 | | 100 | | 200 | |
| 1.0% | 1.0% | 590849 | 5908 | 758729 | 7587 | 861430 | 8614 | 884989 | 8850 | 1060491 | 10605 | 1096636 | 10966 | 1186306 | 11863 | 1315274 | 13153 |
| 2.5% | 1.5% | 630164 | 9452 | 806790 | 12102 | 918134 | 13772 | 940645 | 14110 | 1127546 | 16913 | 1168303 | 17525 | 1262919 | 18944 | 1399413 | 20991 |
| 5.0% | 2.5% | 676140 | 16904 | 864717 | 21618 | 983265 | 24582 | 1008050 | 25201 | 1210182 | 30255 | 1252492 | 31312 | 1354130 | 33853 | 1510490 | 37762 |
| 10.0% | 5.0% | 796075 | 39804 | 1024277 | 51214 | 1159273 | 57964 | 1191016 | 59551 | 1429071 | 71454 | 1478499 | 73925 | 1596944 | 79847 | 1770057 | 88503 |

| | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 20.0% | 10.0% | 944926 | 94493 | 1219049 | 121905 | 1382448 | 138245 | 1417584 | 141758 | 1703725 | 170373 | 1762282 | 176228 | 1902477 | 190248 | 2113175 | 211318 |
| 25.0% | 5.0% | 985123 | 49256 | 1269639 | 63482 | 1440237 | 72012 | 1477445 | 73872 | 1774493 | 88725 | 1836254 | 91813 | 1982686 | 99134 | 2209691 | 110485 |
| 30.0% | 5.0% | 1020583 | 51029 | 1313654 | 65683 | 1489958 | 74498 | 1528121 | 76406 | 1836321 | 91816 | 1901523 | 95076 | 2051137 | 102557 | 2289666 | 114483 |
| 35.0% | 5.0% | 1054072 | 52704 | 1357358 | 67868 | 1541241 | 77062 | 1578158 | 78908 | 1898347 | 94917 | 1962793 | 98140 | 2120572 | 106029 | 2360549 | 118027 |
| 40.0% | 5.0% | 1090978 | 54549 | 1406416 | 70321 | 1595967 | 79798 | 1634517 | 81726 | 1966104 | 98305 | 2033593 | 101680 | 2197093 | 109855 | 2441570 | 122079 |
| 45.0% | 5.0% | 1126484 | 56324 | 1451916 | 72596 | 1647247 | 82362 | 1687779 | 84389 | 2028691 | 101435 | 2098883 | 104944 | 2265439 | 113272 | 2527693 | 126385 |
| 50.0% | 5.0% | 1162853 | 58143 | 1500202 | 75010 | 1700902 | 85045 | 1743360 | 87168 | 2095844 | 104792 | 2166536 | 108327 | 2341040 | 117052 | 2613152 | 130658 |
| 55.0% | 5.0% | 1212039 | 60602 | 1558924 | 77946 | 1770464 | 88523 | 1814134 | 90707 | 2180678 | 109034 | 2254609 | 112730 | 2434218 | 121711 | 2715818 | 135791 |
| 60.0% | 5.0% | 1264684 | 63234 | 1628014 | 81401 | 1847868 | 92393 | 1891455 | 94573 | 2277929 | 113896 | 2354017 | 117701 | 2539093 | 126955 | 2837657 | 141883 |
| 65.0% | 5.0% | 1335362 | 66768 | 1721318 | 86066 | 1951839 | 97592 | 2000981 | 100049 | 2404174 | 120209 | 2486604 | 124330 | 2685303 | 134265 | 2997025 | 149851 |
| 70.0% | 5.0% | 1418782 | 70939 | 1832323 | 91616 | 2076740 | 103837 | 2127425 | 106371 | 2562125 | 128106 | 2647596 | 132380 | 2857334 | 142867 | 3188319 | 159416 |
| 75.0% | 5.0% | 1511401 | 75570 | 1950685 | 97534 | 2211332 | 110567 | 2267962 | 113398 | 2728327 | 136416 | 2822629 | 141131 | 3045907 | 152295 | 3405470 | 170274 |
| 80.0% | 5.0% | 1614416 | 80721 | 2085151 | 104258 | 2366120 | 118306 | 2419622 | 120981 | 2916712 | 145836 | 3015702 | 150785 | 3253884 | 162694 | 3626727 | 181336 |
| 90.0% | 10.0% | 1849679 | 184968 | 2382565 | 238257 | 2704003 | 270400 | 2773897 | 277390 | 3339114 | 333911 | 3451751 | 345175 | 3723400 | 372340 | 4163404 | 416340 |
| 95.0% | 5.0% | 2032312 | 101616 | 2618359 | 130918 | 2961833 | 148092 | 3039214 | 151961 | 3653169 | 182658 | 3780023 | 189001 | 4079978 | 203999 | 4560928 | 228046 |
| 97.5% | 2.5% | 2176766 | 54419 | 2801026 | 70026 | 3177482 | 79437 | 3254520 | 81363 | 3917006 | 97925 | 4049721 | 101243 | 4365386 | 109135 | 4893693 | 122342 |
| 99.0% | 1.5% | 2303357 | 34550 | 2963714 | 44456 | 3361997 | 50430 | 3446963 | 51704 | 4150599 | 62259 | 4292100 | 64381 | 4625225 | 69378 | 5176090 | 77641 |
| Area under distribution chart | | 1281953 | | 1651862 | | 1873531 | | 1920436 | | 2309840 | | 2388794 | | 2578292 | | 2876764 | |