

UNIVERSITY OF BIRMINGHAM

PhD in Civil Engineering

A Risk-Based Framework for Strategic Management of Railway Drainage

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Abstract

Adequate drainage is a critical factor for the proper functioning of railway infrastructures and an important element of track maintenance. Railway drainage systems are complex and consists of various components, which can directly or indirectly affect the performance of other assets such as earthwork, track and signalling equipment. This has made the management of railway drainage systems challenging. Furthermore, with budget constraints, selecting appropriate maintenance strategies are essential. This study attempted to develop a risk-based decision making framework, for the strategic management of assets. The developed framework is capable of handling the uncertainty associated with inconsistent historic data and the probabilistic nature of asset deterioration. Moreover, it can identify significant contributing factors that affect the deterioration rate of asset and predict the future condition of them. The framework enables decision-makers to proactively manage their network and to determine the optimum maintenance strategy, by considering factors such as budget, maintenance intervals, maximum allowable risk, and the overall condition of the network. The developed framework is demonstrated via a case study on a section of the UK's railway.

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List of Contents

ABSTRACT ..... **I**

ACKNOWLEDGEMENTS ..... **II**

LIST OF CONTENTS ..... **III**

LIST OF FIGURES ..... **IX**

LIST OF TABLES ..... **XIII**

LIST OF ACRONYMS ..... **XVI**

1. INTRODUCTION **1**

1.1 Background 1

1.2 Aim and objectives 3

1.3 Scope 3

1.4 Research significance and novelty 4

1.5 Thesis structure 5

2. RAILWAY DRAINAGE FUNCTION AND DETERIORATION PROCESSES **6**

2.1 Introduction 6

2.2 Railway drainage system definition 6

2.3 Drainage asset classifications 8

2.3.1 Surface drainage systems 9

2.3.1.1 Channels 9

2.3.2 Sub-surface drainage systems 14

2.3.2.1 Pipes 14

2.3.2.2 Culverts and syphons 15

2.3.2.3 Catch-pits 16

2.4 Asset deterioration and contributing factors 17

2.4.1 Catch-pit deterioration 17

2.4.1.1 Factors affecting catch-pit deterioration 18
2.4.2 Pipe deterioration 19
2.4.2.1 Factors affecting pipe deterioration 21
2.4.3 Culvert deterioration 24
2.4.3.1 Factors affecting culvert deterioration 24
2.4.4 Channel deterioration 27
2.4.4.1 Factors affecting channel deterioration 27
2.5 Summary 28
3. ASSET AND RISK MANAGEMENT 29
3.1 Introduction 29
3.2 Asset management levels and data quality 29
3.2.1 Network- and Project-Level models 30
3.2.2 Information quality levels 31
3.3 Homogenous asset grouping 32
3.3.1 Regression models in asset grouping 33
3.3.1.1 Multiple regression 35
3.4 Risk analysis 41
3.4.1 Deterioration probability analysis 42
3.4.1.1 Markov models 43
3.4.2 Deterioration consequence analysis 45
3.4.2.1 Road network consequences 46
3.4.2.2 UK Railway consequence analysis 48
3.5 Consequence criteria weighting factors 56
3.5.1 Analytical Hierarchy Process 58
3.5.1.1 Determination of weighting factors 60
3.5.1.2 Consistency ratio 62
3.6 Summary 63
4. RESEARCH METHODOLOGY 65
4.1 Literature review 65

4.2 Framework development 65
4.3 Case study 66

5. FRAMEWORK DEVELOPMENT 68

5.1 Introduction 68
5.2 Homogenous asset groups 70
5.2.1 Multiple regression 70
5.2.1.1 Independent variables 71
5.2.1.2 Dependent variables 71
5.3 Markov model 76
5.3.1 Condition progression 79
5.3.1.1 Chapman–Kolmogorov equation 80
5.3.2 Model calibration 81
5.3.2.1 Metropolis–Hastings algorithm 83
5.3.3 Maintenance 84
5.3.4 Model validation 85
5.3.5 Climate change 86
5.4 Consequence analysis 86
5.4.1 Proposed consequence measures 87
5.4.1.1 Common consequences tool 88
5.4.1.2 Track category 89
5.4.1.3 Route criticality 89
5.4.2 Analytical hierarchy process 90
5.5 Framework assumptions and limitations 91
5.5.1 Assumptions 91
5.5.2 Limitations 91
5.6 Framework step-by-step guide 92
5.7 Summary 96

6. CASE STUDY 97

6.1 Introduction 97

6.2 Multiple Regression model development 98
6.2.1 Independent Variables 98
6.2.1.1 Catch-pit independent variables 98
6.2.1.2 Pipe independent variables 101
6.2.1.3 Culvert independent variables 105
6.2.1.4 Channel independent variables 107
6.2.2 Model size 111
6.2.3 Data quality and assumptions check 112
6.2.3.1 Multicollinearity 112
6.2.3.2 Linearity, normality and homoscedasticity 114
6.2.4 Data transformation 117
6.2.5 Multiple Regression results 124
6.3 Transition probability matrices 130
6.3.1 Model validation 134
6.4 Consequence analysis 137
6.4.1 Consequence area weighting factor 137
6.4.2 Anticipated increase in consequence measures 138
6.5 Maintenance policy options 139
6.6 Risk horizon results and discussion 143
6.6.1 Probability 144
6.6.2 Consequences 145
6.6.3 Risk calculation 146
6.6.4 Maintenance intervals 148
6.6.4.1 Cost 148
6.6.4.2 Accumulative risk 152
6.6.4.3 Peak risk 153
6.7 Summary 159

7. DISCUSSION 160

7.1 Research summary 160

7.2 Achievement of the research objectives 162
7.3 Critical review of the research 166
7.3.1 Strategic-level management 166
7.3.2 Railway drainage deterioration 168
7.3.3 Deterioration probability analysis 169
7.3.4 Deterioration consequence analysis 170
7.3.5 Practicality of the developed framework 172
7.4 Value of the research 173
7.5 Discussion summary 174
8. CONCLUSIONS AND RECOMMENDATIONS 176
8.1 Accomplished work 176
8.2 Conclusions 176
8.3 Findings 177
8.4 Recommendations for future work 179
REFERENCES 181
APPENDIX A – MCMC CODE 188
APPENDIX B – MULTIPLE REGRESSION MULTICOLINEARITY CHECK 189
B.1 Pipes 189
B.2 Culverts 191
B.3 Channels 192
APPENDIX C – TRANSITION PROBABILITIES 195
C.1 Catchpits structural deterioration – group 1 195
C.2 Catchpits structural deterioration – group 2 200
C.3 Catchpits service deterioration – group 1 205
C.4 Catchpits service deterioration – group 2 210
C.5 Culverts structural deterioration 215
C.6 Culverts service deterioration 220

C.7 Pipes structural deterioration – group 1 225
C.8 Pipes structural deterioration – group 2 229
C.9 Pipes service deterioration – group 1 234
C.10 Pipes service deterioration – group 2 239
C.11 Channels structural deterioration – group 1 244
C.12 Channels structural deterioration – group 2 249
C.13 Channels structural deterioration – group 3 254
C.14 Channels service deterioration – group 1 259
C.15 Channels service deterioration – group 2 264
C.16 Channels service deterioration – group 3 269

List of Figures

Figure 2-1 – A typical railway drainage system (Network Rail, 2017a) 9

Figure 2-2 – Example of open channel crest drain in construction 11

Figure 2-3 – Example of open channel cess drain 11

Figure 2-4 – Example of open channel toe drain in construction 12

Figure 2-5 – Example of stepped cascade drain 13

Figure 2-6 – Example of flume drain 13

Figure 2-7 – Example of brick culvert 15

Figure 2-8 – Example of syphon inlet with trash screen 16

Figure 2-9 – Example of catch-pit 16

Figure 3-1 – Standard multiple regression (forced entry) outcome 37

Figure 3-2 – Sequential/hierarchical multiple regression (block-wise entry) outcome 38

Figure 3-3 – Statistical/stepwise multiple regression outcome 39

Figure 3-4 – Effect of outliers on regression analysis 40

Figure 3-5 – Possible state transitions based on Multi-State Markov chain theory 45

Figure 3-6 – Track category plot of Equivalent Million Gross Tonnes per Annum (EMGTPA) against line speed in miles per hour (Network Rail, 2016) 55

Figure 3-7 – Principal consequence areas identified for the railway network 58

Figure 4-1 – Stages of the research 67

Figure 5-1 – Schematic of the proposed framework 69

Figure 5-2 – Deterioration rate slope analysis 75

Figure 5-3 – Typical distribution of asset condition grades 78

Figure 6-1 – Catch-pit topography distribution in the LNW route 99

Figure 6-2 – Catch-pit material distribution in the LNW route; GRP: glass (fibre) reinforced plastic 100

Figure 6-3 – Catch-pit shape distribution in the LNW route 101

Figure 6-4 – Pipe topography distribution in the LNW route 102

Figure 6-5 – Pipe function distribution in the LNW route 103

Figure 6-6 – Pipe size distribution in the LNW route 104

Figure 6-7 – Pipe material distribution in the LNW route; uPVC: un-plasticised polyvinyl chloride plastic 105

Figure 6-8 – Culvert shape distribution in the LNW route 106

Figure 6-9 – Culvert material distribution in the LNW route 107

Figure 6-10 – Channel drainage location distribution in the LNW route; UTX: under track crossing; 6 ft: the area between two tracks; 10 ft: the area between two double tracks 108

Figure 6-11 – Channel topography distribution in the LNW route 109

Figure 6-12 – Channel shape distribution in the LNW route 110

Figure 6-13 – Channel material distribution in the LNW route 111

Figure 6-14 – Catch-pit structural deterioration – regression standardised residual plots 115

Figure 6-15 – Examples of standardised residuals against predicted values (Tabachnick and Fidell, 2013).....116

Figure 6-16 – Catch-pit structural deterioration – regression standardised residual versus predicted values 117

Figure 6-17 – Catch-pit structural deterioration – frequency of deterioration rate.....118

Figure 6-18 – Structural deterioration – comparison of standardised residual plots before and after data transformation.....121

Figure 6-19 – Structural deterioration – comparison of normal P-P plot of standardised residual plots before and after data transformation 122

Figure 6-20 – Structural deterioration – comparison of standardised predicted/residual scatterplots before and after data transformation.....123

Figure 6-21 – Catch-pit group 1 structural deterioration – transition probability distributions 133

Figure 6-22 – Network Rail maintenance policy (Network Rail, 2017a).....140

Figure 6-23 –Trend of structural deterioration of pipe asset group 2 with no maintenance..145

Figure 6-24 – Cost of maintenance options (M1–4) applied at different intervals (every year to every 10 years) for the analysis period 2018–2040 149

Figure 6-25 – Cost ranges of maintenance options (M1–4) applied at different intervals (every year to every 10 years) for the analysis period 2018–2040 151

Figure 6-26 – Total cost of maintenance options (M1–4) applied at different intervals (every year to every 10 years) for the analysis period 2018–2040 with a budget limit 152

Figure 6-27 – Cost and AR for maintenance options (M1–4) applied at different intervals (every year to every 10 years) for the analysis period 2018–2040 153

Figure 6-28 – Cost and PR for maintenance options (M1–4) applied at different intervals (every year to every 10 years) for the analysis period 2018–2040, budget of £40m and Low critical risk level (0.5–1) 155

Figure 6-29 – Risk horizon for maintenance option 4 (M4) applied every 2 years with Low critical risk level (0.5–1) 156

Figure 6-30 – Percentage/probability of assets in condition grade 5 under different maintenance options (M1–4) applied every 2 years 157

Figure 6-31 – Cost and PR for maintenance options (M1–4) applied at different intervals (every year to every 10 years) for the analysis period 2018–2040, a budget of £20m and Minimal critical risk level (0–0.5) 158

Figure 6-32 – Risk horizon for maintenance option 4 (M4) applied every year with Minimal critical risk level (0–0.5) 158

List of Tables

Table 3-1 – Lifelines resilience consequence measures specifications (Rebello et al., 2019) 48

Table 3-2 – Track asset criticality contribution (Network Rail, 2017b).....53

Table 3-3 – Route criticality specification (Network Rail, 2017b) 56

Table 3-4 – AHP pairwise comparison relative importance scale (Saaty, 2008) 59

Table 3-5 – Random index (RI) values (Triantaphyllou and Mann, 1995) 63

Table 5-1 – Dummy variable example for drainage pipes with four materials 71

Table 5-2 – Deterioration rate analysis example 73

Table 5-3 – Description of structural and service condition grades (Network Rail, 2017a) ...77

Table 5-4 – Likelihood distribution example.....83

Table 5-5 – Critical values of chi-square (χ^2) (Tabachnick and Fidell, 2013).....86

Table 5-6 – CCT scale ranges (Network Rail, 2014).....88

Table 5-7 – TC conversions to a 1–5 grading system.....89

Table 5-8 – RC conversions to five bands grading system.....90

Table 6-1 – Model size analysis.....112

Table 6-2 – Correlations between catch-pit IVs 114

Table 6-3 – Model size with transformed data (deterioration rate of 0 eliminated).....119

Table 6-4 – Catch-pit IV contributions to structural and service deterioration – significance level of 0.05 126

Table 6-5 – Pipe IV contributions to structural and service deterioration – significance level of 0.05 127

Table 6-6 – Culvert IV contributions to structural and service deterioration – significance level of 0.05 128

Table 6-7 – Channel IV contributions to structural and service deterioration – significance level of 0.05 129

Table 6-8 – Network-level asset groups for structural and service deterioration models 130

Table 6-9 – Catch-pit structural deterioration TPM – group 1 131

Table 6-10 – TPMs for structural and service deterioration models 134

Table 6-11 - Validation result – catch-pit group 1 structural deterioration for 2019 137

Table 6-12 – Comparison Matrix 138

Table 6-13 – Consequence weighting scores for the proposed model 138

Table 6-14 – Anticipated passenger and freight traffic growth on the LWN route, UK 139

Table 6-15 – Proposed maintenance option matrices 140

Table 6-16 – Estimated cost associated with maintenance options 143

Table 6-17 – Approximate increase in consequence levels due to anticipated traffic growth 146

Table 6-18 – Risk calculation example – group 2 pipe structural deterioration model 147

Table 6-19 – Risk value ranges 148

Table 6-20 – Total maintenance cost with budget limit of £40m for the analysis period 2018–2040.....152

List of Acronyms

Term	Definition
AHP	Analytical Hierarchy Process
CCT	Common Consequences Tool
CI	Consistency Index
CM	Comparison Matrix
CR	Consistency Ration
DV	Dependant Variable
EMGTPA	Equivalent Million Gross Tonnes per Annum
FWI	Fatalities and Weighted Injuries
HAVS	Hand-Arm Vibration Syndrome
IQL	Information Quality Level
IV	Independent Variable
LR	Logistic Regression
MCMC	Markov Chain Monte Carlo
MHA	Metropolis-Hastings Algorithm
MR	Multiple Regression
NCACM	Normalised Criteria Comparison Matrix
NL	Network-Level
ONRC	One Network Road Classification
ORR	Office of Rail and Road
PL	Project-Level
PWC	Pair Wise Comparison
RC	Route Criticality
SHE	Safety, Health and Environment
TC	Track Category
TP	Transition Probability
TPM	Transition Probability Matrix

1. INTRODUCTION

1.1 Background

Adequate drainage is a critical factor for the proper functioning of railway infrastructure and an important element of track maintenance (Selig, 1994, Lichtberger, 2005, Li et al., 2015). Inadequate railway drainage can directly result in flooding and pollution of the railway track and adjacent land, and indirectly lead to a variety of issues such as earthwork slope instability, landslides, track geometry faults and reduced track strength and longevity (USACE, 2000, ARTC, 2006). These issues can result in delays and unplanned reactive maintenance works, as well as more significant incidents such as derailment (Network Rail, 2017a). All of these consequences can be costly yet the adequate management of drainage infrastructure is often overlooked and, as a result, the budgets available for railway track drainage maintenance are often restricted. Therefore, the adequate management of railway drainage systems to ensure the best use of available funds is of great importance. However, the management of such systems is challenging due to a number of factors.

i) Railway drainage systems are complex systems: they are designed to collect water on the track as well as water from other sources, such as groundwater and runoff from adjacent land, and to safely dispose of it. These systems are normally large and cover extensive lengths of the railway track and associated catchment areas.

ii) A large portion of railway drainage assets are buried under the ground and hard to access.

iii) Drainage assets deteriorate at different, potentially unknown, rates: they are constructed of different materials, have different functions and have varying ages with often unknown historic performance and maintenance. Therefore, each asset

has a different deterioration rate and there is a high level of uncertainty in the current and future condition of assets (Usman, 2019).

iv) Drainage assets have different modes of deterioration: deterioration of drainage assets is generally classified into two categories, namely structural and service deterioration (Network Rail, 2017a). Structural deterioration is the continuous, age-related disintegration of the fabric or cracks and breaks that are caused by random incidents. Service deterioration, also referred to as hydraulic deterioration, is associated with the reduction in asset capacity caused by the accumulation of debris and reduced flow velocity caused by increased roughness and sedimentation. Like other similar networks, such as those in sewers and water mains, railway drainage assets exhibit different structural and service deterioration rates which need to be considered separately due to their different natures.

Furthermore, despite the significant influence of drainage system performance on railway operation, drainage asset management has not traditionally been considered as a primary element of railway asset management (Hay, 1982, Li et al., 2015). However, considering the consequences of drainage failure, limited budgets, and the challenges of planning maintenance works, it is indubitable that there is a need to develop approaches and tools to support the strategic, tactical and operational requirements of drainage asset management. This research focuses on the development of an approach for strategic drainage asset management. Such an approach should address three main challenges. First, it should be capable of facilitating the management of large drainage networks. Second, it should incorporate a risk-informed approach, which allows the likely impact of drainage failure over a network to be determined and which can address the uncertainties associated with railway drainage deterioration. Third,

to address the challenge of a limited budget and to identify the most cost-effective maintenance approach, the tool should allow assessment of different maintenance strategies.

1.2 Aim and objectives

To address the above aspects, the aim of this research is to develop a risk-based asset management framework for the strategic management of railway drainage systems, taking into account uncertainty, the effects of asset deterioration and different maintenance strategies.

To achieve this aim, the following objectives were set:

1. To review the literature and railway standards on drainage systems and to identify their components, functions and physical boundaries.
2. To review the literature to identify the factors which contribute to the deterioration of drainage assets.
3. To explore strategic-level asset management approaches and techniques that could be useful for the task in hand.
4. To develop a risk-based asset management framework from objectives 1, 2 and 3, and to demonstrate its practicality using a case study.

1.3 Scope

The purpose of this thesis is to develop an asset management framework that is based on the factor of risk, which is the product of probability and consequence of an undesired event. The undesired event considered in this study is asset deterioration; therefore, the framework will analyse the probability and consequence of railway drainage asset deterioration. Factors that affect the deterioration, such as maintenance option and frequency of intervals will be incorporated in the decision making framework developed herein.

The probability of asset deterioration will be thoroughly studied with appropriate mathematical techniques and probabilistic models. Moreover, the factor of uncertainty in asset deterioration probability will also be explored with quantitative approaches. Due to the limited time and cost constraints of this PhD project, a detailed consequence analysis is outside the scope of the study. Consequence analysis will be limited to the currently available approaches in the literature and standards; nevertheless, this study will aim to optimise and improve the assessment of consequences on strategic levels. Detailed consequence analysis of railway drainage assets requires an extensive amount of work, which is suggested for future research.

The risk-based framework will be developed for the strategic management of railway drainage assets, which is applicable for the analysis of large populations of assets (e.g. an entire country or route). Therefore, analysis of individual assets, both in terms of deterioration probability and risk, is outside the scope of this study. Furthermore, due to the limited literature and data available for the entire railway drainage components, this study will only focus on the major components, namely, catch-pits, pipes, culverts, and channels.

1.4 Research significance and novelty

There has been no previous attempt to develop a risk-based decision-making framework for the strategic management of railway drainage assets. Such a tool can assist decision makers to select the appropriate preventive maintenance options and intervals based on drainage failure risk, taking into account available budgets. In addition, such a framework can provide risk horizons and asset condition distributions for the analysis of long-term investment options. This can assist with the development of standards, budget allocation and maintenance planning.

The contribution of this thesis to the body of knowledge is primarily associated with the following innovations.

- The developed strategic management framework identifies case-specific asset deterioration factors by using statistical techniques. These factors are identified to develop homogeneous asset groups, which makes the framework flexible and more specific to the task at hand.
- The developed management framework enables risk-informed decision-making by incorporating the probability and consequences of asset deterioration. Moreover, the framework addresses the uncertainties associated with asset deterioration and data inconsistency using mathematical techniques.

1.5 Thesis structure

This thesis consists of nine chapters. Chapter 1 (the current chapter) presents the background, motivations, aim, objectives, significance and novelty of this research. Chapter 2 defines the railway drainage system for the purposes of this research and reviews the literature on drainage assets and their deterioration. Chapter 3 reviews the levels of asset management, data quality and the available mathematical techniques suitable for railway drainage system management. Chapter 4 presents the research methodology. Chapter 5 presents the components of the developed risk-based management framework. Chapters 6 demonstrates the practicality of the framework using a case study of sections of the UK mainline railway network. Chapter 7 presents a critical discussion of the research and, finally, Chapter 8 concludes the research and provides recommendations for future developments.

2. RAILWAY DRAINAGE FUNCTION AND DETERIORATION PROCESSES

2.1 Introduction

As discussed in Chapter 1, taking into account the complexity and criticality of railway drainage operations, development of a comprehensive asset management tool is highly demanded. That is the aim of this study and to achieve this, a review of the literature on the main aspects of the research was carried out and is presented in this and the following chapter. Section 2.2 presents a definition review of railway drainage as a system, which highlights the various terminologies used in the literature to describe the railway drainage system and its physical boundaries. Section 2.3 demonstrates the components, function and different applications of assets used in a typical railway drainage system. Section 2.4 discusses the deterioration mechanisms and contributing factors that affect the structural and service deterioration of drainage assets; finally, section 2.5 provides a summary of this chapter.

2.2 Railway drainage system definition

To develop an effective management model, an understanding of the physical system boundaries to which the model is applied must be developed (BSI, 2010). This section describes the various definitions of railway drainage as a system. According to Network Rail (NR), a railway drainage system includes all the drainage components in the track infrastructure, from where the water enters to where it exits the railway boundaries from a suitable outlet (Network Rail, 2018). Based on this definition, railway drainage systems include every component on the track, earthworks and off-track land, and structures within the catchment area that collect different sources of water. Sources of water entering railway

boundaries can be precipitation (rain and snow), surface water from adjacent lands or sub-surface flows from underground water (Lichtberger, 2005).

The Ministry of Railways in India (MORI, 2005), defines a drainage system as a mean of interception, collection and quick disposal of water from all track support systems. Although this definition does not specify the boundaries of the system, it is in agreement with NR's description. Both definitions emphasise collection of the water in the catchment areas, and conveyance and disposal of it safely through an outlet. The Australian Rail Track Corporation (ARTC) also defines a railway track drainage system as 'drainage of the track formation, including the diversion of water from cuttings and embankments' (ARTC, 2006). This is similar to the previous two definitions; however, it does not elaborate on the term 'diversion' or how the water is removed from the railway track.

According to Selig and Cantrell (2001), a complete drainage system must include a means of handling water that flows over the ground towards the track, shedding or draining water falling onto the track, and controlling water from the subgrade. This definition is quite comprehensive; however, it does not specify the importance of draining earthwork structures such as cuttings and embankments. Li et al. (2015) similarly defined railway drainage systems, dividing them into two sub-systems, namely internal and external drainage. Internal sub-systems are designed for quick disposal of water on the track, and external sub-systems are for minimising sources of water flowing towards the track and for disposal of water from internal sub-systems.

These descriptions and definitions of railway drainage systems are all in general agreement; however, different terminologies have been used. In conclusion, the primary purpose and boundaries of a railway drainage system are to collect any water from rain or snow, flowing on the surface or seeping from underground that runs towards or onto track infrastructures, transport it and effectively dispose of it through an outfall.

2.3 Drainage asset classifications

In the previous section, the purpose, and physical boundaries of railway drainage systems were discussed. This section focuses on the components (i.e. assets) within a drainage system. Railway drainage assets are used at different locations and for various functions, which potentially make the deterioration behaviour of assets unique and specific to the case. This section aims to describe these classifications and functions.

Generally, linear drainage systems such as those in railways, highways and airports are categorised into two groups, surface and sub-surface drainage systems (MORI, 2005, ARTC, 2006, RailCorp, 2009, Highways England, 2016). Surface drainage systems are usually constructed at surface level and can be accessed easily, while sub-surface systems are mostly buried, with restricted access. Depending on the network, the specification of surface and sub-surface drainage systems can vary. For instance, NR classifies railway drainage assets in more detail than simply as surface and sub-surface systems: railway drainage assets can be further classified into sub-systems such as asset group, construction type and location (Network Rail, 2017a).

Asset groups – Railway drainage assets are categorised as links or nodes. Links are linear assets (e.g. pipes, culverts and channels) which form a network that directs the water to an outfall; nodes are locational assets (e.g. catch-pits, inlets and outlets) that are connected by link assets.

Construction types – This refers to the material or function of the asset. Drainage assets can be in different construction groups such as hard assets (e.g. concrete-lined channels, steel pipes), soft assets (e.g. earth channels, ponds) and electrical/mechanical assets (e.g. pumps).

Location – This refers to the asset's location, for instance, drainage assets used in earthworks, tracks and buildings (e.g. stations).

A typical drainage system configuration is presented in Figure 2-1.

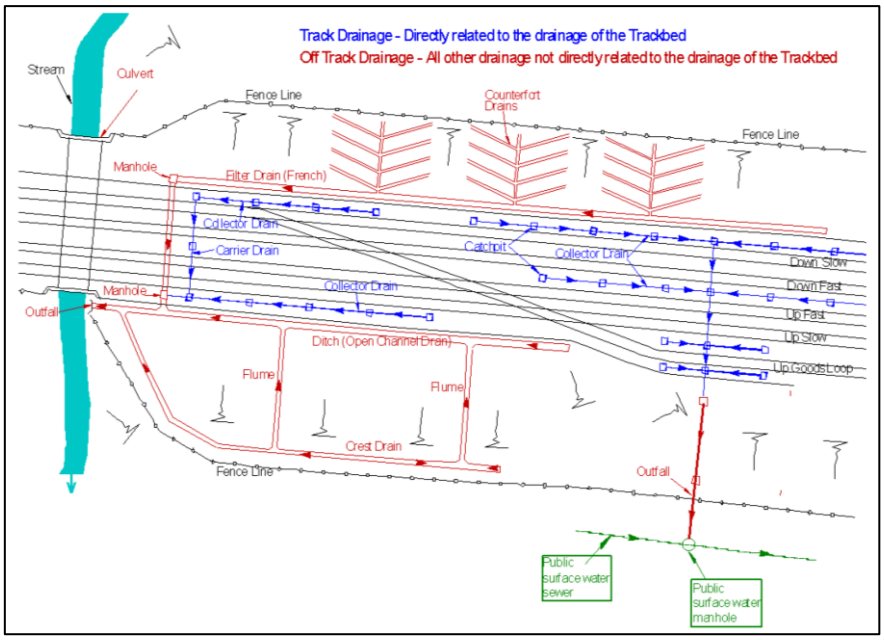


Figure 2-1 – A typical railway drainage system (Network Rail, 2017a)

2.3.1 **Surface drainage systems**

Surface drainage systems are commonly constructed at ground level and are easily accessible (Network Rail, 2017a). Usually, surface drains are preferred to sub-surface systems as they are simple and cheaper to construct, inspect and maintain. Surface drainage systems mostly collect surface runoffs and prevent the ingress of water into critical areas such as earthwork slopes and track components (MORI, 2005, RailCorp, 2009). The following sections discuss the main assets used in railway surface drainage systems and their applications.

2.3.1.1 **Channels**

Channels are one of the most common forms of surface drainage asset (MORI, 2005). Depending on the location and site constraints, channels are constructed in different sizes and

shapes such as trapezoidal, U-shaped and V-shaped. To protect the channel surface and reduce the deterioration rate, channels are commonly lined with materials such as concrete, stone and geotextiles. The selection of lining material is influenced by factors such as flow volume, channel slope and environmental conditions (Network Rail, 2018). Vegetation can also be used for channel surface linings. In earth channels (i.e. ditches dug into the ground), vegetation is recommended to maintain the stability of the channel's banks and to reduce the erosion risk. However, in artificially lined channels, vegetation growth can reduce the design flow capacity and cause multiple issues such as sedimentation, blockage and flooding (Network Rail, 2011b).

2.3.1.1.1 Channels used in crest drains

Crest drains are located on top of cutting sections and drain runoffs from adjacent catchment areas that slope towards the track. The presence of crest drains is critical as they help to reduce both erosion of the slope face and the risk of slope failure by preventing water from entering the upper parts (crest area) of the slope (ARTC, 2006). Channels are used extensively in crest drains, where the majority of water sources are surface runoffs. In the presence of sub-surface water, crest drains are usually fitted with a pipe to collect the underground flows (Network Rail, 2018). Figure 2-2 presents an example of an earth channel used in a crest drain.



Figure 2-2 – Example of open channel crest drain in construction

2.3.1.1.2 Channels used in cess drains

Cess drains are located at track level on each side of the line. They are designed to collect and drain runoff from the track itself and also the slopes in cutting sections. Channels are commonly used in cess drains where there is enough space. Similar to crest drains, where sub-surface water flows are present, cess drains are fitted with a pipe (Network Rail, 2018). Figure 2-3 presents an example of a channel used in a cess drain.



Figure 2-3 – Example of open channel cess drain

2.3.1.1.3 Channels in toe drains

Toe drains are located at the bottom of embankment slopes. They may also be constructed in cuttings if the track is at some distance to the slope base. Toe drains collect and drain runoffs from embankment structures and, more importantly, from adjacent catchment areas that slope towards the bottom of embankments. Channels are the most common asset used in toe drains; however, a combination of pipes and channels is recommended in sections with underground water (Network Rail, 2018). Figure 2-4 presents an example of a channel used in a toe drain.



Figure 2-4 – Example of open channel toe drain in construction

2.3.1.1.4 Channels in slope drains

Slope drains are located on cutting or embankment slopes. They carry runoffs from the slope to the cess drain in cuttings or the toe drain in embankment sections. Cascades (for more significant flows) and flumes (for smaller flows) are two common types of open channel used

in slope drains. To prevent damage from high runoff velocities, cascades are generally stepped in high slopes to prevent water flowing at supercritical velocity. This is because high flow velocities can significantly erode the channel and damage the cess or toe drain (Network Rail, 2011a, MORI, 2005). Examples of a cascade drain (Figure 2-5) and a flume drain (Figure 2-6) are presented below.



Figure 2-5 – Example of stepped cascade drain



Figure 2-6 – Example of flume drain

2.3.2 **Sub-surface drainage systems**

Sub-surface drainage systems are entirely or partially below ground level. In general, sub-surface drainage systems are designed to lower the water table level as well as draining any underground water flows if required. They also drain the surface run-off which have percolated into the track infrastructures through the soil or the track ballast. According to NR, a sub-surface drainage system starts when collected surface runoffs enter an inlet, and it ends where the runoffs exit through an outlet (Network Rail, 2017a). Based on the work of Chandra and Agarwal (2007), sub-surface drainage systems are required at locations with problematic soil conditions where surface water has percolated into the rail formations. This can have an adverse effect on track safety and stability. This statement, however, does not address the issues of existing water tables or changes in their level at cutting sections. In cutting sections, where the water table is at or near ground level, sub-surface drainage systems are necessary to maintain the stability of the slope and avoid track flooding (MORI, 2005, RailCorp, 2009). Sub-surface drainage is also used in sections with space constraints such as junctions, multiple track sections, bridges and cuttings with no space at the sides of the track (UFC, 2004, RailCorp, 2009).

2.3.2.1 **Pipes**

Sub-surface pipes are generally in the form of carrier or collector drains (Network Rail, 2017a). Carrier pipes are solid surface pipes designed to move the water to the outfall, and collector pipes have perforations on the surface to allow the collection of water as well as carrying it to the outfall. Sub-surface pipes are usually surrounded with appropriate granular filter material and associated permeable geotextile in a rectangular ditch (Network Rail, 2018). This is to minimise the ingress of silt into the drainage system while allowing water to pass freely. As

mentioned in the previous section, pipes are used in various applications, including crest, cess, toe and slope drains.

2.3.2.2 **Culverts and syphons**

Culverts are considered as any type of structure that allows conveyance of water through an embankment while withstanding the track's dead load, as well as the live load of passing trains (RailCorp, 2009). Culverts are constructed in various shapes such as circular, rectangular and arch-shaped, and with different materials such as concrete, steel and brick. To avoid blockage failures, culverts are commonly fitted with trash screens at their inlets (Network Rail, 2011a). Figure 2-7 presents an example of a brick culvert. Syphons are similar to culverts; however, they are mostly used in cutting sections. Syphons are U-shaped pipe drains that pass the flow under the track or any other obstacle in a cutting section. A syphon's inlet and outlet are located at the top of the cutting and are also commonly fitted with trash screens (ARTC, 2006). Figure 2-8 presents an example of a syphon with fitted trash screen.



Figure 2-7 – Example of brick culvert



Figure 2-8 – Example of syphon inlet with trash screen

2.3.2.3 **Catch-pits**

Catch-pits act as a sump and filter silt and debris from the drainage system (Network Rail, 2011a). The inlet pipe in catch-pits is located higher than the outlet, allowing a constant flow of water through the catch-pit. Silt and debris are then accumulated at the bottom of the catch-pit, which needs to be cleaned and maintained regularly. Catch-pits are usually located no more than 30 m apart along the track. Figure 2-9 shows an example of a catch-pit drain.



Figure 2-9 – Example of catch-pit

2.4 Asset deterioration and contributing factors

The deterioration process of drainage assets broadly falls into two categories, structural and service defects. Structural deterioration of assets generally occurs when the fabric and integrity of the asset are affected. This can include breakage, cracking, misalignment and collapse. Service deterioration, which is also referred to as hydraulic deterioration, is associated with a reduction in asset capacity. This can be the result of issues such as blockage, siltation and increased surface roughness. This section discusses the structural and service deterioration of railway drainage assets and its contributing factors. Due to the lack of literature available on specific drainage components, this thesis focuses on four main railway drainage assets, namely catch-pits, pipes, culverts and channels. Furthermore, since the literature on railway drainage assets is limited, other similar networks, including roads and highways, watermains and sewer networks, were also reviewed.

2.4.1 **Catch-pit deterioration**

Structural deterioration of catch-pits typically includes breakage and collapse of the pit and cover damage. Generally, any factor affecting the structural integrity of the catch-pit is considered as structural deterioration. Catch-pit service deterioration reduces the functionality of the asset, which usually is associated with a reduction in capacity. This can occur by excessive sedimentation and blockage, root intrusion or ballast ingress. It is worth noting that although sedimentation reduces the design volume of a catch-pit, sediment collection is a function of the catch-pit. Catch-pits are designed to collect and retain flow sediments to prevent sedimentation and blockage in other assets where maintenance is more difficult (e.g. pipes). Sediment collection by catch-pits also prevents water pollution downstream of the system (ARTC, 2006, Network Rail, 2011b, Network Rail, 2017a).

2.4.1.1 **Factors affecting catch-pit deterioration**

Catch-pit flow rate – Lager et al. (1977) carried out several laboratory tests on catch-pit performance and solids removal efficiency. As a part of these tests, the effect of flow velocity on the rate of particle settlement was reviewed. Based on their findings, the removal of medium to large particles is not affected by flow velocity. Nevertheless, the settlement rate is still reduced to approximately 35% when the inflow rate reaches its maximum design rate. This is explained by the fact that faster flows remove particles from the catch-pit quicker and do not allow enough time for settlement. This is, however, slightly different for finer particles as their settlement rate is susceptible to flow rate. According to Lager et al. (1977), increasing the flow rate reduces the removal rate of finer particles. The removal rate is assumed to be almost negligible, even at 40% of the maximum design flow rate of the catch-pit.

Butler et al. (2004) carried out similar laboratory tests to evaluate the rate of sedimentation at different flow rates (0.5, 1, 4, 12, 20 L/s) and for different particle sizes (< 100, 100–500, 500–1000, 1000–10000 µ). The results of this study were in agreement with Lager et al.'s study. According to Butler et al. (2004), 100% of larger particles (> 500 µ) were removed even at the maximum flow rate of 20 L/s. For particles between 100 and 500 µ, the rate of sedimentation was 75% at 0.5 L/s, which was reduced to 47% by increasing the flow rate to 20 L/s. For smaller particles (< 100 µ), the sedimentation rate was considerably lower compared to other particle sizes: 33% at 0.5 L/s, reducing to 18% at 20 L/s. The study by Pennington and Kennedy (2008) on quantification of catch-pit sedimentation also confirmed the effect of flow rate. This study was commissioned in Auckland for evaluation and quantification of road catch-pit sedimentation, where flow velocity was shown to have little influence on larger particles.

Capacity and plan area – Memon and Butler (2002) studied the effect of capacity and base plan area on the ability of road catch-pits to retain solids. The simulation test was conducted

on three catch-pit sizes (50, 100, 200 L) for over 50 weeks. According to Memon and Butler, increasing the catch-pit capacity can significantly improve solid retention. For the base plan area test, two catch-pit volumes (100 and 200 L), with plan areas of 0.159 and 0.318 m^2, were tested. Similar to capacity, plan area also resulted in an increase in annual accumulation of suspended solids. The improvement in solids removal in larger catch-pits is explained by the fact that larger catch-pits hold a larger volume of water in the pit for a longer time. This will eventually allow more settlement of suspended solids. It should be noted that sedimentation is in fact the purpose of catch-pits, which is to remove suspended solids and prevent downstream contamination. However, any type of sedimentation reduces the capacity of the pit, which is considered as service deterioration over a long period, and needs to be removed.

Catch-pit frequency – Following on from the capacity and plan area tests, Memon and Butler (2002) further assessed the impact of catch-pit frequency on the accumulation of suspended solids. Catch-pit frequency refers to the distance between catch-pits, or the total number of catch-pits in a defined area. Two frequencies of 20 and 40 catch-pits per hectare were simulated in Memon and Butler's study. The result showed that lower frequencies of catch-pits result in lower rates of solid retention.

2.4.2 **Pipe deterioration**

Most forms of pipe deterioration are the result of random probabilistic events such as a storm or an accident during excavation. According to Tran (2007), this makes the deterioration modelling of pipes difficult. The structural deterioration of pipes is associated with undesired changes in the integrity and fabric of pipes. Apart from gradual time-dependent deterioration such as brittleness, corrosion and weathering of the fabric or joint mortar, pipes can also fail by compression, collapse, cracking and misalignment (Network Rail, 2017a). According to NR, collapse, or cracking of pipes under compression may happen by increased traffic load;

however, assets are more likely to deteriorate due to time-dependent factors such as loss of mortar, corrosion in steel pipes and culverts, and brittleness of plastic pipes.

Similar to that observed for other drainage assets, service deterioration of pipes is generally the result of reduced capacity. Siltation is the most common form of service deterioration in all types of drainage assets including pipes (Highways Agency, 2009, Network Rail, 2011a, Rodríguez et al., 2012, Network Rail, 2017a). Siltation in pipes reduces the cross-sectional area and results in loss of capacity and total blockage. Siltation can also increase bed roughness, which can reduce the flow velocity and result in loss of capacity, and eventually allow more siltation over time. In fact, for small proportions of deposits, increased bed roughness is the main factor affecting a loss of discharge capacity (Highways Agency, 2009). Siltation is also one of the most critical service deterioration factors in sewer systems, leading to a reduction of cross-sectional area and an increase in roughness and potential flooding (Banasiak, 2008, Rodríguez et al., 2012, Ebtehaj and Bonakdari, 2016).

It is suggested that even in pipes with no siltation at the invert level, the presence of silt in normal operational flow can reduce pipe capacity by up to 4%. This is due to losses in flow energy, resulting from the presence of silt (Highways Agency, 2009). The study carried out by Banasiak (2008) on the hydraulic performance of silted sewer pipes also confirmed this. According to Banasiak, an increase in siltation depth from 2% to 10% can decrease the flow capacity by 10–20%. According to the NR drainage asset policy (Network Rail, 2017a), siltation in pipes and culverts can be exacerbated by a lack of sufficient slope for self-cleaning, poor structural condition and lack of maintenance. Intrusion of tree roots is another form of service deterioration, which can reduce capacity and increase bed roughness. Root intrusion into underground pipes is also one of the major issues in sewer systems. Root intrusion often results in a reduction of cross-sectional area and reduced flow capacity which can cause total

blockage and flooding. This issue in sewer sectors can be hazardous due to the probable contamination from potential surcharge and flooding (Kuliczkowska and Parka, 2017). Furthermore, land use and land changes in the catchment area can have a critical effect on the amount of siltation in a drainage system (Highways Agency, 2009).

2.4.2.1 Factors affecting pipe deterioration

Pipe material – Baik et al. (2006) conducted a study on the deterioration modelling of wastewater pipe systems. Pipe material, among other variables, was considered as a contributing factor in the modelling process. This study considered two pipe materials, namely vitrified clay and PVC. The results of the study revealed that pipe material has an insignificant effect on the deterioration process. However, in another study conducted by Micevski et al. (2002) on stormwater pipe deterioration, the effect of pipe material was revealed to be statistically significant. The two materials considered in this study were vitrified clay and concrete. Therefore, it can be suggested that the varying effect of pipe material on the deterioration rate is specific to the case and the function of the pipe.

Pipe diameter – Various studies suggest that pipes with a smaller diameter degrade at a faster rate. Fares and Zayed (2010) carried out a case study on a water supply distribution system where the pipe population was divided into two groups, small (< 250 mm) and medium (250–500 mm). According to Fares and Zayed, greater beam strength in large diameter pipes results in less pipe breakage. Kabir et al. (2015a) also applied this principle in the development of a failure prediction model for watermain networks. Their review of the network showed that smaller diameter pipes experienced more breakage than larger pipes. Hence, pipes were divided into two groups, small (< 150 mm) and large (> 150 mm). The study by Rajani and Tesfamariam (2007) on the failure of cast-iron watermains also confirmed this. According to this study, thinner pipes were shown to be more prone to corrosion failure. Alvisi and Franchini

(2010) carried out a similar case study on water distribution pipes. Analysis of the data revealed that the highest number of pipe breakages is associated with the smallest pipe diameter (< 100 mm), which covered 50% of their network. According to Alvisi and Franchini, this is justified by the fact that the wall thickness in smaller pipes is usually thinner and more susceptible to breakage and failure.

According to some other studies, the effect of pipe diameter on the deterioration process can be dependent on pipe material. Vanrenterghem-Raven (2007) considered pipe diameter as one of the main contributing factors in the structural deterioration of water distribution pipes. Similar to other studies, larger pipes were grouped together. Nevertheless, this study revealed that larger diameter pipes had a higher probability of breakage, which is in contradiction to the results of other studies. However, it should be noted that the large pipes in this study were all made out of steel. This suggests that the effectiveness of pipe diameter on deterioration can be statistically dependent on pipe material. The study carried out by Singh (2011) also confirmed this. Singh studied the probability of water supply pipe failure, considering several factors including pipe diameter. This study showed that in concrete cylinder pipes, the probability of failure is higher for larger diameters (16, 24, 30, 36, 42 inches). Contradictory to that, cast-iron pipes are more likely to fail at smaller diameters (4, 6, 8, 12 inches). Similar to pipe material discussed in the previous section, it can also be suggested that the effect of pipe diameter on deterioration is case-specific.

Pipe age – Age is generally considered as a critical factor in asset deterioration modelling for drainage and other similar networks. Wood and Lence (2009) studied the critical data required for breakage prediction models in watermain assets, where pipe age was found to be the most critical factor. However, a review of the data showed that the distribution of asset age was not

even for a valid statistical model. As a result, asset groups were developed based on having a sufficient number of breakages in each age period.

In other studies, where pipe age was considered as a deterioration factor, asset groups were developed based on fixed intervals. The study by Singh (2011), on causes of watermain pipe failure, considered a 10-year age interval, and Kabir et al. (2015b) study on watermain pipe failure risk considered a 20-year interval. Several other studies, including those of Baik et al. (2006), Tran (2007), Le Gat (2008) and Sempewo and Kyokaali (2016), also considered pipe age as a critical deterioration factor. However, these studies modelled the deterioration of individual assets rather than asset populations, and no age grouping strategy was suggested.

Pipe length – Kabir et al. (2015b) studied the effect of pipe length for evaluating the risk of watermain pipe failure. Pipes were divided into ranges of very short (< 25 m), short (25–100 m), medium (100–200 m), long (200–500 m) and very long (> 500 m). These ranges were based on the standard pipe designs used in the network. The outcome of this analysis showed that the effect of pipe length on failure risk was relatively small compared to age, diameter and flow velocity. The study of Baik et al. (2006) also considered pipe length in a deterioration model of wastewater systems. According to them, shorter pipes are more likely to fail compared to longer pipes. This is explained by the fact that shorter pipes are usually associated with more bends, which can cause more siltation, reduce the flow velocity and increase the likelihood of blockage.

Soil type – Jafar et al. (2010) conducted a study on the failure prediction of watermain pipes, using an artificial neural network model. While they assumed that the soil type around the pipe would be a significant factor in failure prediction, the outcomes of the model revealed otherwise. Therefore, the effect of soil type was neglected in the modelling process. However, the study carried out by Fares and Zayed (2010) showed that soil type is the most critical factor

among the environmental factors which affect the failure of watermain pipes. In their study, soil types were divided into five categories, very highly, highly, moderately, lightly and very lightly deteriorative. These ranges were based on multiple soil characteristics including soil corrosivity, pH value, soil uniformity and soil type. The study by Kabir et al. (2015b) on failure evaluation of watermain pipes also considered several soil factors, including soil pH. In this study, soil pH was divided in five ranges, very low (> 2), low (2–4), medium (4–7.5), high (7.5–8.5) and very high (> 8.5); however, its effect on failure evaluation was considered to be minimal.

2.4.3 **Culvert deterioration**

Similar to the challenges of pipe deterioration models, culvert deterioration is also considered an engineering challenge for transportation agencies (Salem et al., 2012). Several structural and environmental factors, including material, shape, dimension and soil type, can influence the deterioration process in culverts. Structural deterioration of culverts, similar to that of pipes, is associated with undesired changes in the structural integrity. This may include scouring at the culvert outlet, corrosion, inlet damage, joint separation and physical breakage or cracks. Service deterioration of culverts, similar to that of other drainage assets, is associated with a reduction in asset capacity. Reduction of culvert capacity, or the flow rate, can be the result of sedimentation, debris accumulation and blockage (Cahoon et al., 2002, McGrath and Beaver, 2004).

2.4.3.1 **Factors affecting culvert deterioration**

Culvert diameter – Mitchell et al. (2005) studied the factors that affect the deterioration process in metal and concrete culverts. According to this study, culvert diameter (i.e. rise) appeared to make a significant contribution to the deterioration process. Noll et al. (2012a) also

studied the factors that influence the structural and service deterioration of culverts, where material was revealed to be a significant factor. According to Noll et al., the effect of culvert diameter on structural deterioration is primarily explained by the load-bearing characteristics of culverts, which vary at different diameters.

Culvert age – Meegoda et al. (2004) used age as an indicating factor in culvert deterioration to design a strategic maintenance plan. They studied culvert service life and proposed a maintenance strategy with three frequencies, every year, every 3 years and every 10 years. Culverts, similar to other infrastructures, were assumed to deteriorate at a faster rate with age (i.e. older culverts degrade at a faster rate compared to younger ones). Therefore, in the proposed maintenance model, older culverts up to 10 years old would receive an inspection at the end of 10 years, culverts up to 15 years old would receive inspection every 3 years and culverts up to 30 years old and more would receive an annual inspection. This study, however, did not specify why the ages of 10, 15 and 30 years old were selected to group the culverts for inspection frequency.

The study by Mitchell et al. (2005) on culvert risk assessment considered initial age ranges of < 30, 30–60 and > 60 years old. However, after noticing the different deterioration behaviour in different materials, and in order to create an unbiased sample population, culverts were grouped differently based on their material. Concrete culverts were grouped in 1–50, 50–75 and > 75 year age ranges, metal culverts were grouped in 1–40, 40–60 and > 60 year age ranges and thermoplastic culverts were grouped in 1–20, 20–40 and > 40 year age ranges. These grouping ranges were selected simply to produce a meaningful cohort of culverts, where the deterioration rate is assumed to be constant in each cohort. Cahoon et al. (2002) also studied the effect of 33 factors contributing to culvert deterioration. By conducting a t-test on those 33

parameters, nine of them, including culvert age, appeared to have a significant effect (statistically significant) on the overall condition of the culverts.

Environmental pH level – Meegoda et al. (2004) study on the maintenance planning of culverts also used the culvert's environmental pH level as an influencing factor on the service life of corrugated steel culverts. The pH level of the culvert environment, including the water and surrounding soil acidity, was considered to be one of the main contributing factors in culvert corrosion. As discussed previously, three maintenance frequencies were developed in this study, where culverts that deteriorate faster receive inspection and maintenance at higher frequencies. To address the environmental effect, culverts in high-acidity environments (i.e. pH < 5) were considered in the annual inspection frequency group. For environments with medium acidity levels (i.e. pH 5–5.8), the 3-year inspection frequency was considered and for low acidity levels (i.e. pH 5.8–8) the 10-year frequency was considered. These pH ranges are recommended by the National Corrugated Steel Pipe Association for normal, mildly corrosive and corrosive conditions (NCSPA, 2002). Mitchell et al. (2005) also used the same recommended pH levels to develop a risk assessment and inspection procedure for highway culverts. Along with environmental condition (pH level), Mitchell et al. also considered other factors such as culvert material, shape, age, size, diameter, soil cover height and road type.

Culvert material – McGrath and Beaver (2004) developed a comprehensive and quantitative method to evaluate the performance of culverts. Three culvert materials were considered in the study, namely steel, concrete and polyethylene. Based on the findings of this study, culvert material variation did not have a significant effect on performance. However, the study carried out by Mitchell et al. (2005) showed a different result. They reviewed metal and steel culverts, where variation in culvert material was revealed to have a significant effect on the deterioration

process. Moreover, culvert types such as shape and surface configuration (e.g. corrugated) were also considered to be significant.

2.4.4 **Channel deterioration**

Structural deterioration of channels mostly occurs on the side slopes, known as bank failure. For unlined channels (earth channels), animal burrowing is another form of structural deterioration. For line channels such as those made from concrete and brick, structural deterioration is mostly associated with misalignment or cracking in the lining material. Similar to other drainage assets, siltation is considered the primary cause of service deterioration in channels. Lack of maintenance and an insufficient slope for self-cleaning can worsen the siltation in channels. Siltation can also reduce the flow capacity, flow velocity and cause blockages over time. Vegetation overgrowth is another form of service deterioration. However, as explained previously, this has a different influence on lined and unlined channels. In lined channels, vegetation can reduce the designed flow capacity, cause more siltation, and increase the risk of debris, trash and leaf accumulation. In contrast, vegetation in unlined channels can provide bank stability and protection and reduce surface erosion. In both cases, regular maintenance is required to avoid overgrown vegetation (Network Rail, 2011b, Network Rail, 2017a).

2.4.4.1 **Factors affecting channel deterioration**

The literature on humanmade drainage channels is significantly small; therefore, natural channels and streams were also reviewed to identify the factors contributing to deterioration. A study carried out on potential causes of surface stream deterioration of subwatershed (catchment areas) in the Santa Ana region in California identified three contributing factors, namely geology type, land cover and slope (RBF Consulting, 2014). However, the study

focused on general characteristics of the catchment area rather than the channel itself. According to this study, the geology factor refers to the combination of soil types that make up the catchment area. For land cover types, catchment areas were divided into agricultural, developed, forest, scrub and other (e.g. water, bare rock); developed land cover was considered the most critical type. It is generally assumed that steeper slopes result in a higher rate of deterioration. The Board's study addressed this by dividing the streams into three slope ranges of 0–10%, 10–20% and > 20%. Although the factors considered in the study are associated with the service deterioration of natural streams, similar approaches can be considered for channels and catchment areas in a drainage system.

2.5 Summary

The literature review in this chapter identified the purpose and physical boundaries of railway drainage systems, which is essential for developing an effective management tool. It was shown that a drainage system includes all components within a catchment area that collect, convey and dispose of the water which flows on and towards the railway boundaries. Furthermore, it was shown that the same asset can be used at different locations and for various applications. This potentially results in a complex deterioration process specific to the application.

The literature also revealed that asset characteristics such as material, shape and dimensions can have varying effects on asset deterioration depending on the network condition. For instance, the effect of pipe material on structural deterioration can depend on the soil condition and pipe diameter. Therefore, it can be suggested that drainage asset deterioration is case-specific to the network. The next chapter presents the literature review on asset management concepts and techniques suitable for the proposed management framework in this study.

3. ASSET AND RISK MANAGEMENT

3.1 Introduction

This chapter presents a literature review on asset and risk management concepts and techniques suitable for the development of a risk-based drainage management framework. Section 3.2 demonstrates the different levels of asset management and the data quality required for each level. Section 3.3 describes an appropriate mathematical approach for developing homogeneous asset groups. Section 3.4 reviews suitable techniques to address the two components of risk, namely probability and consequence analysis, and Section 3.5 describes a suitable analytical approach for assessing multiple consequence criteria. Finally, Section 3.6 provides a summary of this chapter.

3.2 Asset management levels and data quality

According to Haas et al. (1994), the need for better transportation management systems began in the mid-1960s, when highway agencies started to shift from constructing new roads to managing and maintaining already constructed large networks. According to Smith et al. (2001), maintenance and rehabilitation management models in transportation networks answer three main questions:

(i) Which section should be maintained first?

(ii) Which maintenance option is required?

(iii) When should the maintenance be carried out?

These management techniques were initially applied to specific sections of the network, which is commonly referred to as tactical/operational planning or Project-Level (PL) management (Spink et al., 2014). However, the need for a more comprehensive management system, capable

of analysing the entire network at strategic levels, became apparent with time (Smith et al., 2001). This led to the development of strategic planning approaches, also referred to as Network-Level (NL) management. The following section highlights the differences between NL and PL management approaches.

3.2.1 **Network- and Project-Level models**

NL models are usually applied to the entire network or extensive sections of it and are designed for the executive managers and main decision-makers to frame policy and standards (Daheshpour, 2018). NL models are commonly used to identify the most appropriate group of assets or network sections to receive maintenance while considering a limited budget. They are also used to determine the state of the network under different maintenance strategies and budget scenarios. Peterson and Faiz (1987) defined this as the 'What if' question, which allows decision-makers to prioritise maintenance and develop short- and long-term budget planning and deterioration models. According to Smith et al. (2001), NL models are usually based on several criteria such as condition, cost and benefit/cost ratio. For instance, if an NL model is based on condition grades, the priority of maintenance and rehabilitation activities is decided based on the criticality of asset condition level. Similarly, for cost or benefit/cost ratio, the priority of activities is typically based on the least expensive activity or that with the highest benefit/cost ratio.

In PL models, the focus is on shorter and more specific sections of the network, with an extensive amount of technical information. According to Peterson and Faiz (1987), unlike those in NL models, decisions in PL models are usually made by medium- to low-level managers. Smith et al. (2001) further described the difference between PL and NL management models by two cost factors. Firstly, PL models require detailed data and specific technical information which are more expensive to collect, maintain, store and run for each specific section of the

network. In addition, considering limited budgets and the competition between infrastructure managers to allocate funds, justifying the high costs of PL model analysis can be difficult. Therefore, with a limited budget, higher managers and executive decision-makers often only opt for NL models.

3.2.2 **Information quality levels**

The level and quality of data required for NL and PL models are different. This is defined as the Information Quality Levels (IQL), developed by the World Bank (Paterson and Scullion, 1990), which provide a guideline for the nature of the data used at different management levels. IQL is developed to ensure that data is used sufficiently and in a consistent way in the model. IQL is classified by four levels (IQL-I, II, III and IV), from IQL-I at which data are most detailed to IQL-IV at which data are mostly a summary. Generally, strategic and long-term planning in NL approaches requires fewer data compared to the specific models in PL models. According to the World Bank, for the long-term planning in NL approaches, which is the purpose of this thesis, IQL-IV is sufficient.

The primary sources of data required for the management framework proposed in this thesis are asset inventory data, condition grades and maintenance unit cost. The World Bank provides specifications for data requirements at different IQL for road networks (Robinson et al., 1998). However, the principles of data quality are the same, and the guidance can be applied to the railway drainage network too. For inventory data at IQL-IV, while the complete list of assets with names is required, many other characteristics can be collected at basic summary levels. For instance, the geometric characteristics of assets can be taken as a low-precision average. This mostly applies to drainage link assets such as pipes where geometric characteristics might vary along the asset length. In general, most inventory data can be collected with qualitative categories where necessary. For condition grading data at IQL-IV, an ordinal scale with open-

ended specifications is preferable. The grading system does not need to be specific with numerical ranges, and it can be based on visual inspection rather than physical measurement. This means that asset condition grades can be collected by visual inspection, and no CCTV recording is required. Finally, for unit cost data at IQL-IV, the national average unit cost of maintenance can be considered for a defined unit, such as per metre or asset.

3.3 Homogenous asset grouping

According to Costello et al. (2005), in strategic asset management models, assets with similar physical and operational characteristics (e.g. deterioration rate, function or geographic location) can be categorised into homogenous groups. Such homogenous grouping reduces the size and complexity of the model and allows the same set of strategic plans and standards to be applied to a group of assets. Although the review of the literature in the previous chapter highlighted a significant number of factors that affect the deterioration rate, few studies provide clear guidelines on how best to group assets. A simple approach could be to group every asset type based on each characteristic that affects its performance. For example, assuming that a culvert's deterioration is affected by material type, size and shape, and that culverts in the network are of two types, three sizes and four different shapes, potentially there will be $2 \times 4 \times 3 = 24$ homogenous groups for culverts alone. It would be significantly time-consuming to analyse and develop a unique deterioration model for each group. There is also a possibility of an unequal distribution of data where not all those 24 groups have enough culverts in them to be sufficient for an accurate statistical or probabilistic model. Furthermore, there is the possibility that some groups could exhibit similar deterioration behaviour which could be categorised in one group. The following section describes a mathematical approach (i.e. regression model) which has been previously used in the literature to address these challenges.

3.3.1 **Regression models in asset grouping**

Regression models have been widely used for asset grouping purposes (e.g. for maintenance and renewals) in both NL and PL management models. Kim et al. (2018) developed a practical management model, capable of identifying road sections with a higher priority of maintenance requirements. According to Kim et al., such models are essential for maintaining a sustainable road network with a limited budget. To achieve this, they utilised a logistic regression model to select NL road sections for maintenance. The outcome of logistic regression models is a dichotomous variable (i.e. Yes, No or 1,0). To accommodate this, Kim et al. considered the outcome variable as the road section being selected or not selected for maintenance. The developed model studied the effect of several predictor variables, including vehicle type, speed limit and road condition on the outcome variable (i.e. selected/not selected for maintenance) and successfully identified their significance level. Mitchell et al. (2005) also used a regression approach to develop a comprehensive risk assessment tool for the management of culverts. In their study, different methods of linear and non-linear regression models were used to identify the characteristics that affect the deterioration rate of culverts (e.g. age, material, dimensions, depth, wall thickness and flow velocity) and their significance level. The findings of the study were used to prioritise maintenance actions for culverts.

Wu et al. (2019) also used a regression analysis to investigate the characteristics of four drainage assets and their influence on service degradation. The following assets and characteristics were studied:

- Channels: material, shape, width, location
- Chambers: material, shape, location
- Culverts: material, inlet size, shape, location

- Pipes: size, material, shape, location

In this study, a linear regression model was used to understand whether the above-mentioned asset characteristics had a statistically significant influence on service degradation, which was then fed into a degradation model. The model was able to identify the influencing factors, however, Linear regressions in this case, only assess the relationship between one input (asset characteristics) and the output (service degradation); therefore, the underlying correlation between asset characteristics will be ignored. For example, if a specific material with only a particular shape was influencing the service degradation, the linear regression model would not be able to detect that. Furthermore, each asset characteristics can include multiple levels (i.e. different shapes, materials, size ranges, etc.). A linear regression model might not be able to precisely assess which level of the input parameter (asset characteristics) is influencing the degradation. For instance, pipe material was found out to have a significant influence on service degradation; however, it is not clear that which specific material is causing that influence. The following sections discuss the general process for selecting the appropriate regression approach.

Generally, selecting the appropriate regression model depends on the type and availability of variables and their associated data (Field, 2013). In statistical terms, variables are commonly characterised as scale or categorical. Scale variables, also referred to as continuous variables, are data that are in order and have a meaningful metric unit. Examples of scale variables in the context of railway drainage include asset age, length and dimensions. Categorical variables can include ordinal and nominal variables. Ordinal variables are also ordered; however, they have no meaningful metric unit. Examples of ordinal variables are asset condition (e.g., serviceable, marginal and poor) and risk level (e.g., low, medium and high). Nominal variables are

categories with no ranking whatsoever, such as asset material, asset location and asset shape (Tran, 2007).

Statistical analyses commonly study the relationship between several predictor variables (Independent Variables – IV) and an outcome variable (Dependent Variable – DV). In this study, potential IVs are asset characteristics such as age, material, dimension and shape, and the DV is asset deterioration behaviour. This implies that the proposed statistical analysis must handle multiple IVs and potentially a single DV. Furthermore, a review of the data in drainage and similar networks showed that IVs can include both scale and categorical variables; therefore, a statistical analysis capable of handling both variables must be selected. According to most statistical analysis guidebooks, for a single DV, the only statistical approaches capable of analysing multiple IVs of both scale and categorical natures are logistic and multiple regressions (Field, 2013). As discussed previously in the study by Kim et al. (2018), in logistic regression models, the DV must be a categorical variable with dichotomous levels. However, in this thesis, it would be challenging to design a DV for asset deterioration with only two categorical levels (i.e. dichotomous). In order to effectively model the deterioration behaviour of assets, the DV will potentially be a scale variable, developed from the numerical condition grades of assets. Therefore, it can be suggested that a multiple regression, capable of analysing scale DVs, is suitable for the proposed framework. The following section provides a background and discusses the requirements of multiple regression models.

3.3.1.1 **Multiple regression**

As discussed in the previous section, Multiple Regression (MR) can incorporate multiple IVs and a DV. The MR formula, as presented in Equation (3-1), is an extension of the general linear regression.

$$Y = b_0 + b_1x_1 + b_2x_2 + \cdots + b_nx_n + \varepsilon \quad (3\text{-}1)$$

Where:

Y is the parameter estimate of the dependent variable

b_0 is the constant intercept of the regression line

x_n is independent variable n

b_n is the correlation coefficient for independent variable n

ε is the error and represents the uncertainty in the model

In order to develop a reliable regression model, the minimum sample size required, n (e.g. the number of assets) should be proportional to the number of IVs, m. As a general rule of thumb, Equation (3-2) can evaluate the minimum sample size (Field, 2013).

$$n \geq 50 + 8m \quad (3\text{-}2)$$

The performance of MR models is significantly affected by the order in which IVs are entered into the model equation (Equation (3-1)) (Tabachnick and Fidell, 2013, Field, 2013). If all IVs are uncorrelated, the order of IV entry into the model will have a minimal effect. Based on the IV entry method, MR models are categorised into three types, which are described below.

Standard multiple regression (forced entry)

In this method, all IVs are entered into the model together, regardless of any underlying correlation between them. Using this method, the model only considers completely isolated correlations between the DV and each IV, and the combined relationships of IVs on the DV will be ignored. This is best presented with the Venn diagram in Figure 3-1 (Tabachnick and Fidell, 2013). It can be seen that although IV2 has a significant correlation with the DV, its contribution to the model is almost neglected because it has a minimal isolated correlation.

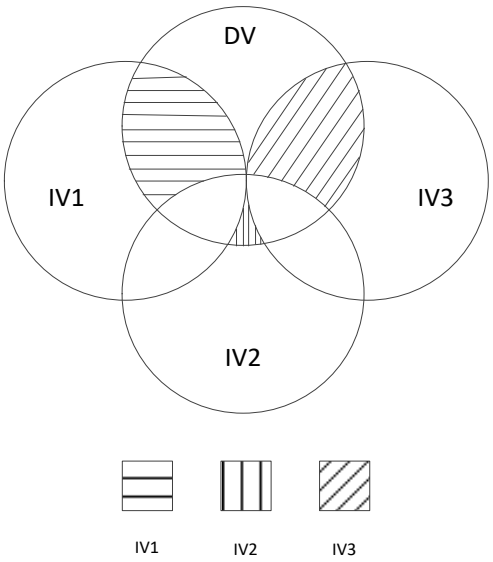


Figure 3-1 – Standard multiple regression (forced entry) outcome

Sequential/hierarchical regression (block-wise entry)

In this method, IVs are entered into the model based on the researcher's judgment. As described in the Venn diagram in Figure 3-2, assuming IV1 is entered into the model first, followed by IV2 and IV3, all the correlation with the DV will be assigned to IV1, while IV2 gets credit for whatever is left. In this method, the area shared between IVs will only be assigned to the IV that enters the model first.

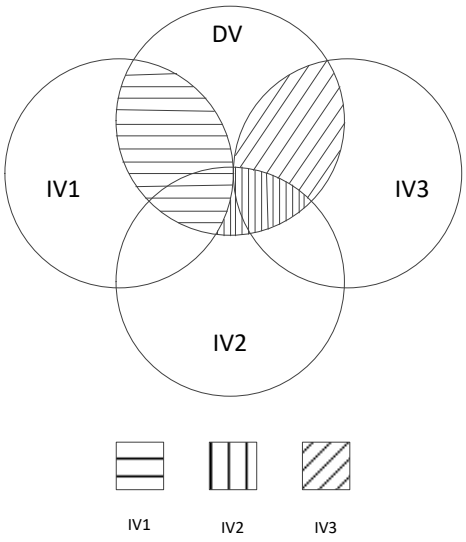


Figure 3-2 – Sequential/hierarchical multiple regression (block-wise entry) outcome

Statistical/stepwise regression

In this method, a statistical analysis determines the order in which IVs are entered into the model, and the IV with the highest correlation (i.e. shared area) enters the model first. As presented in Figure 3-3, assuming that IV1 has the highest correlation with the DV, followed by IV3 and IV2, IV1 enters the model first and gets credit for all of the correlation, even though the correlation is shared with IV2. IV3 is entered into the model after IV1, and therefore the correlation between IV2 and the DV is almost neglected because it is entered last in the model.

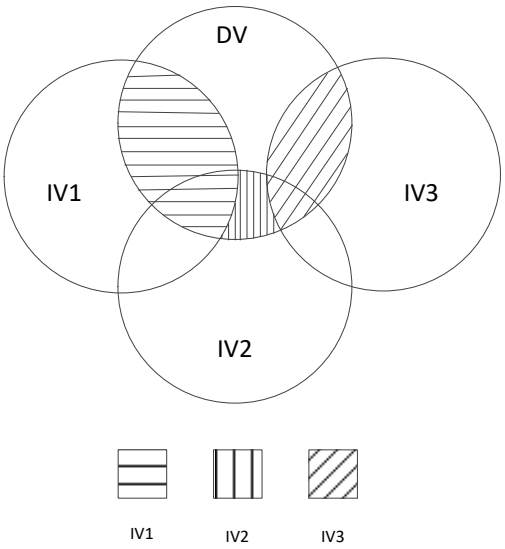


Figure 3-3 – Statistical/stepwise multiple regression outcome

3.3.1.1.1 Data quality in multiple regression

Applying MR to a dataset using a computer program will always generate an output regardless of the quality of the data (Field, 2013). Hence it is essential to ensure that the input data are of sufficient quality and that critical assumptions concerning the quality and quantity of data are met. This section describes these assumptions and methods that can be used to amend poor-quality data for MR models.

3.3.1.1.1.1 Outliers

Outliers are data points whose values are inconsistent with those of other data points. Including outliers in a regression analysis can result in the misinterpretation of data. As shown in Figure 3-4, a single outlier can significantly alter the regression line by shifting the mean estimate towards the outlier. Apart from the mean, outliers can also erroneously affect other parameters such as standard deviations, confidence intervals and the sum of squares. The most common forms of outliers are errors in data collection and data entry into the model. To best represent the true nature of data, outliers can be removed from the dataset, or replaced with the next

closest value. It should be noted that not all outliers are the results of errors. Therefore, outliers must be reviewed carefully and only removed if proven to be erroneous.

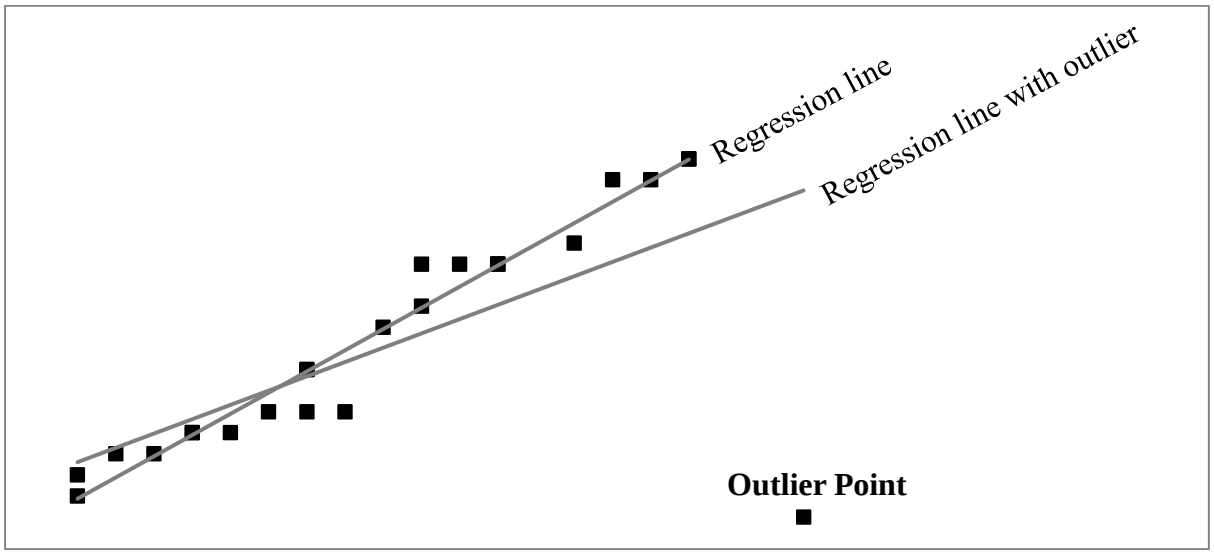


Figure 3-4 – Effect of outliers on regression analysis

3.3.1.1.1.2 Linearity

This is the assumption of linearity for the relationship between the DV and each IV (Field, 2013). Although a lack of linearity does not invalidate the results of the MR, it does weaken them. If linearity is violated, a number of data conversion methods can be used to cope with the lack of linearity. These methods include log transformation, square root transformation, and reciprocal and reverse score transformations (Field, 2013). It should be noted that any data transformation also transforms the outcomes, which needs to be considered in the final interpretation of the model (Tabachnick and Fidell, 2013).

3.3.1.1.1.3 Normality

Normality does not necessarily imply that the data should be normally distributed (Field, 2013). Although most techniques assume normality of samples, this assumption is not of concern for

large data sets. According to the central limit theorem, the distribution of sample means, taken from a larger non-normal population, approximates to a normal distribution (Pallant, 2016). Hence, regardless of the type of data distribution, the parameter estimate will be normally distributed if the data set is sufficiently large (Field, 2013). A lack of normality can make the estimates of regression parameters less optimal, but it does not invalidate them. If only the estimation of model parameters is required, then the assumption of normality is not critical. However, for estimating confidence intervals or significance level testing, the assumption of normality is essential (Tabachnick and Fidell, 2013).

3.3.1.1.1.4 Homoscedasticity and multicollinearity

Homoscedasticity, or homogeneity of variance, assumes that the variability of data points is constant between a continuous IV, or across all levels of a categorical IV (Tabachnick and Fidell, 2013). Similar to linearity, lack of homoscedasticity does not invalidate regression parameter estimates but does weakens them. However, there are data conversion techniques available to overcome homoscedasticity issues (Field, 2013).

Multicollinearity assumes that the relationship between IVs is not statistically significant. Such relationships are problematic and make it challenging to identify which IV is responsible for the variations in the DV. For example, if there is a relationship between pipe dimension and wall thickness (i.e. larger pipes having thicker walls and smaller pipes having thinner walls), the MR model cannot predict which factor is responsible for the deterioration rate (Tabachnick and Fidell, 2013).

3.4 Risk analysis

As discussed previously, this thesis aims to develop a management framework which is based on the risk of drainage asset deterioration. According to Vose (2008), an understanding of risk

and its associated uncertainties can improve the decision-making process in management models. The British standard of risk management defines risk as the product of probability (i.e. likelihood) and the consequences of an undesired event (BSI, 2010). The following sections discuss the mathematical and management techniques suitable for analysing the probability and consequences in the proposed framework.

3.4.1 **Deterioration probability analysis**

Morcous et al. (2002a) investigated the deterioration models used for infrastructure management and classified them into three types, namely Deterministic, Soft computing/Artificial intelligence and Statistical/Stochastic models.

Deterministic models are often mathematically simple and used in situations where the relationship between the model input and output is certain and straightforward (Tran, 2007). Such models use a mathematical formulation to deterministically describe the relationship between the factors affecting deterioration and the condition of assets (Morcous et al., 2002a). As discussed previously, deterioration of drainage assets, similar to that of most infrastructures, is a probabilistic process with high levels of uncertainty. This makes deterministic models, which neglect such uncertainty and error in deterioration models (Madanat et al., 1995), unfit for the proposed framework.

Soft computing/Artificial intelligence models aim to imitate, generalise and automate the intelligent behaviour of the human brain (oise Fogelman-Souli and Gallinari, 1998). These models are generally driven by data rather than the model. Such approaches are also referred to as black-box models, where the model input and output are more important than the underlying modelling mechanism and assumptions (Tran, 2007). As discussed previously, the uncertainty associated with drainage deterioration is partially due to inconsistent and

incomplete historical data, which makes Soft computing and Artificial Intelligence models unfit for the proposed framework.

Statistical/Stochastic models are the most common approach used for infrastructure asset management (Morcous et al., 2002b). Such models are capable of addressing the randomness and uncertainty in asset deterioration (Tran, 2007). Consequently, they are a suitable technique for the framework proposed in this study. Within stochastic approaches, Markov models are the most common technique used for infrastructure deterioration models (Morcous et al., 2002a); they are discussed in the following section.

3.4.1.1 Markov models

According to Tran (2007), Markov theory has been used extensively in asset management models, because of their reliability and robustness. In the context of asset deterioration models, Markov theory implies that the future condition of an asset only depends on its current condition. One of the predominant applications of Markov theory is the deterioration modelling of road networks. Kerali et al. (1992) developed a computer program (NETCOM) for predicting the medium- to long-term effect of different maintenance strategies on the performance of roads. Similarly, Costello et al. (2005) developed a stochastic Markov model for road pavement deterioration under different maintenance regimes and Gao and Zhang (2013) studied the user costs of various road maintenance strategies using a Markov-based approach for road surface deterioration. Markov theory has also been used in railway network deterioration models. Bai et al. (2015) developed a Markov-based model to evaluate the deterioration rate of railway tracks. Prescott and Andrews (2015) and Burrow et al. (2009) also successfully used Markov theory to predict track performance under various maintenance strategies.

Wu et al. (2019) used the Markov theory to model the service degradation of railway drainage systems in the UK. This model was incorporated with a linear regression model (see section 3.3.1) to improve the accuracy of the degradation probability estimates. Similar to most Markovian models, this study also used a continues time Markov Chain model, which assumes that the future condition of assets only depends on their current state. The concept of Markov theory has also been widely used in similar networks to drainage, such as those in stormwater, watermain and sewer systems. Micevski et al. (2002) used a Markov model to study the structural deterioration of stormwater pipes. According to this study, pipe diameter, material, soil type and environmental conditions have a significant influence on the structural deterioration of stormwater pipes. Following on from the successful study by Micevski et al., Tran (2007) compared a similar Markov deterioration model in stormwater pipes with four other practical models, namely Multiple Discriminant, Ordered Probit, Neural Network and Probabilistic Neural Network. According to Tran, the Markov model was revealed to be the most suitable approach for both structural and hydraulic deterioration models. The Markov model developed by Tran, which was applied to populations of pipes, was able to successfully cope with the high levels of uncertainty associated with inconsistent and snapshot data.

There are two types of Markov models, namely State-Based and Time-Based (Tran, 2007). State-Based models estimate the probability of assets transiting between condition states over a specific unit of time. In Time-Based Markov models, the time required for assets to transit to another condition state is estimated. This requires consistent historical data, which are commonly scarce in buried infrastructures such as drainage systems. Therefore, this thesis will focus on a State-Based Markov model approach.

The structure of Markov models is based on Markov chain theory (Ross, 2003). The basic principle of Markov chain theory implies that for any asset in condition *i* at time Y, there is a

probability P_{ij} that the asset will move to condition *j* at time Y + t (i.e. t is the analysis period). In Multi-State transition Markov models, transitions between more than two states are allowed (Tran, 2007). This means that assets can either stay in the same condition or move to any poorer condition. This is illustrated in the example in Figure 3-5, for a network with five condition states. Based on Markov chain theory, condition progression of assets can be estimated by using the Transition Probability Matrix (TPM), presented in Equation (3-3).

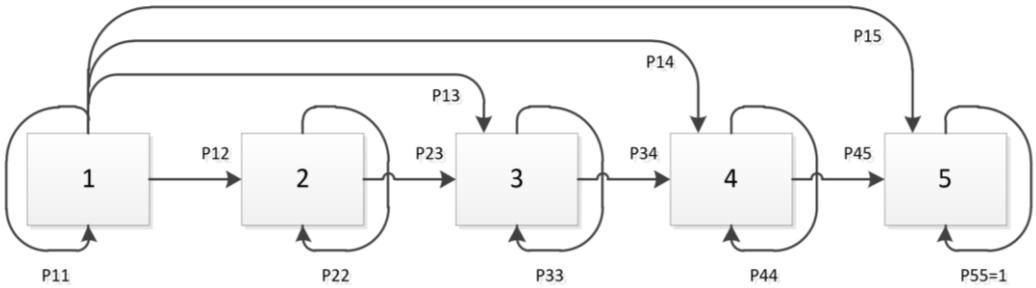


Figure 3-5 – Possible state transitions based on Multi-State Markov chain theory

$$\mathrm{TPM} = \begin{bmatrix} P_{11} & P_{12} & P_{13} & \cdots & P_{1j} \\ 0 & P_{22} & P_{23} & \cdots & P_{2j} \\ 0 & 0 & P_{33} & \cdots & P_{3j} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & P_{ij} \end{bmatrix} \quad (3\text{-}3)$$

Where:

P_{ij} is the probability of assets transiting from condition *i* to condition *j* over a time unit.

For any $i > j$, P_{ij} is 0 (i.e. assets cannot improve on their own).

3.4.2 **Deterioration consequence analysis**

As mentioned previously, risk is the product of the probability and consequences of an undesired event. While the probability component was discussed in the previous section, this section provides a review of consequence analysis in transportation networks, including road/highway and railways.

3.4.2.1 **Road network consequences**

Prioritisation of road sections by criticality level has been commonly practised in various road networks. In these approaches, criticality is associated with the serious consequences of an incident. The Department of Planning, Transport and Infrastructure in South Australia developed a land transport network criticality measure which applies to various modes of transport including roads, cycling routes and railways (Government of South Australia, 2013). This document, which provides a criticality hierarchy for the transportation networks, uses the following criteria:

(i) **Type of public transport** – In railway dedicated priority corridors, this is addressed as high speed, high frequency and high capacity lines between major centres.

(ii) **Average line usage** – This is addressed as Major Traffic Routes, measured by the number of vehicles per day on the route. Major Traffic Routes are divided into two levels, Metropolitan areas (> 20,000 vehicles per day) and regional areas (> 3,000 vehicles per day).

(iii) **Major freight routes** – This refers to major freight services between critical centres such as economic regions, industrial lands, ports and business centres.

(iv) **Peak hour routes** – These are critical routes which are heavily used by commuters between residential and employment areas.

(v) **Tourist routes** – This criterion mainly addresses the operation of road networks and highlights critical routes to major tourist destinations.

The New Zealand Transport Agency also developed a similar road criticality system, One Network Road Classification (ONRC) (New Zealand Transport Agency, 2013), which considers the following criteria:

- Average daily traffic volume

- Linking centres of populations, specifically daily work commutes
- Critical sole transportation modes with no alternatives
- Critical freight operation
- Critical routes to airports
- Hospital access
- Significant tourism areas

The road network in Scotland is prioritised based on three criteria: Economic, Social and Integrated Transport (Transport Scotland, 2016). Similar to the previous approach, this standard also assesses criticality based on traffic volume, economic criticality and tourism. In addition, Trans-European routes are also considered as highly critical due to their strategic role in the movement of passengers and freight internationally. Furthermore, in terms of social consequences, heavily populated areas (> 20,000 residents) are considered more critical. Access to health facilities and defence-related locations is also considered critical; however, this is mainly applicable to road networks. In rural Scotland, access to health centres and hospitals is often only viable via a single road, hence their accessibility is critical. Additionally, in terms of Integrated Transport, higher criticality is given to routes connecting to airports and ports to maintain an optimum service both nationally and internationally.

Criticality can also be measured by the potential number of customers affected in a failure event. Lifelines Infrastructures is a system used in New Zealand to assess the criticality of lifeline services such as transportation, water, wastewater, stormwater, energy and telecoms (Auckland Engineering, 2014). In this document, criticality is assessed based on three levels, Nationally Significant (affecting most of a significant region), Regionally Significant (affecting > 20,000 customers) and Locally Significant (affecting > 2,000 customers).

In another study by Rebello et al. (2019), four consequence measures, namely traffic volume, road function, lifeline assets and essential services, were used to prioritise road network criticality. As presented in Table 3-1, road criticality is measured by five priority levels, with quantitative traffic volume ranges and qualitative road function types. For lifeline assets and essential services, a scoring system was defined, which is based on the number of services and the number of affected customers. Lifeline and essential services include hospitals and large age-care facilities, ambulance, fire, police and emergency centres, major utility control centres (e.g. energy, telecoms), welfare centres, major outlet centres, major schools and industrial centres.

Table 3-1 – Lifelines resilience consequence measures specifications (Rebello et al., 2019)

Priority	Traffic volume (vehicles per day)	Road function	Lifeline assets	Essential services
5	> 10,000	Strategic	Score > 5	
4	5,000–10,000	Arterial	Score 3–4	
3	2,000–5,000	Arterial/collector	Score 1–2	
2	1,000–2,000	Collector	Score 0.5–1	
1	< 1,000	Local	Score < 0.5	

3.4.2.2 **UK Railway consequence analysis**

3.4.2.2.1 Corporate risk assessment matrix

Components of risk in the UK railway network, including the likelihood of events and their consequences, are evaluated by the Corporate Risk Assessment Matrix (CRAM) (Network Rail, 2019b). CRAM consequence areas are measured on a five-point grading system, where score 1 is the lowest and score 5 is the highest consequence level. CRAM assesses the consequence level based on four categories, namely Safety/Health/Environment (SHE), Performance, Finance and Satisfaction/Reputation. These categories (referred to as Impact

Areas in CRAM) are further specified into more detailed sub-categories which are discussed in the following sections.

3.4.2.2.1.1 Safety, health and environment

Safety – Safety consequences are measured based on the Fatalities and Weighted Injuries (FWI) index. This index is mainly used for derailment events where minor injuries or fatalities to passengers are measured. The safety sub-category is also applicable to staff and workers on site, specifically inspection and maintenance staff at risk of injury and fatality from moving trains. At the moment, an FWI value is predicted for a number of derailment scenarios on approximately every 100 metres of track.

Health – The Health sub-category is measured based on possible short- or long-term health effects and their severity. Examples of health issues provided in CRAM include work-related stress, Hand-Arm Vibration Syndrome (HAVS), and silica and asbestos issues. Similar to the Safety sub-category, Health effects are also measured by FWI.

Environment – This is measured by the Severity (i.e. negligible, minor, moderate and major effects) and Duration of adverse environmental effects (i.e. temporary reversible, minor reversible (< 1 month), moderate reversible (< 6 months), major reversible (> 6 months) and major non-reversible (> 5 years)). Route sections with significant environmental values (e.g. protected animal species, plants, bodies of water, etc.) are considered more critical, specifically for events such as flooding and pollution.

Energy and Carbon – This is assessed by the increased percentage in operational energy and greenhouse gas emissions, as a consequence of an undesired event.

3.4.2.2.1.2 Performance

Network Disruption – This is assessed by the duration of disruption measured in days. In general, unplanned disruptions are considered more critical than planned disruptions for maintenance or repair works.

Service Delivery – This is measured as the poor or non-performance of critical activities in days, which can cause customer disruption. Critical activities can include frequent passenger and freight services.

Asset reliability – This is measured by the percentage loss of asset reliability from the target for a defined period. Asset reliability is a management index developed by NR.

3.4.2.2.1.3 Finance

Cost (£) – This is measured by the cost of issues on the railways, which can include delays and cancellation costs, compensation, inspection, maintenance and renewals.

Budget – This sub-category assesses the cost consequence level as the percentage of the allocated budget for a defined period. Higher costs with low budget limits are considered more critical.

Efficiency – This is measured based on delivery of the efficiency target. Delivering 100% of the efficiency target indicates a low consequence level, while a reduction in the target delivery to less than 60% is considered as the highest consequence level. The efficiency target is another management index developed by NR.

Asset sustainability – This is assessed based on the cost of asset renewals differed from the allocated target.

3.4.2.2.1.4 Satisfaction and reputation

Media and Stakeholders – This is based on the level of media and stakeholder reactions to an issue. Sections with more stakeholders or critical routes connecting major locations are considered more critical.

Legal – This is assessed based on the level of legal consequences, given that an undesired event has occurred. These legal consequences can include breach of regulations, investigations and fines, major litigation, criminal prosecution, high fines and possible prison terms for executives.

Regulatory – This is assessed based on the involvement of the Office of Rail and Road (ORR). A 1–5 risk score on the ORR regulatory escalator is used, with higher scores indicating higher reputation and regulatory consequences.

Government – This is assessed based on the involvement of the Department of Transport (DFT) or Transport Scotland at intervention or management level. Greater involvement of these two bodies indicates a higher reputational consequence.

Internal – This is assessed based on internal disengagement affecting the efficiency of critical activities.

3.4.2.2.2 Track asset criticality

Track asset criticality was developed by NR to identify assets with the highest contribution to safety, performance (delay), maintenance and renewal costs (Table 3-2) (Network Rail, 2017b). This approach allows the whole-life analysis process to focus more on essential assets and assist with prioritisation of maintenance, work volume and budget. In this approach, safety consequences are measured by potential injury or death of passengers and staff. A Safety Risk Model (SRM), developed by the British Rail Safety and Standards Board (RSSB), is used to

address this. This model combines a fault tree of several track failure modes, calibrated by the total recorded train derailments and FWI over a long period, and provides an estimation of the expected mean number of FWI each year (Network Rail, 2017b). For delays, renewals and maintenance costs, historical data were reviewed to identify track assets with the highest contribution. As presented in Table 3-2, the highest contribution belongs to Switch and Crossing (S&C) assets.

Table 3-2 – Track asset criticality contribution (Network Rail, 2017b)

Asset	Failure modes (top events)	Contribution to **safety** risk	Contribution to **delay** costs	Contribution to **renewal** costs	Contribution to **maintenance** costs
Plain line (PL)					
Rail	Buckled rail	38%	35%	28%	25%
	Broken rail	6%			
	Fishplates	2%			
Sleeper	Gauge spread	2%	0%	22%	11%
Rail pads			0%	-	-
Ballast	Track twist	37%	13%	21%	17%
	Cyclic top	0%			
Formation			3%	1%	1%
Total PL			**51%**	**71%**	**54%**
S&C					
Half-sets			22%	4%	6%
Crossings			4%	4%	8%
Other rail			0%	0%	1%
Bearers			1%	9%	4%
Ballast			11%	8%	9%
Formation			3%	1%	0%
Total S&C		14%	**41%**	**27%**	**27%**
Other		1%			
Unattributed			8%		
Remainder				2%	19%

3.4.2.2.3 Drainage asset criticality

According to NR's Drainage Asset Policy (Network Rail, 2017a), drainage assets that are closer to outfalls are considered more critical. Almost all failures in outfalls or assets closer to outfalls can cause immediate flooding upstream of the system. Furthermore, similar to track standards, sections with S&C assets are considered more critical. Poor drainage can directly affect the stability of track formation and increase the derailment risk in sections with S&C assets. Also, drainage assets used on track are considered more critical than earthwork assets, because of their immediate effect on operations (e.g. delays, cancellation and speed restrictions) and safety issues (e.g. derailment) (Spink et al., 2014).

3.4.2.2.4 Common consequences tool

The Common Consequences Tool (CCT) is a probabilistic event tree analysis which is used by NR to assess the safety consequences of derailment (Network Rail, 2014). CCT is expressed as FWI per event, and considers the following locational line information:

- **Track number** – which determines the probability of the derailment path (e.g. train derails to cess or onto another track).
- **The number of trains per track per hour** – which determines the probability of two trains colliding in a derailment event.
- **The average number of passengers per train** – which affects the average FWI per event.
- **Type of secondary train (e.g. passenger, hazardous and non-hazardous freight)** – which determines the probability of the derailed train colliding with a second train.

CCT is currently only used for derailment risks caused by earthwork failure; however, with further development, it could consider other scenarios.

3.4.2.2.5 Track category

Track Category (TC) is a consequence measure which is mostly used in track and structure (e.g. culverts) standards within NR (Network Rail, 2016). These track categories are used to evaluate the frequency of inspection, repair timescale and renewal specifications. TC is derived from Equivalent Million Gross Tonnes per Annum (EMGTPA) (i.e. a factor of traffic volume) and line speed (i.e. a factor of derailment safety). TC has seven categories which are demonstrated in Figure 3-6.

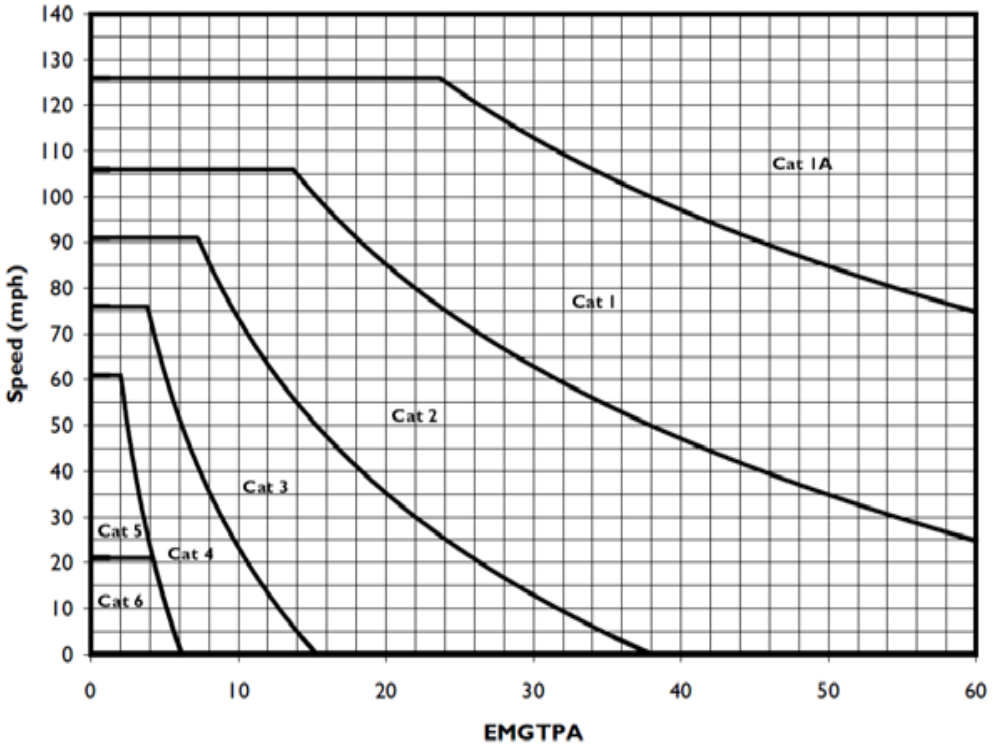


Figure 3-6 – Track category plot of Equivalent Million Gross Tonnes per Annum (EMGTPA) against line speed in miles per hour (Network Rail, 2016)

3.4.2.2.6 Route criticality

Route Criticality (RC) is a consequence measure used by NR (Network Rail, 2017b). In the development of RC, various segmentation methods were considered. However, Strategic Route

Sections (SRS), which segment the network into similar traffic levels and infrastructure types, was identified as an appropriate approach.

Previously, only two criticality levels were considered, which did not produce a reliable and accurate output. In the most recent development, it was decided that five criticality bands offer a good balance between accuracy and over-complexity (Network Rail, 2017b). In order to define the boundaries between the criticality bands, the national mean cost per train delay incident was considered. For instance, those SRS with a historical cost per incident of more than two times the mean are in RC band 1 (Table 3-3).

Table 3-3 – Route criticality specification (Network Rail, 2017b)

Route criticality band	Definition
Band 1	SRS with cost per incident more than two times the mean
Band 2	SRS with cost per incident between the mean and two times the mean
Band 3	SRS with cost per incident between the mean and half the mean
Band 4	SRS with cost per incident between half the mean and one quarter the mean
Band 5	SRS with cost per incident of less than one quarter the mean

3.5 Consequence criteria weighting factors

Based on the transportation consequence criteria reviewed in the previous sections, an ideal consequence analysis must consider the primary areas, namely safety, performance, finance and social. An outline of these transportation consequence criteria, which are applicable to the railway network, is presented in Figure 3-7.

An identified challenge in considering multiple criteria in the consequence analysis is estimating the relative importance of each area. To address this, a Multicriteria Analysis

(MCA), namely the Analytical Hierarchy Process (AHP), was studied. It has been suggested that AHP is an effective decision-making tool which can straightforwardly and conveniently determine the relative importance of multiple criteria (Joshua et al., 2017).

Ortiz-García et al. (2005) reviewed MCA approaches to develop a decision-making tool capable of considering social, political and environmental issues in determination of highway maintenance standards. Based on the findings of this study, AHP was revealed to be the most appropriate approach for the initial determination of maintenance standards. Joshua et al. (2017) conducted a similar study, where AHP was used to straightforwardly establish the relative importance of multiple weighting factors for determining road maintenance plans. The following section describes the AHP process.

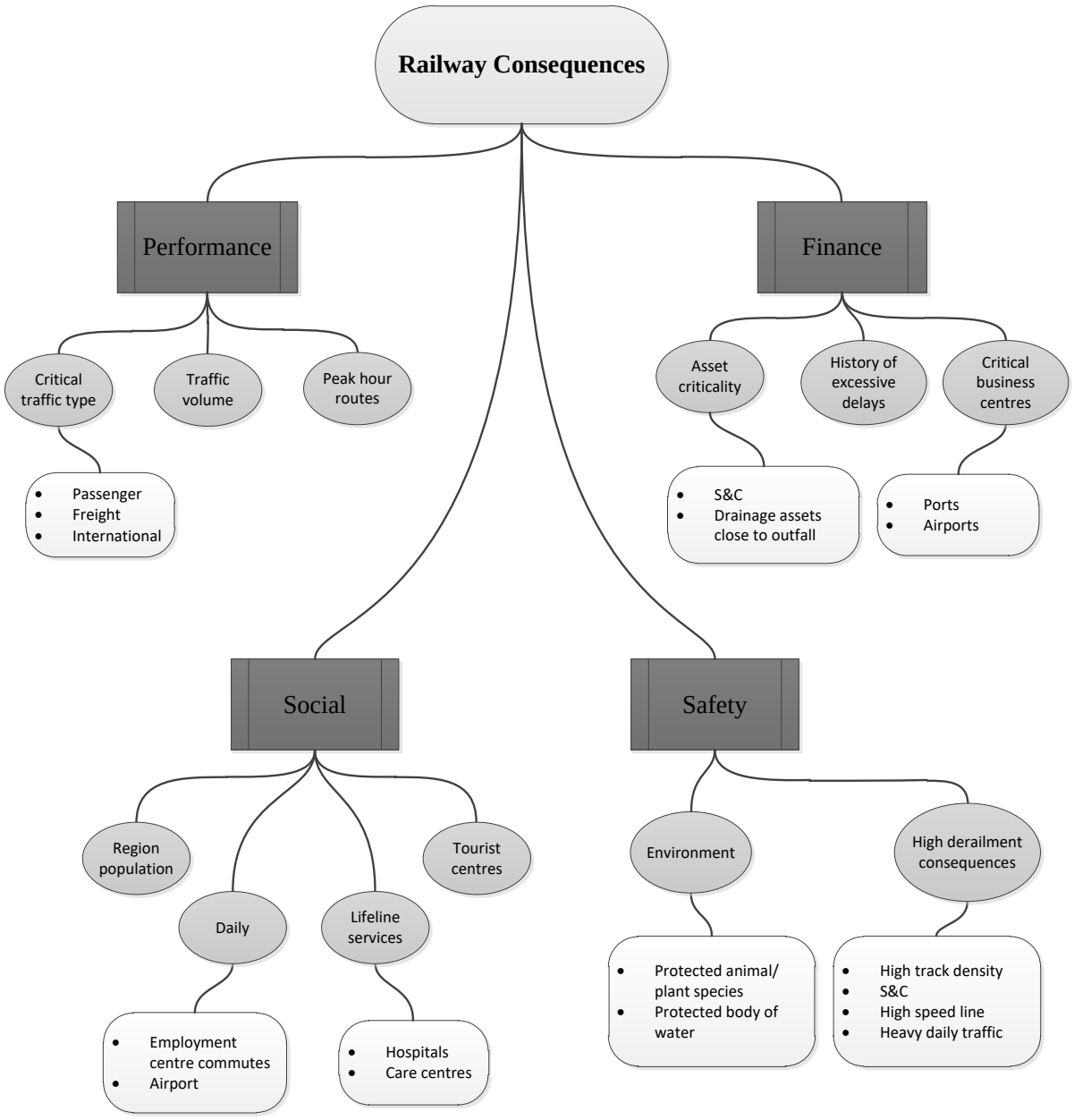


Figure 3-7 – Principal consequence areas identified for the railway network

3.5.1 **Analytical Hierarchy Process**

AHP relies on a rather simple yet robust process of PairWise Comparison (PWC). It has been suggested that the comparison ability of human brains is only limited to a few items at a time. The PWC process resolves this by allowing the study of multiple criteria while comparing only two items at a time (Saaty, 1980). The AHP approach estimates the relative importance of each criterion and demonstrates it with weighting factors that add up to 1. The relative importance

of criteria is determined by experts, based on the comparison scale proposed by Saaty (Table 3-4). In the process of PWC, the values in this table answer the question of 'which area is more important?' and 'how strongly?'

The comparison values, determined by expert opinion, are entered in the Comparison Matrix (CM) presented in Equation (3-4). The CM represents the comparison of areas in the left column with the areas in the top row. The total number of comparisons required for the CM, excluding reciprocal comparisons, is determined by Equation (3-5).

Table 3-4 – AHP pairwise comparison relative importance scale (Saaty, 2008)

Importance rate (x)	Definition	Explanation
1	Equal importance	Two activities contribute equally to the objective
3	Moderate importance	Experience and judgment slightly favour one activity over another
5	Essential or strong importance	Experience and judgment strongly favour one activity over another
7	Demonstrated importance	An activity is strongly favoured and its dominance demonstrated in practice
9	Extreme importance	The evidence favouring one activity over another is of the highest possible order of affirmation
2, 4, 6, 8	For compromise between the above values	
1/x	Reciprocals of relations	If A1 to A2 is 5, then A2 to A1 is 1/5

$$CM = \begin{bmatrix} CA_{11} & CA_{12} & \cdots & CA_{1n} \\ CA_{21} & CA_{22} & \cdots & CA_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ CA_{n1} & CA_{n2} & \cdots & CA_{nn} \end{bmatrix} \quad (3\text{-}4)$$

$$\frac{n(n-1)}{2} \tag{3-5}$$

Where:

CM is the comparison matrix

CA is consequence area

n is the number of consequence areas

CA_{nn} = 1 (i.e. the comparison of an area to itself is equal to 1)

$CA_{n1} = 1/CA_{1n}$

3.5.1.1 **Determination of weighting factors**

3.5.1.1.1 Eigenvector method

This is the original method developed by (Saaty, 1980) to determine the weighting factor of each area. In this method, weights are calculated by determining the principal eigenvector of the CM. In order to do this, it is valid to transform the CM to ratios of weights, demonstrated by matrix A in Equation (3-6).

$$A = \begin{bmatrix} \frac{w_1}{w_1} & \frac{w_1}{w_2} & \cdots & \frac{w_1}{w_n} \\ \frac{w_2}{w_1} & \frac{w_2}{w_2} & \cdots & \frac{w_2}{w_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{w_n}{w_1} & \frac{w_n}{w_2} & \cdots & \frac{w_n}{w_n} \end{bmatrix} \tag{3-6}$$

Where:

n is the number of areas in the study

W_n is the weight of area n

By assuming the vector of weights are as presented in Equation (3-7), Equation (3-8) is valid based on the principal right eigenvector equation. Thus, to solve for W (weightings), Equation (3-9) can be derived from Equation (3-8). Final weights are then determined by normalising the values obtain for eigenvector of W.

$$W = \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_n \end{bmatrix} \tag{3-7}$$

$$AW = \lambda W \tag{3-8}$$

$$(A - \lambda I)W = 0 \tag{3-9}$$

Where:

W is the eigenvector representing the weight of areas

λ is the associated eigenvalue for eigenvector W

I is the identity matrix

Geometric mean method

This is a simplified method which can produce quick and sufficiently accurate results compared to the eigenvector method (Saaty, 2008). In this method, first, the CM values in each column are normalised by the column sum. This produces the Normalised Criteria Comparison Matrix (NCACM) presented in Equation (3-10). Average values in each row are then taken as the final weights, which are presented in Equation (3-11).

$$\text{CACM} = \begin{bmatrix} \text{CA}_{11} & \text{CA}_{12} & \cdots & \text{CA}_{n1} \\ \text{CA}_{21} & \text{CA}_{22} & \cdots & \text{CA}_{n2} \\ \vdots & \vdots & \ddots & \vdots \\ \text{CA}_{n1} & \text{CA}_{n2} & \cdots & \text{CA}_{nn} \end{bmatrix} \tag{3-10}$$

$$\textbf{\textit{Sum}} \qquad \sum_{i=1}^{n} \text{CA}_{i1} \quad \sum_{i=1}^{n} \text{CA}_{i2} \qquad \sum_{i=1}^{n} \text{CA}_{ni}$$

$$\text{NCACM} = \begin{bmatrix} \frac{\text{CA}_{11}}{\sum_{i=1}^{n} \text{CA}_{i1}} & \frac{\text{CA}_{12}}{\sum_{i=1}^{n} \text{CA}_{i2}} & \cdots & \frac{\text{CA}_{n1}}{\sum_{i=1}^{n} \text{CA}_{ni}} \\ \frac{\text{CA}_{21}}{\sum_{i=1}^{n} \text{CA}_{i1}} & \frac{\text{CA}_{22}}{\sum_{i=1}^{n} \text{CA}_{i2}} & \cdots & \frac{\text{CA}_{n2}}{\sum_{i=1}^{n} \text{CA}_{ni}} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\text{CA}_{n1}}{\sum_{i=1}^{n} \text{CA}_{i1}} & \frac{\text{CA}_{n2}}{\sum_{i=1}^{n} \text{CA}_{i2}} & \cdots & \frac{\text{CA}_{nn}}{\sum_{i=1}^{n} \text{CA}_{ni}} \end{bmatrix} \begin{bmatrix} \textbf{\textit{Average}} \\ \text{W}_1 \\ \text{W}_2 \\ \vdots \\ \text{W}_n \end{bmatrix} \tag{3-11}$$

Sum	1	1	1	1

Where:

NCACM is the normalised consequence area comparison matrix

W_n is the weighting factor of area n

$$\sum_{i=1}^{n} \text{W}_i = 1$$

3.5.1.2 **Consistency ratio**

The Consistency Ratio (CR) is a measure which ensures the scores assigned in the CM by experts are consistent. AHP allows minor inconsistency as long as it is not higher than the significant CR. CR values greater than 0.1 are problematic and mean that the CM needs to be revised (Saaty, 2016). To determine the CR, first, a Consistency Index (CI) needs to be determined from Equation (3-12). CR is then calculated by dividing the CI by the Random

Index (RI) value presented in Equation (3-13). RI values are taken from Table 3-5 where n is the number of areas included in the study.

$$\mathrm{CI} = \frac{\lambda_{\max} - \mathrm{n}}{\mathrm{n} - 1} \tag{3-12}$$

$$\mathrm{CR} = \frac{\mathrm{CI}}{\mathrm{RI}} \tag{3-13}$$

Where:

λ_{max} is the principal (maximum) eigenvalue

n is the number of areas in the study

RI is the random index value

Table 3-5 – Random index (RI) values (Triantaphyllou and Mann, 1995)

n	1	2	3	4	5	6	7	8	9
RI	0	0	0.58	0.90	1.12	1.24	1.32	1.41	1.45

3.6 Summary

This chapter provides a review of asset and risk management approaches suitable for the proposed risk-based framework. Management levels, as well as the data required for each level, were discussed. It was shown that strategic level management (i.e. NL) is suitable for overall standard determination and policy framing. Furthermore, descriptive data at summary levels are sufficient for such models. For the purpose of strategic level asset management, MR was identified as a suitable approach for developing homogenous asset groups.

It was shown that using risk in asset management can assist with decision-making. Suitable techniques for analysing the two components of risk (i.e. probability and consequence) were

reviewed. It was revealed that Markov models are appropriate for infrastructure deterioration probability analysis, and can produce reliable results where data are inconsistent with high levels of uncertainty. For consequence analysis, road and railway practices were reviewed, and four principal areas, namely safety, performance, finance and reputation, were identified. To consider multiple criteria in the consequence analysis, a type of MCA, namely AHP, was shown to be a reliable and straightforward approach.

The following chapter presents the research methodology adopted to develop a risk-based drainage asset management framework, capable of addressing the uncertainties associated with asset deterioration. The methodology is based on the findings from the literature review presented in this and the previous chapter.

4. RESEARCH METHODOLOGY

The literature review, covered in Chapters 2 and 3, revealed that there is a need for a strategic risk-based railway drainage asset management framework that can be used to argue for funds for drainage maintenance and is capable of dealing with uncertainties. Such a framework would assist with long-term strategic decision-making (including assessing maintenance strategy, budget allocation and setting maintenance standards). The research methodology adopted in this study to develop such a framework is summarised in Figure 4-1 and described more fully in the following sections.

4.1 Literature review

A comprehensive literature review was carried out to:

- Identify and understand the components and physical boundaries of railway drainage systems. This included a detailed review of the functions of each type of drainage asset (e.g. pipes, channels, catch-pits, culverts, etc.) and factors contributing to their deterioration (e.g. material, dimension, location, etc.). These are discussed in Chapter 2.
- Identify asset management, modelling and data preparation techniques suitable for the development of a strategic risk-based management framework, taking into account the probability and consequences of drainage asset deterioration. These aspects are discussed in Chapter 3.

4.2 Framework development

The strategic risk-based deterioration framework was developed by using a number of the modelling techniques identified in Chapter 3. The literature review conducted in Chapters 2 and 3 revealed that the framework should consist of two elements, a multiple regression-based

model to group homogenous assets (required for strategic-level asset management) and a risk model to estimate the probability and consequences of drainage asset deterioration.

The multiple regression model was developed using Microsoft Excel™ and the IBM Statistical Package for the Social Sciences (SPSS™) software. From the review of the literature, it was found that the most appropriate approach for the risk model was to use Markov chain theory for the probability-based analysis of drainage failure and the Analytical Hierarchy Process (AHP) for analysis of the consequences of drainage failure. The risk model was developed using a combination of Microsoft Excel™ and the R™ coding platform, including the JAGS package (R, 2020).

4.3 Case study

To validate and demonstrate the practicality of the developed framework, a case study was conducted with data obtained from Network Rail's London North West (LNW) route in the UK. The obtained dataset consists of approximately 105,000 data points (assets), including the asset characteristics and the historical condition of each asset determined for 2009 to 2018. The case study is described in Chapter 6.

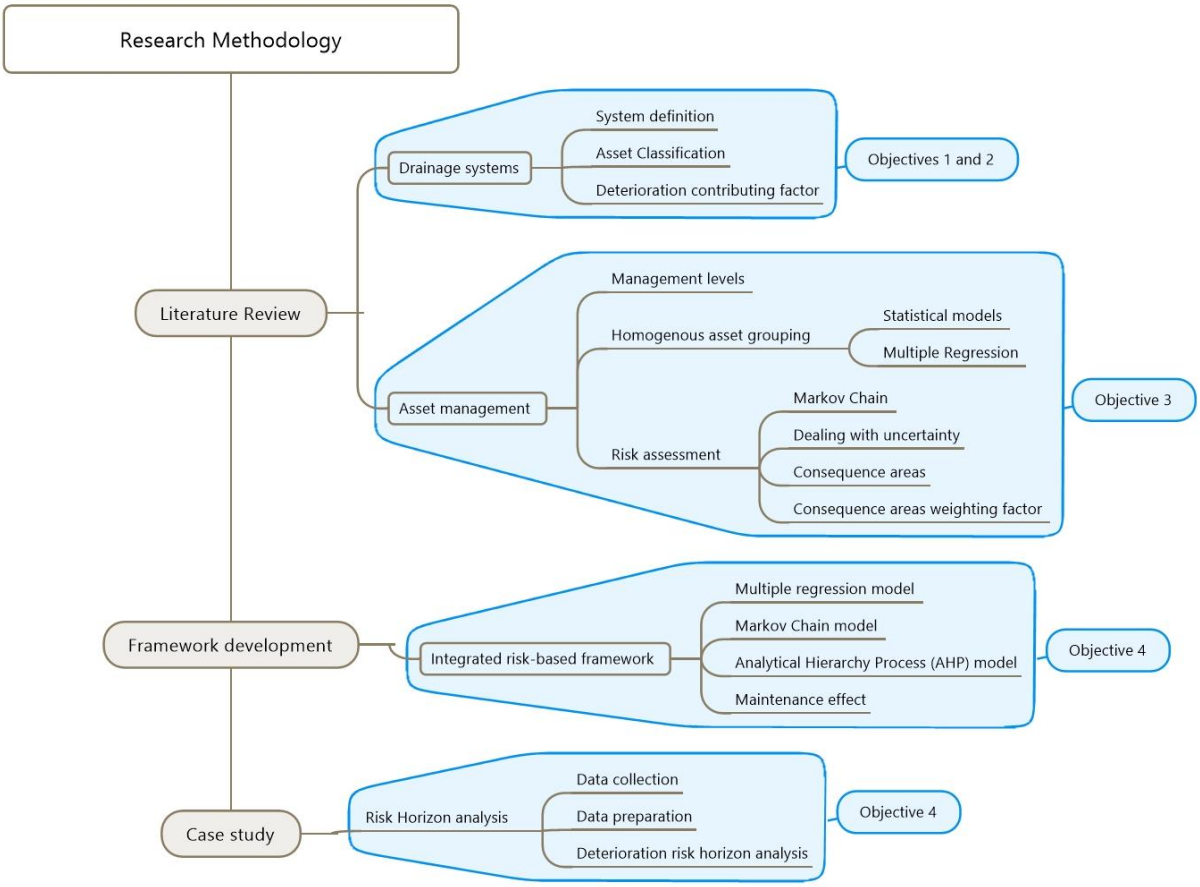


Figure 4-1 – Stages of the research

5. FRAMEWORK DEVELOPMENT

5.1 Introduction

As discussed in Chapters 2 and 3, drainage issues on the railway are amongst the main causes of service disruption and damage to parent and third-party assets and can result in significant safety and financial consequences. Furthermore, it was shown that there is a need for a risk-based approach that can be used to support strategic-level drainage asset management. Such an approach deals with uncertainties associated with inconsistent/lacking historical maintenance and condition data and the deterioration process of drainage assets. The approach will also help decision makers to construct maintenance policies, develop standards, argue for funds and prioritise budgets. In this chapter, a proposed framework which facilitates such an approach is presented. The components of the framework are illustrated in Figure 5-1 and discussed in the following sections.

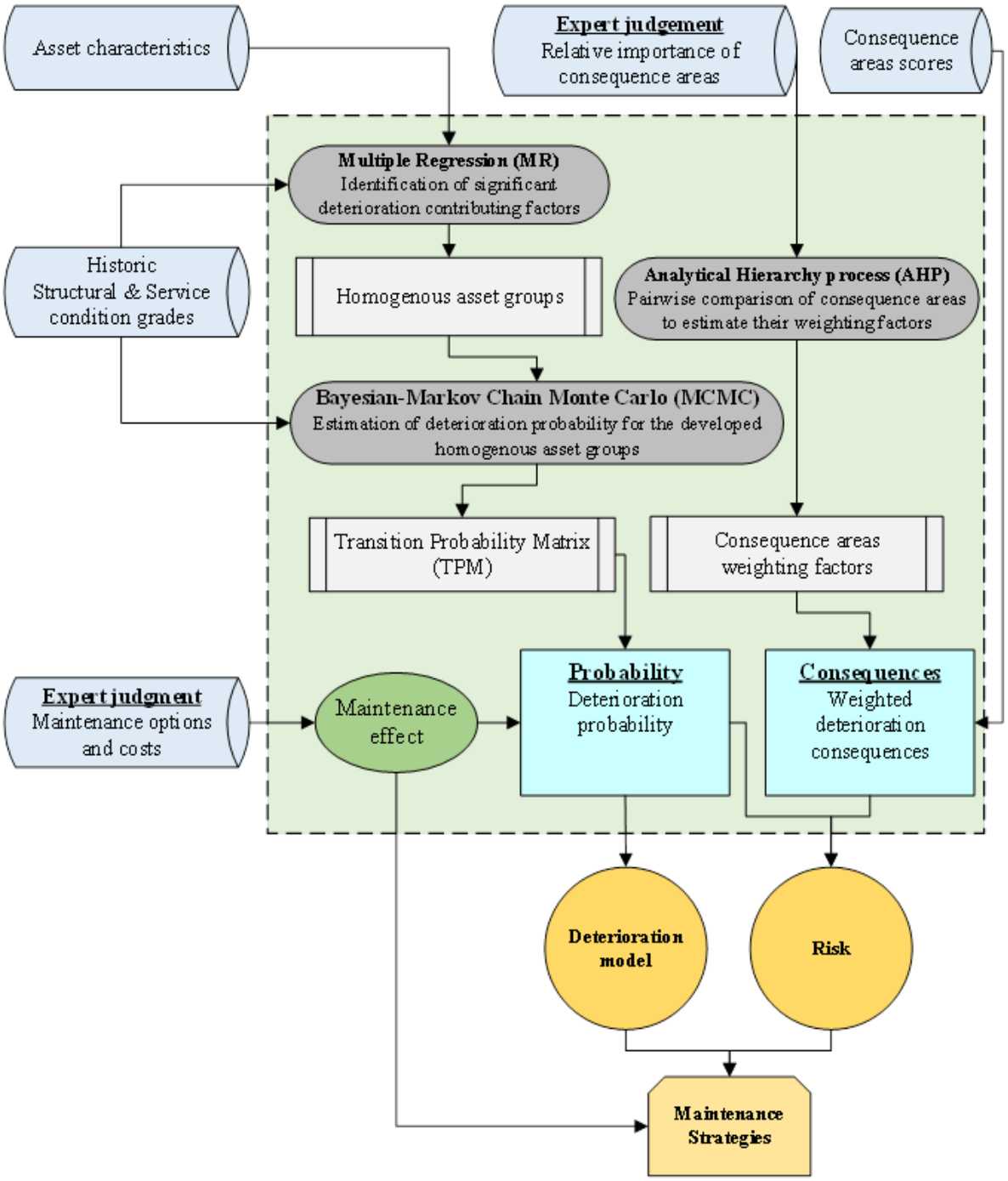


Figure 5-1 – Schematic of the proposed framework

5.2 Homogenous asset groups

As mentioned previously, the purpose of this research is to develop a framework that can be used to facilitate the strategic management of drainage assets. For this purpose, a Network-Level (NL) model which is applied to homogenous groups of assets was developed. As discussed in Section 2.4, the literature shows that deterioration of drainage assets is a function of asset characteristics (e.g. material, shape, size) which can be considered homogenous for groups of assets. To address this, a method was proposed to group assets based on statistical analysis of the data that identifies the factors making a statistically significant contribution to asset deterioration. The results of such analysis will be specific to the data used in the study and potentially makes the developed deterioration model more accurate for the task at hand. In the development of the statistical model, the following were considered:

1. The characteristics affecting the deterioration of drainage assets (contributing factors).
2. The relative importance of the characteristics of an asset to deterioration.
3. The significance of the identified characteristics of deterioration.

As discussed in the literature review (Section 3.3.1), Multiple Regression (MR) is a suitable approach to identify factors significantly contributing to deterioration of assets. The following section describes the MR model developed for this purpose.

5.2.1 Multiple regression

A review of the nature and availability of drainage data revealed that potential contributing factors can include variables of both scale (e.g. age, length, size, etc.) and categorical (e.g. shape, material, location, etc.) nature. MR models can be particularly beneficial for this because they can analyse both scale and categorical variables. In this study, the SPSS statistical analysis program was used to perform the MR (for more information about SPSS, see (IBM, 2020).

Heretofore, in this section reference is made to the MR function in SPSS. The following sections describe the process of variable development for the MR model.

5.2.1.1 **Independent variables**

In this study, possible Independent Variables (IV), or predictors of the MR model, are drainage asset characteristics such as size, material type and shape which can affect the rate of deterioration. As discussed in Section 3.3.1.1, in MR models, categorical IVs with more than two levels (i.e. category) need to be converted into dichotomous dummy variables which only have two levels. This results in a new variable for each category of the IV. Table 5-1 provides an example of dummy variables for a categorical IV (i.e. pipe material) with multiple levels (i.e. plastic, brick, concrete, steel). Each new dummy variable will correspond to one level of the original IV which is presented with two levels, 1 and 0 (or Yes and No). For example, dummy variable 1 will represent plastic pipes, where value 1 means the pipe material is plastic, and value 0 means pipe material is NOT plastic.

Table 5-1 – Dummy variable example for drainage pipes with four materials

Pipe material	Dummy Variable 1 *Plastic pipe*	Dummy Variable 2 *Brick pipe*	Dummy Variable 3 *Concrete pipe*	Dummy Variable 4 *Steel pipe*
Plastic	1	0	0	0
Brick	0	1	0	0
Concrete	0	0	1	0
Steel	0	0	0	1

5.2.1.2 **Dependent variables**

In MR models, the DV must be a continuous variable that is dependent on the variation of several IVs. Since the nature of the MR model developed in this study is based on asset deterioration behaviour, the DV was taken to be associated with the deterioration rate of assets. This is estimated with the rate of change in asset condition grades during the analysis period.

Table 5-2 presents an example of the DV development process for six assets which are assessed on a 1–5 condition grading system for 10 years. An Excel spreadsheet was designed to estimate the deterioration rate by determining the slope of the trendline (best line of fit) on the plot of condition grade versus year (Figure 5-2). Steeper deterioration gradients have a larger slope value, which indicates a faster change in condition grades in shorter periods and consequently faster deterioration. On the other hand, a gentler deterioration slope with a smaller slope value indicates a steadier transition over a longer period and therefore a slower deterioration rate.

To estimate a more accurate deterioration rate, maintenance was taken into account. Assets with no maintenance (i.e. stayed in the same or moved to poorer conditions) are labelled as 'No Maintenance' in the spreadsheet. The deterioration rate for these assets will be a single value (Table 5-2). For assets that received maintenance, the deterioration rate is determined separately for the period before and after the maintenance. The spreadsheet was designed to automatically identify assets with a maintenance history and highlight the years in which the asset received maintenance. For instance, if an asset received maintenance in year seven of the analysis period, this is labelled as 'M7' in the spreadsheet. For these assets, the final deterioration rate is determined by the average deterioration rate between maintenance years.

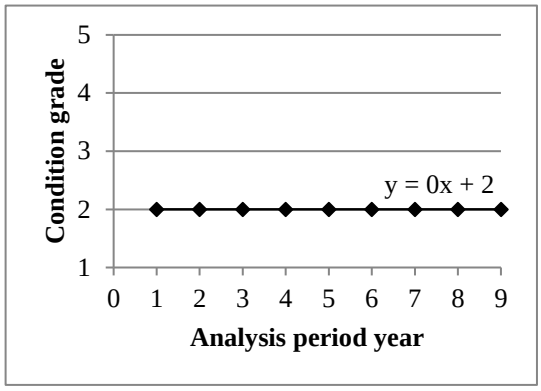
Table 5-2 – Deterioration rate analysis example

	Analysis period year									
	0	1	2	3	4	5	6	7	8	9
Asset #	Condition grade									
1	2	2	2	2	2	2	2	2	2	2
2	1	2	2	2	2	3	3	3	3	4
3	1	2	3	4	4	4	4	1	2	3
4	1	2	3	3	4	1	1	1	2	2
5	5	2	2	2	2	3	3	3	3	3
6	3	4	5	1	2	3	4	1	2	3

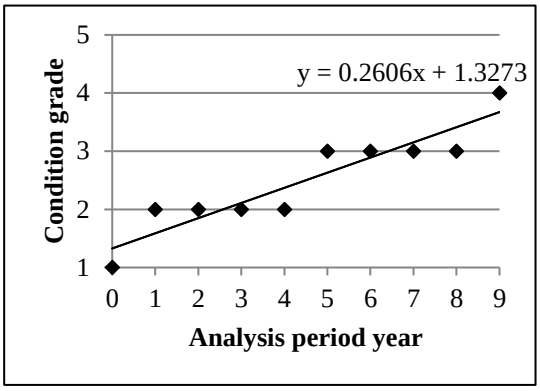
Asset #	Deterioration rates									Average
1	**No maintenance**	0								0
2	**No maintenance**	0.26								0.26
3	0.5					M 6	1			0.75
4	0.7			M 4	0.3					0.5
5	M 0	0.166								0.166
6	1		M 2	1			M 6	1		1

As presented in Table 5-2, asset numbers 1 and 2 received no maintenance during the 10-year analysis period. However, asset number 1 stayed in the same condition grade; therefore, the deterioration rate is equal to 0. This is also illustrated in Figure 5-2 for asset number 1, where the deterioration slope is a flat line with a slope coefficient of 0. Asset numbers 3 and 4 both received maintenance in different years, hence the final rate is determined by the average deterioration rates before and after the maintenance years. Asset number 5 received maintenance in year 0 and the deterioration rate is only considered for years 1 to 9. Asset

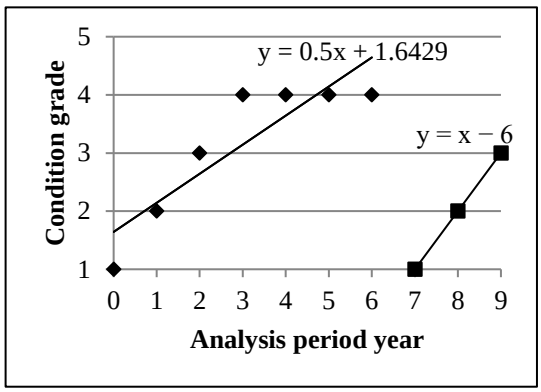
number 6 received maintenance in two years, with a constant deterioration rate of 1 between maintenance years, which results in a final deterioration rate of 1.



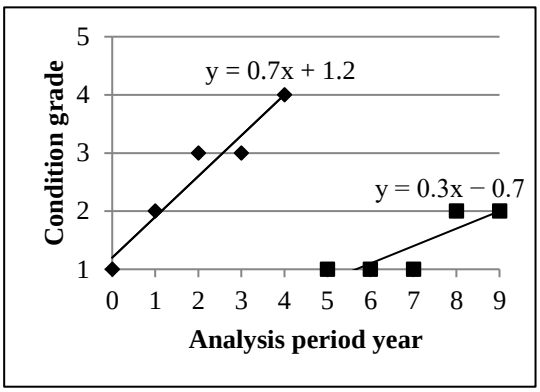
Asset # 1, degradation rate of 0



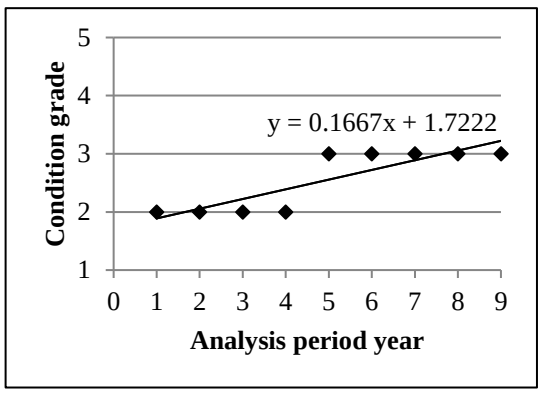
Asset # 2, degradation rate of 0.26



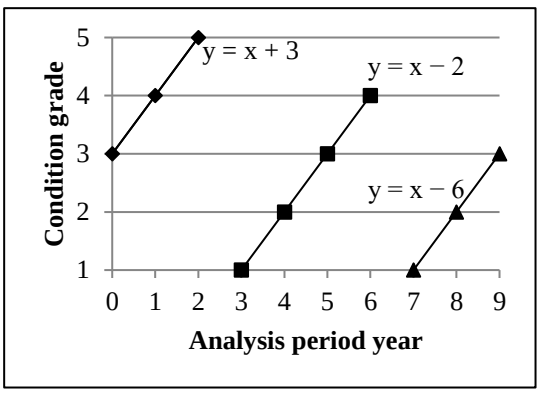
Asset # 3, average degradation rate of 0.75



Asset # 4, average degradation rate of 0.5



Asset # 5, degradation rate of 0.166



Asset # 6, average degradation rate of 1

Figure 5-2 – Deterioration rate slope analysis

5.3 Markov model

As discussed previously in Section 3.4, risk is defined as the product of the probability and consequences of an undesired event (Equation (5-1)). The undesired event in this study is considered to be the deterioration of railway drainage assets.

$$\text{Risk} = \text{P} \times \text{C} \tag{5-1}$$

Where:

P is the probability of the undesired event

C is the consequence of the undesired event

As discussed in the literature review presented in Chapter 3, a Markov model capable of dealing with the uncertainty associated with inconsistent data was shown to be a suitable approach for modelling the deterioration of the identified homogenous asset groups. Structural deterioration of drainage assets progresses at a different rate to service deterioration and they cannot be modelled together. However, the theoretical Markov model is capable of analysing both deterioration processes as long as they are calibrated separately. The proposed Markov model is based on the simulation process used by Tran (2007). This is a state-based Markov model, which means that the condition of assets over a time unit in the future is dependent on the present condition (Mauch and Madanat, 2001). For the purposes of this research, the unit of time was considered to be 1 year, to reflect the annual inspection and maintenance regime commonly practised for railway drainage networks.

To study the deterioration behaviour of drainage assets, a measure of condition was identified to assess asset condition at any given time. With the current level of data availability on drainage inventory and historic condition data, it is difficult to develop a detailed numerical system for condition grading. Such systems will be particularly sophisticated, requiring

extensive records of visual inspection such as CCTV, computer programs to detect defects from the recordings and a translation algorithm to convert them into condition grades (Tran et al., 2007).

As discussed in Section 3.2.2 on the data quality required for the strategic management of assets, a descriptive grading system is proposed in this study (such data satisfies IQL III–IV). This is a five-band grading system, as used in the UK's railway drainage standards, and is considered to be an appropriate balance between accuracy and over-complexity (Table 5-3). It should be noted that the developed framework is flexible and, depending on the requirements of decision makers, can incorporate different condition grading systems.

Table 5-3 – Description of structural and service condition grades (Network Rail, 2017a)

Condition grade	Structural Condition Description	Service Condition Description
1	No defects	Clear
2	Superficial defects	Superficial deposits with no loss of capacity
3	Minor defects	Capacity slightly reduced
4	Major defects	Capacity severely reduced
5	Not fir for purpose or unsafe	Blocked or unsafe condition

By considering a condition grading system with five bands, the entire network for any asset type can be represented by structural and service condition distributions of the assets in each condition grade. Figure 5-3 illustrates an example of the structural and service condition distributions of catch-pits in the year 2012 on the London–North West (LNW) route in the UK.

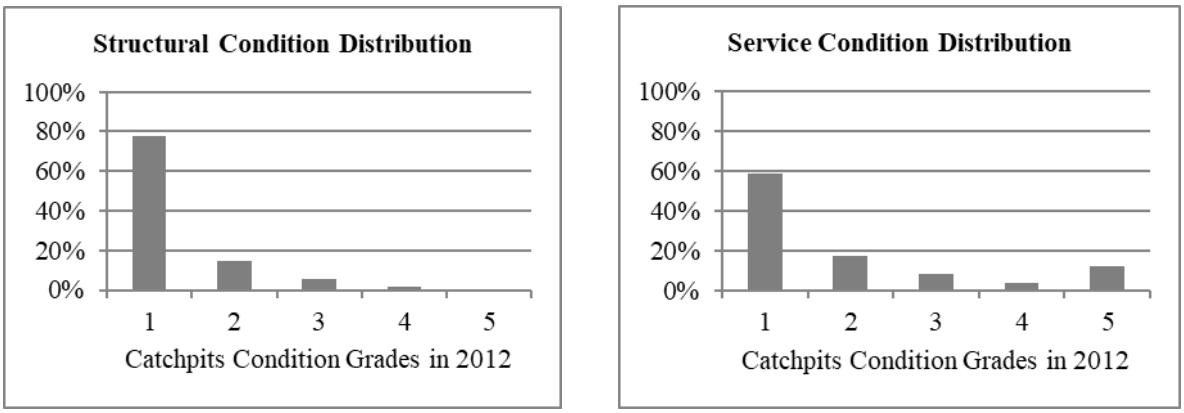


Figure 5-3 – Typical distribution of asset condition grades

Considering the above example, the condition of the network at any time can be presented by the following equation.

$$C_y = \begin{bmatrix} C11 & C12 & C13 & \cdots & C1m \\ C21 & C22 & C23 & \cdots & C2m \\ C31 & C32 & C33 & \cdots & C3m \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ Cx1 & Cx2 & Cx3 & \cdots & Cxm \end{bmatrix} \quad (5\text{-}2)$$

Where:

C_y is the condition distribution at year y

Cxm is the proportion of network for condition parameter x and severity band m

Since in this study only two condition parameters (structural and service condition) and five condition grades are considered, Equation (5-2) can be modified to Equation (5-3) for combined condition parameters or Equations (5-4) and (5-5) for specific structural and service condition parameters.

$$C_y = \begin{bmatrix} C11 & C12 & C13 & C14 & C15 \\ C21 & C22 & C23 & C24 & C25 \end{bmatrix} \quad (5\text{-}3)$$

Where:

C_y is the condition distribution at year y

C11, C12, C13, C14 and C15 are structural condition distribution in five grades

C21, C22, C23, C24 and C25 are service condition distribution in five grades

$$\mathrm{ST_y} = [\mathrm{C1} \quad \mathrm{C2} \quad \mathrm{C3} \quad \mathrm{C4} \quad \mathrm{C5}] \tag{5-4}$$

$$\mathrm{SE_y} = [\mathrm{C1} \quad \mathrm{C2} \quad \mathrm{C3} \quad \mathrm{C4} \quad \mathrm{C5}] \tag{5-5}$$

Where:

$\mathrm{ST_y}$ is structural condition distribution at year y

$\mathrm{SE_y}$ is service condition distribution at year y

5.3.1 **Condition progression**

As discussed in Section 3.4.1, the condition progression of assets can be estimated using Transition Probability Matrices (TPMs). TPMs are specific to one asset group and one parameter of condition. For instance, for three homogeneous pipe asset groups, there will be six TPMs (i.e. three TPMs for pipe structural and three TPMs for pipe service deterioration). By considering a five-band condition grading system, the TPM format is as presented in Equation (5-6).

$$\mathrm{TPM_{xg}} = \begin{bmatrix} \mathrm{P_{11}} & \mathrm{P_{12}} & \mathrm{P_{13}} & \mathrm{P_{14}} & \mathrm{P_{15}} \\ 0 & \mathrm{P_{22}} & \mathrm{P_{23}} & \mathrm{P_{24}} & \mathrm{P_{25}} \\ 0 & 0 & \mathrm{P_{33}} & \mathrm{P_{34}} & \mathrm{P_{35}} \\ 0 & 0 & 0 & \mathrm{P_{44}} & \mathrm{P_{45}} \\ 0 & 0 & 0 & 0 & \mathrm{P_{55}} \end{bmatrix} \tag{5-6}$$

Where:

$\mathrm{TPM_{xg}}$ is the TPM for condition parameter x (i.e. ST (structural) or SE (service)) and asset group g (i.e. 1, 2, 3, …)

$\sum_{i=1}^{5} \mathrm{P}_{1i} = \sum_{i=2}^{5} \mathrm{P}_{2i} = \sum_{i=3}^{5} \mathrm{P}_{3i} = \sum_{i=4}^{5} \mathrm{P}_{4i} = \sum_{i=5}^{5} \mathrm{P}_{5i} = 1$

For any $i > j$, $\mathrm{P}_{ij} = 0$ (i.e. assets cannot improve on their own)

$P_{55} = 1$ (condition 5 is an absorbing state)

Asset condition distribution over a time unit (1 year) is estimated by multiplying the current condition distributions in Equations (5-4) and (5-5) by the TPM in Equation (5-6). This is presented in Equations (5-7) and (5-8).

$$ST_{y+1} = ST_y \bullet TPM_{STg} \quad (5\text{-}7)$$
$$SE_{y+1} = SE_y \bullet TPM_{SEg} \quad (5\text{-}8)$$

Where:

ST_y and SE_y are structural and service condition distribution in year y

ST_{y+1} and SE_{y+1} are structural and service condition distribution in year y + 1

TPM_{STg} is structural TPM for asset group g

TPM_{Seg} is service TPM for asset group g

5.3.1.1 **Chapman–Kolmogorov equation**

By considering a 1-year time unit, for assets in year y, Equations (5-7) and (5-8) estimate the condition distribution in year y + 1. However, using the Chapman–Kolmogorov equation (Ross, 2003), transition probabilities at the n^{th} step can be determined. The Chapman–Kolmogorov equation implies that the condition distribution at the n^{th} step can be estimated by raising the TPM to the power of n. Hence, the equation to estimate the condition distribution in the n^{th} year can be presented as follows.

$$ST_n = ST_0 \bullet \left(TPM_{STg}\right)^n \quad (5\text{-}9)$$
$$SE_n = SE_0 \bullet \left(TPM_{SEg}\right)^n \quad (5\text{-}10)$$

Where:

ST_n and SE_n are structural and service condition distribution in the n^{th} year

ST_0 and SE_0 are structural and service condition distribution in year 0 (initial year)

TPM_{STg} is the structural TPM for asset group g

TPM_{Seg} is the service TPM for asset group g

n = 1, 2, 3…

5.3.2 **Model calibration**

Model calibration in this work involved determining the parameters of the Transition Probabilities (TPs). Model calibration was applied to 70–80% of the data and the remaining data was used for model validation, which will be later discussed in this chapter. For model calibration, a Bayesian methodology, in the form of a Bayesian Markov Chain Monte Carlo (MCMC) was used. MCMC is a powerful simulation that is proven to produce reliable results with inconsistent data (Tran, 2007, Coursera, 2018). This will be particularly useful for addressing the high levels of uncertainty associated with drainage asset data inconsistency and unpredicted deterioration processes.

Bayesian theorem estimates the Markov model parameter (from the posterior distribution) by reversing the direction of conditioning, using prior knowledge (prior distribution) and the likelihood of the parameter. The general form of the Bayesian formula used in this study is shown in Equation (5-11) (Coursera, 2018):

$$P(\theta|D) = \frac{P(D|\theta) \times P(\theta)}{\int P(D|\theta)P(\theta)d\theta} \quad (5\text{-}11)$$

Where:

θ is the random variable – Markov model parameter (TPs)

D is the random variable with a known probability distribution

$P(\theta|D)$ is the posterior distribution of θ based on D

$P(D|\theta)$ is the likelihood of observing D based on unknown θ

$P(\theta)$ is the prior probability of θ

$\int P(D|\theta)P(\theta)d\theta$ is the normalising factor

$\int P(D|\theta)P(\theta)d\theta$ is always in the form of a constant value, hence it can be stated that the posterior distribution of parameter θ based on known variable D is proportional to the product of the likelihood function for variable D and the prior distribution of θ. In this study, θ represents the TPs or the P_{ij} that need to be estimated and D is the available data. This is presented in the following equation.

$$P(\theta|D) \approx P(D|\theta) \times P(\theta) \quad (5\text{-}12)$$

Where:

$P(\theta|D)$ is the posterior distribution of TPMs

$P(D|\theta)$ is the likelihood function of the available data

$P(\theta)$ is the prior distribution or our prior knowledge of TPs

Bayesian theorem allows the use of both prior knowledge of TPs and available knowledge obtained from the data (D) to estimate the true value of TPs. In this model, the approach used to estimate the probability of transitions was evaluating the number of assets that have moved from each condition to a poorer condition. To best present this, a binomial distribution, B (n, p), was used for the likelihood function where n is the number of trials and p is the success rate. By assuming the number of trials to be the total number of assets in each condition, the number of assets that have moved to a poorer condition is considered as the success rate. For instance, assuming that in the year 2019 there are a hundred pipes in condition 1, and by the year 2020,

eighty pipes are still in condition 1, ten have moved to condition 2, five to condition 3, four to condition 4 and one to condition 5 (failed), the likelihood distributions for the analysis year 2019–2020 is as presented in Table 5-4.

Table 5-4 – Likelihood distribution example

Transition	Binomial likelihood distribution
1–1	B(100, 80)
1–2	B(100, 10)
1–3	B(100, 5)
1–4	B(100, 4)
1–5	B(100, 1)

According to the Bayesian theorem, the conjugate prior for binomial likelihoods is a Beta distribution, Beta (α, β), where α and β are the parameters of the distribution. Due to the lack of prior knowledge regarding the true distribution of TPs, the prior distribution is assumed to be a non-informative Beta distribution with parameters α and β as 1 (Beta (1, 1)). This helps the model to rely more on the data rather than prior knowledge.

5.3.2.1 **Metropolis–Hastings algorithm**

After generating the posterior distribution of each TP in the previous section, the Metropolis–Hastings Algorithm (MHA) was used to sample from the posterior distribution. MHA is a member of the MCMC simulation family which allows sampling from almost any generic probability distribution (Tran, 2007). The general theory of MCMC is to use a Markov chain that its stationary probabilities are identical to the target distribution, which in this case is the posterior TP distributions. To achieve this, the Markov chain must be allowed to converge to its stationary distribution by running a large number of trials and, once converged, the sampling process starts to determine the true distribution of posterior TPs (Coursera, 2018). MHA

sampling starts by choosing an arbitrary starting value and, based on an acceptance rate, it is iteratively accepted or rejected. The JAGS package within R™ coding language was used to perform this. The programming code used for model calibration is presented in Appendix A.

5.3.3 **Maintenance**

In order to take into account the effect of maintenance, a Maintenance Transition matrix, as presented in Equation (5-13), was applied to the condition distributions at the end of the analysis period (y + 1). Similar to the TPMs, the maintenance matrix is 5 × 5, and its application results in a new 1 × 5 matrix for the condition distributions at year y + 1.

$$\text{Maintenance} = \begin{bmatrix} M_{11} & M_{21} & M_{31} & M_{41} & M_{51} \\ M_{21} & M_{22} & M_{32} & M_{42} & M_{52} \\ M_{31} & M_{32} & M_{33} & M_{43} & M_{53} \\ M_{41} & M_{42} & M_{43} & M_{44} & M_{54} \\ M_{51} & M_{52} & M_{53} & M_{54} & M_{55} \end{bmatrix} \quad (5\text{-}13)$$

M_{11} is assumed to be equal to 1 because, in terms of maintenance, condition 1 is an absorbing state. This means that assets in condition 1 cannot move to any better condition. Furthermore, to avoid duplications, the upper right side of the maintenance matrix is considered to be zero because those transitions are already considered in the lower left side of the matrix. Hence, the maintenance matrix can be modified to Equation (5-14). Each column in the maintenance matrix presents the portion of assets that move to the condition in that column. For instance, the first column represents the portion of assets moving from conditions 2, 3, 4 and 5 to condition 1. Each column also represents a portion of assets that stay in the same condition because it is assumed that 100% asset maintenance cannot be achieved. For example, if 70% of assets in condition 2 must be maintained, M_{21} will be 0.7 and M_{22} will be 0.3.

$$\text{Maintenance} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ M_{21} & M_{22} & 0 & 0 & 0 \\ M_{31} & M_{32} & M_{33} & 0 & 0 \\ M_{41} & M_{42} & M_{43} & M_{44} & 0 \\ M_{51} & M_{52} & M_{53} & M_{54} & M_{55} \end{bmatrix} \quad (5\text{-}14)$$

5.3.4 **Model validation**

Hypothesis testing, in the form of the goodness of fit, was used to validate the calibrated model against the validation data set (remaining 20–30% of data). This test was based on the null hypothesis that the predicted condition distributions, estimated using the TPMs, match the observed condition distributions. In other words, it tests whether the difference between the observed and predicted distributions are completely random and not statistically significant. A chi-squared test was used for the hypothesis testing procedure, which is described in the following equation.

$$\chi^2 = \sum_{i=1}^{5} \frac{(\text{Observed}_i - \text{Predicted}_i)^2}{\text{Predicted}_i} \quad (5\text{-}15)$$

Where:

χ^2 is chi-square value

Observed_i is the observed distribution of condition *i*

Predicted_i is the predicted distribution of condition *i*

Since a five-band condition grading system is considered in this study, there will be five possible outcomes in any given year. Hence, the degrees of freedom in the analysis (n − 1) is 5 – 1 = 4 (Field, 2013). Critical values of chi-square at 4 degrees of freedom are listed in Table 5-5. It is common to consider a 95% confidence interval or higher for the validation test. If the

estimated χ^2 value is greater than the critical χ^2, the null hypothesis is rejected, and it is assumed that the difference between predicted and observed distributions are not random.

Table 5-5 – Critical values of chi-square (χ^2) (Tabachnick and Fidell, 2013)

Degrees of freedom	Confidence interval						
	0.250	0.100	0.050	0.025	0.010	0.005	0.001
	85%	90%	95%	97.5%	99%	99.5%	99.99%
4	5.38527	7.77944	9.48773	11.1433	13.2767	14.8602	18.467

5.3.5 **Climate change**

It is noted that with future predictions of climate change and higher anticipated precipitation levels, inflow volumes entering railway drainage systems can increase significantly. Assuming that there will be no change in the current system's capacity, climate change can significantly increase the service deterioration rate and alter the TPMs. Network Rail has predicted a peak increase of daily precipitation in February 2050 by 13% in north-west England and 17% in the West Midlands. These forecasts are almost doubled by 2080 where increases of 26% and 31% are predicted, respectively (Networkrail, 2014). The implication of climate change in the TPMs requires further research that is outside the scope of this thesis. However, with further development of the framework, the effect of climate change on TPMs can be considered. An approach similar to that adopted by Daheshpour (2018) could be adapted for this work.

5.4 Consequence analysis

The literature review presented in Section 3.4.2 revealed that consequences in transportation networks such as roads and railways must take into account multiple areas such as safety, performance, finance and reputation. Therefore, for this study, it was suggested to disaggregate

the consequences of drainage deterioration into its main components and address their relative importance using a multi-criteria decision-making process suggested by (Saaty, 2016). Equation (5-16) presents the Total Consequence (TC) formula adopted for this study.

$$TC = \sum_{i=1}^{N} W_i \times C_i \quad (5\text{-}16)$$

Where:

TC is the total consequence

C_i is consequence area i

N is the number of consequence areas

W_i is the weighting of C_i

The following sections describe the consequence areas used in this study (Section 5.4.1) and the method used to determine the consequence area weightings (i.e. relative importance) (Section 5.4.2).

5.4.1 **Proposed consequence measures**

The CRAM framework developed by Network Rail (see Section 3.4.2.2) provides a comprehensive outline for consequence analysis. However, unlike the approaches used in the reviewed road networks, the CRAM approach is heavily dependent on specific events. For instance, to evaluate the performance consequences of an undesired event, network disruption is measured in the number of days. However, it is challenging to estimate an exact number of days for each event such as asset failure, flooding, earthwork failure, etc. At this level of the framework development, such approaches will not be feasible. A more practical option is to use the road network criticality approach (see Section 3.4.2.1). In road networks, several criteria are identified which can indicate the criticality or importance of any given road section. Therefore, regardless of the event type, more critical sections are considered to result in more severe consequences, and accordingly have a higher risk level. A similar approach was used in

this study for drainage assets. The following sections describe three consequence measures that were found to be suitable for the proposed approach. These factors are used as criticality measures in the UK's railway standards. These consequence areas are used to demonstrate the practicality of the model and it should be noted that any other consequence area, depending on the requirements of the decision maker, can be used in the framework.

5.4.1.1 Common consequences tool

NR's Common Consequences Tool (CCT) was discussed in Section 3.4.2.2.4. The CCT can highlight critical line sections with high passenger numbers, high traffic volumes, high track density and the significant presence of signalling, control and power infrastructures. These factors can increase the level of consequences in case of an undesired event.

To keep the framework consistent, the same grading system is used for both the probability and consequence elements of the risk. Therefore, similar to the asset condition grades discussed in previous sections, consequence measures were also assessed on a 1–5 scoring system. The CCT scale is based on Fatalities and Weighted Injury (FWI) estimates specified by Network Rail (Table 5-6). The CCT scale is already measured on a 1–5 scoring system and does not require conversion.

Table 5-6 – CCT scale ranges (Network Rail, 2014)

CCT scale (consequence rate)	FWI range
1	< 0.1
2	0.1–0.5
3	0.5–2
4	2–10
5	> 10

5.4.1.2 **Track category**

Track Category (TC), as described in Section 3.4.2.2.5, was used as a measure of consequence for the proposed framework because it considers two critical elements, line speed and annual line usage (Equivalent Million Gross Tonnes per Annum – EMGTPA). Line speed is considered as a measure for safety consequences. Drainage asset deterioration on lines with a higher operational speed could result in more severe safety consequences (e.g. derailment). Furthermore, annual line usage can be considered as a measure for performance and finance consequences. This means that asset deterioration on lines with a higher EMGTPA can result in more significant delays, cancellations and loss of revenue. To convert the seven categories of TC to a 1–5 grading system, in line with the requirements of IQL IV, categories 1 and 1A as well as categories 5 and 6 were combined. This is presented in Table 5-7.

Table 5-7 – TC conversions to a 1–5 grading system

Track category	Speed range (mph)	EMGTPA range	Converted consequence grade
Cat 6	0–20	0–6	1
Cat 5	20–60	0–4	
Cat 4	0–75	0–15	2
Cat 3	0–90	0–38	3
Cat 2	0–105	0–60	4
Cat 1	25–125	0–60	5
Cat 1A	75–140	0–60	

5.4.1.3 **Route criticality**

Route Criticality (RC), as discussed in Section 3.4.2.2.6, is assessed based on historic cost per incident and was used as a measure of the consequence of drainage failure. This consequence measure was developed for track infrastructure and therefore most incidents are associated with track faults (Network Rail, 2017b). However, due to the significant effect of drainage

performance on track infrastructure, RC is a suitable consequence measure for the drainage management framework proposed in this study. The RC bands converted to the 1–5 grading system used in this study are presented in Table 5-8.

Table 5-8 – RC conversions to five bands grading system

Route Criticality Bands	Definition	Converted Consequence grade
Band 5	SRS with costs per incident of less than one quarter the mean	1
Band 4	SRS with costs per incident between half the mean and one quarter the mean	2
Band 3	SRS with costs per incident between the mean and half the mean	3
Band 2	SRS with costs per incident between the mean and two times the mean	4
Band 1	SRS with costs per incident more than two times the mean	5

5.4.2 **Analytical hierarchy process**

In order to identify the relative importance of the weightings used in Equation (5-16), the Analytical Hierarchy Process (AHP) developed by Saaty (1980) was used (see Section 3.5.1). This tool allows the use of expert judgement in a pairwise comparison of multiple criteria and identification of their relative importance (i.e. weighting factor). Although at the moment only three criteria are suggested, with future development of the framework and for a more accurate consequence analysis, other consequence measures can be incorporated. AHP will be particularly beneficial in this regard, as it can be easily expanded to include more criteria in the future, without increasing the mathematical complexity.

For this study, a geometric mean method was used, as described in Section 3.5.1. This approach was selected due to its simplicity and accuracy. To achieve this, an Excel spreadsheet was designed to perform the pairwise comparison and to evaluate the weighting factor for each criterion.

5.5 Framework assumptions and limitations

5.5.1 Assumptions

The developed framework is based on the following assumptions:

- It is assumed that in the Markov deterioration model, the future condition of assets is only depended on the current state. This is the basis of State-Based Markov models, which was revealed to be more suitable for this study (see section 3.4.1.1).
- The undesired event considered in the framework, which the risk is based on, is assets moving to the worst condition grade (asset deterioration). Therefore, the probability component of risk is taken as the transition probability of assets moving to the worst condition grade.
- The maintenance strategies and matrices are based on the requirements and expectations of the decision-makers, which can vary according to the maintenance strategies available for the studied network. Assumptions made for the effect of maintenance on asset include the portion of assets receiving maintenance and moving to better condition grades, maintenance unit cost and other costs such as labour and possession.

5.5.2 Limitations

The limitations of the developed framework are as follow:

- The consequence component of the framework, at this stage, is limited to the already existing criticality measures available in the literature and the network which the framework is applied to. The framework does not consider specific consequences of asset deterioration (e.g. flooding, earthwork failure, etc.). Such an analysis could benefit more detailed management frameworks that deal with particular assets and specific events.
- The consequence analysis of the framework will be limited to the criticality level of the line sections where assets are located. Therefore, individual drainage assets within a section or a specific length of the line cannot be compared in terms of consequences.
- The accuracy of the model and the level of uncertainty is limited to the available historic data. However, the framework is designed in a way to deal with those uncertainties and present the outcomes in an acceptable format. Furthermore, it is noted that with more data on asset characteristics, such as accurate information on asset age, type, material, size, etc., the deterioration probability model will be more accurate.

5.6 Framework step-by-step guide

This section provides a step-by-step guide for the process of the developed framework and explains its inputs and outputs.

This section provides a step-by-step guide for the process of the developed framework and explains its inputs and outputs.

1. Select a railway network for which the framework will be applied to. This could be an entire country or a railway route.

2. Collect the data on drainage asset characteristics and historic condition grades. Collect the maintenance records if available.

3. Split the data for calibration (approximately 80%) and validation (approximately 20%) datasets.

4. Analyse the calibration dataset for quality/quantity and Multiple Regression (MR) assumptions. Demonstrated in section 5.2.1.1.

5. Using the historic condition grades from the calibration dataset, evaluate the degradation rates (this is the Dependent Variable (DV) for the MR model). Demonstrated in section 5.2.1.2.

6. Using the asset characteristics data from the calibration dataset, identify the Independent Variables (IV) for the MR model (e.g. shape, material, size, etc.).

7. Convert the continues and categorical IVs (with more than two levels) into dummy variables. Demonstrated in section 5.2.1.1.

8. Check for data quality and quantity again (required for the MR model) after developing dummy variables.

9. Run the MR model on the calibration dataset to identify the contributing IVs to drainage asset deterioration. Based on those IVs with statistically significant influence on asset deterioration, develop homogenous asset groups.

10. Run the Markov Chain Monte Carlo (MCMC) deterioration model on the calibration dataset to develop the Transition Probability Matrix (TPM) for all the homogenous asset groups identified in the previous step.

11. Validate the developed TPM with the observed dataset (validation dataset). Demonstrated in section 5.3.4.

12. Identify the maintenance strategies required for the network.

13. From the previous step, estimate the maintenance matrices. This includes:

    a. The approximate percentage of assets that will be maintained to better conditions or stay in the same condition.

    b. Approximate maintenance cost units.

    c. Other maintenance expenditures for the analysis period, such as labour, possession, etc.

14. Identify the available consequence areas. It is recommended to identify at least one factor from the main impact areas, namely Safety, Performance, Finance and Reputation.

15. Conduct the pairwise comparison of consequence areas by experts. Demonstrated in section 5.4.2.

16. Run the AHP analysis on the consequence areas to estimate the weighting factor for each area. Demonstrated in section 5.4.2.

17. To estimate risk, select an asset and identify which asset group it belongs to (e.g. pipe structural group 2, catch-pit service group 1, etc.).

18. Use the specific TPM for the group (identified in the previous step) to estimate the probability of failure in the following years (probability of failure is assets moving to the worst condition grade).

19. Apply the appropriate maintenance matrix for the analysis period.

20. Identify where the selected asset is located in the network (geographical location), or which line it belongs to.

21. According to the consequence measures selected from the network (criticality level), evaluate the criticality levels of the section or line identified in the previous step. Once the scores from each consequence area are specified, apply the weighting factor estimated by the AHP analysis to determine the total weighted consequence measure.

22. Risk is then determined by the quantitative product of the probability (transition probability of moving to the worst condition) and the total weighted consequences calculated in the previous steps.

23. If individual assets in a specific section are compared (e.g. two catch-pits next to each other), although their failure probabilities will be calculated separately, their consequence scores will be the same. This is because the framework does not estimate the individual failure consequences of assets, but the criticality of the line section where the asset is located.

24. The framework can also calculate the risk for a group of assets, as long as they belong to the same homogenous asset group (e.g. pipe structure group 1) and have the same consequence area measures (e.g. all assets are located in line sections with scores of CCT=1, RC=1, TC=2).

25. Once risk is calculated, the effect of different maintenance strategies can be assessed on the long term condition of the network.

5.7 Summary

This chapter describes the development of a risk-based management framework for railway drainage assets, which can be used by executive managers and decision makers to strategically assess and determine preventive maintenance strategies. A schematic of the framework is presented in Figure 5-1. The framework comprises three components: (i) an MR model for developing homogenous asset groups with similar deterioration characteristics, (ii) a Markov model for determining the probability of asset deterioration and (iii) a multi-criteria analysis, namely AHP, for assessing the consequences of asset deterioration and to determine the relative importance of multiple consequence criteria. The uncertainty associated with inconsistent and lacking historic data and the probabilistic nature of asset deterioration are dealt with using MCMC simulation.

The MR model studies the relationship between asset characteristics and structural/service deterioration. Homogenous asset groups are then developed based on those asset characteristics that have a significant effect on the deterioration rate. The risk in the framework is based on the undesired event of asset deterioration. This is represented as assets moving to the worst condition grade. The probability component of risk is determined by the TPM developed by the Markov model, and the consequence component is determined by the AHP model.

The following chapter demonstrates the practicality of the risk-based framework via a case study on a section of the UK railway network.

6. CASE STUDY

6.1 Introduction

This chapter presents a case study in which the theoretical framework developed in Chapter 5 is applied to real data. The data used in this case study were collected from drainage assets on the London–North West (LNW) route in the United Kingdom. Section 6.2 presents the multiple regression model used to identify significant asset groups in the deterioration and the homogenous asset grouping process. In Section 6.3, transition probability matrices are developed for the identified asset groups and validated against the observation dataset. Section 6.4 presents the consequence analysis, where the weighting factor for each consequence area is determined. In Section 6.5, the proposed maintenance options and their estimated costs for this case study are presented. Finally, Section 6.6 presents the results from the risk horizon analysis, where the risk effect of different maintenance options applied at different intervals is discussed.

The dataset used in this case study was provided by Network Rail (NR; the owner and infrastructure manager of the UK's railway). The route studied (LNW), has 4,500 miles of track and stretches from London to Carlisle, connecting major cities including Birmingham, Manchester, Liverpool and Edinburgh. The dataset consists of nearly 105,000 data points of drainage assets, including asset characteristics and structural/service condition grade recordings from 2009 to 2018. Due to the unavailability and inconsistency of data on some assets, it was decided to conduct the case study on four major assets including 22,500 pipes, 1,100 culverts, 25,900 catch-pits and 2,800 channels.

6.2 Multiple Regression model development

This section describes the Network-Level (NL) asset grouping process, which was discussed in Section 3.3. This process includes a Multiple Regression (MR) analysis to identify the significant factors contributing to deterioration and to group those assets that are assumed to have a significantly different deterioration behaviour to the rest. The development process for the Dependent Variable (DV) was previously discussed in Section 5.2.1.2. The following section describes the Independent Variables (IVs) used in this case study.

6.2.1 **Independent Variables**

As discussed in Section 5.2.1.1, IVs are the variables for which their variation affects the DV's outcome. Since in this study the DV is based on the deterioration rate, IVs are considered as factors contributing to asset deterioration. These factors include physical and functional characteristics, which are discussed in the following sections for each asset. It should be noted that the developed framework can consider any number of IVs; however, in this case study, only the variables discussed in the following sections were available in the dataset.

6.2.1.1 **Catch-pit independent variables**

Topography

Topography data are recorded for almost every asset in the dataset and are categorised as At Grade, Cutting and Embankment sections. Topography was considered in the MR model to examine whether it has a significant effect on the structural and service deterioration of catch-pits. In general, assets in cutting sections exhibit more issues because of the typical high groundwater tables and slope stability problems. The distribution of catch-pit topography in the LNW route is presented in Figure 6-1.

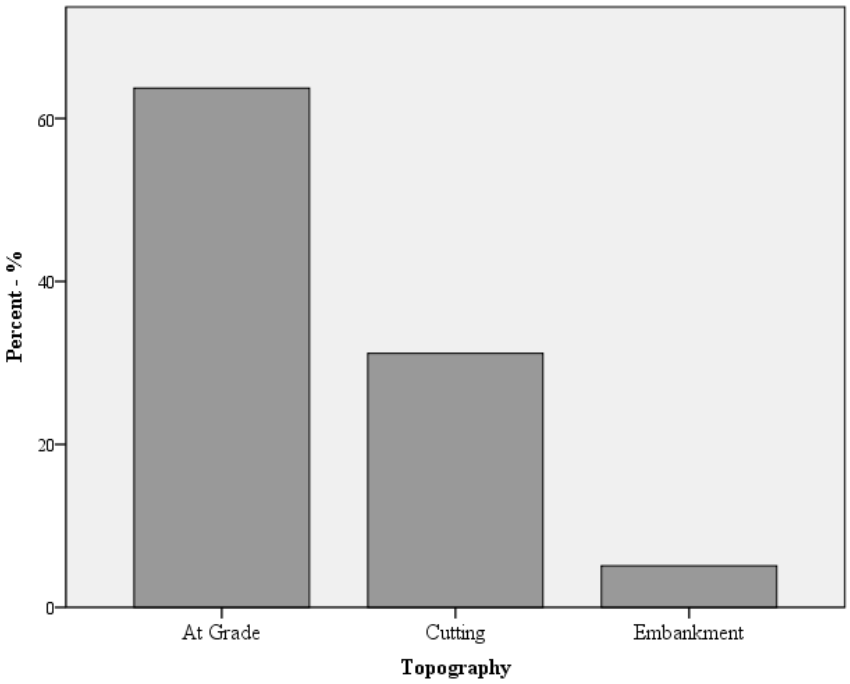


Figure 6-1 – Catch-pit topography distribution in the LNW route

Material

The distribution of catch-pit material in the LNW route is presented in Figure 6-2. It can be seen that the majority of catch-pits (i.e. over 70%) are made of brick, which is considered as the traditional choice for catch-pit construction.

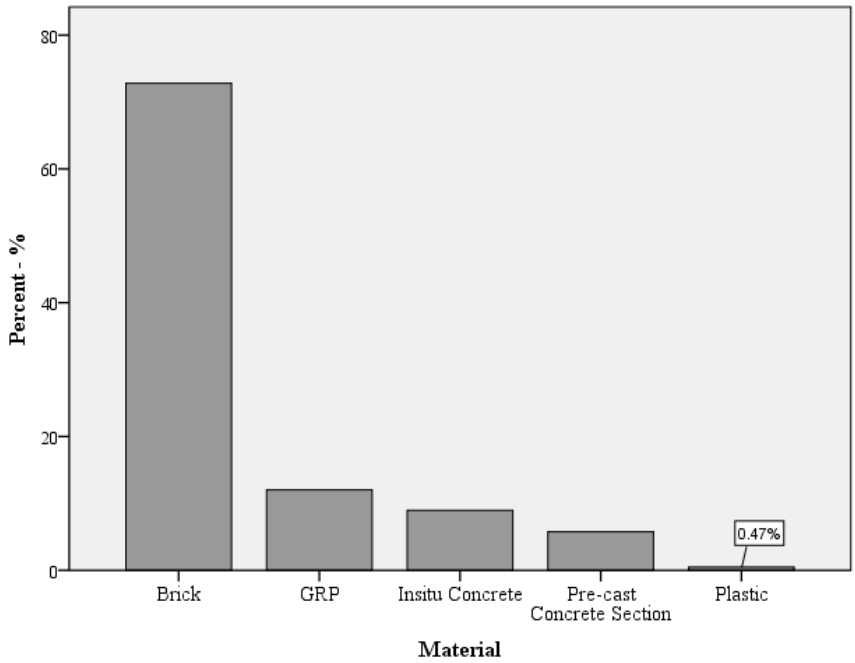


Figure 6-2 – Catch-pit material distribution in the LNW route; GRP: glass (fibre) reinforced plastic

Shape

The literature suggests that the plan area of a catch-pit base can affect the service deterioration rate (see Section 2.4); however, this factor was not available in the dataset. It can be argued that a similar available factor, such as catch-pit shape, could affect service deterioration too. This was considered in the MR model to examine whether different shapes (e.g. circular, rectangular) can affect the deterioration rate, by altering the pit's flow circulation and sedimentation rate. Moreover, the effect of shape on the structural stability and integrity of catch-pits can also be studied. As presented in Figure 6-3, Catch-pits in the LNW are of two shapes: circular and rectangular.

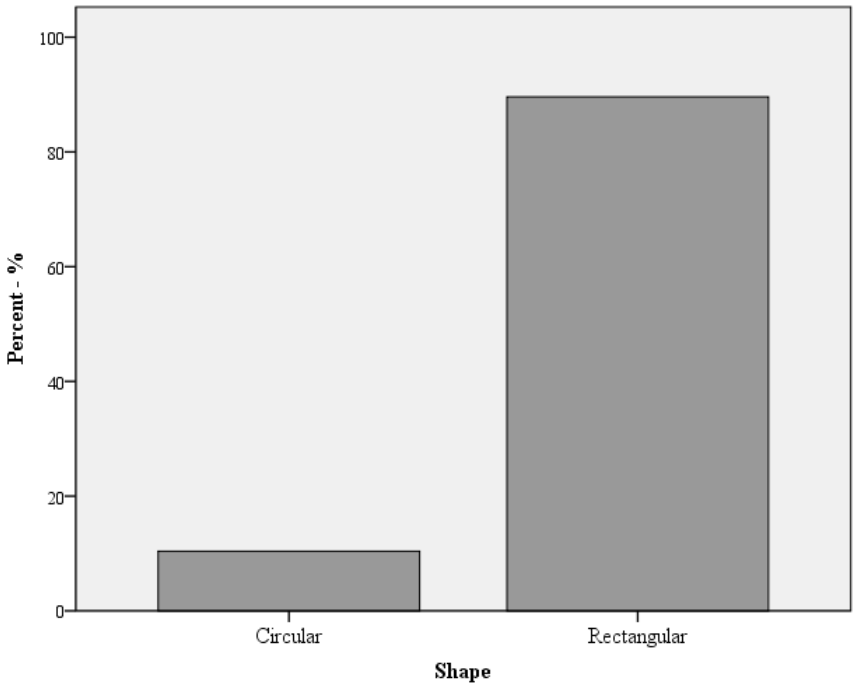


Figure 6-3 – Catch-pit shape distribution in the LNW route

6.2.1.2 **Pipe independent variables**

Topography

As discussed in the literature review (Section 2.3.2.1), pipes are used in various locations on the railways. The topography of the section in which a pipe is used is considered a potential contributing factor in the MR model. The distribution of pipes in sections with different topography in the LNW route is presented in Figure 6-4. It can be seen that most pipes are used in At Grade topography sections, less than 40% are in Cuttings, and 5% are in Embankments.

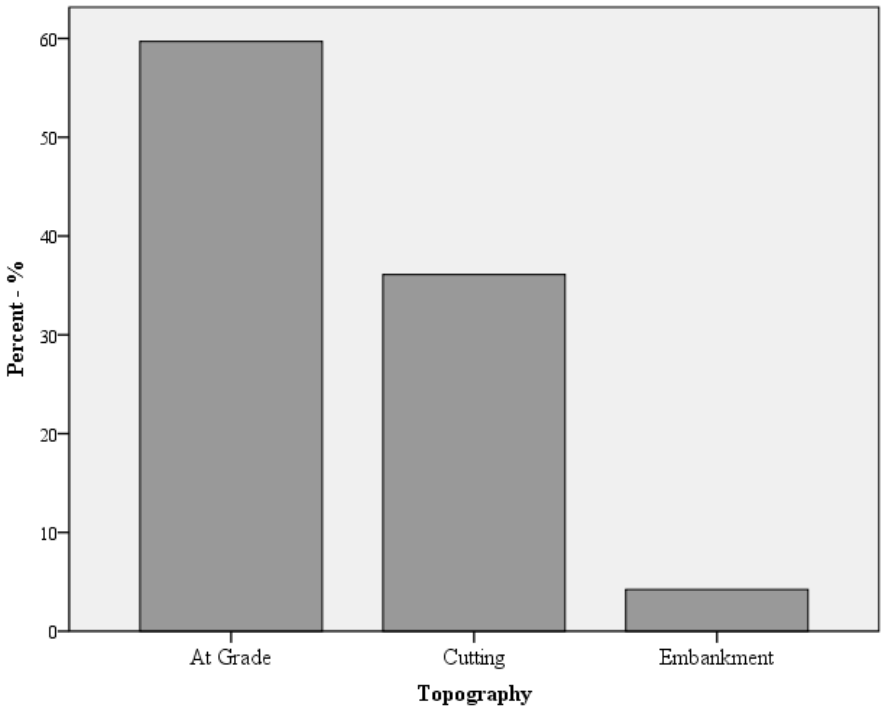


Figure 6-4 – Pipe topography distribution in the LNW route

Function

As discussed in Section 2.3.2.1, pipes are commonly categorised as collectors or carriers. The perforations on the surface of collector pipes can reduce structural integrity and affect the deterioration rate. Furthermore, the amount of siltation in collector and carrier pipes varies, which can affect the service deterioration rate. It was therefore decided to include pipe function in the MR model to examine these effects. The distribution of pipe functions in the LNW route is presented in Figure 6-5.

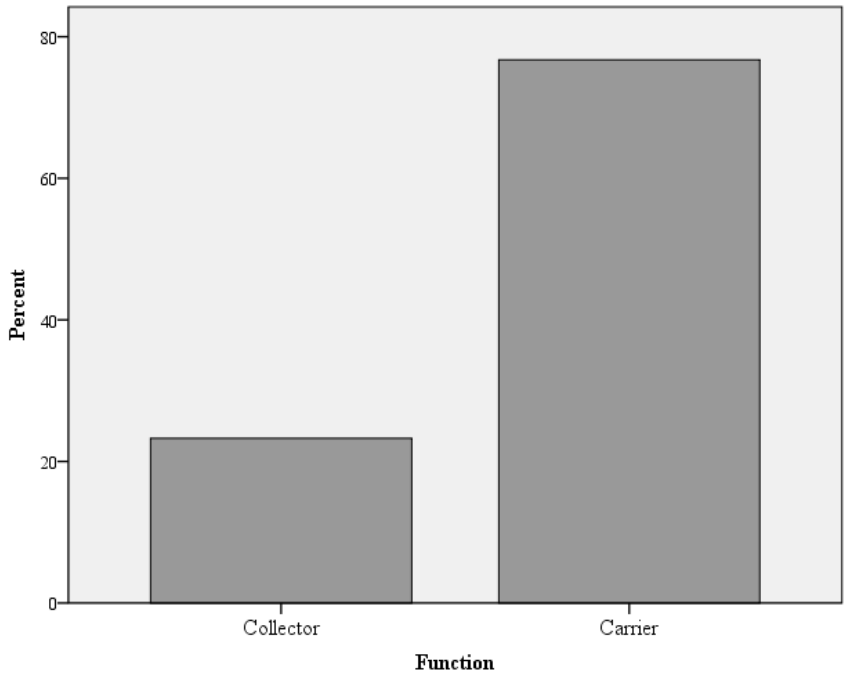


Figure 6-5 – Pipe function distribution in the LNW route

Size

Pipe size is considered one of the main structural deterioration factors in the literature (see Section 2.4.2.1). In the dataset, pipe size is recorded as a categorical variable with four levels (i.e. < 150, 151–300, 301–450 and > 451 mm). The distribution of these four size ranges is presented in Figure 6-6. It can be seen that most pipes are in the size range of 151–300 mm and less than 10% are larger than 451 mm. It should be noted that pipes larger than 500 mm are typically considered as culverts.

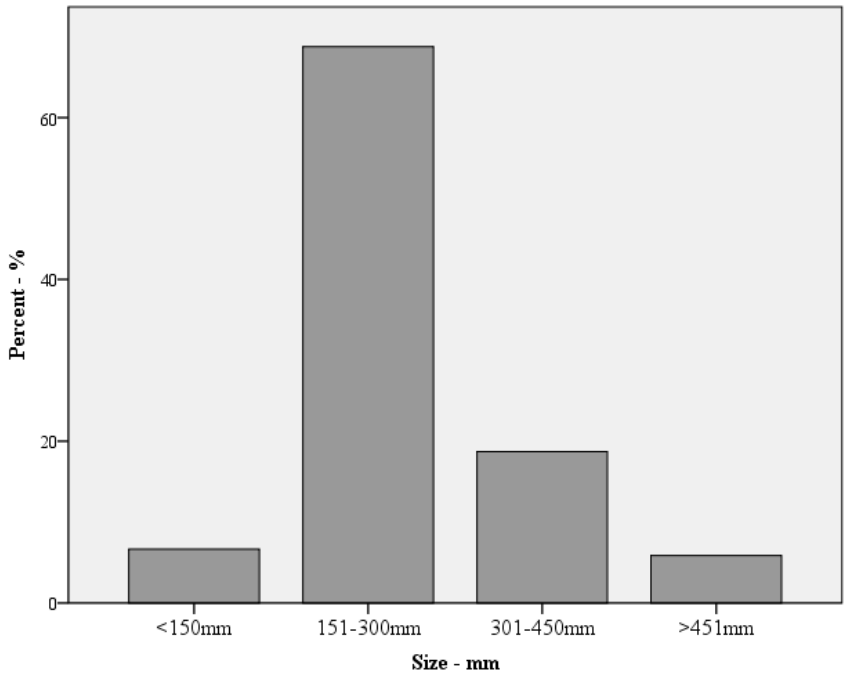


Figure 6-6 – Pipe size distribution in the LNW route

Material

Material is another critical factor which is considered in most deterioration studies in the literature (see Section 2.4.2.1). It has been suggested that load and soil conditions around the pipe can affect the structural deterioration rate in different pipe materials. As presented in Figure 6-7, the most used material for pipes in the LNW route is vitrified clay, followed by uPVC, polyethylene, concrete, spun iron and steel.

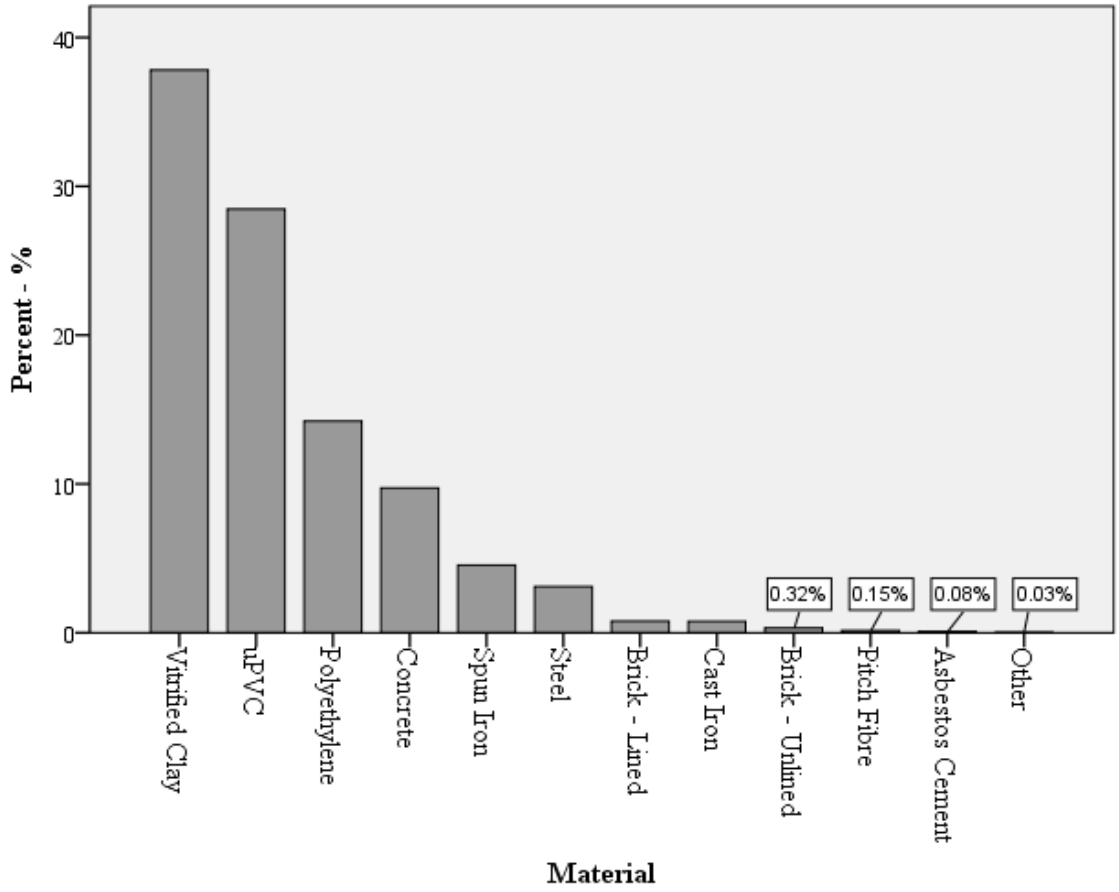


Figure 6-7 – Pipe material distribution in the LNW route; uPVC: un-plasticised polyvinyl chloride plastic

6.2.1.3 **Culvert independent variables**

Shape

Similar to pipe shape, culvert shape is also included in the MR model to examine its effect on the deterioration rate. It is assumed that shape can have a significant effect on structural deterioration. Culverts in the LNW route are constructed in arch, barrel and box shapes and their distribution is presented in Figure 6-8.

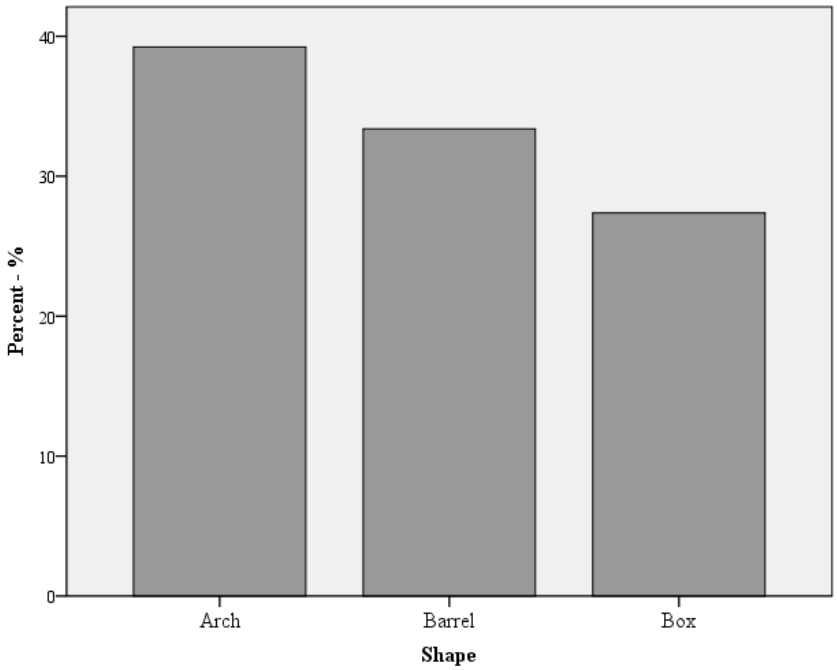


Figure 6-8 – Culvert shape distribution in the LNW route

Material

Culvert material, similar to pipe material, is considered to contribute significantly to the structural deterioration rate. The distribution of culvert materials is presented in Figure 6-9, where it can be seen that most culverts are constructed of brick and concrete.

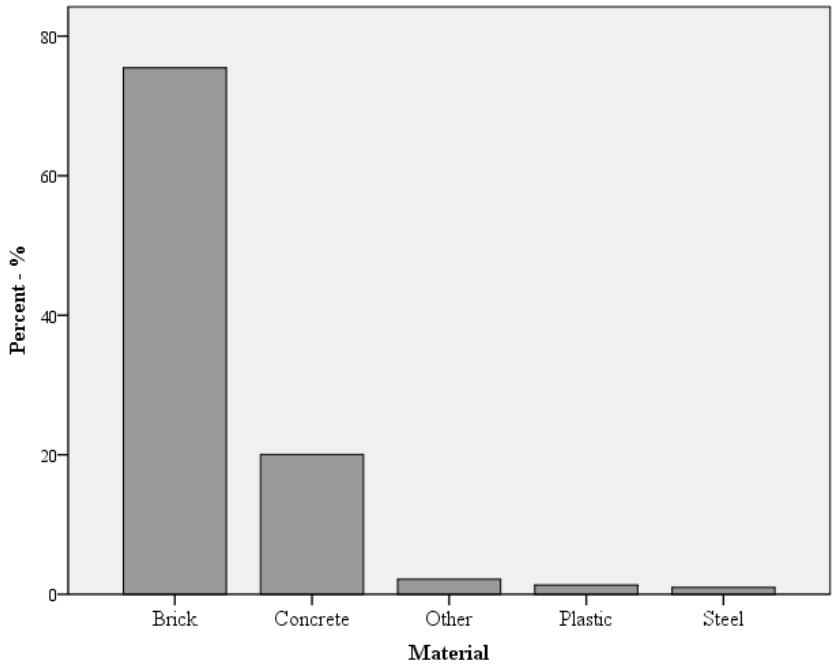


Figure 6-9 – Culvert material distribution in the LNW route

6.2.1.4 **Channel independent variables**

Drainage location

Channels are used extensively in both track and off-track drainage systems. It is therefore assumed that the location of a channel can have a significant effect on both structural and service deterioration. As presented in Figure 6-10, most channels are located in the Cess, Outside Network Rail Boundary or Toe of embankments.

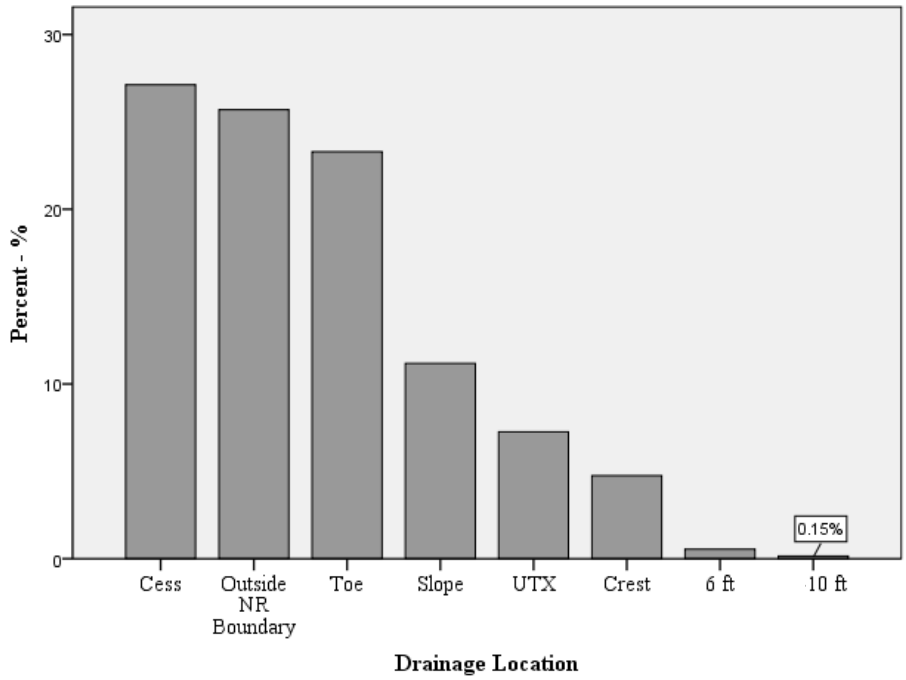


Figure 6-10 – Channel drainage location distribution in the LNW route; UTX: under track crossing; 6 ft: the area between two tracks; 10 ft: the area between two double tracks

Topography

Similar to other assets, the line section topography for channels is also considered in the MR model. The distribution of channel topography sections (i.e. At Grade, Cutting and Embankment) in the LNW is presented in Figure 6-11. It can be seen that most channels are used in Embankment sections, followed by Cutting and At Grade sections.

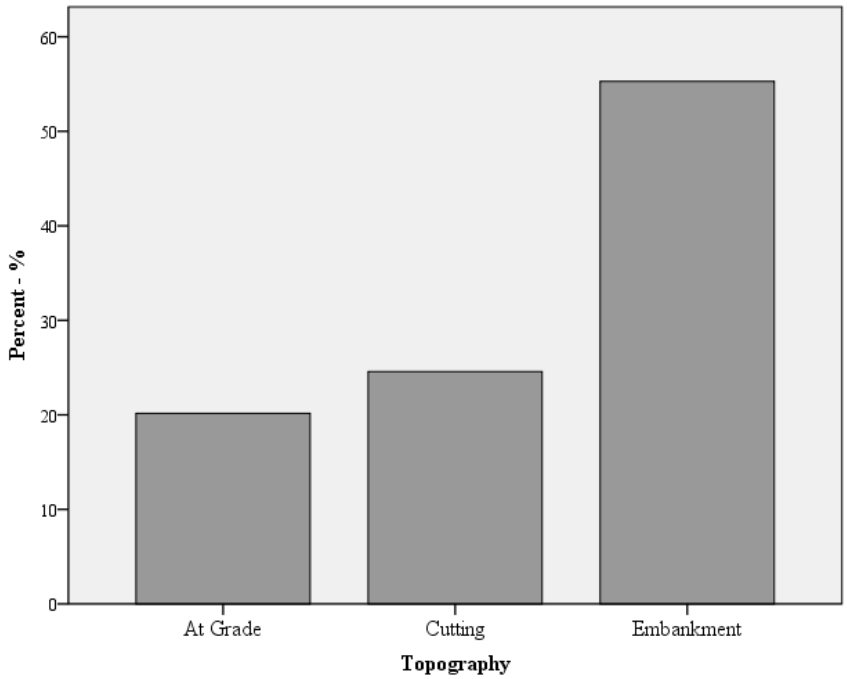


Figure 6-11 – Channel topography distribution in the LNW route

Shape

As discussed in Section 2.3.1.1, channels are commonly constructed in various shapes for specific purposes. In this case study, channel shapes are considered as an IV in the MR model to examine their effect on the structural and service deterioration rate. The distribution of channel shapes is presented in Figure 6-12, where it can be seen that the majority of channels are semi-circular, followed by trapezoidal, rectangular and V-shaped.

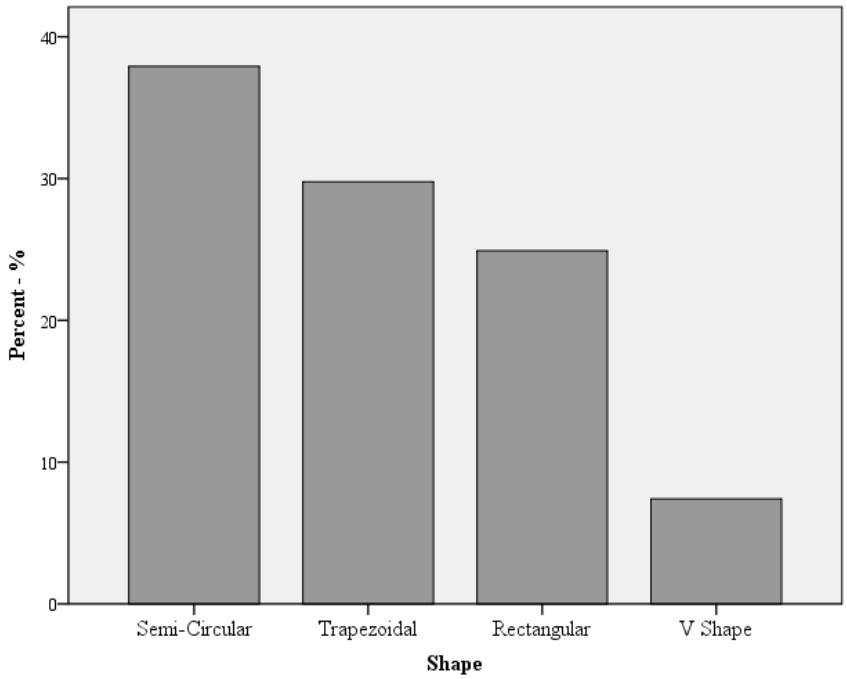


Figure 6-12 – Channel shape distribution in the LNW route

Material

Similar to channel shape, material (i.e. lining material) is also considered a critical factor in structural and service deterioration. The distribution of channel materials is presented in Figure 6-13, where it can be seen that most channels are simple ditches dug in the ground (i.e. earth channels).

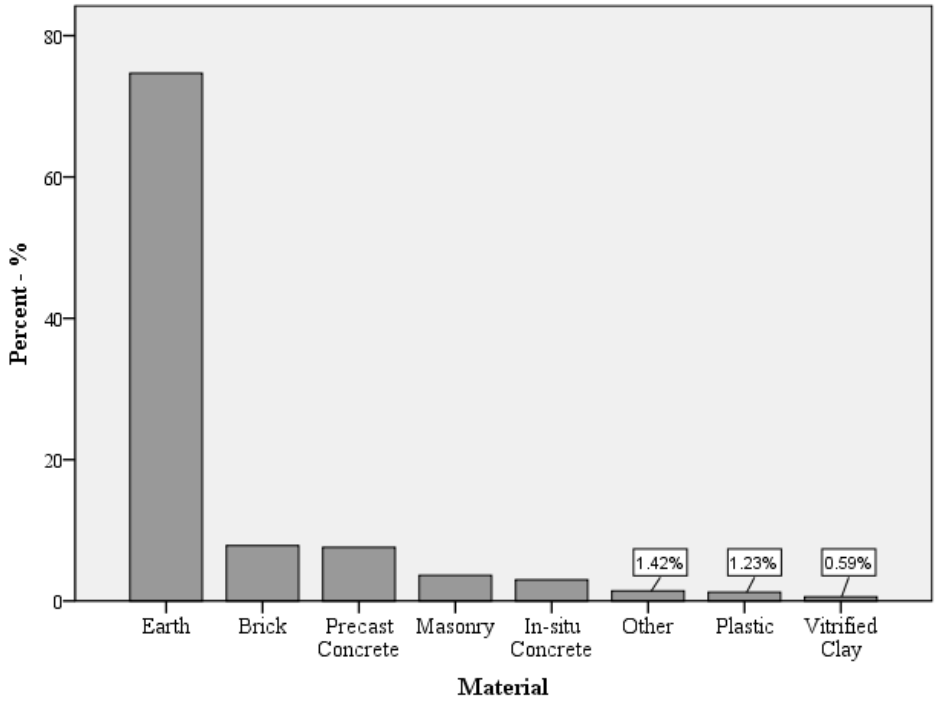


Figure 6-13 – Channel material distribution in the LNW route

6.2.2 **Model size**

As discussed in Section 3.3.1.1, the number of data entries (i.e. sample size) in the MR model should be proportional to the number of IVs considered. Table 6-1 compares the minimum and available sample size in this case study. It can be seen that the available sample size for all four assets is larger than the minimum size required, which indicates that the model size is sufficient. It should be noted that all IVs in this study are categorical and are converted into dummy variables for the MR model. This will eventually increase the number of IVs as each level of the categorical variable is considered as a separate IV. For instance, the two culvert variables of shape (with three levels) and material (with five levels) result in 3 + 5 = 8 dummy variables.

Table 6-1 – Model size analysis

	IV	Number of levels	Total number of dummy variables (m)	Minimum sample size required (50 + 8m)	Available sample size
Catch-pit	Topography	3	10	130	24,616
	Shape	2			
	Material	5			
Pipe	Topography	3	21	218	34,491
	Function	2			
	Size	4			
	Material	12			
Culvert	Shape	3	8	114	599
	Material	5			
Channel	Drainage location	8	23	234	2,039
	Topography	3			
	Shape	4			
	Material	8			

6.2.3 **Data quality and assumptions check**

As discussed previously in Chapter 3, it is essential to ensure that the assumptions of the developed MR model are met. This section discusses analysis of the MR assumptions, including outliers, multicollinearity, linearity, normality and homoscedasticity. The dataset was first reviewed in an Excel spreadsheet, and outlier points, which appeared to be missing data and obvious errors, were removed. The remaining MR model assumptions are discussed in the following sections.

6.2.3.1 **Multicollinearity**

Assumption of multicollinearity ensures that there is no significant correlation between the IVs. Heavily correlated IVs do not allow the model to identify which IV is responsible for a change in the DV. Multicollinearity is assessed in the descriptive section of the SPSS regression

analysis with the Pearson correlation value. For this test, IVs with Pearson correlation values greater than 0.9 and a significance level less than 0.001 are assumed to be heavily correlated. Table 6-2 presents an example of IV correlation analysis for catch-pits. The correlation analysis tables for pipes, culverts and channels are included in Appendix B. As presented in Table 6-2, no two IVs have a correlation level higher than 0.9 with a significance level less than 0.001. Similarly, no correlation was detected between the IVs for pipes, culverts and channels. Based on this finding, no IV was omitted from the model for any asset. As it can be seen from the correlation tables, IVs with only two categories have a −1 correlation (e.g. Table 6-2, rectangular and circular catch-pits). This means that any catch-pit that is not rectangular has a circular shape; therefore, circular catch-pits are 100% inversely correlated with rectangular catch-pits.

Table 6-2 – Correlations between catch-pit IVs

		Topography			Material					Shape	
Catch-pits	**Deterioration rate**	At Grade	Cutting	Embankment	Brick	GRP	In-situ Concrete	Pre-cast Concrete	Plastic	Circular	Rectangular
Deterioration rate	1	.040	−.038	−.006	.023	.001	−.010	.008	−.024	−.025	.025
At Grade	.040	1	−.892	−.307	.017	.033	.085	−.073	.017	.028	−.028
Cutting	−.038	−.892	1	−.156	−.030	−.027	−.079	.088	−.033	−.043	.043
Embankment	−.006	−.307	−.156	1	.026	−.016	−.019	−.027	.031	.031	−.031
Brick	.023	.017	−.030	.026	1	−.022	−.078	−.513	−.116	−.070	.070
GRP	.001	.033	−.027	−.016	−.022	1	−.017	−.113	−.025	−.013	.013
In-situ Concrete	−.010	.085	−.079	−.019	−.078	−.017	1	−.404	−.091	−.072	.072
Pre-cast Concrete	.008	−.073	.088	−.027	−.513	−.113	−.404	1	−.605	−.523	.523
Plastic	−.024	.017	−.033	.031	−.116	−.025	−.091	−.605	1	.832	−.832
Circular	−.025	.028	−.043	.031	−.070	−.013	−.072	−.523	.832	1	−1
Rectangular	.025	−.028	.043	−.031	.070	.013	.072	.523	−.832	−1	1

6.2.3.2 **Linearity, normality and homoscedasticity**

A practical approach to assess the assumption of linearity, normality and homoscedasticity is to analyse the standardised residual plots available in the SPSS program. Figure 6-14 presents an example of the standardised residual plots for catch-pit structural deterioration. Figure (**a**) addresses the normality assumption, where the distribution of standardised residuals should follow a normal distribution, and figure (**b**) addresses the linearity assumption, where the normal P-P plot points should follow the linear diagonal line. As presented in Figure 6-14, it can be seen that both assumptions of normality and linearity are violated. The distribution in

figure (**a**) is not normal (i.e. positively skewed), and in figure (**b**), P-P plot points do not follow the linear diagonal line.

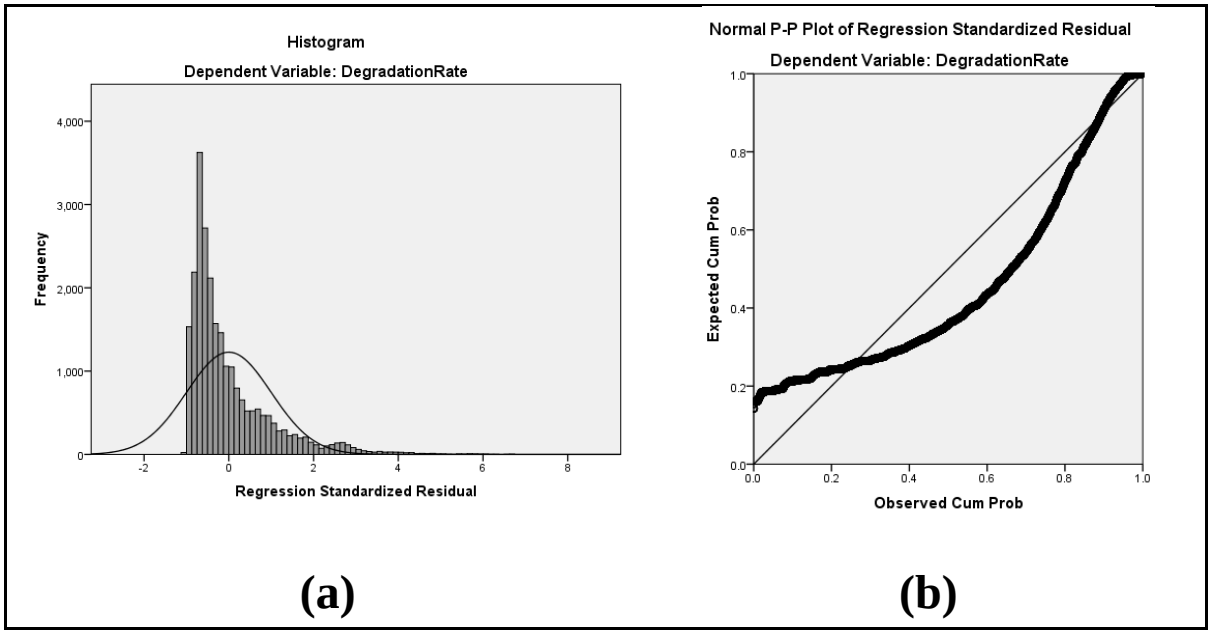


Figure 6-14 – Catch-pit structural deterioration – regression standardised residual plots

To examine the assumption of homoscedasticity, the plot of regression standardised residuals versus the predicted values in the SPSS program was used. Tabachnick and Fidell (2013) best present the function of this plot in Figure 6-15. Figure (1) presents an example of good data where points are equally spread. Homoscedasticity is defined as the consistency of data variation across the sample. This is presented in Figure (2) where this assumption is violated. It can be seen that the variation of points towards the right side of the plot is significantly different from that on the left side. The plot of standardised residuals and predicted values can also be used to check normality and linearity assumptions. Figure (3) shows an example where normality is violated as the concentration of points is much higher on the upper side of the plot than the lower side, and Figure (4) shows an example where linearity is violated as the points follow a curved line rather than a straight line.

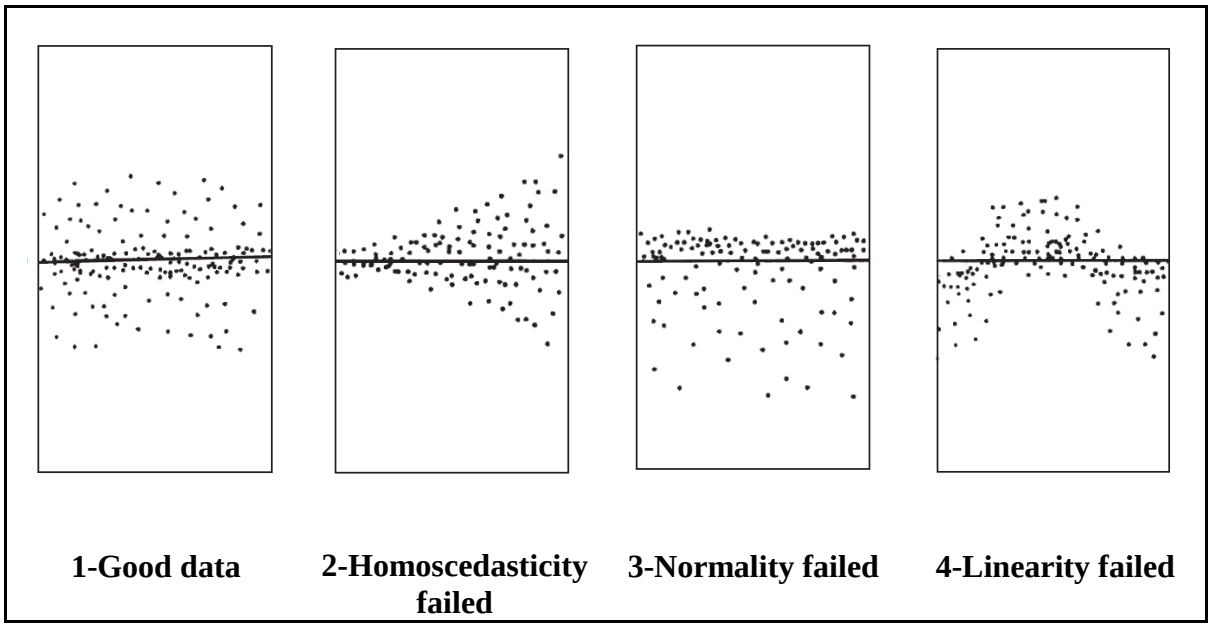


Figure 6-15 – Examples of standardised residuals against predicted values (Tabachnick and Fidell, 2013)

Figure 6-16 presents the plot of regression standardised residual and predicted values for catch-pit structural deterioration. It can be seen that the assumption of homoscedasticity is met as the variation of points is constant across the plot. However, the normality assumption is violated because points are heavily concentrated on the lower side of the plot. This plot is also a great way to detect any remaining outlier points; one was detected and is highlighted in Figure 6-16.

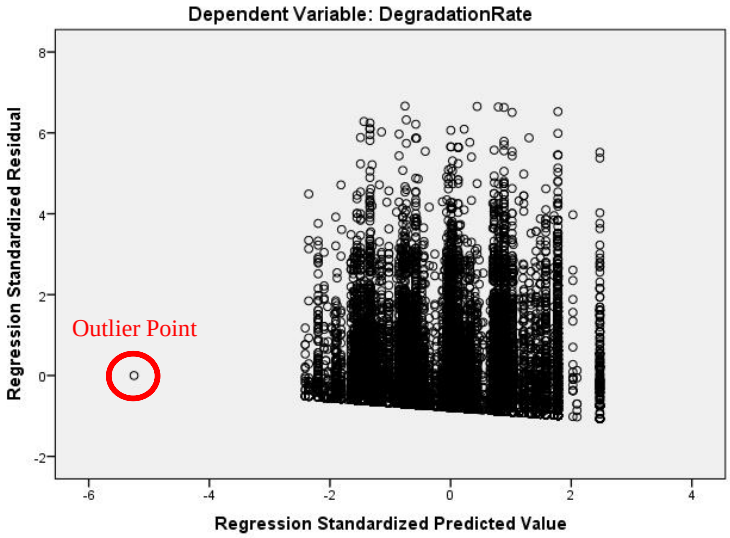


Figure 6-16 – Catch-pit structural deterioration – regression standardised residual versus predicted values

6.2.4 **Data transformation**

The analysis of the data in the previous section showed that most MR assumptions were violated. This section describes the transformation technique adopted to amend the data. Lack of normality in the dataset is mainly due to the nature of average deterioration data. It was shown that most assets usually stay in the same condition or only move to the next poorest condition, which results in more deterioration rate values closer to 0 than 2.33 (i.e. highest deterioration rate).

Figure 6-17 presents the distribution of catch-pit structural deterioration rate, where the rate of 0 has the highest frequency (6,796 cases). This value is significantly different from the rest of the cases and is mainly responsible for the MR assumption issues.

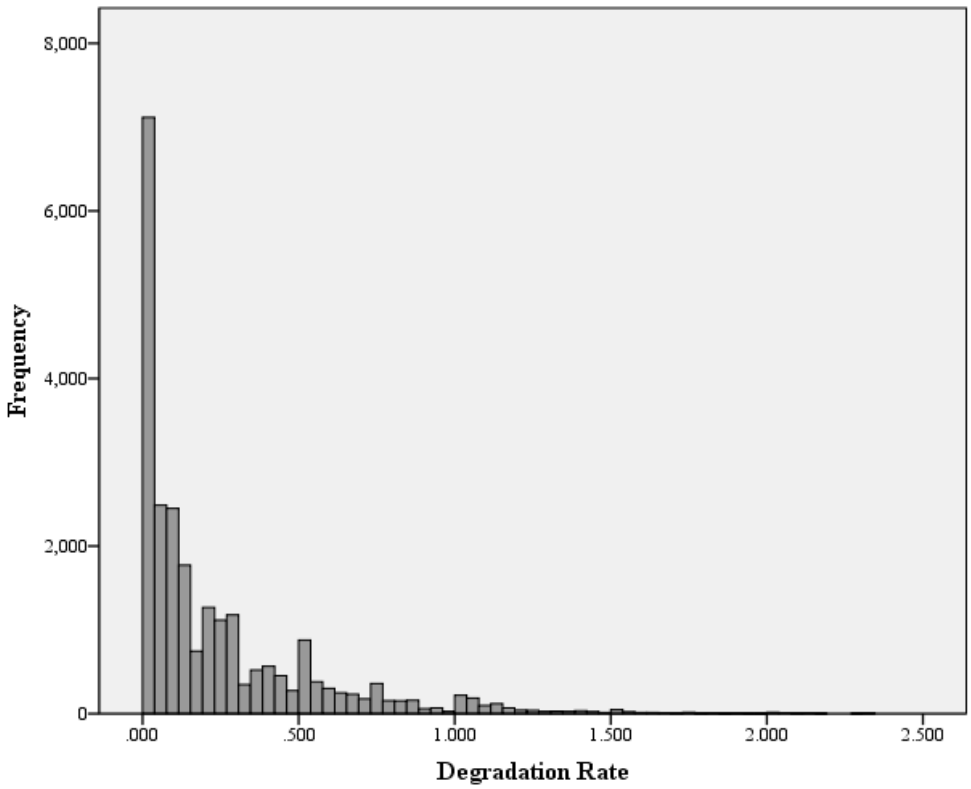


Figure 6-17 – Catch-pit structural deterioration – frequency of deterioration rate

The purpose of the MR model developed in this study is to understand the effect of asset characteristics on the deterioration progress. As discussed previously in Section 5.2.1.2, a deterioration rate of 0 represents a flat deterioration slope. This means that the asset has not changed in condition and consequently has not experienced any deterioration. Hence, rates of 0 were removed from the dataset, as they do not represent the true nature of asset deterioration behaviour. The updated sample size, where assets with a deterioration rate of 0 are eliminated, is presented in Table 6-3. It can be seen that the transformed sample size is still sufficiently larger than the minimum required size.

Table 6-3 – Model size with transformed data (deterioration rate of 0 eliminated)

	IV	Total number of dummy variables (m)	Minimum required sample size (50 + 8m)	Available sample size	Transformed sample size
Catch-pit	Topography	10	130	24,616	**17,819**
	Shape				
	Material				
Pipe	Topography	21	218	34,491	**25,562**
	Function				
	Size				
	Material				
Culvert	Shape	8	114	599	**328**
	Material				
Channel	Drainage location	23	234	2,039	**1,450**
	Topography				
	Shape				
	Material				

The MR analysis was run for the second time after eliminating the deterioration rate of 0; however, although data quality was improved slightly, most assumptions were still violated. Therefore, it was decided to use one of the transformation techniques available in MR analysis. Among the available techniques, the square root method appeared to be the most appropriate approach. The square root function in SPSS was carried out four times, which means that the deterioration rate was transformed into the 16^{th} root. It was only after this transformation that the residual plots showed acceptable levels of normality, linearity and homoscedasticity. It should be noted that the transformation of data also transforms interpretation of the regression coefficient. Hence any numerical assessment of the regression coefficient should be transferred back to the original format.

Figure 6-18 presents the comparison of regression standardised residual plots before and after data transformation for all assets. It can be seen that the plots for the original data were all positively skewed, while after data transformation they follow a normal distribution. Furthermore, Figure 6-19 shows that the assumption of linearity is met. It can be seen that after data transformation, most points on the plot follow the linear diagonal line, whereas original data significantly differed from it. Finally, Figure 6-20 presents an excellent level of homoscedasticity after data transformation. It can be seen that the points are distributed evenly over the plots for all assets. This figure is also particularly useful for detecting any remaining outlier points. Although an initial review was carried out to identify outlier points, some outliers were still detected in the data. This can be seen in the 'before transformation' scatterplots in Figure 6-20 where a few outlier points were identified. These points were removed before the data transformation.

It can be concluded that the data transformation was successful, and the assumptions of normality, linearity and homoscedasticity are met. Service deterioration data also showed the same issues with MR assumptions and data quality. Therefore, the same principles of data transformation were applied to the service deterioration dataset.

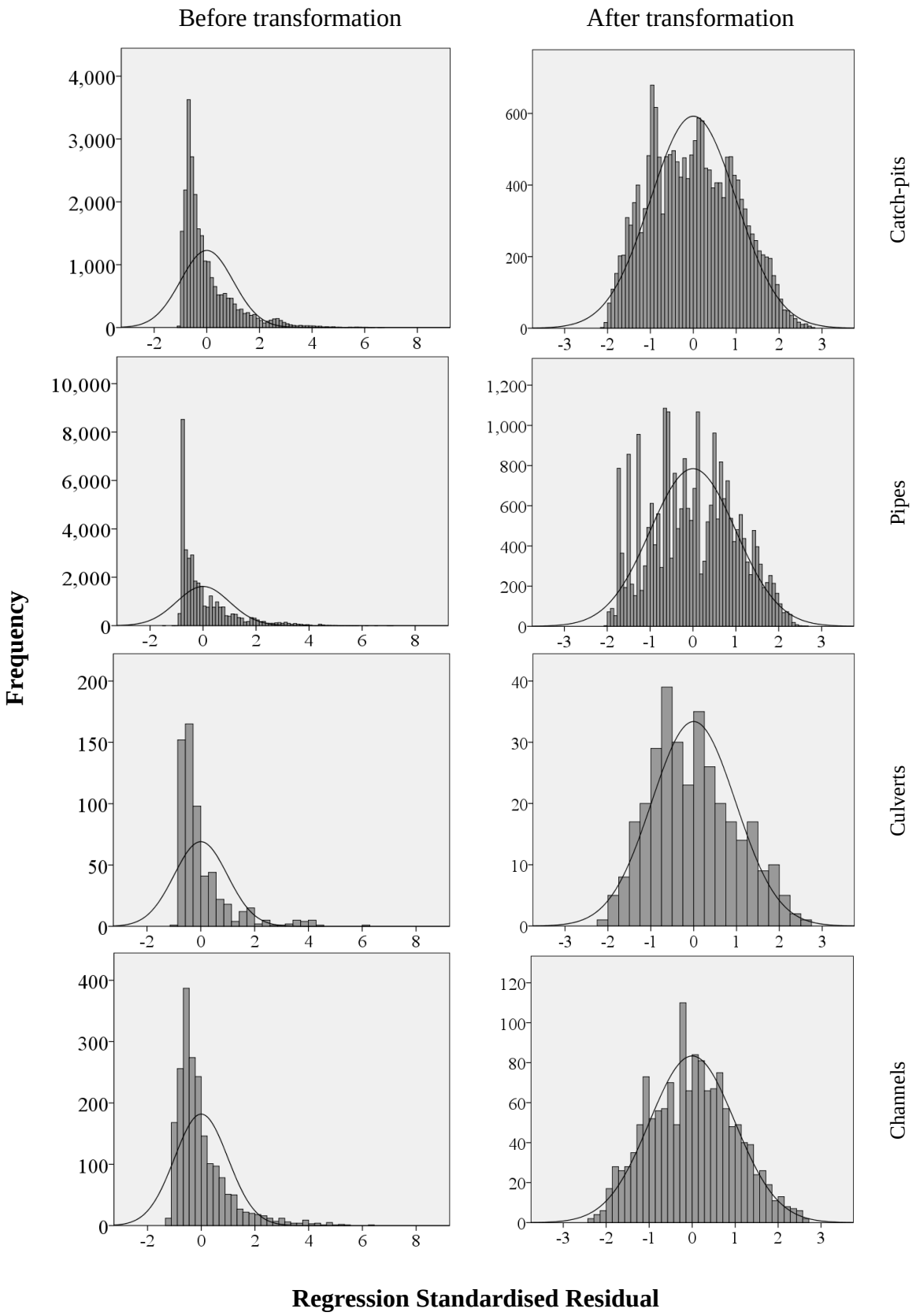


Figure 6-18 – Structural deterioration – comparison of standardised residual plots before and after data transformation

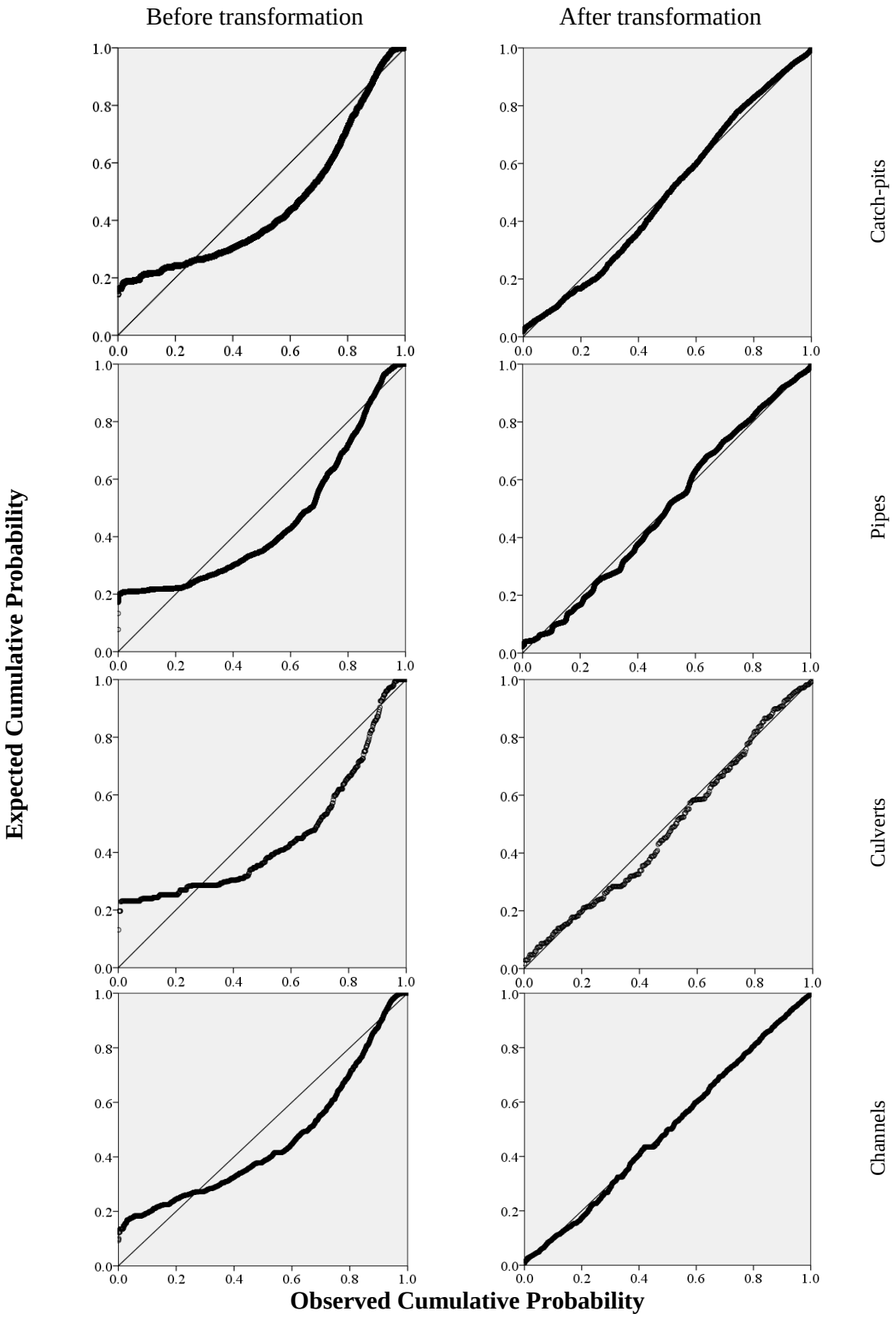


Figure 6-19 – Structural deterioration – comparison of normal P-P plot of standardised residual plots before and after data transformation

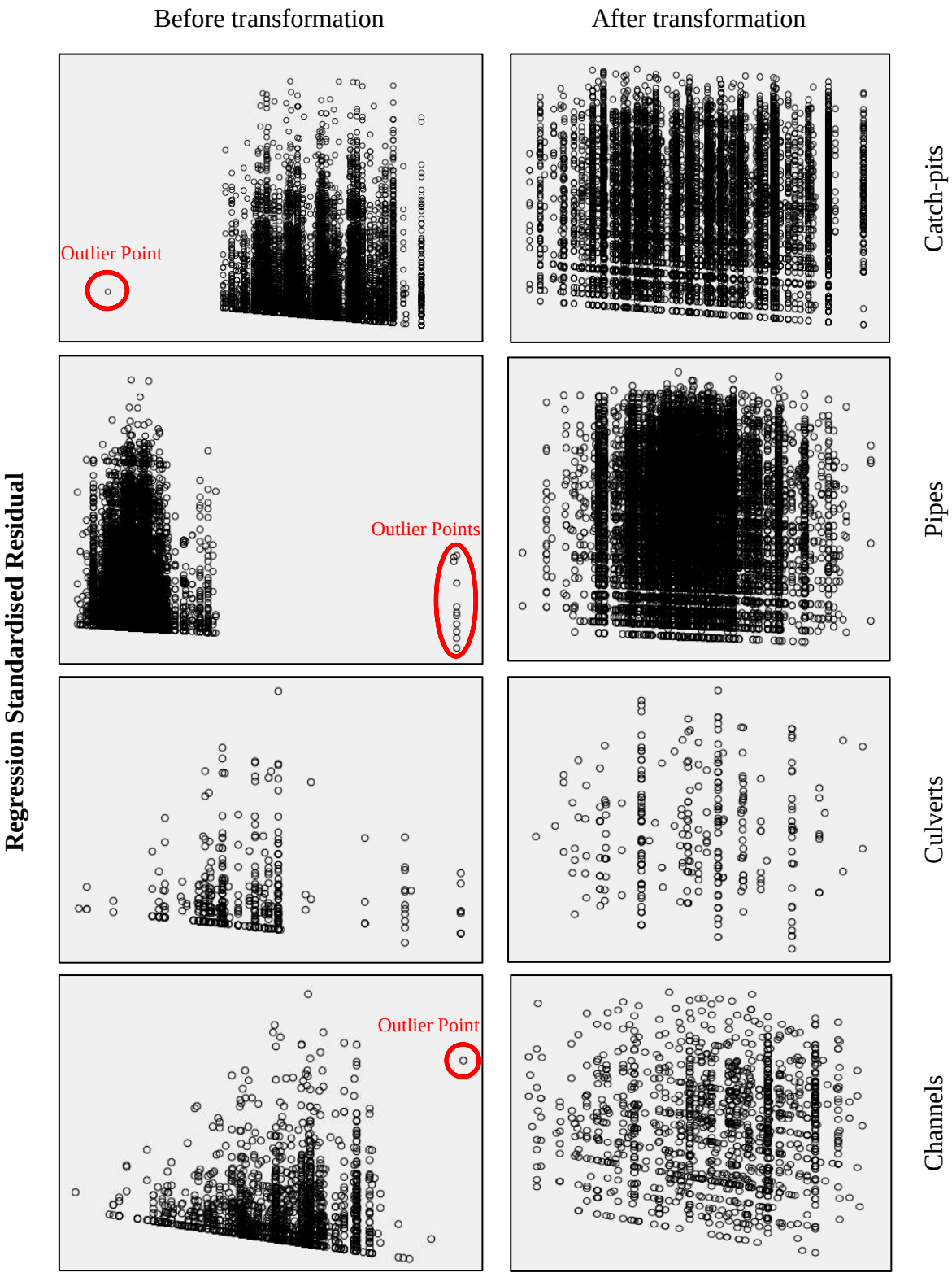


Figure 6-20 – Structural deterioration – comparison of standardised predicted/residual scatterplots before and after data transformation

6.2.5 **Multiple Regression results**

Further investigation of the data revealed that the available IVs explain a very small portion of the variation in the DV. This means that there are other significant variables responsible for DV variation, which are not available in the data (e.g. asset age). Due to the weak explanation of the DV with the available IVs, the order of IV entry into the model will not make a significant difference (see Section 3.3.1.1). However, in this case, a sequential entry method can be more beneficial. The order of IV entry in a sequential MR is based on the decision of the researcher, which can be based on previous research, the literature and logical decision. Consequently, IVs were entered into the model based on their assumed level of importance, which was discussed with NR engineers.

This section analyses the contribution of each IV to the DV. This is achieved by reviewing the model parameters (b coefficients) of the MR model. The review of model parameters is the final analysis in this section, where those IVs with significant contributions are selected for asset grouping. The b coefficient for each IV category indicates how much the DV will increase if that specific IV is raised by one unit. It should be noted that the b value for each IV is true only if the effect of other IVs in the model is held constant (zero).

In this study, b coefficients with a significance level of less than 0.05 are considered significant. The 95% confidence interval was used to examine the accuracy of b coefficients. Generally, smaller ranges of confidence interval indicate a better fit of the model and more accurate b coefficients. SPSS MR analysis automatically assigns a reference category for each categorical IV, and the b coefficient values are compared to the reference group in each IV. Assignment of the reference group is based on a combination of correlation level and data size.

b coefficients for catch-pits are presented in Table 6-4. The reference group for Topography IV is At Grade, for Material it is Pre-cast Concrete Section and for Shape it is Circular catch-

pits. As can be seen in the table, for structural deterioration, the contribution of catch-pits in cutting sections made of brick to the deterioration rate is significant. The significance of b coefficient for Cutting sections is 0, and for Brick it is 0.013, which are both less than the 0.05 significance level. This means that catch-pits in Cutting sections have a significant contribution to structural deterioration, compared to the ones in At Grade sections (the reference group). Similarly, Brick catch-pits contribute significantly to structural deterioration, compared to the reference group of Pre-cast Concrete Section catch-pits. This is different for service deterioration where only the contribution of In-situ Concrete catch-pits (significance level of 0.15) was significant. Therefore, In-situ Concrete catch-pits are considered to make a significant contribution to service deterioration, compared to Pre-cast Concrete Section catch-pits. Based on this information, it is concluded that Brick catch-pits at Cutting sections are significantly different to the rest in terms of structural deterioration. Hence, when developing NL asset groups for the structural deterioration model, Brick catch-pits in Cutting sections are grouped separately. Similarly, for the service deterioration model, where deterioration of In-situ Concrete catch-pits was significantly different, a separate asset group is considered.

The significant groups for pipes, culverts and channels are presented in Table 6-5, Table 6-6 and Table 6-7, respectively. For the pipe structural deterioration model, only pipes smaller than 150 mm (significance value of 0.011), and for the service deterioration model, Unlined Brick pipes, had a significant b coefficient (significance value of 0.017). Hence, for the pipe structural deterioration model, pipes smaller than 150 mm, and for the service deterioration model, Unlined Brick pipes, were grouped separately. None of the IV categories for culverts made a significant contribution to structural or service deterioration. Therefore, all culverts were considered in the same group for both structural and service deterioration models. For channel structural deterioration, Rectangular or Trapezoidal masonry channels in the Cess location make a significant contribution; for service deterioration, Rectangular or Trapezoidal Pre-cast

Concrete channels are significant. The result of NL grouping of assets, based on their significant contribution to deterioration, is presented in Table 6-8.

Table 6-4 – Catch-pit IV contributions to structural and service deterioration – significance level of 0.05

Catch-pits	**Structural Deterioration**				**Service Deterioration**			
	Unstandardised coefficients	**Sig.**	**95.0% confidence interval for b**		**Unstandardised coefficients**	**Sig.**	**95.0% confidence interval for b**	
	b				**b**			
Reference	**At Grade group**				**At Grade group**			
Cutting	**−.005**	**.000***	−.006	−.003	−.001	.148	−.003	.000
Embankment	−.003	.094	−.007	.001	−.002	.212	−.005	.001
Reference	**Pre-cast Concrete Section group**				**Pre-cast Concrete Section group**			
Brick	**.003**	**.013***	.001	.006	.002	.116	−.001	.005
GRP	−.001	.892	−.012	.011	−.003	.520	−.014	.007
In-situ Concrete	−.003	.061	−.007	.000	**−.004**	**.015***	−.007	−.001
Plastic	−.001	.525	−.006	.003	−.002	.294	−.006	.002
Reference	**Circular group**				**Circular group**			
Rectangular	.003	.167	−.001	.008	.003	.145	−.001	.007

Table 6-5 – Pipe IV contributions to structural and service deterioration – significance level of 0.05

Pipes	**Structural Deterioration**				**Service Deterioration**			
	Unstandardised coefficients	Sig.	95.0% confidence interval for b		Unstandardised coefficients	Sig.	95.0% confidence interval for b	
	b				**b**			
Reference	**151–300 mm group**				**151–300 mm group**			
< 150 mm	**.004**	**.011 ***	**.001**	**.007**	−.001	.248	−.002	.001
301–450 mm	5.379E−5	.955	−.002	.002	.000	.951	−.001	.001
> 451 mm	−.002	.270	−.005	.001	.001	.290	−.001	.002
Reference	**Vitrified Clay group**				**Vitrified Clay group**			
Asbestos Cement	.001	.945	−.025	.027	.005	.421	−.007	.018
Brick – Lined	−.005	.245	−.013	.003	−.001	.481	−.005	.003
Brick – Unlined	−.003	.658	−.015	.009	**−.007**	**.017***	**−.014**	**−.001**
Cast Iron	.001	.821	−.007	.009	.000	.955	−.004	.004
Concrete	.000	.852	−.003	.002	.000	.752	−.001	.001
Polyethylene	−.001	.286	−.004	.001	.000	.902	−.001	.001
Pitch Fibre	−.003	.774	−.020	.015	.005	.226	−.003	.014
Spun Iron	−.003	.062	−.007	.000	−.001	.310	−.003	.001
Steel	.002	.434	−.002	.006	.000	.708	−.002	.002
uPVC	−.001	.526	−.002	.001	.000	.474	−.001	.001
Reference	**At Grade group**				**At Grade group**			
Cutting	.001	.186	.000	.003	.001	.052	.000	.002
Embankment	.002	.311	−.002	.005	.000	.739	−.001	.002
Reference	**Collector group**				**Collector group**			
Carrier	.000	.997	−.002	.002	.000	.653	−.001	.001

Table 6-6 – Culvert IV contributions to structural and service deterioration – significance level of 0.05

Culverts	**Structural Deterioration**				**Service Deterioration**			
	Unstandardised coefficients	Sig.	95.0% confidence interval for b		Unstandardised coefficients	Sig.	95.0% confidence interval for b	
	b				**b**			
Reference	**Barrel group**				**Barrel group**			
Arch	−.011	.083	−.024	.001	.006	.331	−.007	.020
Box	−.002	.733	−.016	.012	.010	.116	−.003	.023
Reference	**Brick group**				**Brick group**			
Concrete	−.002	.749	−.016	.012	−.008	.190	−.021	.004
Other	−.005	.777	−.037	.028	−.042	.082	−.088	.005
Plastic	−.024	.279	−.068	.020	−.022	.354	−.069	.025
Steel	−.041	.234	−.110	.027	−.013	.661	−.074	.047

Table 6-7 – Channel IV contributions to structural and service deterioration – significance level of 0.05

Channels	**Structural Deterioration**				**Service Deterioration**			
	Unstandardised coefficients	Sig.	95.0% confidence interval for b		Unstandardised coefficients	Sig.	95.0% confidence interval for b	
	b				**b**			
Reference	**Earth group**				**Earth group**			
Brick	.002	.790	−.010	.014	−.004	.492	−.015	.007
In-situ Concrete	.003	.687	−.014	.020	.002	.809	−.015	.019
Masonry	**−.019**	**.016***	**−.035**	**−.004**	.006	.513	−.011	.022
Other	−.014	.287	−.041	.012	.000	.986	−.030	.029
Pre-cast Concrete	−.009	.163	−.021	.004	**−.015**	**.010***	**−.027**	**−.004**
Plastic	−.045	.121	−.070	−.519	−.036	.706	−.061	−.010
Vitrified Clay	−.038	.056	−.077	.001	−.046	.071	−.096	.004
Reference	**Semi-Circular group**				**Semi-Circular group**			
Rectangular	**−.011**	**.004***	**−.019**	**−.004**	**−.013**	**.001***	**−.021**	**−.005**
Trapezoidal	**−.016**	**.000***	**−.022**	**−.009**	**−.010**	**.004***	**−.016**	**−.003**
V	−.006	.325	−.018	.006	−.012	.055	−.023	.000
Reference	**Outside NR Boundary group**				**Outside NR Boundary group**			
6 ft	−.016	.537	−.068	.035	−.044	.270	−.083	−.005
10 ft	−.017	.738	−.118	.084	−.057	.264	−.156	.043
Cess	**.009**	**.031***	**.001**	**.018**	−.001	.766	−.010	.008
Crest	−.004	.636	−.019	.012	−.004	.611	−.021	.012
Slope	−.001	.902	−.012	.011	−.008	.455	−.015	.000
Toe	.006	.098	−.001	.014	−.012	.416	−.023	−.001
UTX (link only)	−.004	.518	−.016	.008	−.017	.070	−.029	−.005
Reference	**Embankment group**				**Embankment group**			
At Grade	−.001	.798	−.009	.007	.002	.669	−.006	.010
Cutting	−.005	.225	−.013	.003	−.004	.297	−.013	.004

Table 6-8 – Network-level asset groups for structural and service deterioration models

Group #	Structural Deterioration	Service Deterioration
Catch-pits		
1	Brick material – Cutting sections	In-situ Concrete material
2	Others	Others
Pipes		
1	< 150 mm	Brick – Unlined material
2	Others	Others
Culverts		
1	All	All
Channels		
1	Masonry material – Rectangular shape – Cess location	PC Concrete material – Rectangular shape
2	Masonry material – Trapezoidal shape – Cess location	Plastic material – Rectangular shape
3	Others	Others

6.3 Transition probability matrices

For demonstration purposes, the process of transition probability matrix (TPM) development for group 1 of catch-pit structural deterioration is presented in this section. This group consists of brick catch-pits in cutting sections.

The Bayesian model developed in the R^{TM} coding platform was applied to each transition of the TPM (14 transitions). Table 6-9 presents the TP values for this group with the 95% confidence intervals. The probability of each transition is taken as the mean value of the 95% confidence interval. As can be seen in this table, transitions between lower condition grades have a smaller 95% confidence interval range compared to higher transitions. This is due to a larger number of cases in the dataset, where assets move between lower grades and stay in good condition. On the other hand, transitions between higher grades such as 4 and 5 occur at

a considerably lower frequency, resulting in a larger confidence interval for the probability output. The TP values in Table 6-9 are presented in the TPM for catch-pit structural deterioration group 1 in Equation (6-1) and the distribution of each transition is presented in Figure 6-21. These are the posterior probability distributions created by the Bayesian Markov chain model, where the MHA technique was used for the sampling process (see Section 5.3.2). It can be seen that the distribution of lower transitions such as P_{11}, P_{12} and P_{13} follow a more normal distribution compared to the transition between higher condition grades. Similar to the confidence intervals, this is also due to the larger population of assets moving between lower grades. The structural and service deterioration TPMs were developed for each asset group and are presented in Table 6-10.

Table 6-9 – Catch-pit structural deterioration TPM – group 1

Transition	**Probability**	**95% Probability Limits**	
P_{11}	0.876	0.849	0.902
P_{12}	0.067	0.048	0.089
P_{13}	0.046	0.031	0.065
P_{14}	0.006	0.001	0.015
P_{15}	0.005	0.001	0.015
P_{22}	0.624	0.099	0.901
P_{23}	0.373	0.003	0.706
P_{24}	0.002	0.000	0.409
P_{25}	0.001	0.000	0.415
P_{33}	0.669	0.013	0.987
P_{34}	0.289	0.013	0.838
P_{35}	0.042	0.099	0.845
P_{44}	0.950	0.000	0.999
P_{45}	0.050	0.000	0.892

$$\text{Catch_Pit TPM}_{ST1} = \begin{bmatrix} 0.876 & 0.067 & 0.046 & 0.006 & 0.005 \\ 0 & 0.624 & 0.373 & 0.002 & 0.001 \\ 0 & 0 & 0.669 & 0.289 & 0.042 \\ 0 & 0 & 0 & 0.950 & 0.050 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \quad (6\text{-}1)$$

Where:

ST1 is the structural deterioration of group 1

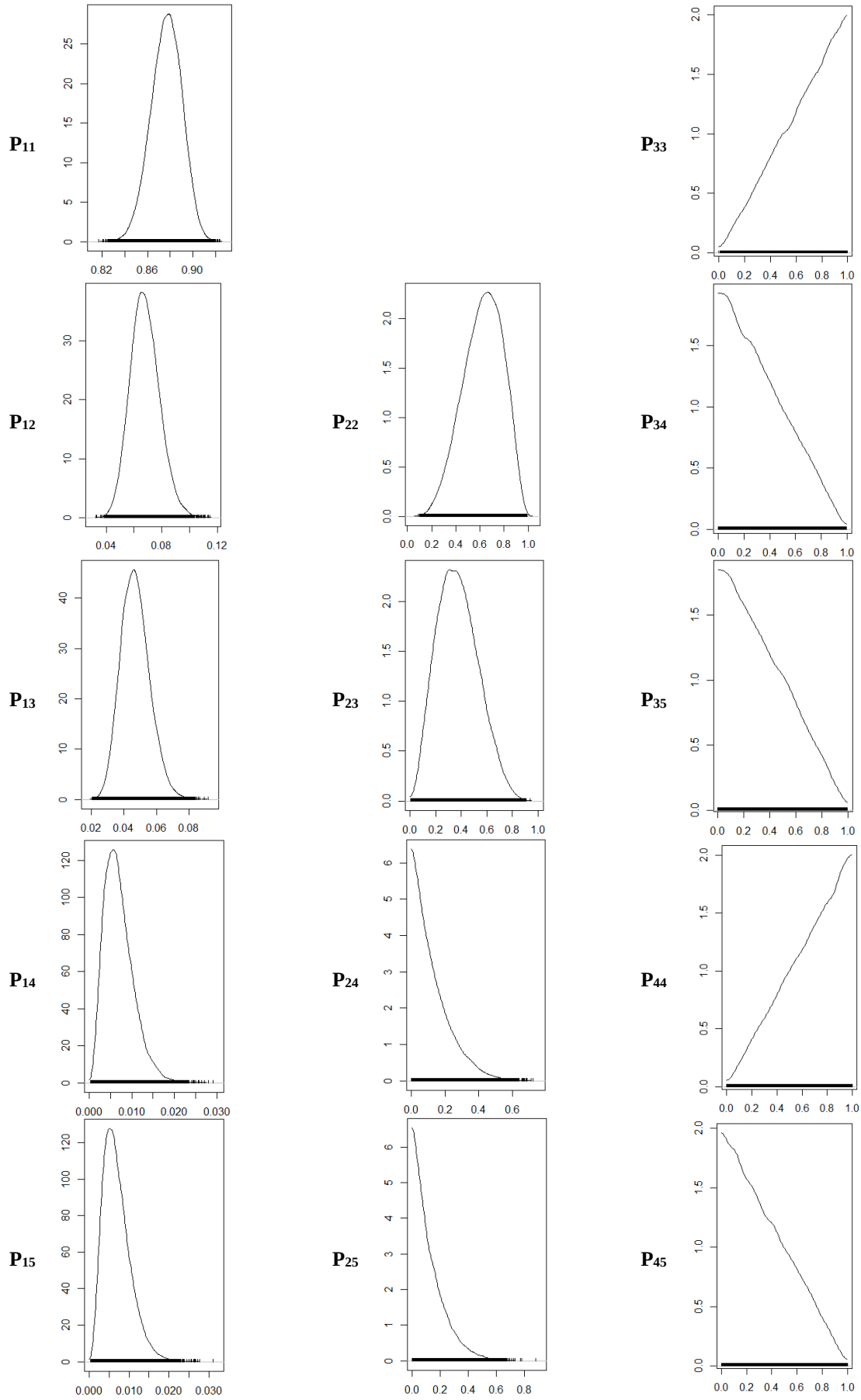


Figure 6-21 – Catch-pit group 1 structural deterioration – transition probability distributions

Table 6-10 – TPMs for structural and service deterioration models

Group	Structural Deterioration	Service Deterioration
Catch-pits		
1	$\begin{bmatrix} 0.876 & 0.067 & 0.046 & 0.006 & 0.005 \\ 0 & 0.624 & 0.373 & 0.002 & 0.001 \\ 0 & 0 & 0.669 & 0.289 & 0.042 \\ 0 & 0 & 0 & 0.950 & 0.050 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$	$\begin{bmatrix} 0.691 & 0.087 & 0.163 & 0.033 & 0.026 \\ 0 & 0.230 & 0.578 & 0.184 & 0.008 \\ 0 & 0 & 0.857 & 0.140 & 0.003 \\ 0 & 0 & 0 & 0.50 & 0.50 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$
2	$\begin{bmatrix} 0.875 & 0.047 & 0.061 & 0.009 & 0.008 \\ 0 & 0.382 & 0.496 & 0.076 & 0.046 \\ 0 & 0 & 0.720 & 0.147 & 0.130 \\ 0 & 0 & 0 & 0.333 & 0.667 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$	$\begin{bmatrix} 0.706 & 0.091 & 0.151 & 0.028 & 0.024 \\ 0 & 0.324 & 0.502 & 0.103 & 0.071 \\ 0 & 0 & 0.678 & 0.20 & 0.120 \\ 0 & 0 & 0 & 0.550 & 0.450 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$
Pipes		
1	$\begin{bmatrix} 0.896 & 0.039 & 0.039 & 0.017 & 0.009 \\ 0 & 0.250 & 0.415 & 0.333 & 0.002 \\ 0 & 0 & 0.428 & 0.423 & 0.149 \\ 0 & 0 & 0 & 0.50 & 0.50 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$	$\begin{bmatrix} 0.970 & 0.02 & 0.005 & 0.003 & 0.002 \\ 0 & 0.314 & 0.375 & 0.192 & 0.119 \\ 0 & 0 & 0.510 & 0.372 & 0.118 \\ 0 & 0 & 0 & 0.698 & 0.302 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$
2	$\begin{bmatrix} 0.894 & 0.036 & 0.039 & 0.018 & 0.013 \\ 0 & 0.242 & 0.376 & 0.320 & 0.062 \\ 0 & 0 & 0.638 & 0.306 & 0.056 \\ 0 & 0 & 0 & 0.746 & 0.254 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$	$\begin{bmatrix} 0.960 & 0.019 & 0.011 & 0.005 & 0.005 \\ 0 & 0.314 & 0.375 & 0.192 & 0.119 \\ 0 & 0 & 0.461 & 0.384 & 0.155 \\ 0 & 0 & 0 & 0.667 & 0.333 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$
Culverts		
1	$\begin{bmatrix} 0.959 & 0.019 & 0.009 & 0.007 & 0.006 \\ 0 & 0.497 & 0.252 & 0.150 & 0.101 \\ 0 & 0 & 0.330 & 0.660 & 0.010 \\ 0 & 0 & 0 & 0.667 & 0.333 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$	$\begin{bmatrix} 0.883 & 0.034 & 0.036 & 0.032 & 0.015 \\ 0 & 0.481 & 0.294 & 0.113 & 0.112 \\ 0 & 0 & 0.413 & 0.547 & 0.040 \\ 0 & 0 & 0 & 0.616 & 0.384 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$
Channels		
1	$\begin{bmatrix} 0.714 & 0.097 & 0.099 & 0.012 & 0.078 \\ 0 & 0.352 & 0.476 & 0.107 & 0.065 \\ 0 & 0 & 0.735 & 0.128 & 0.137 \\ 0 & 0 & 0 & 0.643 & 0.357 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$	$\begin{bmatrix} 0.684 & 0.091 & 0.196 & 0.019 & 0.010 \\ 0 & 0.374 & 0.502 & 0.093 & 0.031 \\ 0 & 0 & 0.675 & 0.196 & 0.129 \\ 0 & 0 & 0 & 0.540 & 0.460 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$
2	$\begin{bmatrix} 0.753 & 0.085 & 0.131 & 0.010 & 0.021 \\ 0 & 0.398 & 0.411 & 0.103 & 0.088 \\ 0 & 0 & 0.704 & 0.212 & 0.084 \\ 0 & 0 & 0 & 0.493 & 0.507 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$	$\begin{bmatrix} 0.659 & 0.098 & 0.181 & 0.021 & 0.041 \\ 0 & 0.304 & 0.494 & 0.102 & 0.100 \\ 0 & 0 & 0.626 & 0.257 & 0.117 \\ 0 & 0 & 0 & 0.585 & 0.415 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$
3	$\begin{bmatrix} 0.741 & 0.093 & 0.115 & 0.012 & 0.039 \\ 0 & 0.292 & 0.527 & 0.106 & 0.075 \\ 0 & 0 & 0.618 & 0.243 & 0.139 \\ 0 & 0 & 0 & 0.605 & 0.395 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$	$\begin{bmatrix} 0.702 & 0.121 & 0.051 & 0.023 & 0.103 \\ 0 & 0.328 & 0.513 & 0.094 & 0.065 \\ 0 & 0 & 0.590 & 0.319 & 0.091 \\ 0 & 0 & 0 & 0.504 & 0.496 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$

6.3.1 **Model validation**

The validation process was discussed in Section 5.3.4. A chi-square test was used to validate the deterioration model against the observed dataset for the year 2019. Group 1 of the catch-

pit structural deterioration model was used to demonstrate the validation process in this section. To validate asset conditions in 2019, the distribution in the previous year (2018) (Equation (6-3)) is multiplied by the associated TPM (Equation (6-2)). Equation (6-3) indicates that in 2018, 87.7% of assets were in structural condition 1, 6.7% were in condition 2, 4.5% were in condition 3, 0.7% were in condition 4 and 0.4% were in condition 5. By multiplying the TPM by the condition grade distributions in 2018, condition grades in 2019 were determined and are presented in Equation (6-4).

$$\text{Catch-pit TPM}_{ST1} = \begin{bmatrix} 0.876 & 0.067 & 0.046 & 0.006 & 0.005 \\ 0 & 0.624 & 0.373 & 0.002 & 0.001 \\ 0 & 0 & 0.669 & 0.289 & 0.042 \\ 0 & 0 & 0 & 0.950 & 0.050 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \quad (6\text{-}2)$$

$$\text{Catch-pit ST1}_{2018} = [0.877 \quad 0.067 \quad 0.045 \quad 0.007 \quad 0.004] \quad (6\text{-}3)$$

$$[0.877 \quad 0.067 \quad 0.045 \quad 0.004 \quad 0.004] \times \begin{bmatrix} 0.876 & 0.067 & 0.046 & 0.006 & 0.005 \\ 0 & 0.624 & 0.373 & 0.002 & 0.001 \\ 0 & 0 & 0.669 & 0.289 & 0.042 \\ 0 & 0 & 0 & 0.950 & 0.050 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

$$\text{Catch-pit ST1}_{2019} = [0.768 \quad 0.100 \quad 0.095 \quad 0.026 \quad 0.011] \quad (6\text{-}4)$$

The structural condition distributions in Equation (6-4) do not consider the maintenance effect and do not represent an actual distribution of condition grades in 2019. The effect of maintenance was discussed in Section 5.3.3. There was no maintenance history available for drainage assets; therefore, to determine the maintenance matrix, a review of the condition transitions was carried out. Equation (6-5) presents the general form of the maintenance matrix and the matrix adopted for catch-pit structural group 1. The values presented in this matrix are approximate percentages for maintained assets over a 1-year analysis period. As discussed previously, 100% of catch-pits in condition 1 will stay in the same condition as there is no better condition available (i.e. maintenance value of 1). For the other condition grades, a

portion of assets stay in the same condition, and the rest are maintained and transit to conditions 1 and 2. For instance, in the second row, 30% of catch-pits in condition 2 stay in the same condition and the remaining 70% are maintained and move to condition 1.

$$\text{Maintenance} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ M_{21} & M_{22} & 0 & 0 & 0 \\ M_{31} & M_{32} & M_{33} & 0 & 0 \\ M_{41} & M_{42} & M_{43} & M_{44} & 0 \\ M_{51} & M_{52} & M_{53} & M_{54} & M_{55} \end{bmatrix}$$

$$\text{Catch-pit ST1 Maintenance} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0.7 & 0.3 & 0 & 0 & 0 \\ 0.5 & 0.2 & 0.3 & 0 & 0 \\ 0.4 & 0.2 & 0 & 0.4 & 0 \\ 0.4 & 0.3 & 0 & 0 & 0.3 \end{bmatrix} \quad (6\text{-}5)$$

By multiplying the maintenance matrix for the structural deterioration of catch-pit group 1 by the structural condition grade distribution in 2019, the actual distribution of structural condition grades considering maintenance in 2019 is estimated. This is presented in the following equation.

$$[0.768 \quad 0.100 \quad 0.095 \quad 0.023 \quad 0.011] \times \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0.7 & 0.3 & 0 & 0 & 0 \\ 0.5 & 0.2 & 0.3 & 0 & 0 \\ 0.4 & 0.2 & 0 & 0.4 & 0 \\ 0.4 & 0.3 & 0 & 0 & 0.3 \end{bmatrix}$$

$$\text{Catch-pit } ST1_{2019} \text{ Maintained} = [0.901 \quad 0.057 \quad 0.029 \quad 0.009 \quad 0.003] \quad (6\text{-}6)$$

In the validation process, the predicted population of assets was compared to the population observed in 2019 for each condition grade. This is presented in Table 6-11. With five condition grades, there will be five possible outcomes, n. Therefore, the degree of freedom (n − 1) for the chi-square equation is 5 − 1 = 4. The critical chi-square value with 4 degrees of freedom and a significance value of 0.05 is 9.487. It can be seen that the chi-square value for the validation process is significantly lower than the critical value (0.001), indicating that the model outcome is reliable.

Table 6-11 - Validation result – catch-pit group 1 structural deterioration for 2019

Structural condition	Observed population 2019	Predicted population 2019
1	0.898	0.901
2	0.064	0.057
3	0.027	0.029
4	0.008	0.009
5	0.003	0.003
Chi-squared χ^2 (0.05, 4) = 9.487		**0.001***

6.4 Consequence analysis

In the previous sections, the developed sub-models of the framework were calibrated and validated. In the following sections, features of the framework are demonstrated with real data from the case study.

6.4.1 **Consequence area weighting factor**

The process of evaluating the weighting factors for the consequence areas was discussed in Section 5.4.2. In this study, three consequence areas were considered, namely Common Consequence Tool (CCT), Track Category (TR) and Route Criticality (RC). For the Analytical Hierarchy Process (AHP), the relative importance scores were obtained in a workshop with experienced NR engineers (Table 6-12). Based on this matrix and according to the comparison table developed by Saaty (1980):

- CCT is moderately more important than TC (relative importance score of 2);
- CCT is strongly more important than RC (relative importance score of 6); and
- TC is strongly more important than RC, and its dominance is demonstrated in practice (relative importance score of 7).

This matrix resulted in a consistency ratio of 0.077, which is below the critical value (i.e. 0.1) (see Section 5.4.2). This indicates that the matrix and the importance scores given by experienced engineers are consistent. The final weighting scores for each consequence area are presented in Table 6-13. According to the estimated consequence area weightings, for any possible scenario, CCT accounts for 55.5% of the consequence, TC accounts for 37.3% and RC for 7.2%.

Table 6-12 – Comparison Matrix

	CCT	***TC***	***RC***
CCT	1	2	6
TC	1/2	1	7
RC	1/6	1/7	1

Table 6-13 – Consequence weighting scores for the proposed model

	CCT	***TC***	***RC***
Consequence weighting score	0.555	0.373	0.072

6.4.2 **Anticipated increase in consequence measures**

The proposed consequence areas estimate the level of consequences at present. However, developing the risk horizon for medium- to long-term periods requires an estimate for future levels of consequences. It cannot merely be assumed that the consequence levels on a specific line section remain constant over time.

For this study, the three consequence measures share the same consideration for traffic volume. In CCT, this is addressed as the number of trains per hour per track. For TC, EMGTPA is

considered, which is based on the annual passenger and freight traffic level, and RC is based on the mean delay cost that is directly related to the traffic level on each line. Hence, it can be suggested that variations in traffic volume in the future could increase the level of consequences. The traffic level on the LNW route is predicted to grow by approximately 105% on passenger lines and by 350% on freight lines by 2043 (Network Rail, 2019a) (Table 6-14). This anticipated growth in traffic will be addressed in the risk horizon development in the next section.

Table 6-14 – Anticipated passenger and freight traffic growth on the LWN route, UK

	Traffic Growth by 2043	
Passenger	West Midlands route	114%
	East Midlands route	95%
Freight	Entire route	350%

6.5 Maintenance policy options

A review of the network to which this case study is applied (NR) identified four maintenance policies (Policies A, B, C and D) (Figure 6-22). These policies assess the condition of assets at three levels of serviceable, marginal and poor. The more detailed five-point grading system used in this study is also presented in Figure 6-22. Policy A is an optimum proactive maintenance approach where assets are kept in the serviceable zone with repeated maintenance. In Policy B, assets are proactively maintained with a minimum approach when they reach a marginal condition. In Policies C and D, assets are only maintained reactively after failure. However, in Policy C, assets are maintained to serviceable (or new) condition. In contrast, in Policy D, assets are maintained to perform bare minimum functions and stay in a poor condition.

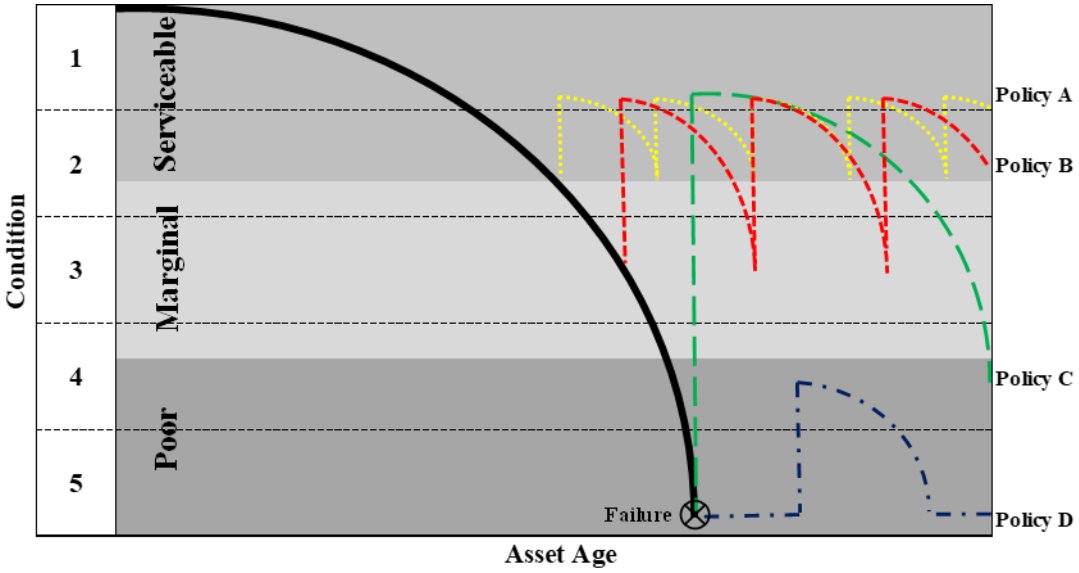


Figure 6-22 – Network Rail maintenance policy (Network Rail, 2017a)

The four maintenance options proposed in this study (Table 6-15) are based on the maintenance policies presented in Figure 6-22. However, it should be noted that depending on the network to which this model is applied, maintenance strategies can vary to accommodate the requirements of decision-makers.

Table 6-15 – Proposed maintenance option matrices

	Maintenance Option 1 (M1)				
	1	***2***	***3***	***4***	***5***
1	1	0	0	0	0
2	0.9	0.1	0	0	0
3	0.8	0.1	0.1	0	0
4	0.7	0.1	0.1	0.1	0
5	0.8	0.1	0	0	0.1

	Maintenance Option 2 (M2)				
	1	***2***	***3***	***4***	***5***
1	1	0	0	0	0
2	0	1	0	0	0
3	0.2	0.3	0.5	0	0
4	0.7	0.1	0	0.2	0
5	0.7	0.1	0	0	0.2

	Maintenance Option 3 (M3)				
	1	***2***	***3***	***4***	***5***
1	1	0	0	0	0
2	0	1	0	0	0
3	0	0	1	0	0
4	0	0	0	1	0
5	0.7	0.1	0	0	0.2

	Maintenance Option 4 (M4)				
	1	***2***	***3***	***4***	***5***
1	1	0	0	0	0
2	0	1	0	0	0
3	0	0	1	0	0
4	0	0	0	1	0
5	0	0	0	0.8	0.2

As presented in Table 6-15, Maintenance Option 1 (M1) is based on policy A, where assets are proactively maintained and kept in a 'Serviceable' condition. To represent this in the maintenance matrix, it is assumed that only 10% of assets stay in the same condition, and the rest are maintained to a better condition. This is represented with the following assumptions for M1:

- For assets in condition 2, 90% are maintained to condition 1.
- For assets in condition 3, 80% are maintained to condition 1. Since maintenance does not recover 100% of assets, the remaining 10% is assumed to move to condition 2.
- For assets in condition 4, 70% are maintained to condition 1, 10% to condition 2 and 10% to condition 3.
- For the failed assets in condition 5, 80% are maintained to condition 1 and 10% to condition 2.

Maintenance Option 2 (M2) is based on Policy B. In M2, only assets in condition 3 and higher are considered for maintenance. This is represented with the following assumptions for M2:

- For assets in condition 3, 20% are maintained to condition 1 and 30% to condition 2.
- For assets in condition 4, 70% are maintained to condition 1 and 10% to condition 2.
- For assets in condition 5, 70% are maintained to condition 1 and 10% to condition 2.

Maintenance Option 3 (M3) is based on reactive Policy C, where failed assets are maintained to a good condition. To represent this, only assets in condition grade 5 are maintained, where 20% stay in the same condition, 70% move to condition 1 and 10% to condition 2.

Maintenance Option 4 (M4) is based on reactive Policy D where assets in failed condition (5) are only maintained to the next functioning condition. To represent this, only assets in condition

5 are maintained, where 20% stay in the same condition and 80% move to the next functioning grade which is condition 4.

For demonstration purposes, the cost estimates for the four maintenance options for pipes are presented in Table 6-16. Two rates of £4.25 and £86 per metre of pipe were selected from NR maintenance standards (Network Rail, 2017a). The lower rate represents the reactive approaches where assets are maintained only to a functioning state or kept in a generally good condition. The more expensive rate represents the proactive optimum approaches where assets are kept in very good condition or refurbished/renewed from failing conditions.

For M1, where approximately 90% of assets from all conditions are maintained, the higher maintenance rate of £86/m is considered. With the assumption that each pipe is 20 m long, this results in a maintenance cost of £1,720 per pipe.

In M2, only assets in condition grades 3, 4 and 5 are assumed to be maintained. This is also a proactive maintenance option; therefore, pipes in condition grades 4 and 5 are maintained at the higher rate of £86/m. Pipes in grade 3 are assumed to be in relatively better condition; therefore, the lower rate of £4.25/m is used.

M3 is a reactive approach where assets are maintained from condition grade 5 to good conditions. To address this, the higher rate of £86/m is used. M4 is the most reactive option where assets are only maintained to the next functioning state. This means that pipes are maintained from condition 5 to 4; therefore, the lower rate of £4.25/m is considered for this option.

For expenditure associated with maintenance activities such as labour and disruption, an additional cost is considered for each maintenance option (Table 6-16). This cost, which is based on private communications with NR engineers, is considered for every year that the

maintenance is carried out. Under M1, a large number of pipes are assumed to be maintained and kept in good condition at all times. Therefore, a cost of £2 million/year is estimated for this maintenance option. For M2, a lower cost of £1.5 million/year is considered since this option allows assets to reach marginal conditions and is not as extensive as M1. For M3 and M4, this cost is assumed to be £1m/year and £750k/year, respectively.

Table 6-16 – Estimated cost associated with maintenance options

	Condition Grade	**2**	**3**	**4**	**5**	
	Unit length	**20 m**	**20 m**	**20 m**	**20 m**	**Labour and disruption cost per year**
Maintenance Option 1 (M1)	Cost/m	£86	£86	£86	£86	£2m
	Cost/20 m pipe	£1,720	£1,720	£1,720	£1,720	
Maintenance Option 2 (M2)	Cost/m		£4.25	£86	£86	£1.5m
	Cost/20 m pipe		£85	£1,720	£1,720	
Maintenance Option 3 (M3)	Cost/m				£86	£1m
	Cost/20 m pipe				£1,720	
Maintenance Option 4 (M4)	Cost/m				£4.25	£750k
	Cost/20 m pipe				£85	

6.6 Risk horizon results and discussion

Risk horizon graphs can be developed for a single asset or a group of assets as long as they belong to the same asset group and have the same consequence levels. In this section, the

process of risk horizon development is demonstrated for the structural deterioration of pipe assets.

6.6.1 **Probability**

The probability component of risk is demonstrated by the values estimated in the TPMs. To demonstrate the process of risk horizon development, group 2 of the pipe structural deterioration model was selected. The TPM for this group is presented in Equation (6-7) and the deterioration trend, without maintenance, is presented in Figure 6-23. It was decided to demonstrate the deterioration trend analysis up to the year 2040. This is to assess the practicality of the model for the long term, as well as medium- and short-term analysis.

Figure 6-23 can be interpreted in two ways. It demonstrates the future percentage of assets in each condition, and also the probability of assets being in different conditions. In a theoretical situation where no maintenance is carried out, it can be seen that approximately 85% of the pipes in group 2 will move to structural condition 5 by 2040. For individual assets in group 2 of the structural deterioration model, there is an 85% probability that any pipe in this group will be in condition 5 by 2040.

$$\begin{bmatrix} 0.894 & 0.036 & 0.039 & 0.018 & 0.013 \\ 0 & 0.242 & 0.376 & 0.320 & 0.062 \\ 0 & 0 & 0.638 & 0.306 & 0.056 \\ 0 & 0 & 0 & 0.746 & 0.254 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \quad (6\text{-}7)$$

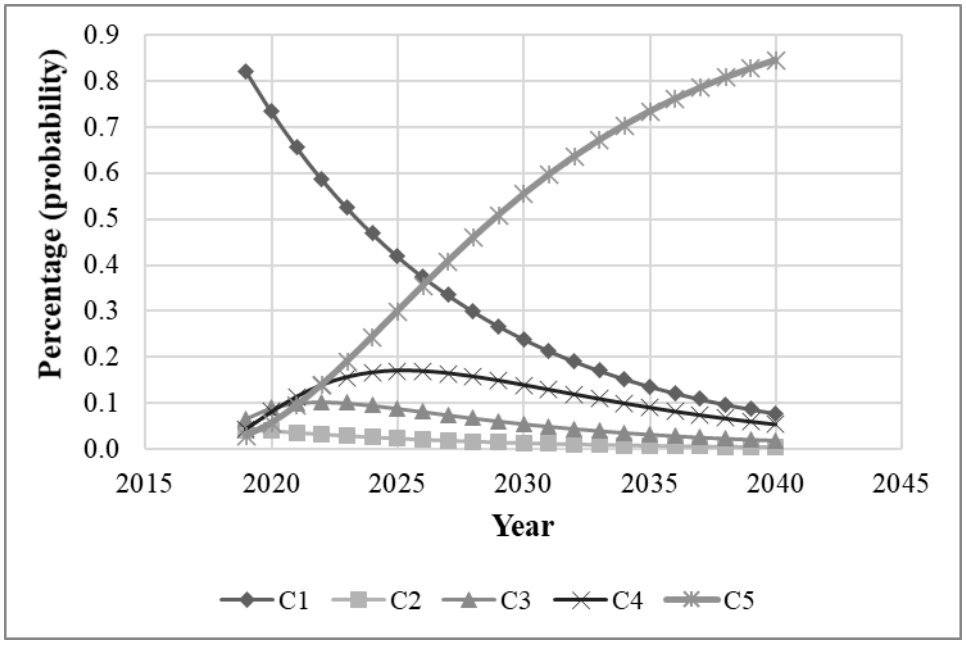


Figure 6-23 –Trend of structural deterioration of pipe asset group 2 with no maintenance

6.6.2 **Consequences**

For demonstration purposes, arbitrary scores of 3, 1 and 2 were considered for CCT, TC and RC, respectively. As discussed previously, the anticipated growth of traffic on LNW is assumed to increase the level of consequences over time. To address this, it was assumed that TC and RC values on this line section would increase by one unit until 2040. This is presented in Table 6-17, where TC in 2030 and RC in 2033 are increased by one unit. It should be noted that these assumptions will vary based on the opinion of decision-makers.

Table 6-17 – Approximate increase in consequence levels due to anticipated traffic growth

	CCT	TC	RC
2018	3	1	2
2019	3	1	2
2020	3	1	2
2021	3	1	2
2022	3	1	2
2023	3	1	2
2024	3	1	2
2025	3	1	2
2026	3	1	2
2027	3	1	2
2028	3	1	2
2029	3	1	2
2030	3	2	2
2031	3	2	2
2032	3	2	2
2033	3	2	3
2034	3	2	3
2035	3	2	3
2036	3	2	3
2037	3	2	3
2038	3	2	3
2039	3	2	3
2040	3	2	3

6.6.3 **Risk calculation**

Table 6-18 illustrates an example of risk calculation in 2021 for a random pipe from group 2 (Pipe A). As discussed previously, the undesired event identified in this study, for which risk is determined, is an asset moving to condition grade 5. Risk level is determined by the product of the probability and the consequences of this undesired event. The probability of Pipe A being in condition 5 in 2021 is 0.09. This is determined by multiplying the TPM by the condition distribution in the previous year (2020). Consequence levels for the section where Pipe A is located are 3, 1 and 2 for CCT, TC and RC, respectively. These values are then transformed into weighted scores by multiplying them by the weighting factors determined in section 6.4.1. The sum of weighted consequence measures is the total consequence level (value of 2.18). Risk is then evaluated by multiplying the probability (0.09) by the consequence (2.18), which results

in a risk level of 0.196. This calculation can also be used for a group of pipes from group 2 of the structural deterioration model with similar CCT, TC and RC values.

Table 6-18 – Risk calculation example – group 2 pipe structural deterioration model

	Condition grade					
Year	**1**	**2**	**3**	**4**	**5**	**Probability of moving to condition 5 in 2021**
2020	0.73	0.03	0.09	0.08	0.05	
2021	0.65	0.03	0.10	0.11	**0.09**	**0.09**

	Consequences			**Weighted consequences**			**Total consequences in 2021**
	CCT	**TC**	**RC**	**CCT** × 0.555	**TC** × 0.373	**RC** × 0.072	(1.66 + 0.37 + 0.14)
	3	1	2	**1.66**	**0.37**	**0.14**	**2.18**
							Total risk in 2021 (0.09 × 2.18)
							0.196

The probability values from the TPM range between 0 and 1, and the total weighted consequence value ranges between 1 and 5. This will result in a risk value which ranges between 0 and 5. It would be logical to assess risk rates similar to the condition grades and consequence measures on a 1–5 system. However, a review of the risk values for the dataset revealed that most assets have a risk range at lower rates between 0.1 and 2. Therefore, it would not be accurate to assume a constant interval between risk values. To address this issue, a proposed risk value range is presented in Table 6-19. To avoid confusion with an inaccurate 1–5 rating system in this case, a descriptive rating system, with Minimal, Low, Medium, High and Extreme levels was adopted. These ranges are in line with the data quality specification required for an NL model which was discussed in Section 3.2.2. The risk value ranges in this

system are based on the observed estimated risk values, which will be discussed later in this section. It should be noted that these ranges are proposed for this case study, and it can be modified at any time based on the opinions of decision-makers. In the next section, the effect of different maintenance options and intervention levels is demonstrated.

Table 6-19 – Risk value ranges

Risk rate	**Risk value**	
	Lower bound	Upper bound
Minimal	0	0.5
Low	0.5	1
Medium	1	1.5
High	1.5	2
Extreme	2	5

6.6.4 **Maintenance intervals**

The intervention level for maintenance options is based on the network policy and several factors including cost, budget and standards. The developed framework is capable of analysing various intervention levels and allows managers and decision-makers to compare different approaches. To demonstrate the practicality of the model, 10 maintenance intervals are studied in this section. These intervals include applying the four identified maintenance options from every year to every 10 years.

6.6.4.1 **Cost**

The maintenance costs were estimated for the analysis period (from 2018 to 2040) and are presented in Figure 6-24. The total cost estimate includes the cost of maintenance applied in each year. For instance, if annual maintenance were carried out, the total cost would include approximately 22 maintenance years until 2040; and if maintenance were carried out every 6 years, the total cost would include approximately 3 maintenance years until 2040.

It should be noted that maintenance costs are not constant, and depend on the year in which they are applied to the asset. Maintenance cost estimation is based on asset condition distributions in each year and the price ranges presented in Table 6-16. While the price range is assumed to be constant, asset condition distributions vary every year. This can be seen in Figure 6-24 where maintenance cost does not show a linear behaviour with interval years.

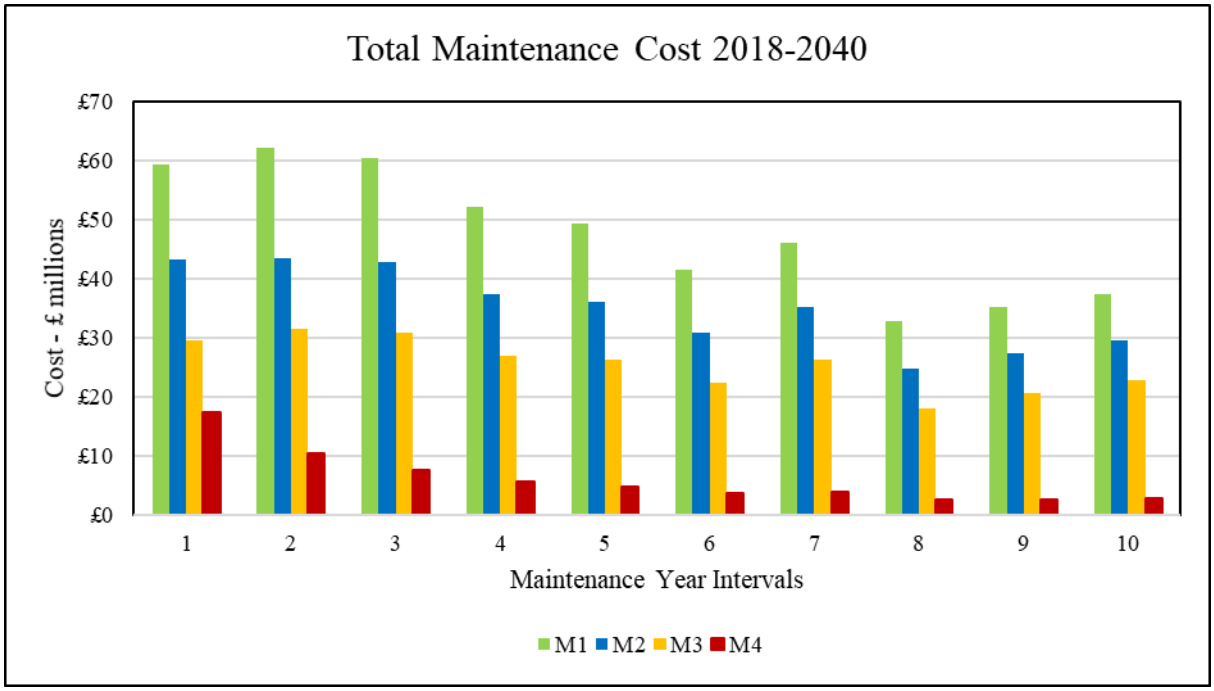


Figure 6-24 – Cost of maintenance options (M1–4) applied at different intervals (every year to every 10 years) for the analysis period 2018–2040

Theoretically, applying maintenance at longer intervals can result in lower labour and disruption costs and reduce the total maintenance cost. However, longer intervals can allow more assets to enter a poor condition where maintenance or refurbishment is more expensive. There is a balance between cost savings, from infrequent maintenance, and spending more on a large asset population that is not maintained. The balance between these two factors seems to be at 7- and 8-year intervals. It can be seen in Figure 6-24 that applying maintenance every 8 years will result in the lowest cost for all four maintenance options. However, after 8-year intervals, the maintenance cost starts to increase. This means that maintaining assets at longer

intervals (more than 8 years) results in more assets moving to a poor condition and costing more to maintain.

It should be noted that the analysis period stopped in 2040, and no future trend estimation was carried out. That is the main reason for the sudden rise in cost at 7-year intervals compared to 6- and 8-year intervals. If the analysis were carried out on a longer period for a few more years, the number of maintenance years for 8-year and longer intervals would be higher, which increases the total maintenance cost. However, for a 22-year analysis period until 2040, there will be approximately one more maintenance year with 7-year maintenance intervals compared to 8-, 9- and 10-year intervals.

Figure 6-25 illustrates a general cost range estimate for the four maintenance options applied at different intervals. Based on this figure, reactive maintenance options applied at longer intervals is the cheapest option (M4 applied every 10 years). The most expensive scenarios will be optimum proactive maintenance options applied at short intervals, such as every year or every 2 years. According to the cost analysis carried out (Figure 6-24 and Figure 6-25), M1 applied every 2 or 3 years is slightly more expensive than when applied annually. Like the balance between long intervals and a large asset population moving to a poor condition, this is also explained by the same principle. If an optimum proactive maintenance option (e.g. M1) is applied on assets every year, theoretically this will keep a large population of assets in condition 1 where no maintenance is required. This will eventually result in a cheaper total maintenance cost compared to when maintenance is applied every 2 or 3 years.

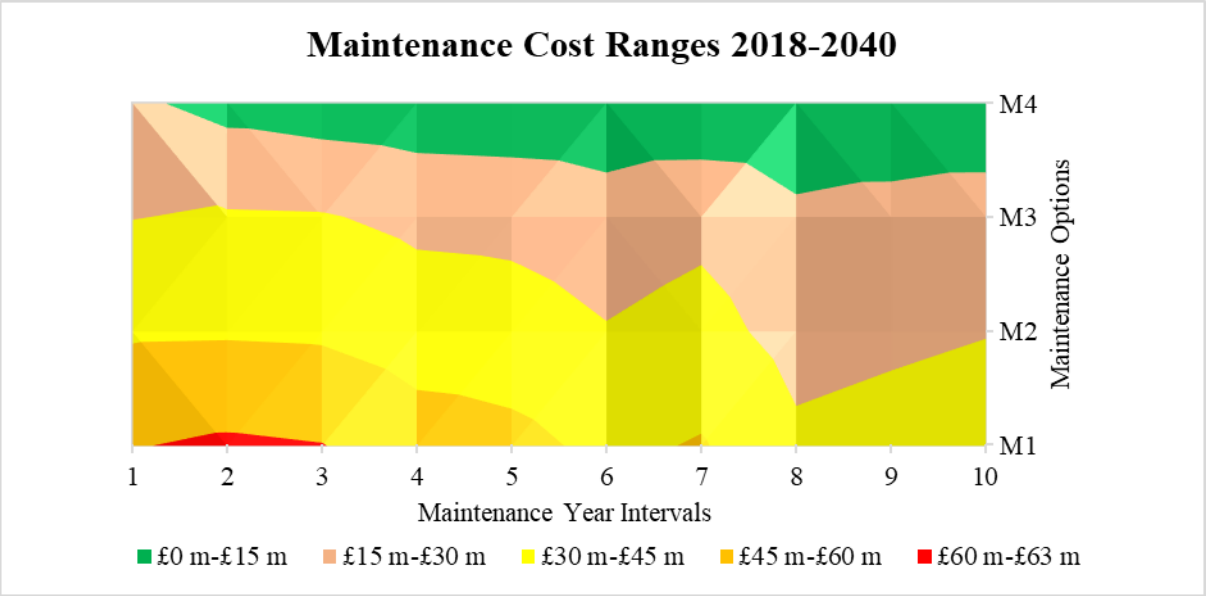


Figure 6-25 – Cost ranges of maintenance options (M1–4) applied at different intervals (every year to every 10 years) for the analysis period 2018–2040

Budget is used as one of the primary decision-making indices in this analysis. The model developed in Excel is capable of highlighting a combination of maintenance options and interval years that will cost more than the allocated budgets. Table 6-20 presents an example where the allocated budget is set at £40 million until 2040. It can be seen that the maintenance scenarios costing more than £40 million are highlighted red. Figure 6-24 can also be updated to Figure 6-26, where the budget limit line highlights maintenance scenarios costing more than £40m until 2040.

Table 6-20 – Total maintenance cost with budget limit of £40m for the analysis period 2018–2040

	Maintenance Year Intervals									
Maintenance Options	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
	Total Maintenance Cost in Million Pound									
M1	£59.40	£62.18	£60.48	£52.20	£49.27	£41.57	£46.17	£32.76	£35.18	£37.32
M2	£43.25	£43.59	£42.86	£37.47	£36.08	£30.77	£35.15	£24.83	£27.29	£29.50
M3	£29.65	£31.43	£30.94	£27.03	£26.23	£22.27	£26.27	£18.10	£20.57	£22.88
M4	£17.32	£10.36	£7.47	£5.55	£4.68	£3.55	£3.82	£2.44	£2.59	£2.71

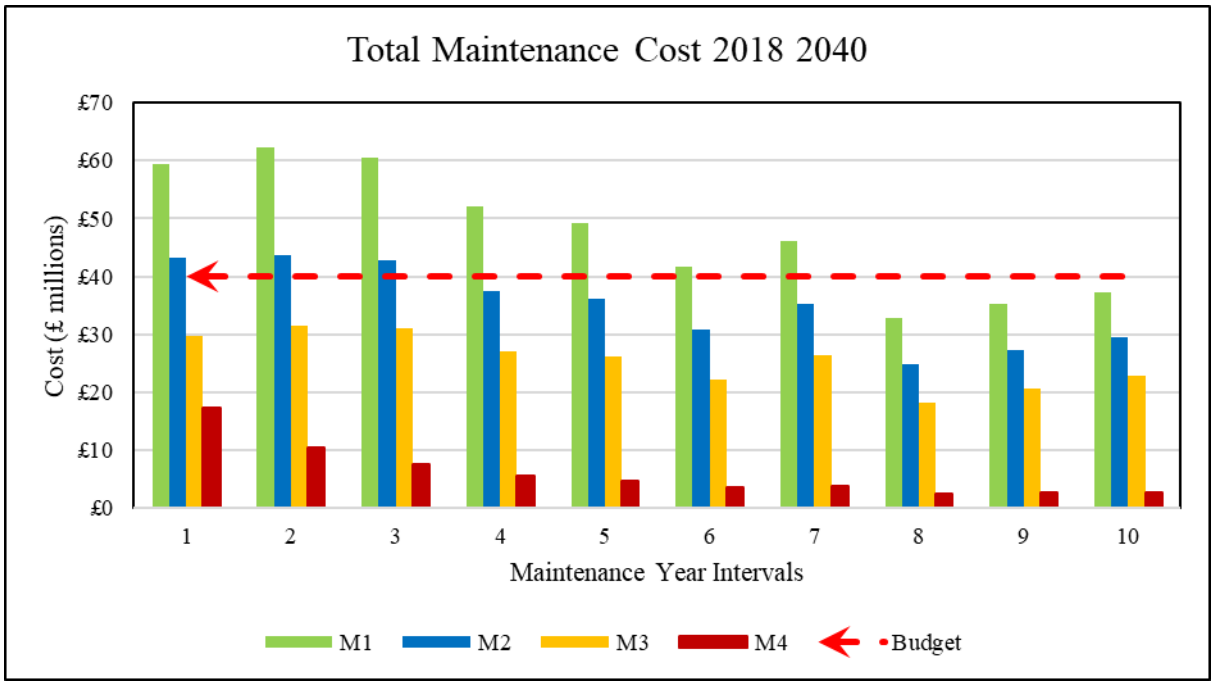


Figure 6-26 – Total cost of maintenance options (M1–4) applied at different intervals (every year to every 10 years) for the analysis period 2018–2040 with a budget limit

6.6.4.2 **Accumulative risk**

Accumulative Risk (AR) is used as another index to access the practicality of maintenance scenarios. While a risk value is estimated for every year of the analysis period, AR presents a single value for the entire analysis period. AR is the area under the risk graph between the first

and last years of the analysis period, or in simple terms it is the sum of risk values for all years. Figure 6-26 can now be updated to Figure 6-27 where AR is presented as a second vertical axis on the right side of the figure. It can be seen that reactive maintenance options such as M4 and M3 generally result in a higher AR than other options.

Moreover, it can be seen that higher maintenance costs are associated with lower AR values. This means that by spending more money on maintenance, the total risk value experienced by the asset or a group of assets is kept at lower levels.

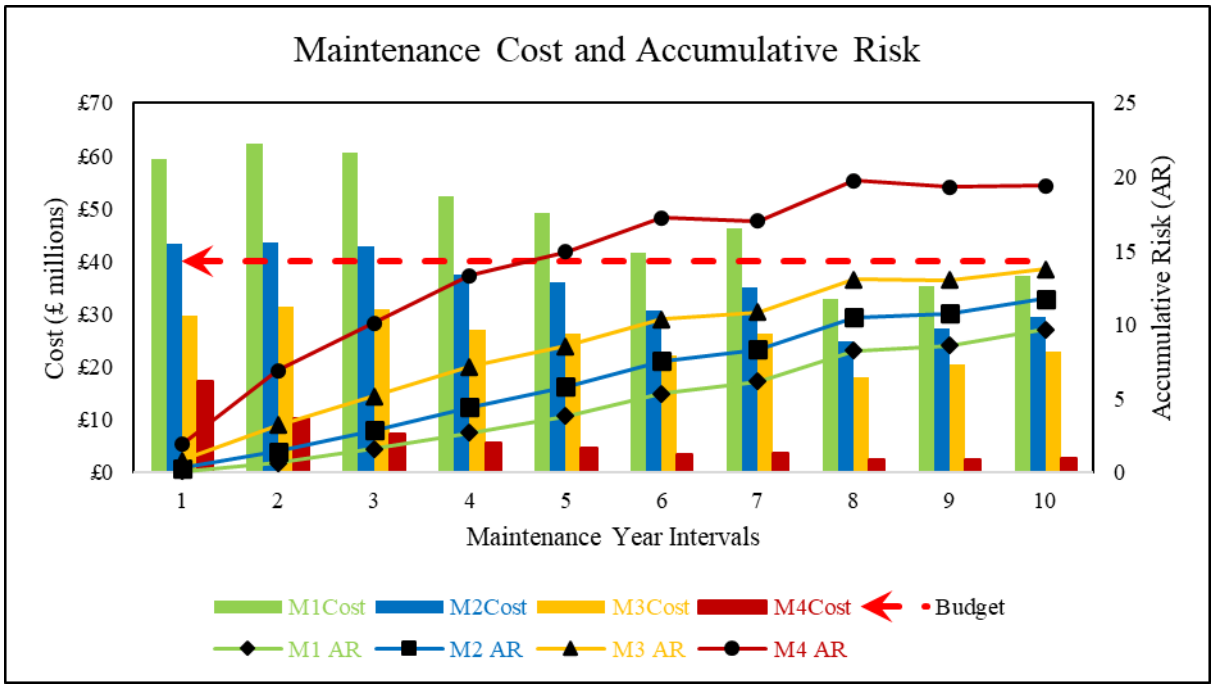


Figure 6-27 – Cost and AR for maintenance options (M1–4) applied at different intervals (every year to every 10 years) for the analysis period 2018–2040

6.6.4.3 **Peak risk**

The main risk index used in this study is the Peak Risk (PR) value. This is the highest risk value reached for each maintenance scenario during the analysis period. Based on the risk ranges identified in Table 6-19, a critical risk level can be identified for the analysis. This means that the risk value in any year should not be higher than the identified critical risk level. For

demonstration purposes, a critical risk level of Low is considered in this section. The upper bound for the Low risk level is 1. This is presented in the updated Figure 6-28, where PR is added as the second vertical axis. The critical risk level of 1 is also indicated with a red dotted line.

Like AR, it can be seen that higher costs are also associated with lower PR values. Moreover, the PR values for M1, M2 and M3 appear to increase linearly with an increase in maintenance intervals. This can be particularly useful for estimating PR values beyond the analysis period year of 2040. M4, unlike other maintenance options, follows a logarithmic growth, which is mainly due to the nature of M4. In this maintenance approach, the majority of assets stay in a poor condition. Over time, this will result in more assets circulating between condition grades 4 and 5 and gradually increase the risk growth rate between each maintenance interval. It should be noted that this minimum proactive maintenance approach (M4) is specific to this case study and could be different in another network.

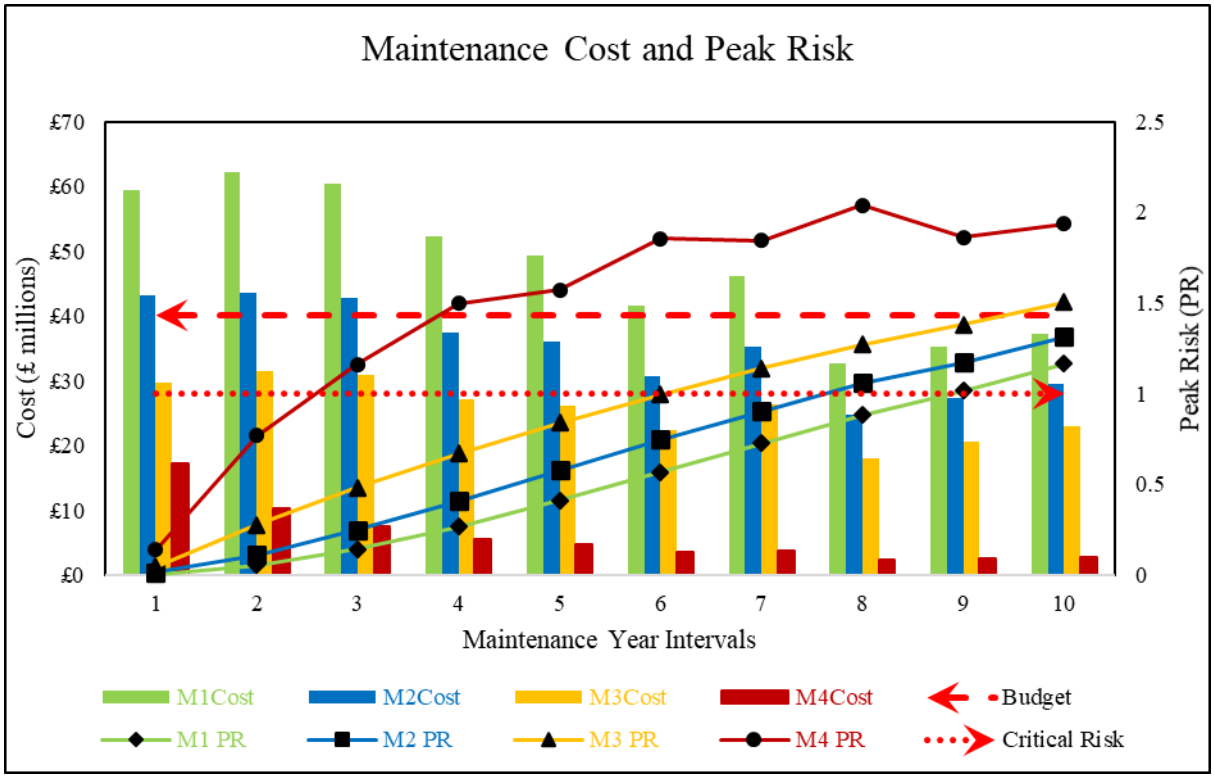


Figure 6-28 – Cost and PR for maintenance options (M1–4) applied at different intervals (every year to every 10 years) for the analysis period 2018–2040, budget of £40m and Low critical risk level (0.5–1)

With a budget limit of £40m and Low critical risk level, the optimum maintenance approach is identified with cost bars below the budget limit line on the left axis (Cost) and the dotted PR lines below the critical risk level of 1 on the right axis (Peak Risk). According to Figure 6-28, the cost of M4 applied at all interval options is significantly below the budget limit line. However, the dotted PR values for M4 are only below the critical risk level at 1- and 2-year intervals. Considering the cost, M4 applied every 2 years is the cheapest scenario and does not allow the risk value to go over the identified critical level at any year.

The risk horizon for this scenario is presented in Figure 6-29, where the critical risk level is shown with the red line. It can be seen that the risk value for M4 is below the critical level during the entire analysis period.

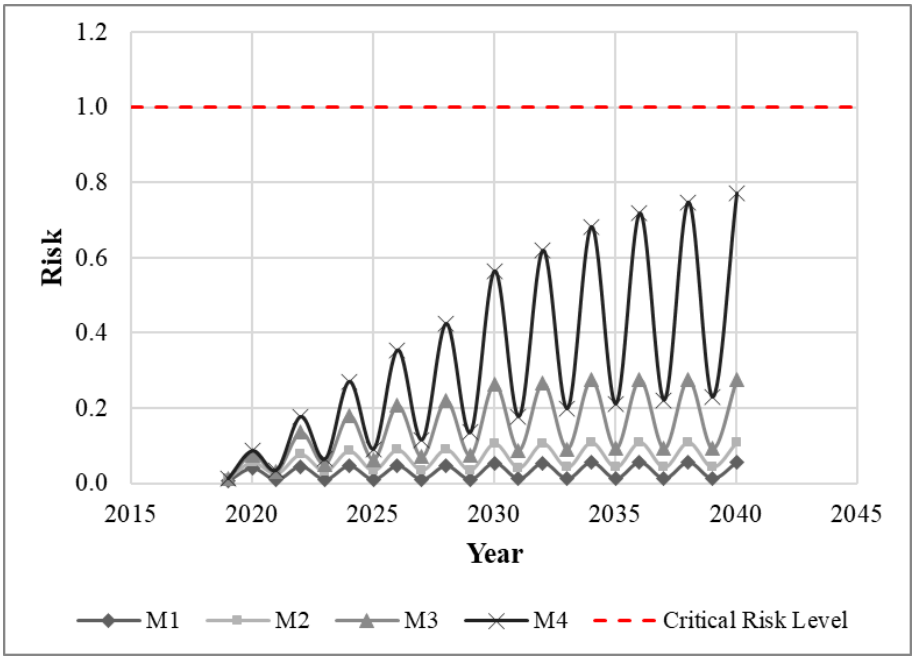


Figure 6-29 – Risk horizon for maintenance option 4 (M4) applied every 2 years with Low critical risk level (0.5–1)

The probability of any pipe from group 2 in condition 5 (the undesired event) under the four maintenance options applied every 2 years is presented in Figure 6-30. It can be seen that M4 results in the highest probability of failure (moving to condition 5). This figure also indicates the probable percentage of pipes in condition 5 under different maintenance options. For instance, if M4 is applied every 2 years, approximately 30% of pipes will be in condition 5 by 2040. It should be noted that this figure will only apply to pipes that share the same characteristics (i.e. pipes that belong to group 2 of the structural deterioration model and have consequence values of 3, 1 and 2 for CCT, TC and RC respectively).

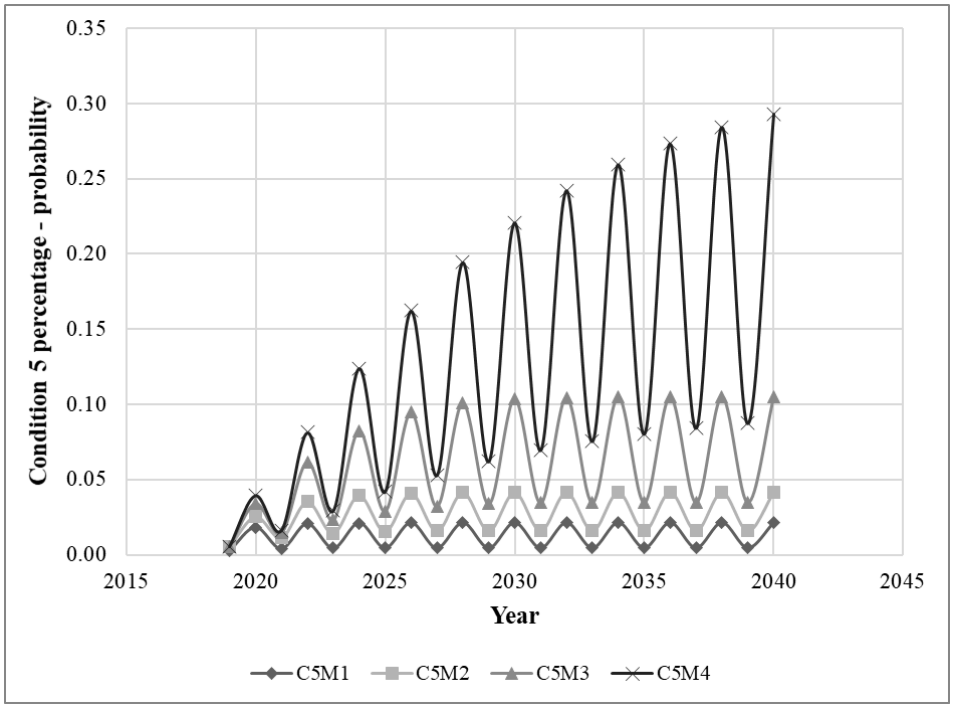


Figure 6-30 – Percentage/probability of assets in condition grade 5 under different maintenance options (M1–4) applied every 2 years

Budget limit and critical PR level are variables in the developed model and can be modified based on the opinion of decision-makers. Figure 6-31 presents another scenario where the budget limit until 2040 is assumed to be £20 million, and critical risk level is set at Minimal level (0–0.5). In this case, the only feasible maintenance scenario is applying M4 annually. The total maintenance cost for the analysis period will be £17.32m, and the PR value is 0.14, which is within the Minimal risk range. This is presented in the risk horizon for this scenario (Figure 6-32) where it can be seen that the PR value for the M4 maintenance option, which occurs in the last year of the analysis period, is below the defined critical risk level.

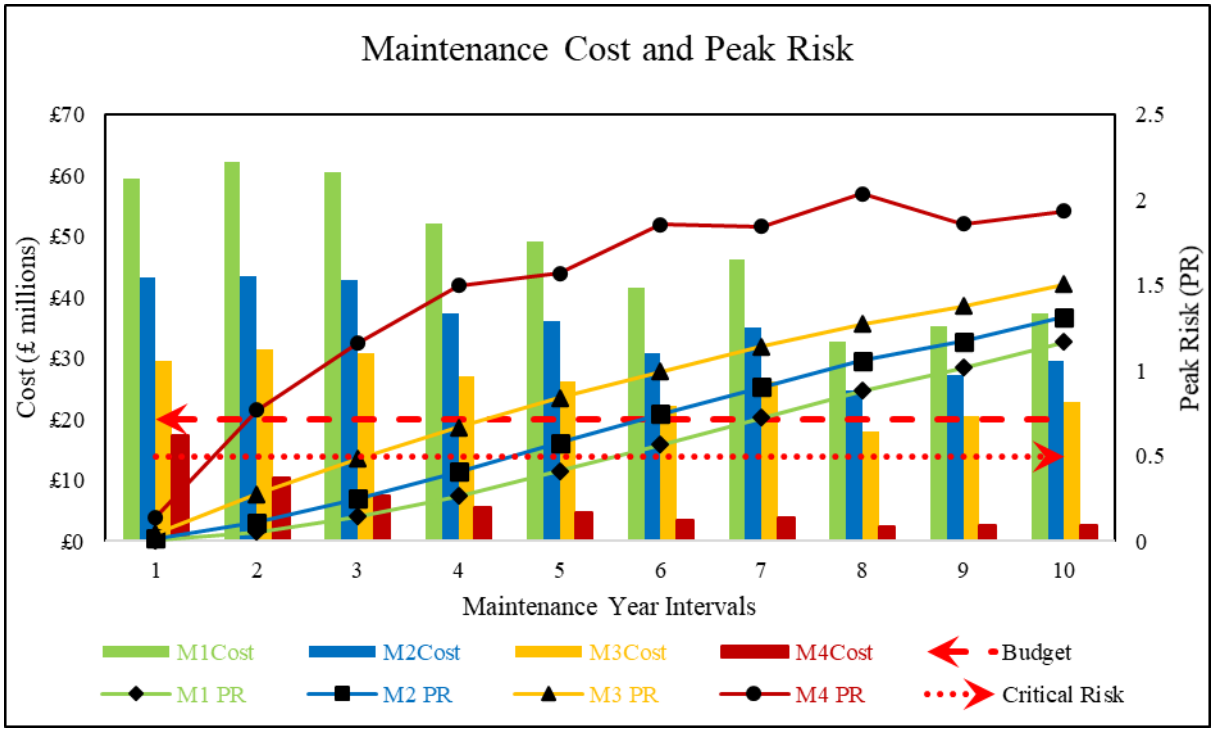


Figure 6-31 – Cost and PR for maintenance options (M1–4) applied at different intervals (every year to every 10 years) for the analysis period 2018–2040, a budget of £20m and Minimal critical risk level (0–0.5)

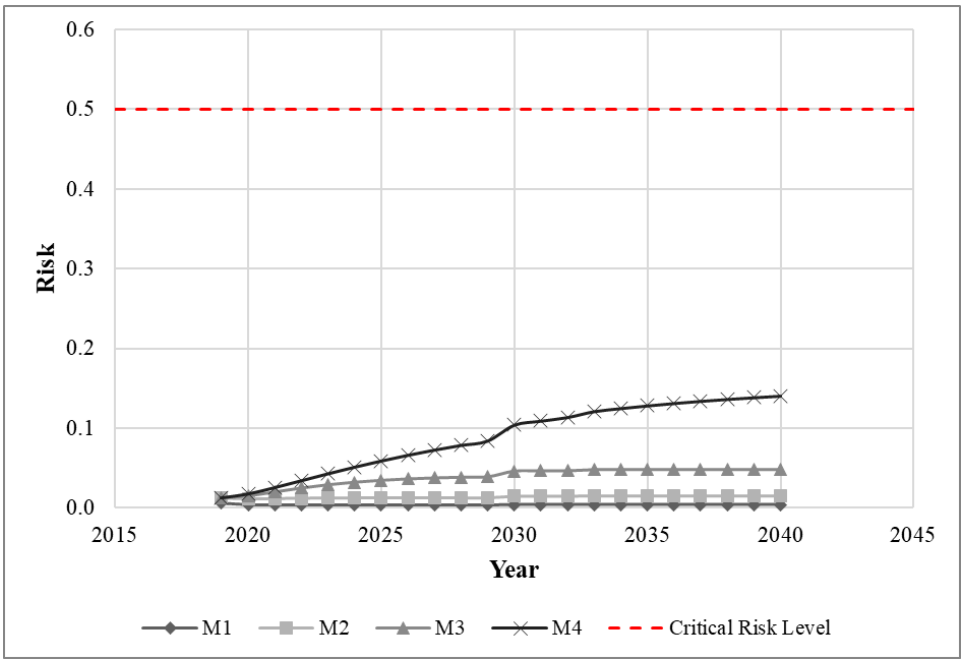


Figure 6-32 – Risk horizon for maintenance option 4 (M4) applied every year with Minimal critical risk level (0–0.5)

6.7 Summary

This chapter presented the practicability of the developed framework with a case study on the LNW route in the UK. The framework consists of sub-models including an MR, a Bayesian Markov chain and an AHP model. The MR and Markov model were calibrated and validated with real data, while the AHP was validated by experts.

The MR model analysed the relationship between available factors, such as the topography, size, material, shape, function and location of assets, and structural and service deterioration rates. Those factors with a significant contribution to structural and service deterioration were used to create NL asset groups. This resulted in two groups for catch-pits, two groups for pipes, one group for culverts and three groups for channels. These NL asset groups are presented in Table 6-8.

The Markov and AHP models were used to estimate the probability and consequences of risk. In the risk horizon analysis, four maintenance strategies of reactive and proactive approaches, applied at interval options of every year to every 10 years, were considered. The model is capable of highlighting the optimum approach, based on the available budget and critical risk level.

It was shown that reactive maintenance options applied at longer intervals result in the cheapest strategies. However, it was revealed that there is a balance between cost savings from infrequent maintenance (longer intervals) and costly maintenance for larger asset populations that are not maintained. The framework is able to identify this balance point, which occurs at maintenance intervals of 7 and 8 years. This means that cheap maintenance options applied at longer intervals start to become more expensive at 8-year intervals and longer.

7. DISCUSSION

This research aimed to develop a risk-based framework which can assist railway drainage asset managers and executive decision-makers to strategically assess and plan preventive maintenance strategies while considering asset deterioration risks and uncertainties. To this end, the framework incorporates a statistical model to develop homogenous asset groups, a stochastic model to evaluate the probability of asset group deterioration, and an analytical model to evaluate the consequences of deterioration across multiple criteria. The framework integrates these sub-models to develop risk horizons, considering the maintenance options and interval periods. Development of the framework was described in Chapter 5, and its practicality was demonstrated via a case study in Chapter 6. In the current chapter, a critical review of the research and the adopted methodology is provided.

7.1 Research summary

The research presented in this thesis can be summarised as follows:

1. **The development of a theoretical framework to assess the deterioration risk of drainage asset groups under uncertainty and to compare the impact of different maintenance strategies**

The literature review conducted in Chapters 2 and 3 showed the need for a framework to support the strategic-level management of drainage assets. It was found that a risk-based approach is suitable for assisting decision-makers to develop maintenance policies and standards, argue for funds and prioritise resources. The developed framework, demonstrated in a detailed schematic (Figure 5-1) and discussed in Chapter 5, consists of statistical, stochastics and analytical models.

The statistical model, namely Multiple Regression (MR), consists of elements that:

i. Deal with bias and insufficient data quality, which is required for a reliable MR model;
ii. Identify the factors which make a statistically significant contribution to asset deterioration;
iii. Group homogenous assets with similar deterioration characteristics, based on the factors identified as contributing to deterioration.

The stochastics model consists of elements that:

i. Estimate the probability (likelihood) of asset deterioration;
ii. Deal with the uncertainty associated with inconsistent historic data and deterioration probability;
iii. Incorporate the effects of maintenance on asset deterioration and network condition.

The analytical model, namely the Analytical Hierarchy Process (AHP) model, consists of elements that:

i. Determine weighting factors for multiple consequence areas;
ii. Estimate the total consequences of asset group deterioration.

The integrated framework determines risk by multiplying the probability and consequence estimations of deterioration and compares the effects of different maintenance strategies on the medium- to long-term condition of the network.

2. The application and practicality of the developed framework to facilitate strategic management of railway drainage assets

The practicality of the developed framework was demonstrated via a case study on sections of the UK mainline railway network, where:

i. Homogenous asset groups were developed by using the MR model to identify the significance of the available asset characteristics (contributing factors) in deterioration;
ii. The probability of asset deterioration under different maintenance strategies was estimated by using a probabilistic Bayesian methodology, which can deal with uncertainty and inconsistent data;
iii. Probability estimates were validated against a set of validation datasets;
iv. The weighting factors for the consequence areas were determined using the AHP model and expert judgment;
v. Deterioration risk was estimated by multiplying the probability and consequence estimations and was demonstrated in meaningful medium- to long-term risk horizons for groups of assets;
vi. The framework was able to successfully highlight the effect of different maintenance strategies by presenting their impact on deterioration risk, their cost and the future condition of the network.

7.2 Achievement of the research objectives

The progress made to meet the four objectives of this research, described in Chapter 1, are discussed below.

Objective 1

To review the literature and railway standards on drainage systems and to identify their components, functions and physical boundaries.

This objective was met in Chapter 2, where the literature on railway drainage studies and international railway standards and manuals were reviewed. The review helped to identify the

physical boundaries of railway drainage systems, which is essential for developing asset management frameworks.

It was shown that drainage systems are often extensively large and complex. Furthermore, they play a crucial role in the performance of other assets such as earthworks and tracks. This has made drainage asset management challenging and critical to railway operation. The review revealed that drainage assets are categorised into surface and sub-surface systems that are often used for various functions. For instance, pipes (i.e. sub-surface drainage) and channels (i.e. surface drainage), are used at different locations such as tracks, slopes and earthwork drainage (see Section 2.3). This finding is particularly important because it highlighted the complexity of drainage asset operations. The achievements of this objective further highlighted the necessity for an asset management framework at strategic levels which can deal with the complexity and criticality of drainage systems.

Objective 2

To review the literature to identify the factors which contribute to the deterioration of drainage assets.

The literature review presented in Chapter 2 identified the different factors that contribute to the deterioration of drainage assets. Due to the limited literature on drainage in railways, similar networks such as those in highways, sewers and watermains were also reviewed. It was shown that asset characteristics such as age, material, dimensions, shape and asset environment such as soil type, water pH level and flow velocity can have a significant effect on deterioration. The literature also revealed that drainage assets exhibit different rates of structural and service deterioration, which need to be considered separately in deterioration models.

The process of drainage asset deterioration is associated with high levels of uncertainty and can be case-specific. This is mainly due to the system's complexity, variable asset age, type,

function and unknown maintenance history. Moreover, it was revealed that factors such as material and dimensions can have an interdependent effect on deterioration. For instance, the effect of pipe material on deterioration can depend on how abrasive the surrounding soil is (Fares and Zayed, 2010), and the effect of culvert dimensions can depend on the rigidity of the culvert material (Noll et al., 2012b). The findings from this section of the literature review highlighted the need for the proposed management framework to be flexible and specific to the task in hand.

Objective 3

To explore strategic level asset management approaches and techniques that could be useful for the task in hand.

This objective was met by the literature review presented in Chapter 3, where asset management at strategic, tactical and operational levels was reviewed. The literature review identified that strategic asset management techniques are suitable for the proposed framework. Within strategic management levels, a Network-Level (NL) approach was selected as the basis for the framework developed herein. This was decided because of the capability of NL models to assist with overall standard development and policy framing. The literature also identified MR as a suitable asset grouping technique which can be used to develop homogenous asset groups required for NL models.

To address the risk element of the framework, various probability and consequences analysis from previous studies related to the task in hand were reviewed. To this end, Micevski et al. (2002), Tran (2007), Kabir et al. (2015b) and Kim et al. (2018) were found to be particularly useful to this research. Based on the findings from the literature review, to estimate the probability of deterioration, a Markov chain methodology, namely Bayesian Markov Chain

Monte Carlo (MCMC), was found to be suitable for dealing with the high degree of uncertainty associated with asset deterioration (see Section 3.4.1.1).

In terms of consequence analysis, the literature showed that in the UK, consequences on the railway are measured in four main areas, namely safety, performance, finance and reputation. Similar approaches have also been identified in other transportation networks such as roads and highways (see Section 3.4.2). The achievement of this objective showed that a risk-based framework with proper sub-models can facilitate strategic-level management of drainage assets.

Objective 4

To develop a risk-based asset management framework from objectives 1, 2 and 3, and to demonstrate its practicality using a case study.

An integrated framework was developed to incorporate the probability and consequences of drainage asset deterioration under various maintenance strategies. A case study was performed in Chapter 6 to demonstrate the practicality of the developed framework. A section of the UK railway network, the London to North West (LNW) route, was selected for the case study. LNW has 4,500 miles of track and stretches from London to Carlisle, connecting major cities including Birmingham, Manchester, Liverpool and Edinburgh. The size and significance of LNW, which is managed under one team, made it a suitable candidate for the case study.

The results from the case study clearly demonstrated the practicality of the framework to assist strategic management of drainage assets. The framework successfully developed homogenous asset groups, and estimated the probability and consequences of their deterioration, while considering uncertainties and the effects of different maintenance strategies. The framework was found to be particularly useful for determining risk horizons and total maintenance costs for medium- and long-term analysis periods.

7.3 Critical review of the research

Development of the risk-based framework, which assesses the risk of drainage asset deterioration under various maintenance strategies, is discussed under the following headings:

i. Strategic-level management
ii. Railway drainage deterioration
iii. Deterioration probability analysis
iv. Deterioration consequence analysis
v. Practicality of the developed framework

7.3.1 **Strategic-level management**

As discussed in section 1.1, the literature and standards suggest that adequate drainage is a critical factor for the proper functioning of railway infrastructure and an essential element of track maintenance. This is because inadequate railway drainage can directly result in flooding and pollution of the railway track and adjacent land, and indirectly lead to a variety of issues such as earthwork slope instability, landslides, falling tree, track geometry faults and reduced track strength and longevity. Furthermore, it can severely affect the availability and reliability of signalling equipment, which can eventually disrupt the operation of trains. These issues can result in delays and unplanned reactive maintenance works, or more significant incidents such as derailment. However, traditionally, such incidents and the required preventive actions, are often dealt with only a limited budget available for railway drainage systems.

It was also revealed that railway drainage systems are quite complex and challenging to manage. They are generally large and cover extensive lengths of the railway track and associated catchment areas. Furthermore, a considerable portion of railway drainage assets is buried under the ground and hard to access. Considering the criticality and complexity of railway drainage systems, their influence on other assets and the overall railway operation, it

is inevitable that adequate management approaches are highly demanded to ensure the best use of available funds.

As a result, the developed framework in this thesis, as demonstrated in the case study, was designed to facilitate the strategic planning of maintenance works and inspections, based on a specific budget limit. The framework is capable of assessing different scenarios based on available maintenance strategies, deterioration level of the network and the risk level of the defined undesired event.

The literature review presented in Section 3.2 revealed that asset management at strategic levels, such as in NL models, is suitable for overall standard development, policy framing, budget allocation and maintenance planning. In terms of asset deterioration management, unlike Project-Level (PL) models where individual assets are studied, NL models are applied to homogenous populations of assets with similar deterioration behaviour.

To develop such asset groups in this study, the literature was reviewed to identify factors contributing to deterioration (e.g. asset dimensions, age, material, shape, etc.), and asset grouping methods (see Section 2.4). In order to use those identified factors in the proposed framework for asset grouping, two issues were identified:

1) Factors contributing to deterioration can be case-specific
2) Asset information records and data inventory can vary between organisations

To overcome these two issues and to develop a more accurate framework for the task in hand, it was decided to use a statistical approach to identify the case-specific factors contributing to deterioration. It was shown that factors contributing to deterioration can be variables of both categorical (e.g. material, location) and scale nature (e.g. dimension, age) (see Section 5.2). To address this, an MR model, capable of analysing both categorical and scale variables, was

utilised. The results of the MR model applied in the case study in Chapter 6 confirmed the findings from the literature. Firstly, it was found that some of the contributing factors most highlighted in the literature, such as asset age and soil environment, were not available in the network's data inventory. Secondly, the contribution of available factors was revealed to be specific to individual sub-categories, which confirmed the case-specific nature of asset deterioration. For instance, for catch-pits, only those constructed of brick were identified as making a significant contribution to structural deterioration. As a result, brick catch-pits were considered in a separate homogenous group in the deterioration model.

The literature review showed that for a valid MR model, data preparation and assumption checks are arguably more important than the model development itself (see Section 3.3.1.1). This was evident in the case study where the data initially violated all assumptions of MR models (i.e. linearity, normality, homoscedasticity and outliers) and resulted in biased model outputs. The assumptions were mainly violated because of the nature of historic deterioration data. It was noticed that the concentration of assets in a good or acceptable condition is significantly larger than those in a poor (deteriorated) condition at any time. This resulted in non-normal asset condition distributions, which were heavily skewed towards good condition states. To overcome this issue, a transformation technique, namely square root transformation, was shown to be capable of normalising the data and resolving most assumption issues.

7.3.2 **Railway drainage deterioration**

The literature reviewed in Section 2.4 showed that drainage deterioration is commonly assessed and measured by the level of structural (e.g. cracks, breakage) and service defects (e.g. reduced capacity and flow velocity). Structural and service deterioration occurs at different rates and the two types are often caused by different contributing factors. This necessitated the framework to consider a separate model for structural and service deterioration. To address

this, while the same mathematical approach (Markov chain) was used to model asset deterioration, model calibration was conducted separately for structural and service historic condition grades.

According to the data quality levels specified for strategic asset management by the World Bank (see Section 3.2.2), it was decided that Information Quality Level 4 (i.e. IQL-IV) is suitable for the condition grading system in this framework. Therefore, semi-quantitative asset condition grading systems, which are based on visual inspection, were used. The limitation identified for visual inspection of buried link assets is that the assessment is limited to the exposed parts of assets. For instance, pipes are only assessed based on their condition at inlets and outlets (e.g. at the end of pipes in catch-pits and outfalls). It is recommended that with future development of the framework, more accurate underground pipe assessment techniques such as ultrasound and CCTV are used for buried link assets.

7.3.3 **Deterioration probability analysis**

The literature review suggested that state-based Markov approaches are suitable for estimating the probability of deterioration with inconsistent data (see Section 3.4.1.1). The study conducted by Wu et al. (2019) on railway drainage systems degradation in the UK also highlighted this. Furthermore, MCMC simulation, capable of dealing with uncertainties, was found to be suitable for the proposed strategic-level asset management framework.

The deterioration process was illustrated by Transition Probability Matrices (TPMs), which were estimated with the MCMC simulation. The adopted MCMC approach is based on the principals of Bayesian theory, where the likelihood and prior knowledge (i.e. prior distribution) of Transition Probabilities (TPs) are combined to estimate the final distributions of TPs (i.e. posterior distributions).

Since the prior knowledge of TPs was limited, the MCMC simulation was designed to be more reliant on historic data, and therefore a non-informative prior distribution was used. Furthermore, the nature of the TPs was shown to follow a binomial likelihood which, according to Bayesian probability theory, allows the selection of a conjugate beta distribution as the prior distribution.

It was noticed that a typical set of historic data in drainage systems, both for asset condition and maintenance, can be limited and inconsistent. Such inconsistency could generate a great deal of uncertainty in the deterioration model. However, with the appropriate statistical and probabilistic approaches utilised in the framework, namely multiple regression and Bayesian MCMC, the level of uncertainty was reduced to an acceptable level. Although at the moment, there are uncertainties associated with the outcome of the framework, these could be further reduced with more complete data and future developments of the deterioration model.

The developed TPMs provided an estimate for each TP with a 95% confidence interval. While these transitions were used in the deterioration model to estimate the future condition of the network under different maintenance strategies, for risk assessment, only the TPs for the worst condition grade (failure) were used. In other words, the probability and consequence elements of risk were estimated for the undesired event of an asset transiting to the worst condition grade.

7.3.4 **Deterioration consequence analysis**

It was shown that a detailed asset deterioration consequences analysis would be challenging to model. This is mainly due to the considerable influence of drainage systems on their neighbouring assets such as earthworks, track and signalling equipment, which makes the consequence areas of drainage issues significantly large. Therefore, a more strategic approach, as used in road transportation standards, was recommended for the consequence analysis (see

Section 5.4.1). In this approach, the consequences of deterioration are assessed as overall impacts on railway operation, regardless of the event causing it.

To this end, three consequence measures, namely Common Consequence Tool (CCT), Track Category (TC) and Route Criticality (RC), were selected for development of the framework. These consequence areas are used in the UK's railway standards and were identified as being suitable for the proposed framework; however, the framework is capable of incorporating any other consequence measure.

CCT was found to be a suitable measure to address safety consequences as it represents several factors including traffic volume, passenger number, derailment probability and potential fatalities. TC, which represents train speed and traffic volume on the line, was used in the framework to address both safety and performance consequences. RC was shown to be an appropriate measure to address financial consequences as it is based on historic mean delay costs. In addition, CCT, TC and RC are measured with semi-quantitative scoring systems, which is ideal for the data quality requirements (i.e. IQL-IV) of the developed framework. However, a few minor modifications and rearrangements were required to develop a scoring system consistent with those of condition grading systems. No measure was identified for reputation consequences.

An identified limitation of the proposed approach was the non-uniformity of the scoring systems across all consequence areas. To address this, a multi-criteria decision-making tool, namely AHP, was used. This approach allowed the use of expert opinion to determine the relative importance of each consequence area and represent it with a weighting factor. The literature showed that the safety consequence is the most critical impact area in transportation networks. The AHP analysis in the case study confirmed this: CCT was revealed to be the most important area with the highest weighting factor.

Since all consequence areas considered are partially based on traffic volume, it can be suggested that higher demand for railway transportation in the future could increase the consequence level estimates. In the network used for the case study (LNW route – UK), traffic volume is predicted to grow by approximately 105% on passenger lines and by 350% on freight lines by the year 2043 (Network Rail, 2019a). To address this in the case study, CCT, TC and RC measures were estimated to increase accordingly for the analysis period up to 2043.

7.3.5 **Practicality of the developed framework**

As presented in Chapter 6, the developed framework was successfully demonstrated via a case study on the LNW railway route in the UK. For demonstration purposes, risk analysis was presented for group 2 pipe structural deterioration (the largest asset population). An analysis period from 2018 to 2040 was selected to examine the capability of the framework for long-term planning.

The framework demonstrated the effects of maintenance with two elements, namely maintenance nature (i.e. minimum/optimum reactive and proactive) and frequency of intervention (i.e. maintaining assets every year to every 10 years). Theoretically, applying minimum maintenance options at longer intervals results in lower total maintenance costs. However, it was shown that over time, longer maintenance intervals allow more assets to enter a poor condition, which can potentially increase maintenance and renewal costs. The analysis was able to identify the balance point at which longer maintenance intervals start to cost more than regular proactive options. The result from the case study showed that depending on the maintenance option, intervals of 6, 7 and 8 years usually result in the lowest total cost. The framework allows decision-makers to adjust for a budget limit according to their requirements, which highlights those maintenance strategies more expensive than their limit.

Risk was also analysed with two other adjustable indices, namely Peak Risk (PR) and Accumulative Risk (AR) limits. PR represented the highest risk value for any asset at any time, and AR represented the total risk value for assets during the analysis period. Similar to maintenance cost, PR and AR values increased for longer interval maintenance options.

7.4 Value of the research

The value of the research conducted in this thesis is the development of a risk-based strategic-level management framework, enabling drainage asset managers to assess the effects of different maintenance strategies, considering network deterioration and risk. Such a tool can assist decision-makers to plan strategic and preventive maintenance approaches, argue for funds and prioritise budgets for asset groups with the highest risk of deterioration. The developed framework could be significantly beneficial since drainage has not traditionally been considered as a primary element of railway asset management.

For strategic asset management, the framework develops homogenous groups of assets based on similar deterioration behaviour. This element of the framework can additionally help drainage asset managers to identify factors with a greater contribution to asset deterioration in a specific section. For instance, certain asset materials or dimensions with a statistically significant contribution to asset deterioration can be avoided in the future design of new drainage systems.

A feature of the developed framework of additional value to the industry is the incorporation of weighted consequence areas, using the AHP approach. This allows the consequence analysis to be more specific to the requirements of decision-makers and identify the relative importance level of each consequence area.

The developed strategic asset management framework was designed in a way to be flexible and modifiable to accommodate the specific requirements of a network. This flexibility enables the framework to be applicable to any other network and asset, specifically in the transportation sector. Such applications could include earthwork and track assets in railways and road surface condition in highways.

7.5 Discussion summary

This chapter presented a critical review of the research carried out in this thesis on the development of a risk-based strategic management framework for railway drainage assets. The critical review included a discussion of the framework's capabilities to deal with uncertainty, its assumptions and limitations, and its practicality in the industry. Furthermore, where appropriate, suggestions for further development of the framework have been offered.

The developed framework provides a strategic-level management platform for homogenous asset populations. This would enable railway managers to deal with larger sections of the network and determine overall maintenance strategies and standards. The MR model, which was used to develop such homogenous asset groups, was found to be particularly useful for identifying case-specific deterioration factors.

The MCMC approach, which was used to model deterioration of the developed asset groups, was shown to be capable of dealing with the high levels of uncertainty associated with inconsistent data and also the probabilistic nature of infrastructure deterioration. Furthermore, it was recommended that to further reduce the uncertainties in the framework, the probabilistic effect of climate change could be incorporated. To achieve this, a similar approach, such as that adopted by Daheshpour (2018), could be used.

A major assumption of the framework concerns the assessment of consequences. The framework assumes that in the event of a failure or incident, high-criticality railway lines (e.g. higher traffic volume, higher line speed, etc.) will result in higher levels of consequences. Although this approach has been used by many transportation networks, the consideration of specific events such as flooding, earthwork failure or track faults, which are caused by inadequate drainage, could allow for a better assessment of consequences.

The following chapter presents the research conclusions, together with the main findings and recommendations for future research.

8. CONCLUSIONS AND RECOMMENDATIONS

8.1 Accomplished work

The accomplished work presented in this thesis is the development of a risk-based framework, that allows railway managers to strategically plan and prioritise drainage maintenance options, by considering risk, the budget, future network condition and its associated uncertainty. The research undertaken to develop the framework, and to meet the objectives outlined in Chapter 1, was demonstrated by:

1. Studying the drainage systems and identifying their physical boundaries.
2. Identifying the type and function of drainage assets in the railways.
3. Investigating the contributing factors, including environmental conditions and asset characteristics, that affect the structural and service deterioration of drainage assets.
4. Developing a regression model to identify significant contributing factors to deterioration and homogenously grouping assets based on them.
5. Developing a stochastic model to determine the deterioration probability of assets, considering deterioration uncertainties.
6. Developing a multi-criteria analysis model to estimate the relative importance of different consequence areas.
7. Developing an integrated asset management framework with the sub-models mentioned in points 4, 5 and 6, for the strategic assessment of various maintenance strategies.
8. Demonstrating the practicality of the developed framework with a case study on a section of the UK's railway network.

8.2 Conclusions

The following key conclusions were drawn from the research:

1. A risk-based approach is suitable for managing railway drainage systems at strategic levels while considering asset deterioration risk and uncertainties.
2. Strategic-level management approaches enable assessment of the maintenance effect and asset deterioration in the broader network and can assist with determining preventive maintenance and renewal strategies.
3. The developed framework for railway drainage assets could potentially provide a management platform which is applicable to other physical assets on the railways (e.g. earthworks, tracks), as well as other transportation networks (e.g. highways, roads).

8.3 Findings

It was found that the components of the developed framework are implemented successfully by using the knowledge and techniques discussed below:

1. Strategic-level (i.e. Network-Level) management of assets can assist executive managers and decision-makers to determine better maintenance standards which can be applied to more extensive sections of the network. Such approaches can allow the comparison of various maintenance strategies and their effect on network condition and risk. Furthermore, it was found that the data quality required for strategic management models can be at summary level (i.e. Information Quality Level 4). Examples of such information can include descriptive asset condition grades obtained from visual inspections or qualitative risk levels defined by the decision-maker.
2. Assets in railway drainage systems are constructed with various materials, and in different shapes and sizes for different functions and applications. The asset deterioration rate is case specific and a function of different factors such as asset material, geometry, dimensions, function, and application. A Multiple Regression (MR) model was found to be a suitable approach to identify which factors make a significant

contribution to the deterioration rate in a specific network. For strategic-level asset management, assets can be homogeneously grouped based on the contributing factors identified, where the same set of standards can be applied.

3. In addition to the case-specific deterioration of drainage assets (discussed above), age variation and unknown historical data also result in high levels of uncertainty in condition prediction and deterioration models. It was found that a Bayesian Markov Chain Monte Carlo (MCMC) technique is appropriate for determining deterioration probability, and is capable of addressing high levels of uncertainty.
4. Four main consequence areas, including safety, performance, finance and reputation, for transportation networks were identified from the literature. To address the various areas of consequence on the railways, a multicriteria analysis, namely the Analytical Hierarchy Process (AHP) was found to be suitable. AHP allows determination of the relative importance of multiple consequence areas, which is presented as weighting factors.
5. The developed risk-based asset management framework integrates the techniques described in points 3 and 4, as the probability and consequence components of deterioration risk. The framework combines these mathematical tools with the available historical asset data and the requirements of decision-makers, such as maintenance options, budget limits and maximum risk level, and provides a comparison platform for various maintenance strategies. This is presented in the Risk Horizon graphs which compare the risk of maintenance strategies in terms of cost and network deterioration.
6. The practicality of the developed framework was presented via a case study where four maintenance strategies and ten interval options were reviewed. The Risk Horizon graphs demonstrated an explicable comparison of the strategies by presenting various factors such as risk, cost and network deterioration condition. The framework was also

able to successfully identify the balance between cheaper infrequent maintenance options and the consequently higher potential costs required for unmaintained asset populations.

8.4 Recommendations for future work

The results of the case study presented in Chapter 6 demonstrated the practicality of the framework and its usefulness to the industry for managing assets, preparing funds and determining maintenance policies. For future development of the approach, the following additional research works are recommended:

1. A more comprehensive asset data collection strategy could benefit the framework in several ways. Firstly, collecting more asset characteristic factors could result in a better understanding of asset deterioration behaviour, which would assist with the development of more accurate homogenous asset groups in the MR model. Furthermore, with more accurate and consistent asset condition grading records, the level of uncertainty in the deterioration model could be reduced.
2. The maintenance strategy input of the framework was considered for strategic level management of assets. Therefore, maintenance approaches were incorporated as general strategies and costs. Further improved of the framework could include the consideration of specific maintenance options and their associated costs.
3. The developed risk-based framework is based on the undesired event of drainage asset deterioration, which is addressed as an asset transiting to the worst condition grade. Future developments of the framework could include other undesired events, such as assets transiting to a lower poor condition rather than complete failure. This would enable decision-makers to prevent asset deterioration more effectively and to determine more efficient proactive maintenance strategies. Furthermore, asset deterioration

follow-up events, such as flooding, earthwork failure and track faults, could be incorporated in the framework to improve the probability estimates and to allow assessment of risk in a broader context of railway operation.

4. Considering the probabilistic effect of climate change on the prediction of asset deterioration could benefit the framework by reducing the level of uncertainty.
5. The consequence estimate in the framework could also benefit from the consideration of uncertainties. Although at the moment the framework considers a level of variation in future estimations of consequence measures, which is sufficient, an actual probabilistic model for the consequence areas scores would improve the framework's risk assessment capability.

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APPENDIX A – MCMC CODE

```
library("rjags")

model_string <- " model {
  for (i in length(y)) {
  y[i] ~ dbinom(theta,n[i])
  }
  theta ~ dbeta(a, b)
} "

set.seed(50)
y <- c(successful trials – number of assets transiting between conditions)
n <- c(total number of trials – total number of assets)
a <- 1
b <- 1

model <- jags.model(textConnection(model_string),
                    data = list(y=y,n=n,a=a,b=b))
update(model, 10000, progress.bar="none"); # Burnin for 10000 samples
samp <- cod
a.samples(model,
                     variable.names=c("theta"),
                     n.iter=30000, progress.bar="none")

summary(samp)

plot(samp)
```

APPENDIX B – MULTIPLE REGRESSION MULTICOLINEARITY CHECK

B.1 Pipes

		Size (Diameter)				Topography			Function	
Pipes 1 **Size** **Topography** **Function**	**Deterioration rate**	<150mm	151-300mm	301-450mm	>451mm	At Grade	Cutting	Embankment	Collector	Carrier
Deterioration rate	1.000	.014	-.002	-.001	-.009	-.009	.007	.004	.001	-.001
<150mm	.014	1.000	-.392	-.126	-.065	.148	-.133	-.044	-.078	.078
151-300mm	-.002	-.392	1.000	-.716	-.372	-.216	.187	.080	.097	-.097
301-450mm	-.001	-.126	-.716	1.000	-.119	.134	-.113	-.057	-.033	.033
>451mm	-.009	-.065	-.372	-.119	1.000	.050	-.043	-.019	-.054	.054
Asbestos Cement	.000	-.007	-.040	.055	-.007	.022	-.020	-.006	-.015	.015
Brick - Lined	-.004	.149	-.068	-.034	.034	-.011	.013	-.003	-.024	.024
Brick - Unlined	-.002	.013	.013	-.020	-.005	.030	-.029	-.005	.062	-.062
Cast Iron	.003	.085	-.065	.016	.012	.061	-.059	-.008	-.046	.046
Concrete	.000	-.049	-.194	.216	.074	.047	-.046	-.005	-.100	.100
Polyethylene	-.002	.285	-.070	-.059	-.062	.216	-.197	-.056	-.056	.056
Pitch Fibre	-.002	-.010	-.014	.029	-.010	.029	-.030	.002	.044	-.044
Spun Iron	-.011	-.046	.098	-.062	-.042	.002	-.016	.032	-.048	.048
Steel	.007	-.005	.039	-.020	-.038	.035	-.030	-.015	.034	-.034
uPVC	-.001	-.058	.000	-.030	.110	-.087	.055	.082	.016	-.016
Vitrified Clay	.006	-.143	.139	-.028	-.078	-.132	.151	-.038	.098	-.098
At Grade	-.009	.148	-.216	.134	.050	1.000	-.915	-.253	-.071	.071
Cutting	.007	-.133	.187	-.113	-.043	-.915	1.000	-.158	.063	-.063
Embankment	.004	-.044	.080	-.057	-.019	-.253	-.158	1.000	.023	-.023
Collector	.001	-.078	.097	-.033	-.054	-.071	.063	.023	1.000	-1.000
Carrier	-.001	.078	-.097	.033	.054	.071	-.063	-.023	-1.000	1.000

	Material										
Pipes 2 **Material**	Asbestos Cement	Brick - Lined	Brick - Unlined	Cast Iron	Concrete	Polyethylene	Pitch Fibre	Spun Iron	Steel	uPVC	Vitrified Clay
Deterioration rate	.000	-.004	-.002	.003	.000	-.002	-.002	-.011	.007	-.001	.006
<150mm	-.007	.149	.013	.085	-.049	.285	-.010	-.046	-.005	-.058	-.143
151-300mm	-.040	-.068	.013	-.065	-.194	-.070	-.014	.098	.039	.000	.139
301-450mm	.055	-.034	-.020	.016	.216	-.059	.029	-.062	-.020	-.030	-.028
>451mm	-.007	.034	-.005	.012	.074	-.062	-.010	-.042	-.038	.110	-.078
Asbestos Cement	1.000	-.002	-.002	-.002	-.009	-.011	-.001	-.006	-.005	-.017	-.021
Brick - Lined	-.002	1.000	-.005	-.008	-.029	-.036	-.004	-.019	-.016	-.056	-.070
Brick - Unlined	-.002	-.005	1.000	-.005	-.019	-.023	-.002	-.012	-.010	-.036	-.045
Cast Iron	-.002	-.008	-.005	1.000	-.030	-.037	-.004	-.020	-.016	-.058	-.072
Concrete	-.009	-.029	-.019	-.030	1.000	-.133	-.013	-.071	-.058	-.207	-.257
Polyethylene	-.011	-.036	-.023	-.037	-.133	1.000	-.016	-.088	-.072	-.256	-.318
Pitch Fibre	-.001	-.004	-.002	-.004	-.013	-.016	1.000	-.009	-.007	-.025	-.031
Spun Iron	-.006	-.019	-.012	-.020	-.071	-.088	-.009	1.000	-.038	-.136	-.169
Steel	-.005	-.016	-.010	-.016	-.058	-.072	-.007	-.038	1.000	-.111	-.138
uPVC	-.017	-.056	-.036	-.058	-.207	-.256	-.025	-.136	-.111	1.000	-.494
Vitrified Clay	-.021	-.070	-.045	-.072	-.257	-.318	-.031	-.169	-.138	-.494	1.000
At Grade	.022	-.011	.030	.061	.047	.216	.029	.002	.035	-.087	-.132
Cutting	-.020	.013	-.029	-.059	-.046	-.197	-.030	-.016	-.030	.055	.151
Embankment	-.006	-.003	-.005	-.008	-.005	-.056	.002	.032	-.015	.082	-.038
Collector	-.015	-.024	.062	-.046	-.100	-.056	.044	-.048	.034	.016	.098
Carrier	.015	.024	-.062	.046	.100	.056	-.044	.048	-.034	-.016	-.098

B.2 Culverts

		Material					Shape		
Culverts **Material** **Shape**	**Deterioration rate**	Brick	Concrete	Other	Plastic	Steel	Arch	Barrel	Box
Deterioration rate	1.000	.028	.002	-.012	-.051	-.056	-.096	.053	.049
Brick	.028	1.000	-.862	-.306	-.227	-.143	.112	-.233	.115
Concrete	.002	-.862	1.000	-.079	-.059	-.037	-.099	.166	-.062
Other	-.012	-.306	-.079	1.000	-.021	-.013	.014	.051	-.067
Plastic	-.051	-.227	-.059	-.021	1.000	-.010	-.051	.134	-.080
Steel	-.056	-.143	-.037	-.013	-.010	1.000	-.064	.118	-.050
Arch	-.096	.112	-.099	.014	-.051	-.064	1.000	-.543	-.528
Barrel	.053	-.233	.166	.051	.134	.118	-.543	1.000	-.426
Box	.049	.115	-.062	-.067	-.080	-.050	-.528	-.426	1.000

B.3 Channels

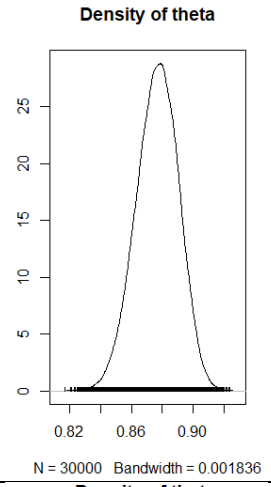
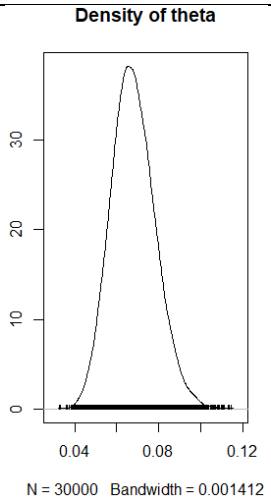
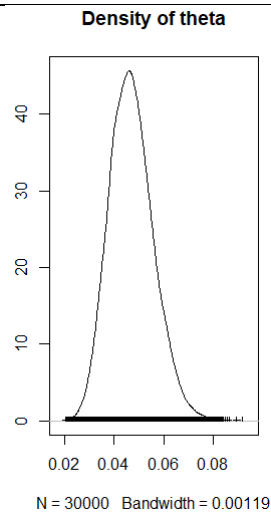
		Material							
Channels 1 **Material**	**Deterioration rate**	Brick	Earth	In-situ Concrete	Masonry	Other	Precast Concrete	Plastic	Vitrified Clay
Deterioration rate	1.000	.003	.092	.007	-.081	-.043	-.035	-.083	-.048
Brick	.003	1.000	-.505	-.046	-.051	-.028	-.070	-.030	-.019
Earth	.092	-.505	1.000	-.320	-.354	-.198	-.485	-.210	-.131
In-situ Concrete	.007	-.046	-.320	1.000	-.032	-.018	-.044	-.019	-.012
Masonry	-.081	-.051	-.354	-.032	1.000	-.020	-.049	-.021	-.013
Other	-.043	-.028	-.198	-.018	-.020	1.000	-.027	-.012	-.007
Precast Concrete	-.035	-.070	-.485	-.044	-.049	-.027	1.000	-.029	-.018
Plastic	-.083	-.030	-.210	-.019	-.021	-.012	-.029	1.000	-.008
Vitrified Clay	-.048	-.019	-.131	-.012	-.013	-.007	-.018	-.008	1.000
Rectangular	-.065	.232	-.391	.081	.251	-.012	.211	-.048	.008
Semi-Circular	.124	-.083	.153	-.044	-.138	-.059	-.082	.126	.025
Trapezoidal	-.085	-.142	.179	-.004	-.076	.059	-.078	-.074	-.046
V	.023	.031	.037	-.044	-.018	.027	-.056	-.029	.023
6 ft	-.016	-.014	-.035	.150	-.010	-.006	-.014	-.006	-.004
10 ft	-.013	-.007	.014	-.004	-.005	-.003	-.007	-.003	-.002
Cess	.023	.021	-.256	.092	.108	-.001	.249	.050	.005
Crest	-.070	-.018	-.104	.004	-.004	.234	-.014	.249	-.015
Outside NR Boundary	.007	-.100	.262	-.084	-.097	-.049	-.150	-.068	-.042
Slope	-.051	.281	-.314	.107	.111	.008	.072	-.017	.075
Toe	.074	-.080	.252	-.102	-.113	-.063	-.123	-.067	-.042
UTX (Link Only)	-.060	-.039	.010	.004	.055	-.002	-.024	-.030	.061
At Grade	-.021	-.028	-.166	.147	-.016	-.002	.175	.071	.066
Cutting	-.074	.251	-.364	.055	.148	.084	.129	.087	.033
Embankment	.080	-.191	.443	-.165	-.113	-.070	-.250	-.131	-.081

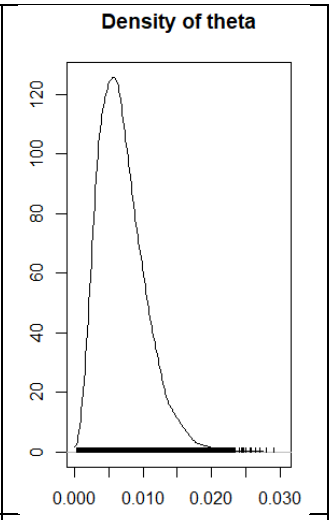
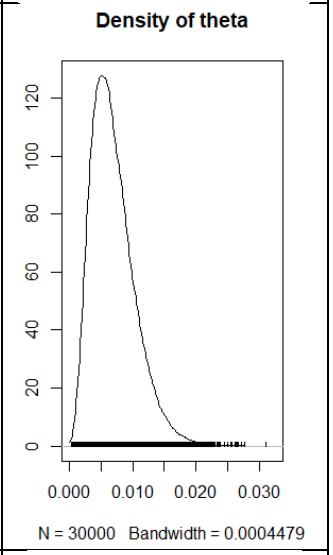
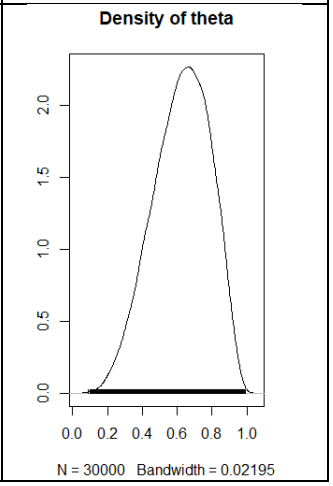
	Drainage Location							
Channels 2 **Drainage location**	6 ft	10 ft	Cess	Crest	Outside NR Boundary	Slope	Toe	UTX (Link Only)
Deterioration rate	-.016	-.013	.023	-.070	.007	-.051	.074	-.060
Brick	-.014	-.007	.021	-.018	-.100	.281	-.080	-.039
Earth	-.035	.014	-.256	-.104	.262	-.314	.252	.010
In-situ Concrete	.150	-.004	.092	.004	-.084	.107	-.102	.004
Masonry	-.010	-.005	.108	-.004	-.097	.111	-.113	.055
Other	-.006	-.003	-.001	.234	-.049	.008	-.063	-.002
Precast Concrete	-.014	-.007	.249	-.014	-.150	.072	-.123	-.024
Plastic	-.006	-.003	.050	.249	-.068	-.017	-.067	-.030
Vitrified Clay	-.004	-.002	.005	-.015	-.042	.075	-.042	.061
Rectangular	.033	-.015	.207	-.096	-.009	.096	-.249	.052
Semi-Circular	.011	-.021	-.159	.011	.149	-.040	.116	-.155
Trapezoidal	-.035	.040	-.094	.106	-.107	-.045	.124	.105
V	-.014	-.007	.135	-.056	-.080	-.004	-.034	.021
6 ft	1.000	-.001	-.031	-.011	-.032	-.018	-.032	-.014
10 ft	-.001	1.000	-.015	-.006	-.016	-.009	-.016	-.007
Cess	-.031	-.015	1.000	-.125	-.351	-.196	-.348	-.156
Crest	-.011	-.006	-.125	1.000	-.130	-.072	-.129	-.058
Outside NR Boundary	-.032	-.016	-.351	-.130	1.000	-.203	-.361	-.162
Slope	-.018	-.009	-.196	-.072	-.203	1.000	-.202	-.090
Toe	-.032	-.016	-.348	-.129	-.361	-.202	1.000	-.160
UTX (Link Only)	-.014	-.007	-.156	-.058	-.162	-.090	-.160	1.000
At Grade	.041	-.013	.316	-.046	.034	-.097	-.267	.008
Cutting	.034	-.014	.185	.202	-.233	.309	-.242	-.028
Embankment	-.061	.023	-.410	-.135	.171	-.185	.419	.018

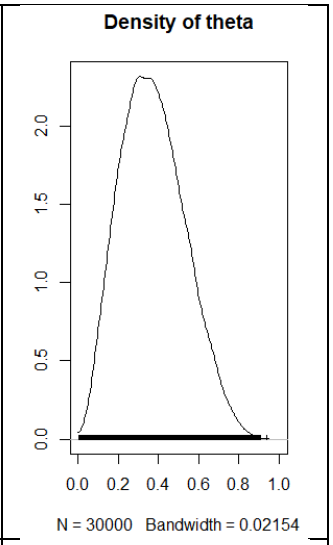
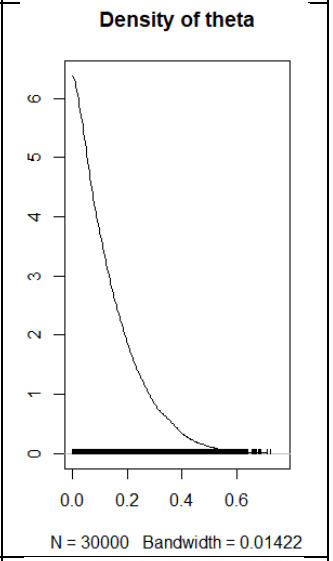
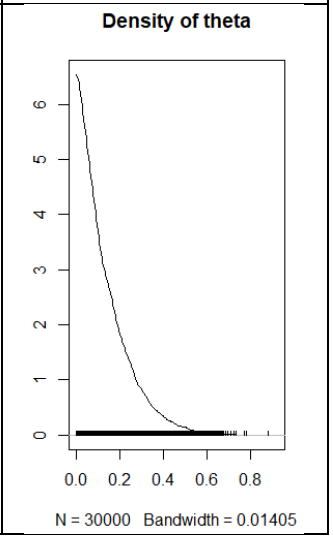
	Shape				Topography		
Channels 3 **Shape** **Topography**	Rectangular	Semi-Circular	Trapezoidal	V	At Grade	Cutting	Embankment
Deterioration rate	-.065	.124	-.085	.023	-.021	-.074	.080
Brick	.232	-.083	-.142	.031	-.028	.251	-.191
Earth	-.391	.153	.179	.037	-.166	-.364	.443
In-situ Concrete	.081	-.044	-.004	-.044	.147	.055	-.165
Masonry	.251	-.138	-.076	-.018	-.016	.148	-.113
Other	-.012	-.059	.059	.027	-.002	.084	-.070
Precast Concrete	.211	-.082	-.078	-.056	.175	.129	-.250
Plastic	-.048	.126	-.074	-.029	.071	.087	-.131
Vitrified Clay	.008	.025	-.046	.023	.066	.033	-.081
Rectangular	1.000	-.451	-.368	-.145	.018	.240	-.218
Semi-Circular	-.451	1.000	-.535	-.211	-.152	-.107	.212
Trapezoidal	-.368	-.535	1.000	-.172	.118	-.101	-.009
V	-.145	-.211	-.172	1.000	.051	-.014	-.029
6 ft	.033	.011	-.035	-.014	.041	.034	-.061
10 ft	-.015	-.021	.040	-.007	-.013	-.014	.023
Cess	.207	-.159	-.094	.135	.316	.185	-.410
Crest	-.096	.011	.106	-.056	-.046	.202	-.135
Outside NR Boundary	-.009	.149	-.107	-.080	.034	-.233	.171
Slope	.096	-.040	-.045	-.004	-.097	.309	-.185
Toe	-.249	.116	.124	-.034	-.267	-.242	.419
UTX (Link Only)	.052	-.155	.105	.021	.008	-.028	.018
At Grade	.018	-.152	.118	.051	1.000	-.268	-.573
Cutting	.240	-.107	-.101	-.014	-.268	1.000	-.636
Embankment	-.218	.212	-.009	-.029	-.573	-.636	1.000

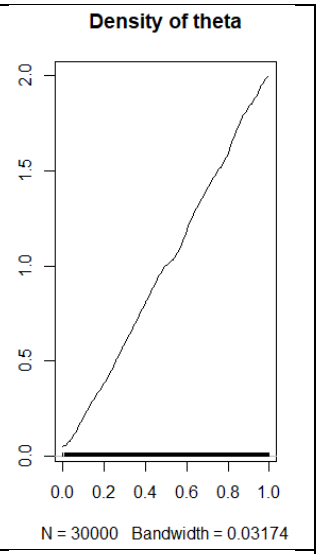
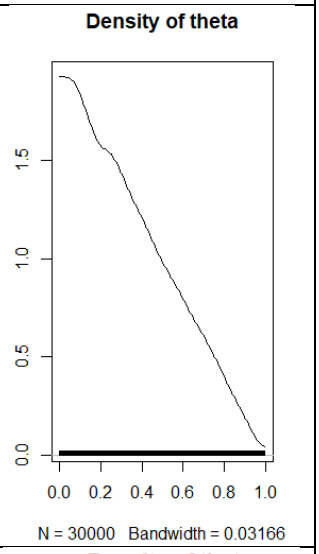
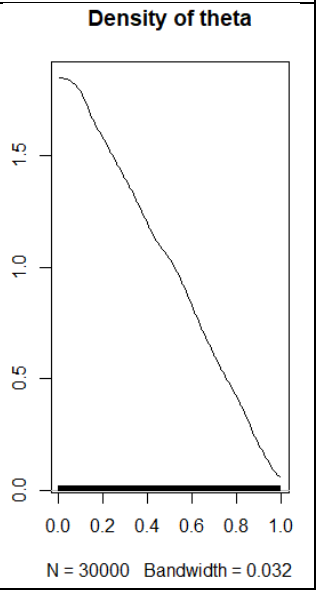
APPENDIX C – TRANSITION PROBABILITIES

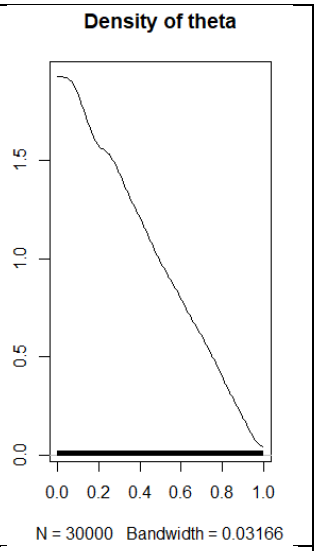
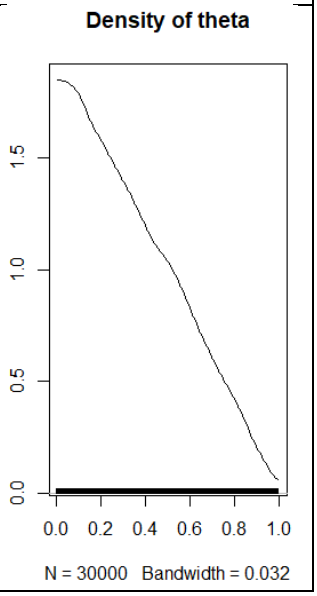
C.1 Catchpits structural deterioration – group 1

Catchpits – Structural deterioration group 1 (Cutting Sections – Brick Material)							
Transition	**Mean**	**Quantiles**					**Posterior Distribution**
		5%	**25%**	**50%**	**75%**	**97.5%**	
P11	8.766e-01	0.8490	0.8676	0.8771	0.8862	0.9020	
P12	6.786e-02	0.04867	0.06059	0.06734	0.07462	0.08983	
P13	4.694e-02	0.03122	0.04067	0.04644	0.05252	0.06558	

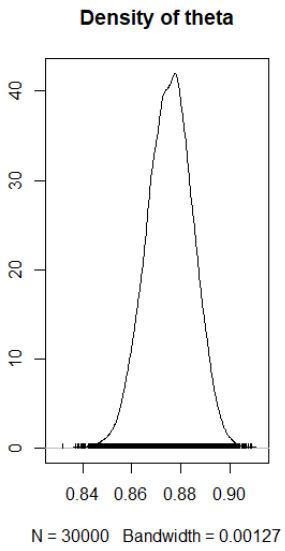
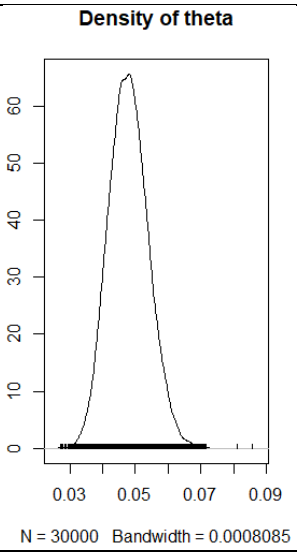
P14	6.963e-03	0.001901	0.004422	0.006427	0.008910	0.015146	
P15	6.929e-03	0.001916	0.004392	0.006348	0.008843	0.015131	
P22	0.6245630	0.2872	0.5118	0.6359	0.7484	0.9015	

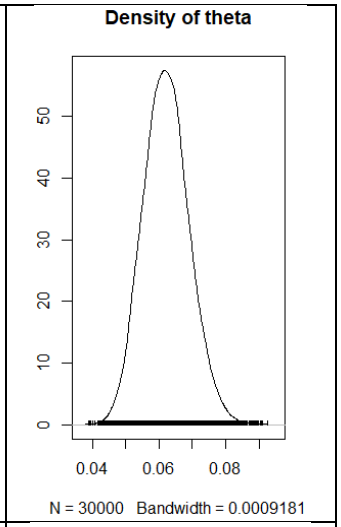
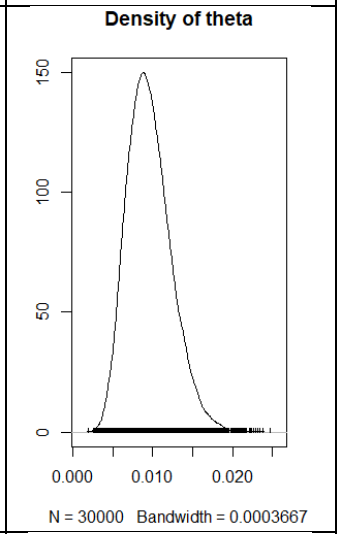
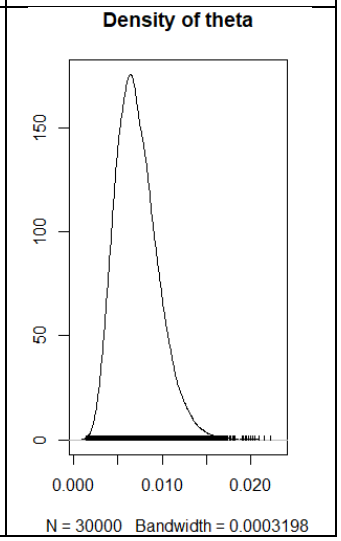
P23	0.3734166	0.09981	0.25320	0.36270	0.48188	0.70660	
P24	0.1267854	0.003769	0.041447	0.096546	0.182697	0.409876	
P25	0.1253246	0.003708	0.040221	0.093544	0.179793	0.415616	

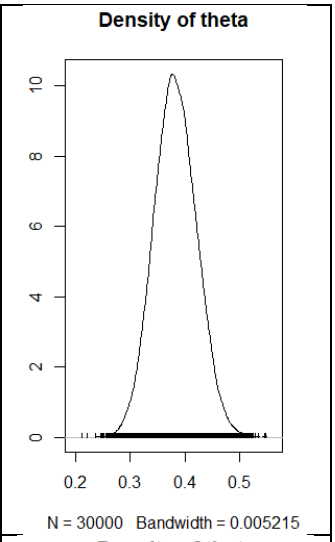
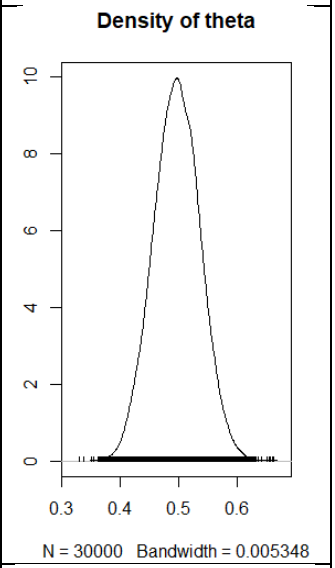
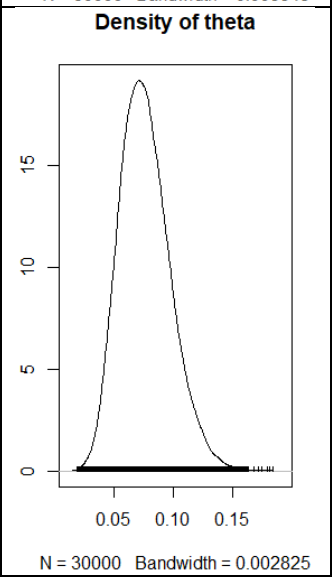
P33	0.669377	0.1569	0.5012	0.7102	0.8684	0.9874	
P34	0.332191	0.01306	0.13320	0.29164	0.49768	0.83827	
P35	0.339306	0.01327	0.13711	0.30056	0.50977	0.84544	

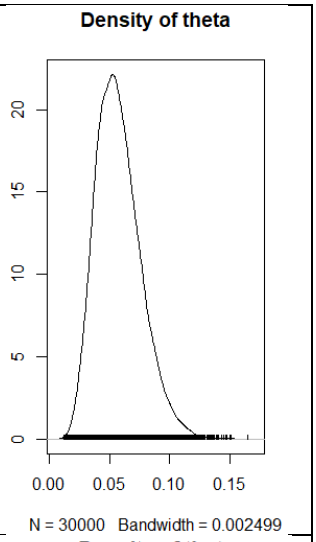
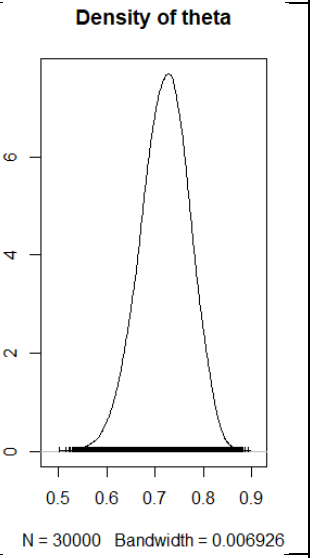
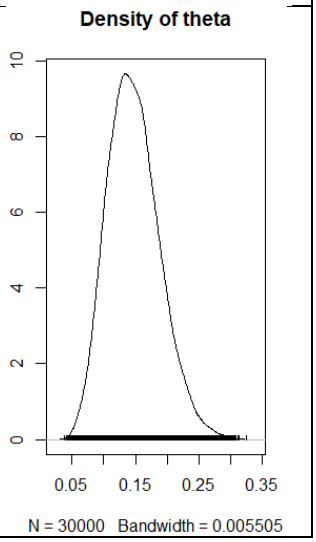
P44	0.958720	0.01345	0.13237	0.95962	0.50623	0.84341	
P45	0.050032	0.01234	0.13782	0.05563	0.50544	0.84795	

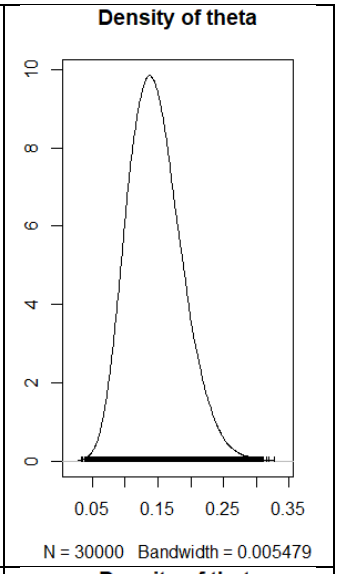
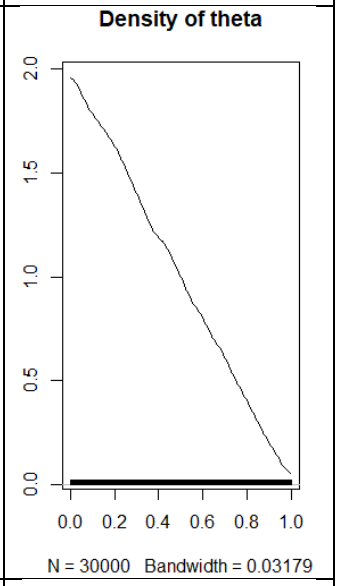
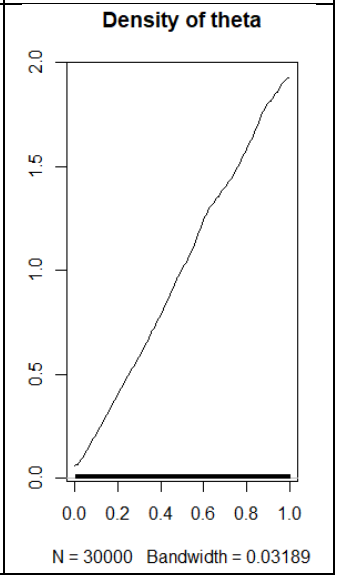
C.2 Catchpits structural deterioration – group 2

Catchpits – Structural deterioration group 2 (Other)							
Transition	**Mean**	**Quantiles**					**Posterior Distribution**
		5%	**25%**	**50%**	**75%**	**97.5%**	
P11	8.755e-01	0.8567	0.8691	0.8757	0.8819	0.8933	
P12	4.791e-02	0.03682	0.04374	0.04773	0.05183	0.06017	

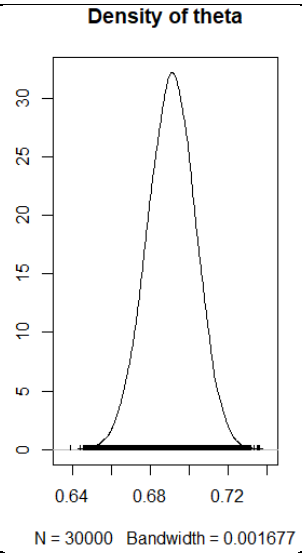
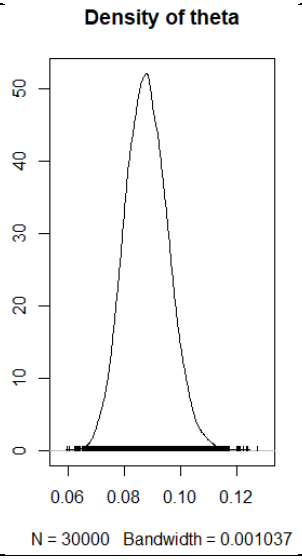
P13	6.216e-02	0.04945	0.05744	0.06197	0.06657	0.07622	
P14	9.579e-03	0.004976	0.007606	0.009314	0.011250	0.015610	
P15	7.175e-03	0.003307	0.005432	0.006894	0.008610	0.012623	

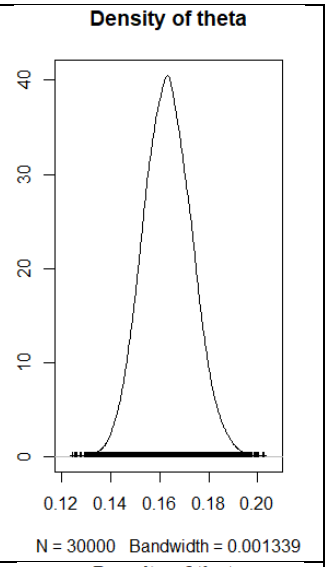
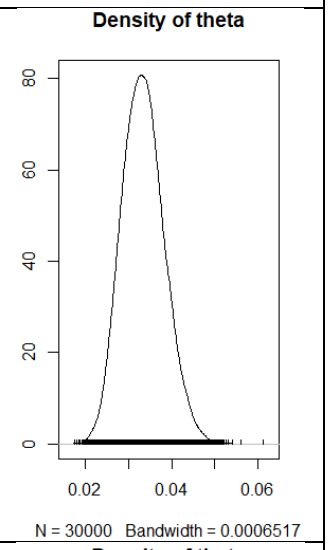
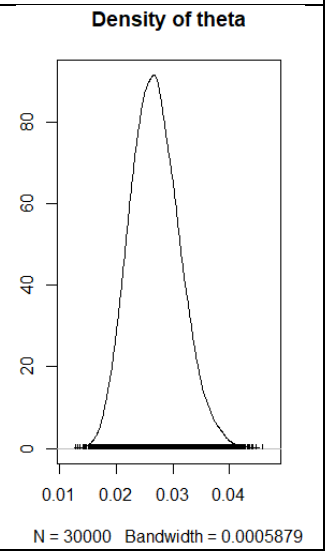
P22	0.3821543	0.3082	0.3558	0.3813	0.4079	0.4594	
P23	0.4967655	0.4192	0.4698	0.4968	0.5237	0.5748	
P24	0.0764160	0.04057	0.06144	0.07471	0.08951	0.12242	

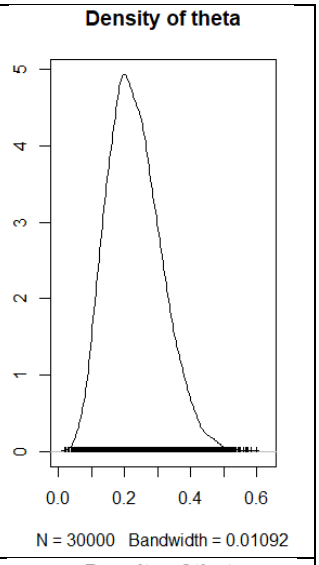
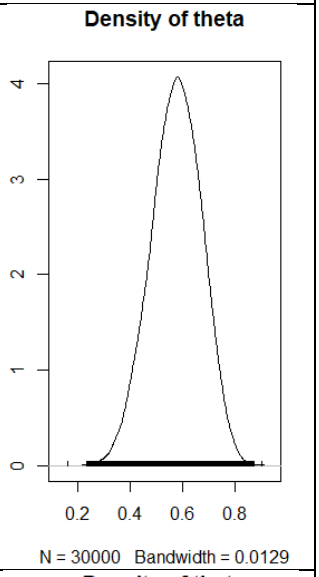
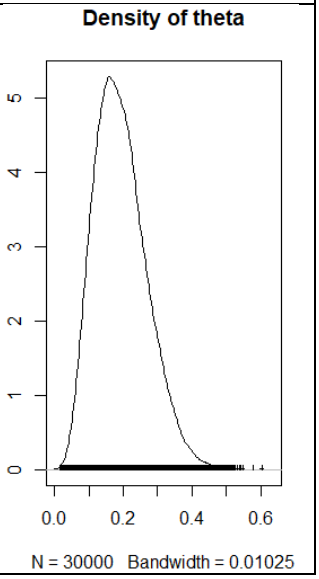
P25	0.0574568	0.02690	0.04397	0.05546	0.06881	0.09929	
P33	0.7202665	0.6147	0.6867	0.7222	0.7559	0.8152	
P34	0.1473089	0.07653	0.11797	0.14427	0.17317	0.23507	

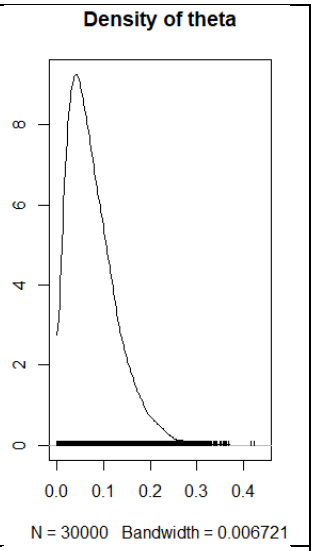
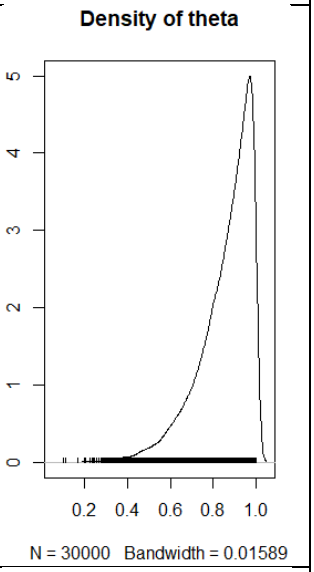
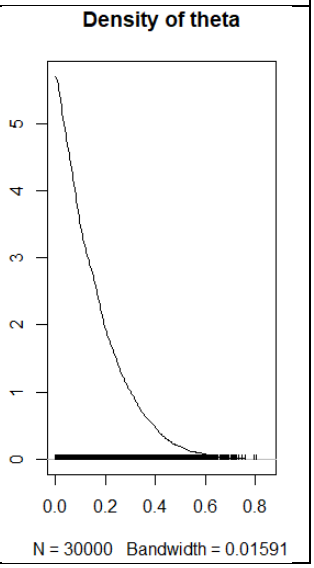
P35	0.1462973	0.07645	0.11719	0.14324	0.17184	0.23377	
P44	0.333093	0.01195	0.13438	0.29107	0.49859	0.84223	
P45	0.664986	0.1513	0.4993	0.7033	0.8655	0.9870	

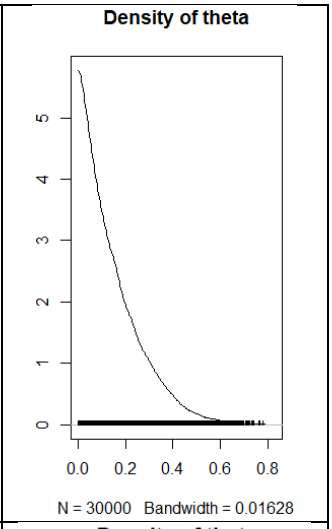
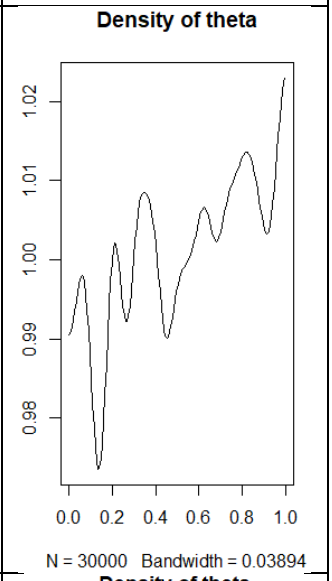
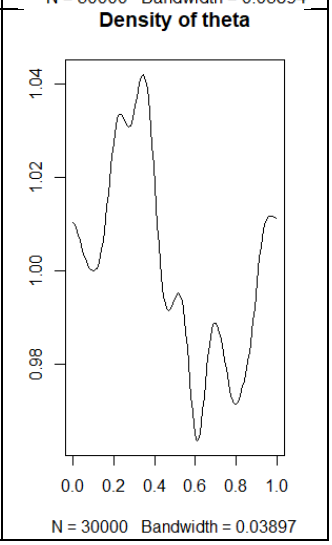
C.3 Catchpits service deterioration – group 1

Catchpits – Service deterioration group 1 (In-Situ Concrete Material)							
Transition	**Mean**	**Quantiles**					**Posterior Distribution**
		5%	**25%**	**50%**	**75%**	**97.5%**	
P11	6.908e-01	0.6659	0.6825	0.6910	0.6993	0.7149	
P12	8.774e-02	0.07332	0.08239	0.08754	0.09278	0.10340	

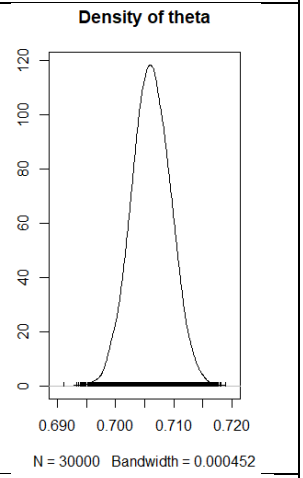
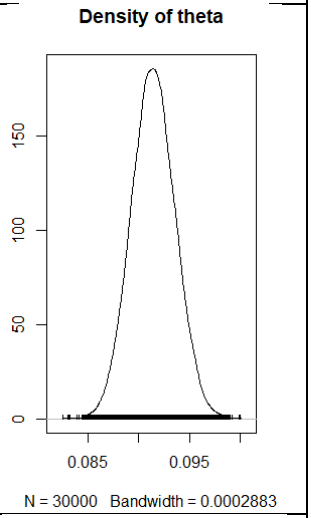
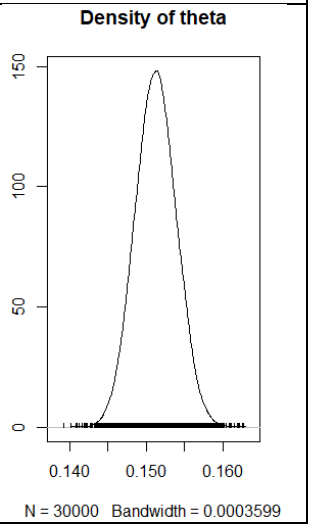
P13	1.632e-01	0.1442	0.1564	0.1631	0.1698	0.1832	
P14	3.336e-02	0.02459	0.02994	0.03317	0.03651	0.04341	
P15	2.686e-02	0.01896	0.02379	0.02665	0.02970	0.03608	

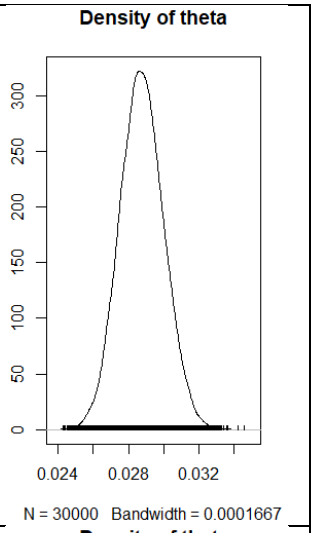
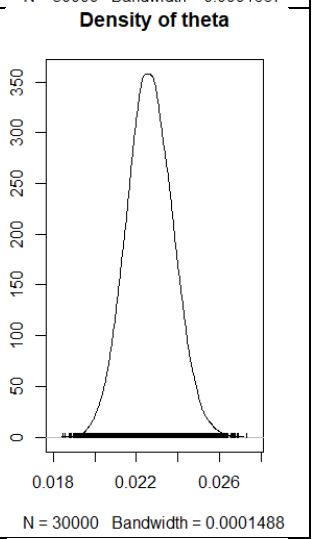
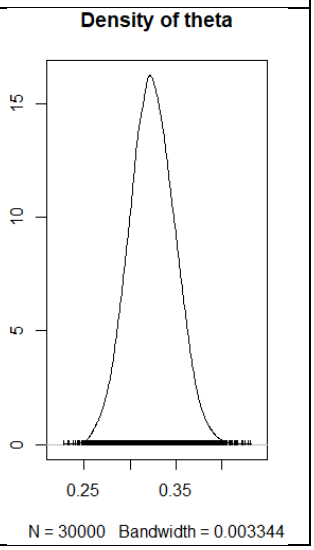
P22	0.2306029	0.09467	0.17186	0.22344	0.28277	0.40605	
P23	0.5760456	0.3834	0.5119	0.5784	0.6437	0.7538	
P24	0.1928981	0.06925	0.13691	0.18495	0.23955	0.35946	

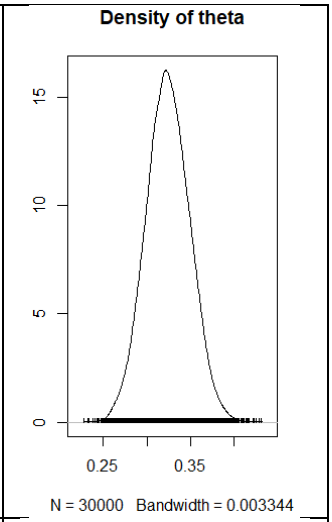
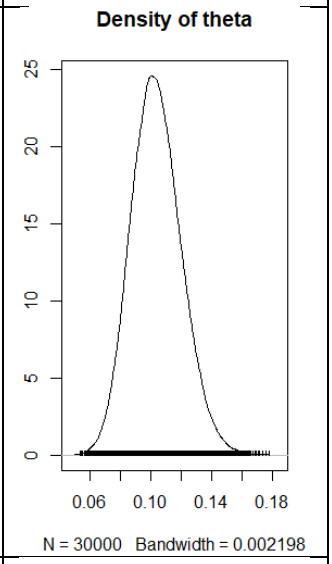
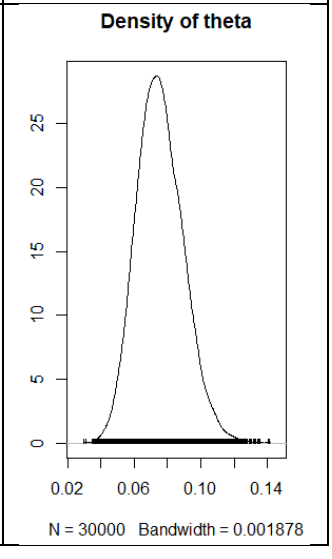
P25	0.0771139	0.009763	0.038257	0.066506	0.105041	0.204641	
P33	0.8574403	0.5366	0.7956	0.8912	0.9535	0.9959	
P34	0.1421856	0.003957	0.047036	0.109424	0.205158	0.455609	

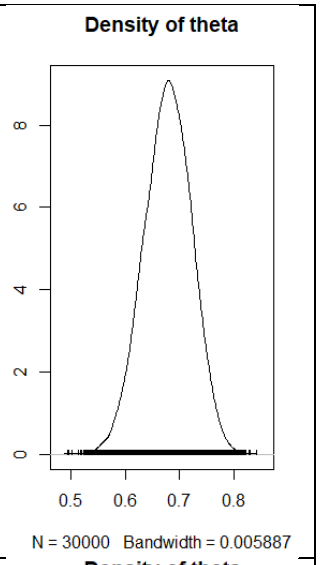
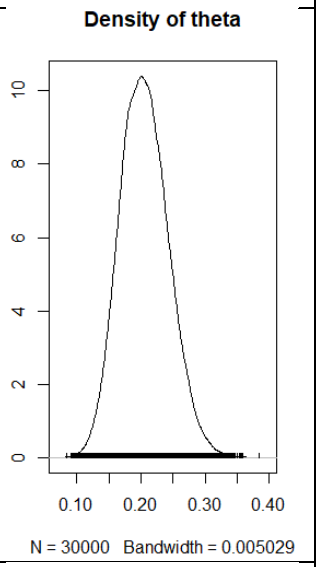
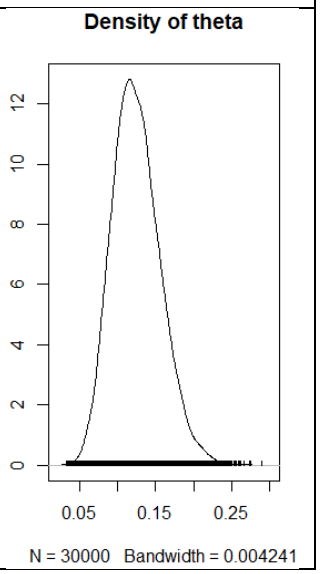
P35	0.1426938	0.004178	0.045840	0.109001	0.207566	0.457042	
P44	0.502134	0.0260	0.2525	0.5030	0.7523	0.9755	
P45	0.496890	0.02409	0.24695	0.49156	0.74670	0.97503	

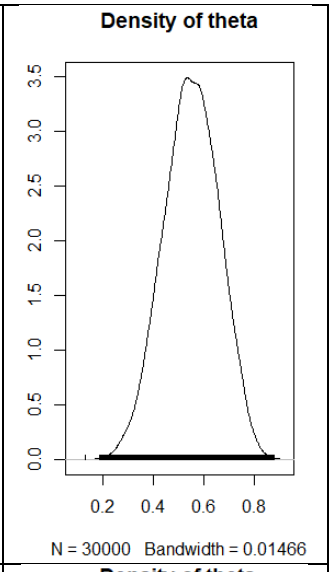
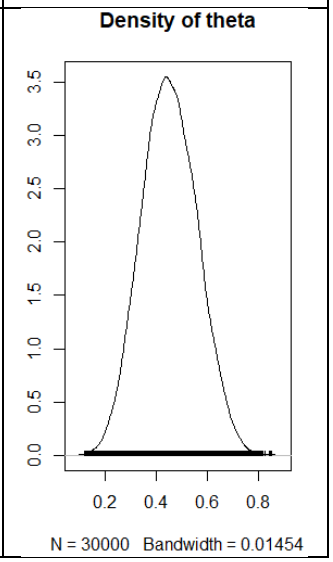
C.4 Catchpits service deterioration – group 2

Catchpits – Service deterioration group 2 (Other)							
Transition	**Mean**	**Quantiles**					**Posterior Distribution**
		5%	**25%**	**50%**	**75%**	**97.5%**	
P11	7.061e-01	0.6995	0.7038	0.7061	0.7084	0.7127	
P12	9.144e-02	0.08730	0.08999	0.09142	0.09287	0.09566	
P13	1.512e-01	0.1461	0.1494	0.1512	0.1530	0.1565	

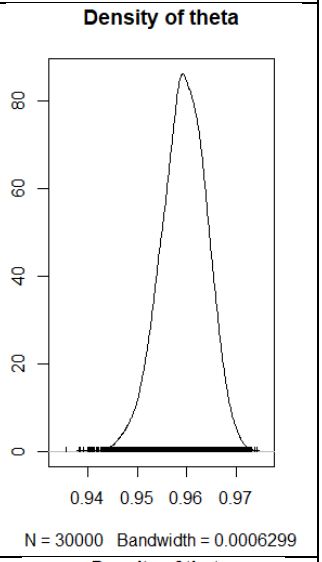
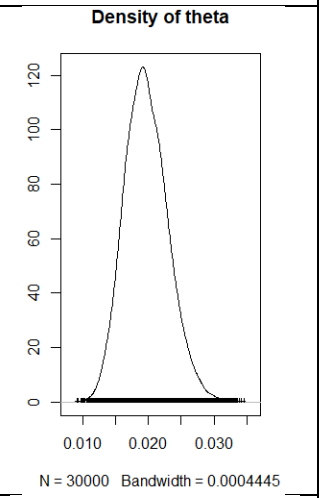
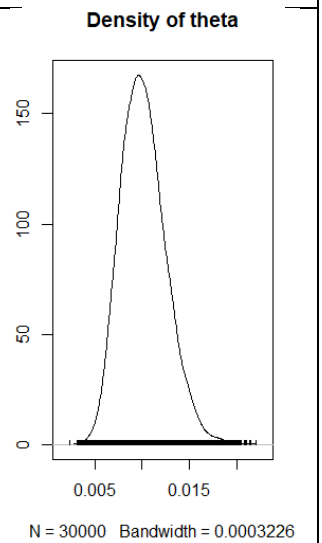
P14	2.876e-02	0.02639	0.02792	0.02873	0.02957	0.03123	
P15	2.265e-02	0.02052	0.02190	0.02263	0.02339	0.02484	
P22	0.3240531	0.2757	0.3073	0.3237	0.3407	0.3729	

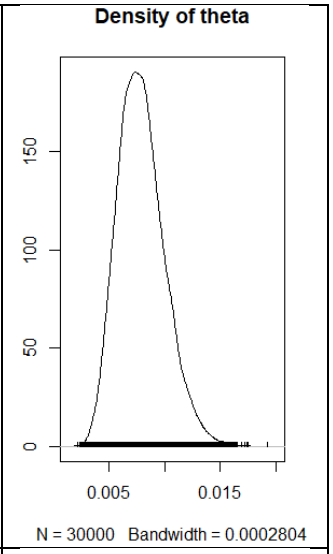
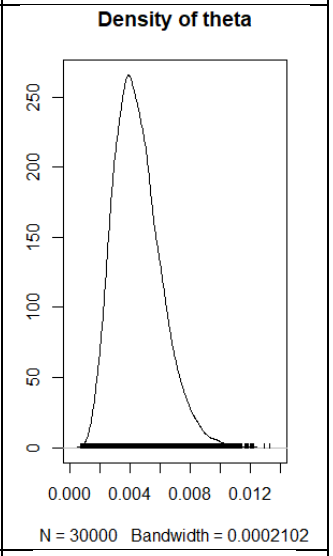
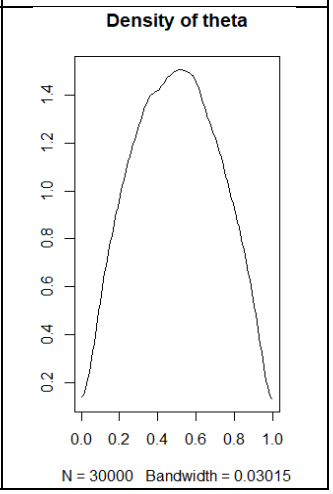
P23	0.5027158	0.4510	0.4848	0.5027	0.5208	0.5543	
P24	1.035e-01	0.07360	0.09213	0.10280	0.11404	0.13766	
P25	0.0755583	0.05047	0.06576	0.07476	0.08469	0.10498	

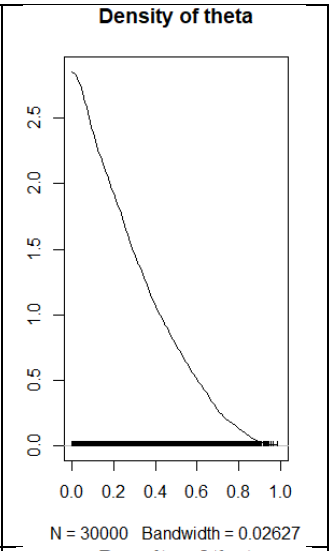
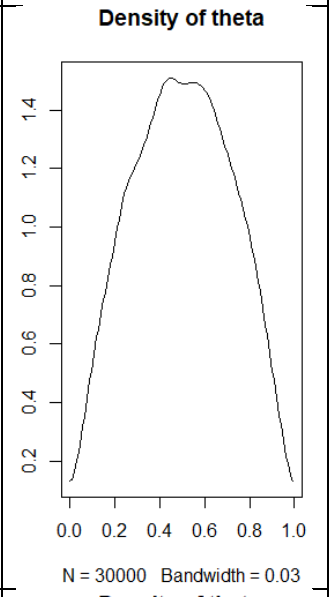
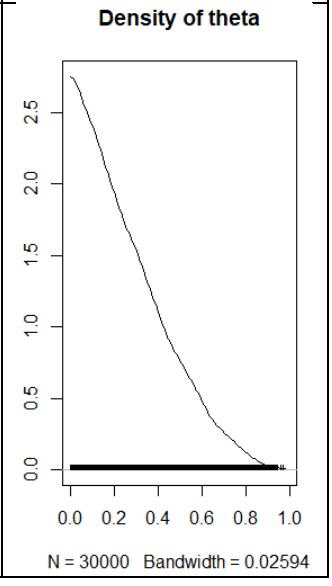
P33	0.6781822	0.5910	0.6490	0.6791	0.7084	0.7609	
P34	0.2053052	0.1372	0.1790	0.2036	0.2299	0.2821	
P35	0.1249173	0.07003	0.10269	0.12255	0.14483	0.19222	

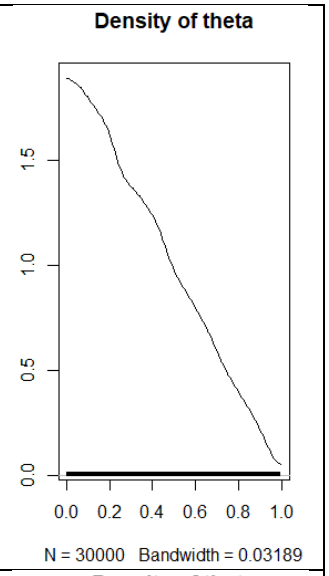
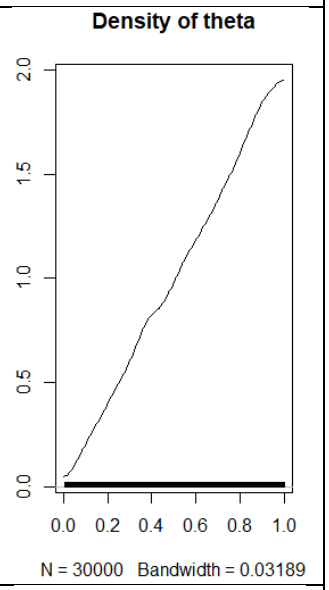
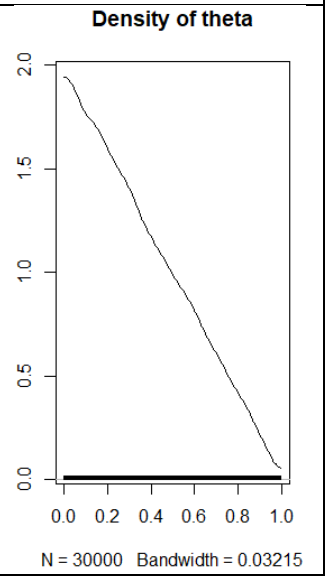
P44	0.5503128	0.3340	0.4759	0.5517	0.6275	0.7540	
P45	0.4509139	0.2475	0.3753	0.4485	0.5258	0.6650	

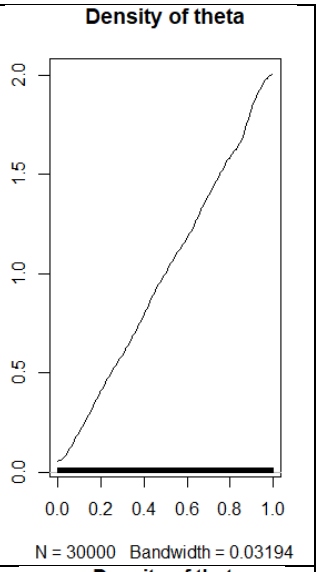
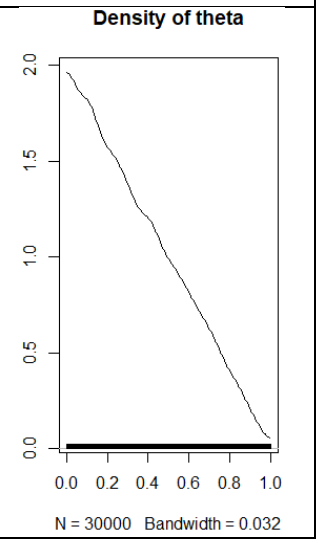
C.5 Culverts structural deterioration

Culverts – Structural deterioration							
Transition	**Mean**	**Quantiles**					**Posterior Distribution**
		5%	**25%**	**50%**	**75%**	**97.5%**	
P11	9.594e-01	0.9497	0.9564	0.9595	0.9627	0.9680	
P12	1.970e-02	0.01377	0.01738	0.01951	0.02181	0.02667	
P13	1.014e-02	0.006014	0.008420	0.009959	0.011625	0.015298	

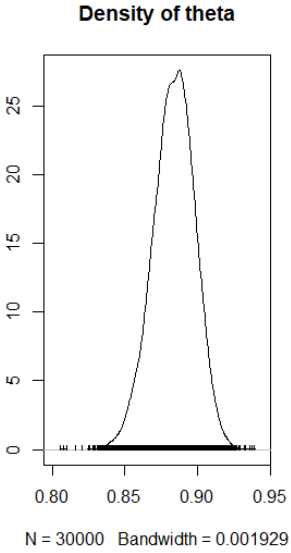
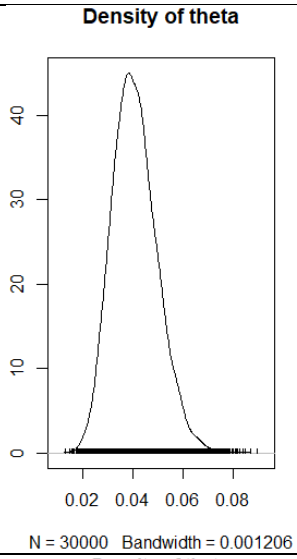
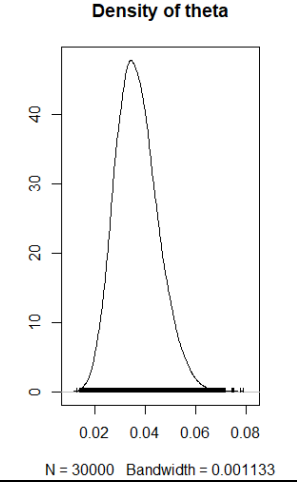
P14	7.885e-03	0.004323	0.006382	0.007716	0.009168	0.012500	
P15	4.502e-03	0.001947	0.003351	0.004312	0.005439	0.008126	
P22	0.497919	0.09638	0.32432	0.49842	0.66961	0.90548	

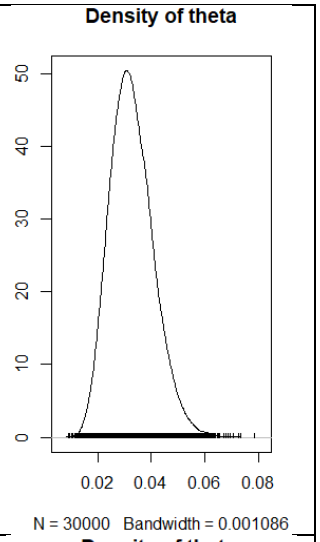
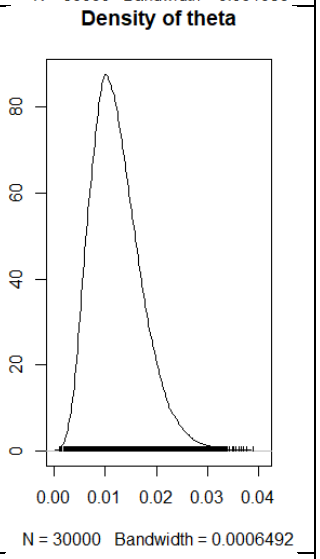
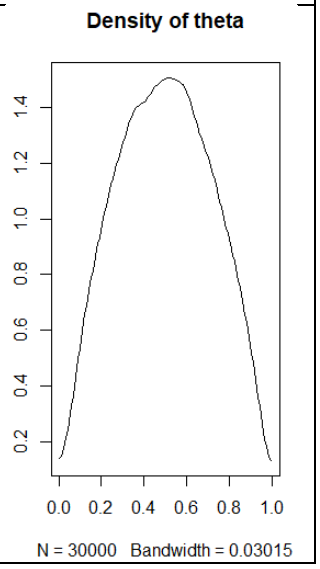
P23	0.252129	0.008779	0.091969	0.208549	0.373166	0.708609	
P24	0.500797	0.09523	0.32824	0.50151	0.67241	0.90324	
P25	0.252381	0.009018	0.095471	0.210964	0.371106	0.707043	

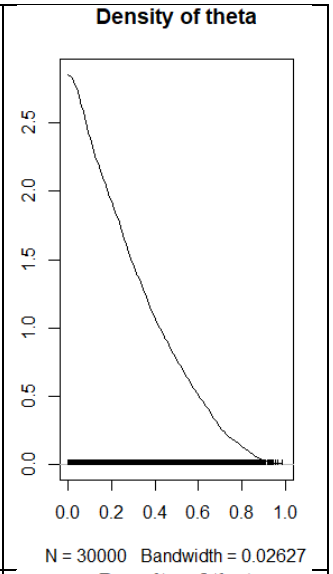
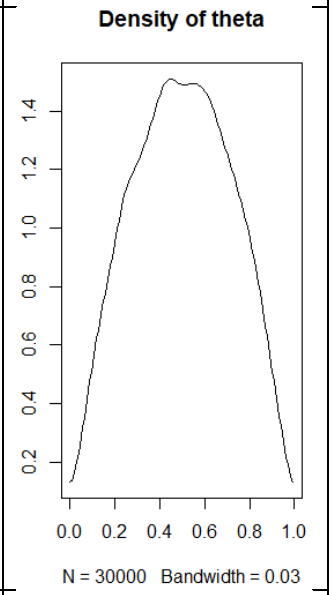
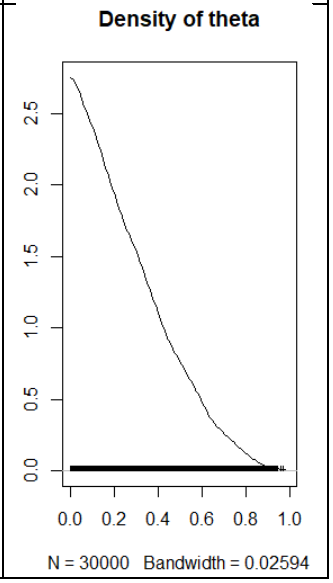
P33	0.335275	0.01278	0.13641	0.29502	0.50072	0.84833	
P34	0.667263	0.1559	0.4985	0.7098	0.8678	0.9879	
P35	0.337014	0.01295	0.13616	0.29557	0.50708	0.84897	

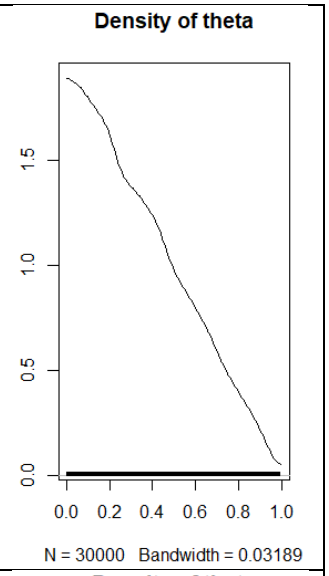
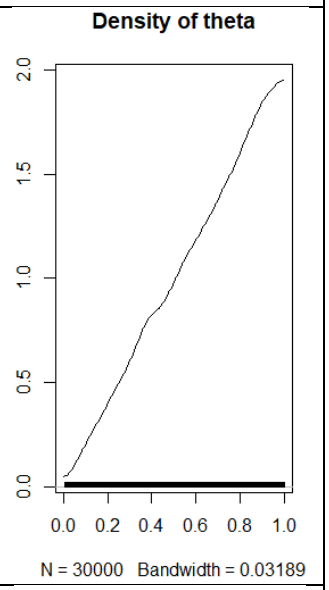
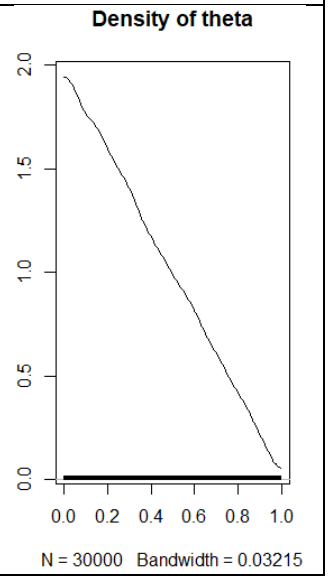
P44	0.667800	0.1575	0.5008	0.7089	0.8694	0.9878	
P45	0.335166	0.01241	0.13292	0.29429	0.50435	0.84484	

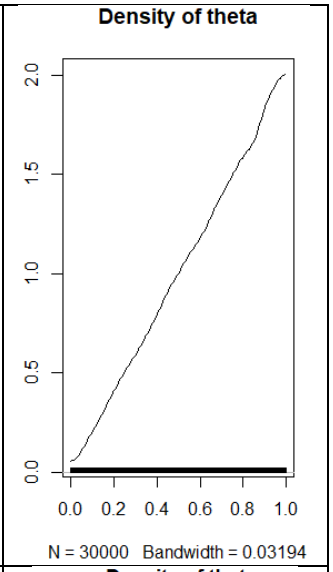
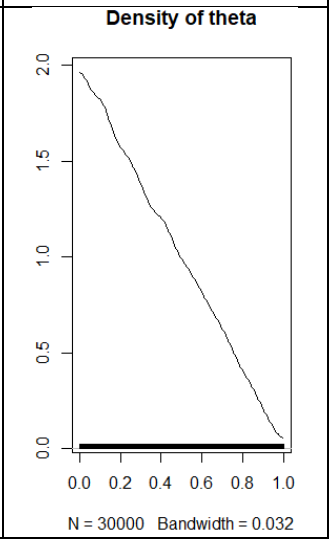
C.6 Culverts service deterioration

Culverts – Service deterioration							
Transition	**Mean**	**Quantiles**					**Posterior Distribution**
		5%	**25%**	**50%**	**75%**	**97.5%**	
P11	8.835e-01	0.8536	0.8742	0.8840	0.8934	0.9101	
P12	4.088e-02	0.02520	0.03452	0.04024	0.04650	0.06006	
P13	3.681e-02	0.02207	0.03082	0.03617	0.04207	0.05496	

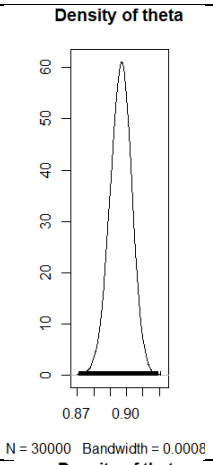
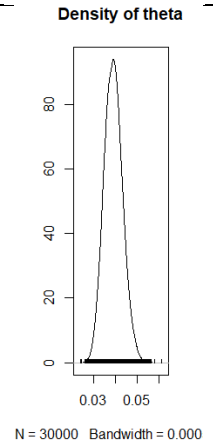
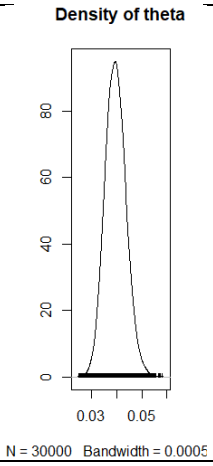
P14	3.269e-02	0.01878	0.02695	0.03207	0.03775	0.05011	
P15	1.526e-02	0.004612	0.008704	0.011602	0.015155	0.023667	
P22	0.481346	0.09845	0.35356	0.4844	0.62861	0.98455	

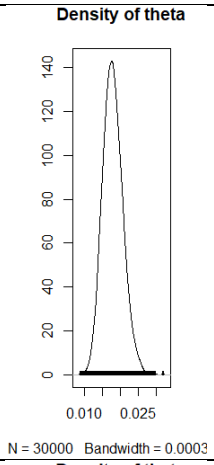
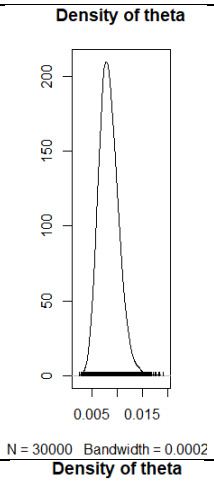
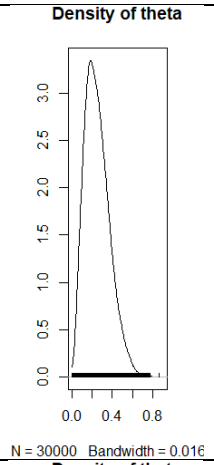
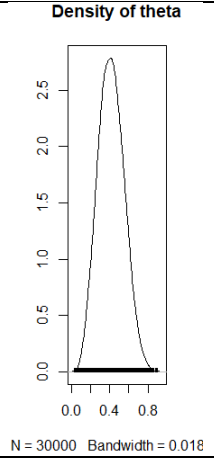
P23	0.294496	0.00874	0.07234	0.2954	0.37866	0.78264	
P24	0.113967	0.08354	0.84564	0.5515	0.67841	0.98247	
P25	0.112894	0.00855	0.07134	0.2136	0.32806	0.78245	

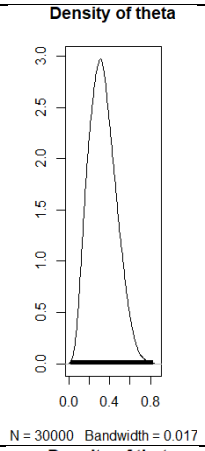
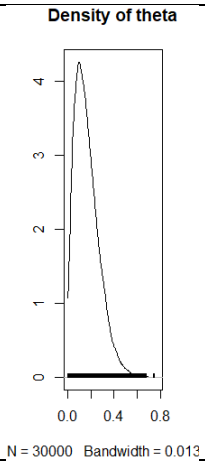
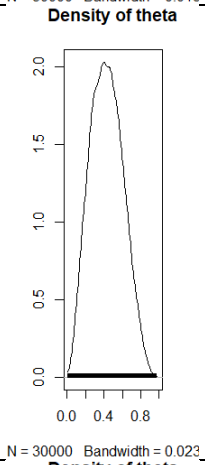
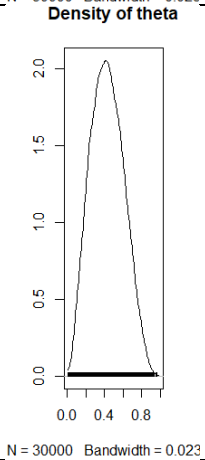
P33	0.413866	0.01885	0.13733	0.2277	0.52872	0.88264	
P34	0.547968	0.18384	0.47458	0.7838	0.92848	0.92824	
P35	0.040552	0.01828	0.18456	0.2987	0.59295	0.84728	

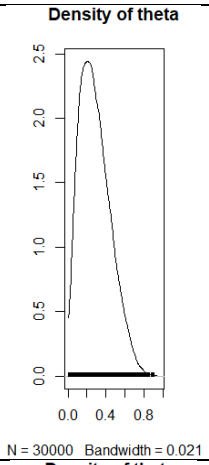
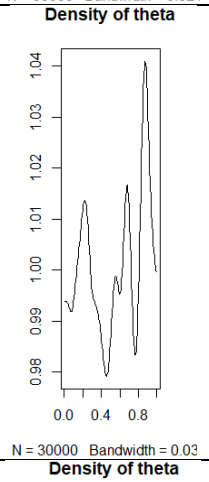
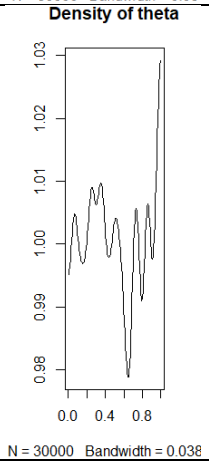
P44	0.616964	0.15772	0.56627	0.7022	0.88965	0.93728	
P45	0.384961	0.01613	0.13824	0.2933	0.58473	0.89844	

C.7 Pipes structural deterioration – group 1

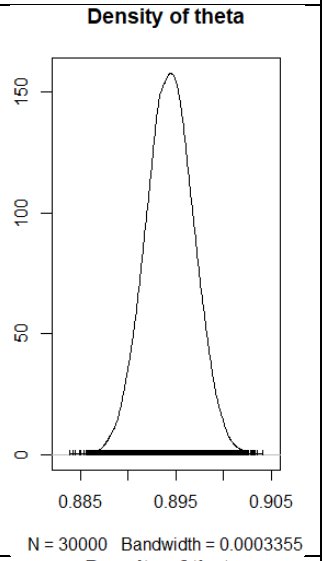
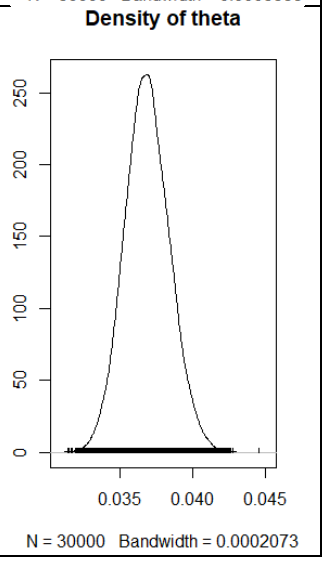
Pipes – Structural deterioration group 1 (Size <150mm)							
Transition	**Mean**	**Quantiles**					**Posterior Distribution**
		5%	**25%**	**50%**	**75%**	**97.5%**	
P11	8.965e-01	0.8832	0.8921	0.8966	0.9009	0.9090	
P12	3.912e-02	0.03140	0.03619	0.03901	0.04185	0.04771	
P13	3.950e-02	0.03175	0.03663	0.03938	0.04224	0.04804	

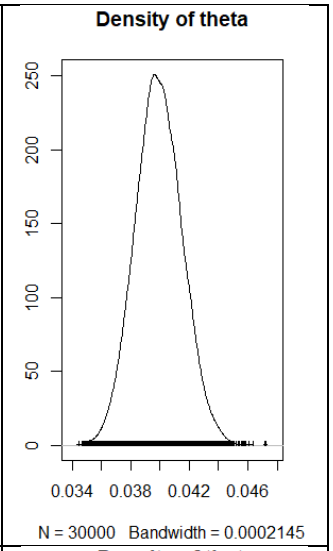
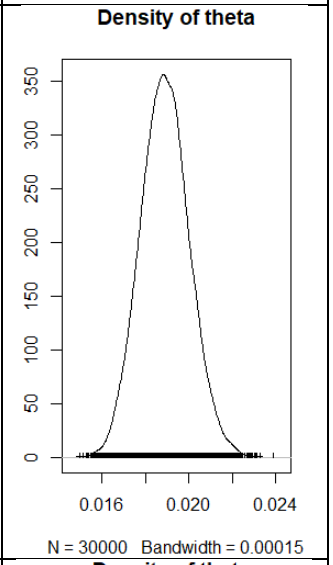
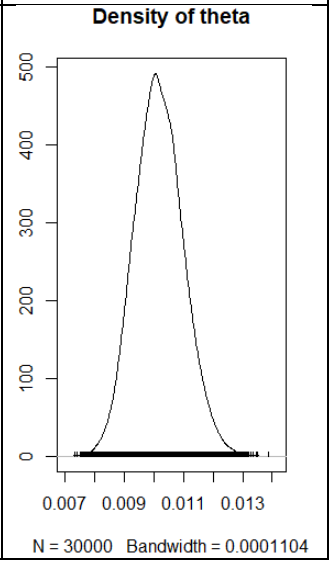
P14	1.790e-02	0.01276	0.01593	0.01776	0.01970	0.02389	
P15	8.294e-03	0.004901	0.006932	0.008143	0.009508	0.012496	
P22	0.2501671	0.06051	0.15953	0.23533	0.32647	0.52208	
P23	0.4152942	0.1681	0.3188	0.4114	0.5077	0.6868	

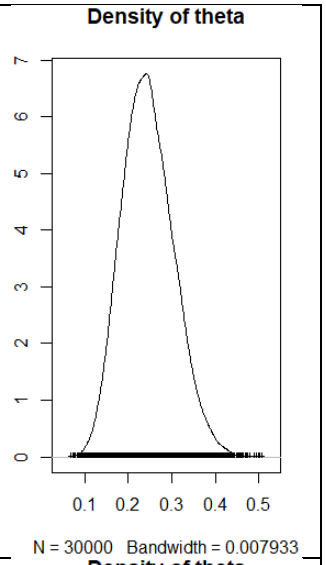
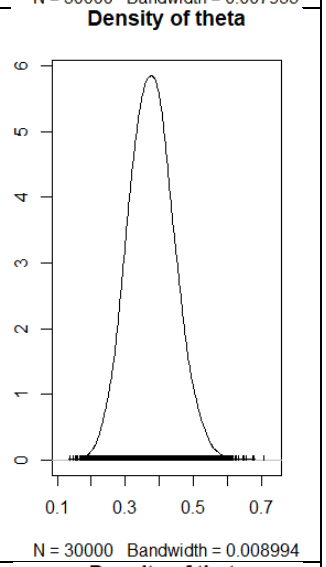
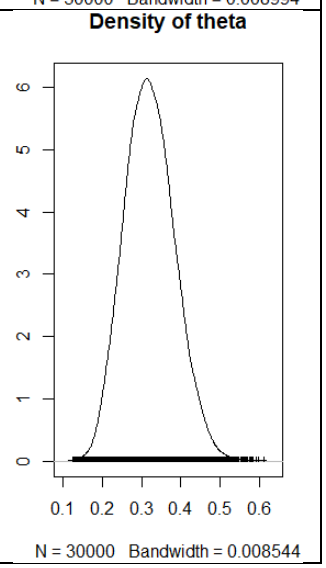
P24	0.3330938	0.1118	0.2367	0.3238	0.4194	0.6066	
P25	0.1662058	0.02264	0.08752	0.14784	0.22593	0.41219	
P33	0.428486	0.1141	0.2943	0.4225	0.5541	0.7772	
P34	0.430433	0.1152	0.2978	0.4239	0.5572	0.7816	

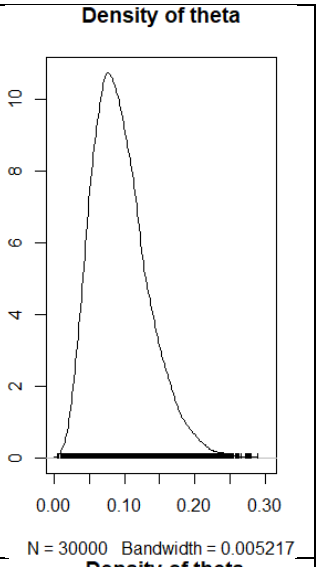
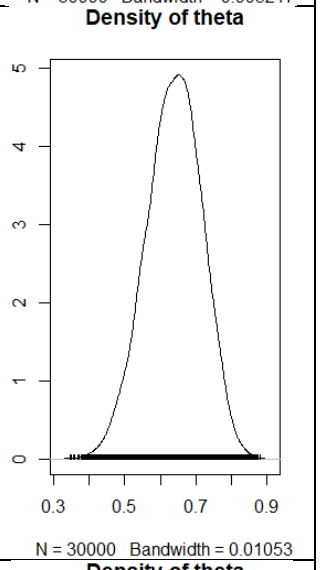
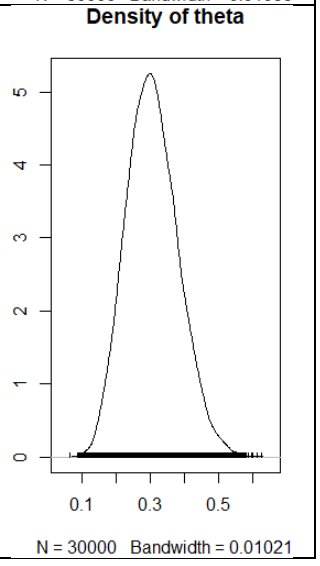
P35	0.2869640	0.0438	0.1623	0.2648	0.3903	0.6419	
P44	0.501547	0.02564	0.24959	0.50320	0.75279	0.97467	
P45	0.500150	0.02552	0.24950	0.50003	0.75023	0.97599	

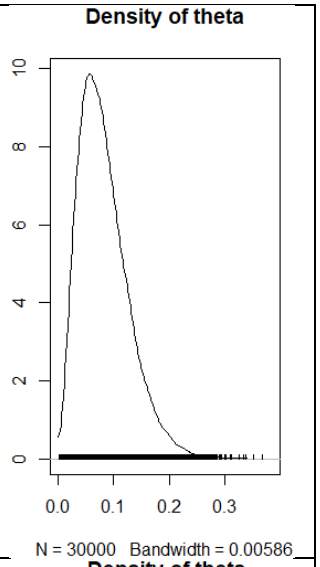
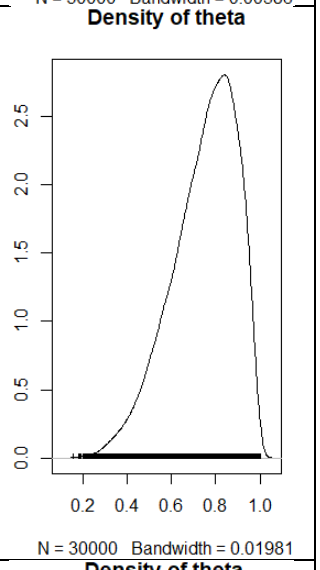
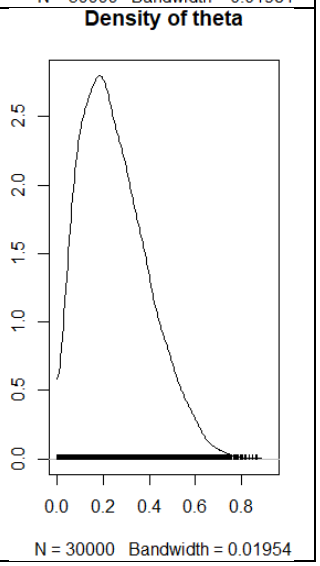
C.8 Pipes structural deterioration – group 2

Pipes – Structural deterioration group 2 (Other)							
Transition	**Mean**	**Quantiles**					**Posterior Distribution**
		5%	**25%**	**50%**	**75%**	**97.5%**	
P11	8.944e-01	0.8895	0.8927	0.8944	0.8960	0.8992	
P12	3.686e-02	0.03391	0.03582	0.03682	0.03788	0.04000	

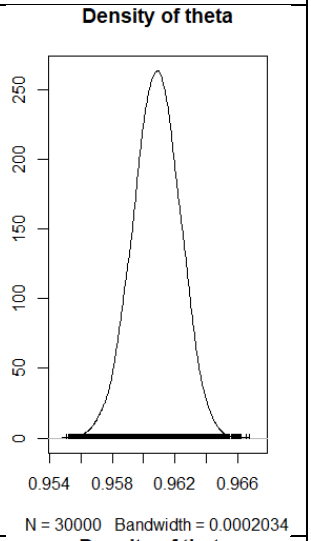
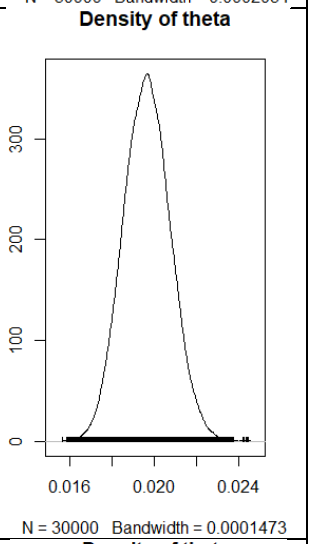
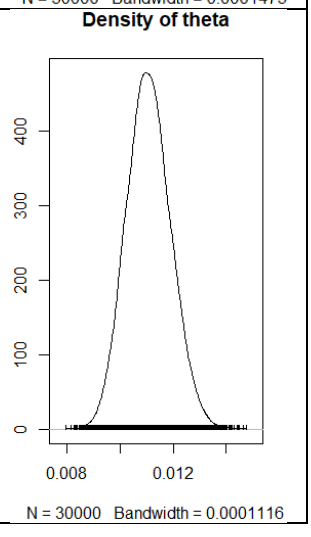
P13	3.992e-02	0.03685	0.03884	0.03988	0.04098	0.04310	
P14	1.889e-02	0.01675	0.01813	0.01887	0.01962	0.02114	
P15	1.018e-02	0.008648	0.009613	0.010150	0.010712	0.011854	

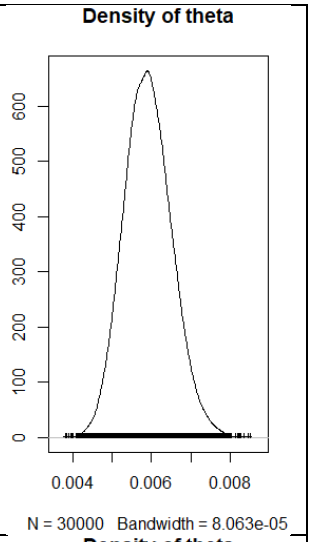
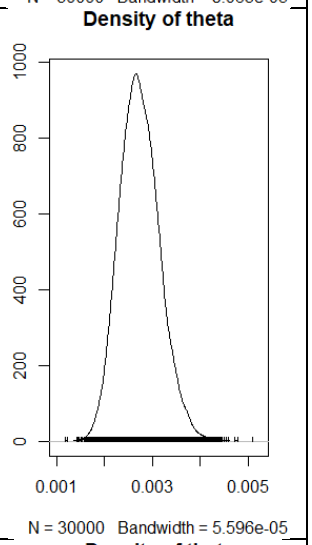
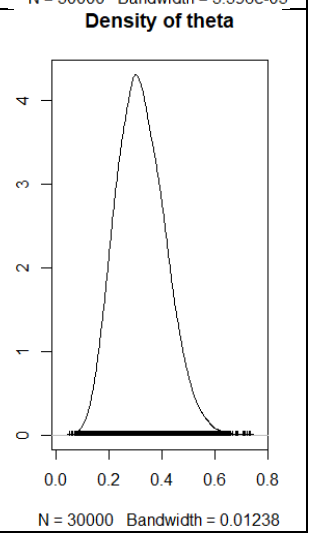
P22	0.2455907	0.1403	0.2038	0.2424	0.2840	0.3697	
P23	0.3767968	0.2506	0.3306	0.3755	0.4207	0.5125	
P24	0.3207454	0.2050	0.2760	0.3182	0.3626	0.4508	

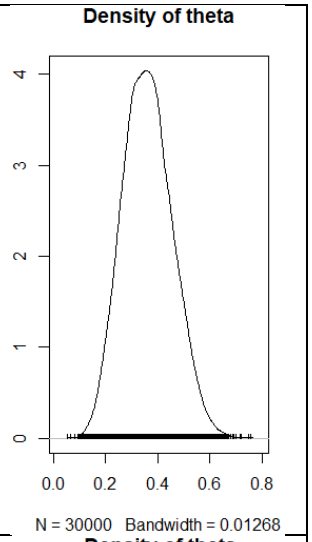
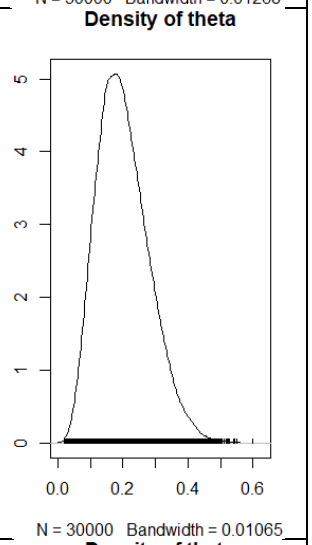
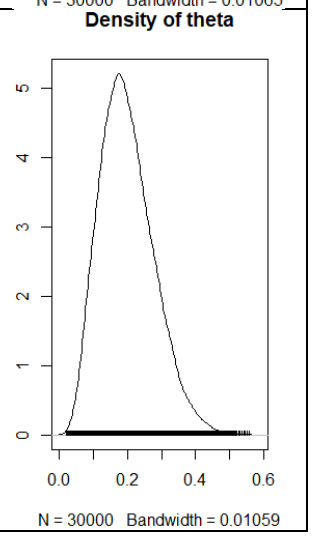
P25	0.0941402	0.03216	0.06529	0.08886	0.11712	0.18594	
P33	0.6386152	0.4789	0.5867	0.6414	0.6934	0.7823	
P34	0.3062157	0.1690	0.2528	0.3025	0.3558	0.4631	

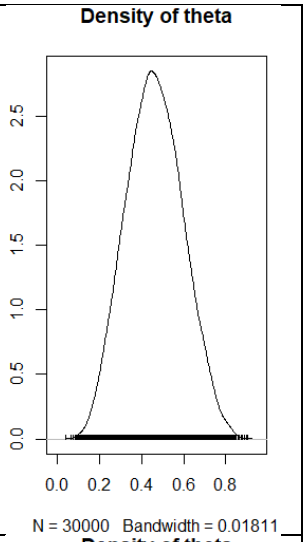
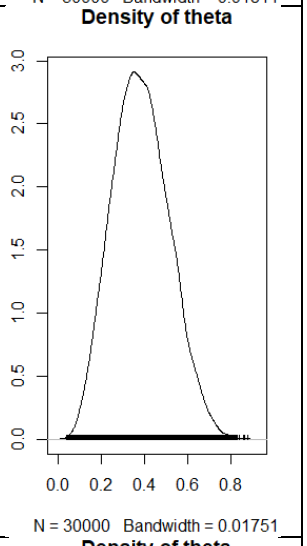
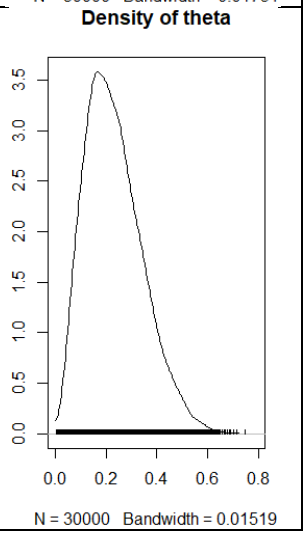
P35	0.0822268	0.01796	0.04924	0.07485	0.10747	0.18835	
P44	0.746568	0.4103	0.6542	0.7698	0.8603	0.9620	
P45	0.2525308	0.03711	0.13994	0.23087	0.34452	0.57975	

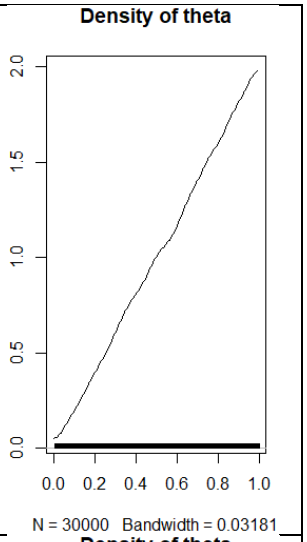
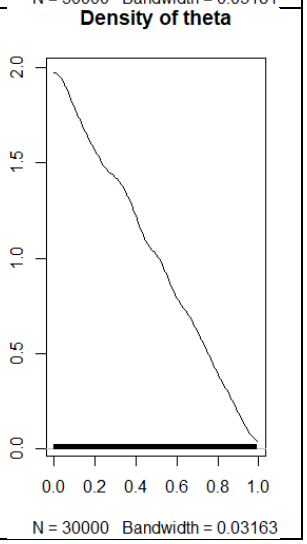
C.9 Pipes service deterioration – group 1

Pipes – Service deterioration group 1 (Unlined Brick Material)							
Transition	**Mean**	**Quantiles**					**Posterior Distribution**
		5%	**25%**	**50%**	**75%**	**97.5%**	
P11	9.707e-01	0.9488	0.9599	0.9708	0.9824	0.9937	
P12	2.006e-02	0.0176	0.0186	0.0265	0.0271	0.0218	
P13	0.507e-02	0.0089	0.0108	0.0050	0.0118	0.0130	

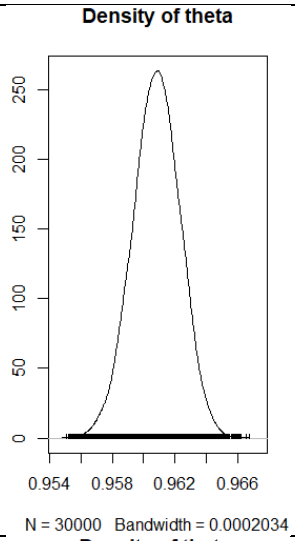
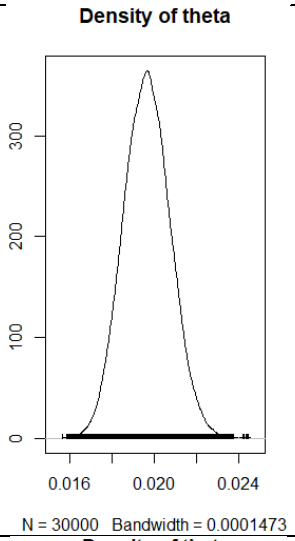
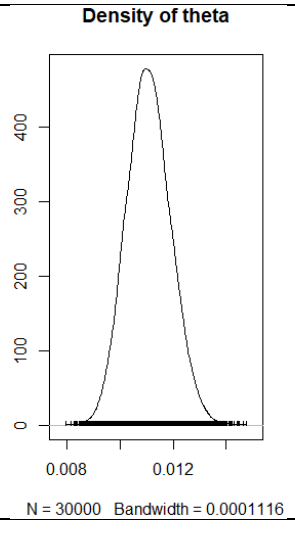
P14	3.088e-03	0.0049	0.0058	0.0035	0.0062	0.0080	
P15	2.737e-03	0.0019	0.0026	0.0027	0.0037	0.0036	
P22	0.3141827	0.1599	0.2565	0.3147	0.4957	0.5133	

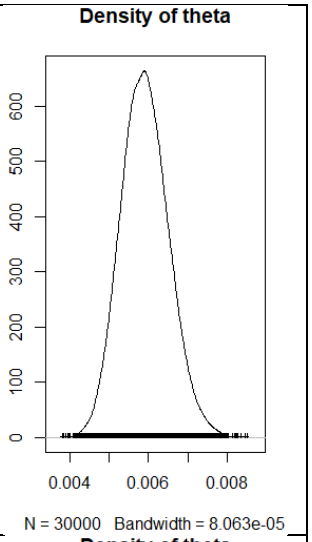
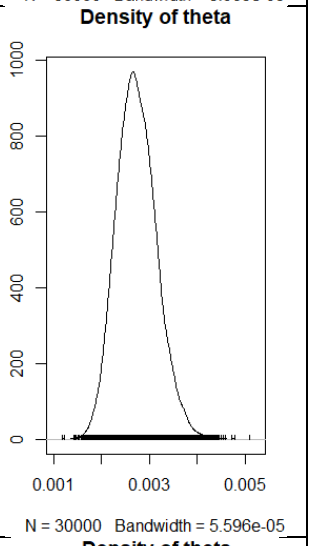
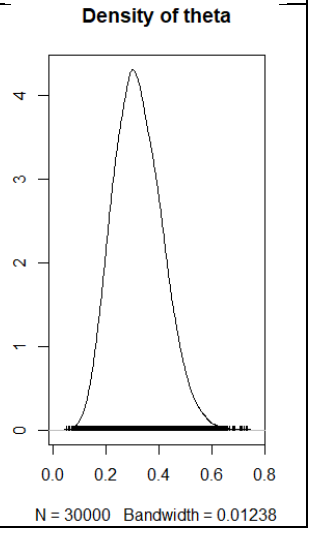
P23	0.3758441	0.1872	0.2978	0.3775	0.4385	0.5534	
P24	0.1921550	0.0796	0.1495	0.1926	0.2521	0.3734	
P25	0.1990095	0.0700	0.1454	0.1998	0.2816	0.3736	

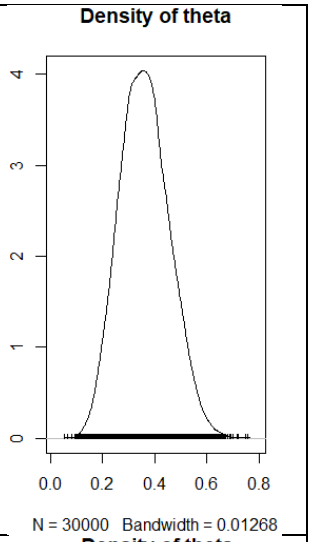
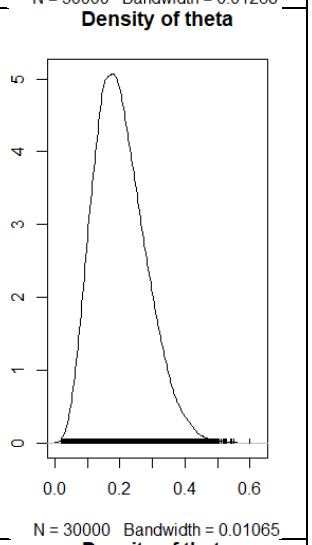
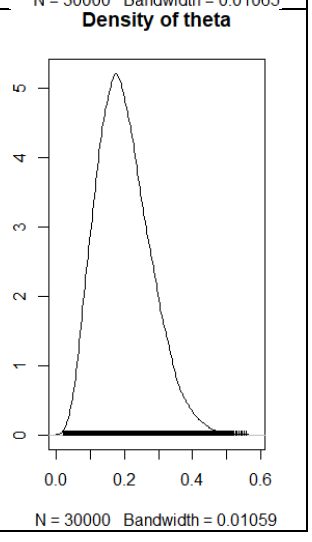
P33	0.5103137	0.2086	0.3459	0.5190	0.5782	0.7568	
P34	0.3722148	0.1440	0.2744	0.3791	0.5929	0.6234	
P35	0.1188572	0.0585	0.1549	0.1187	0.3592	0.4887	

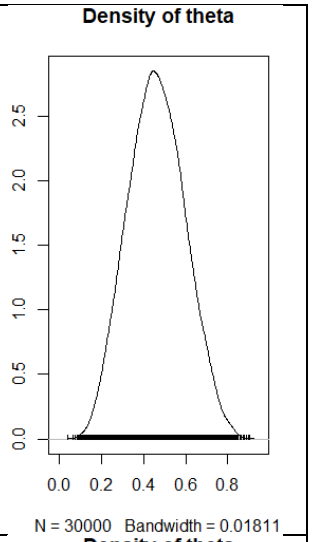
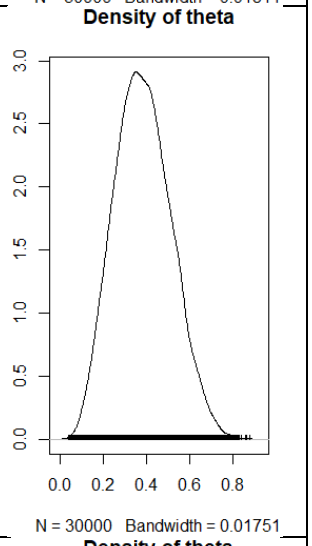
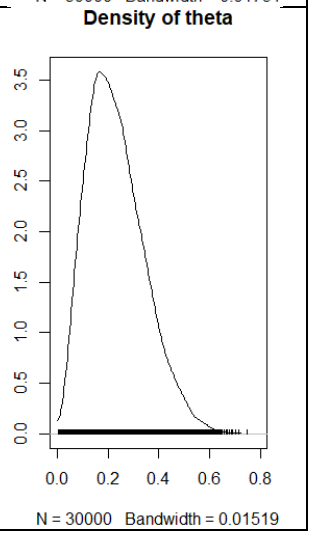
P44	0.698783	0.1665	0.4567	0.7087	0.8674	0.9893	
P45	0.302092	0.0124	0.1354	0.2990	0.5572	0.8392	

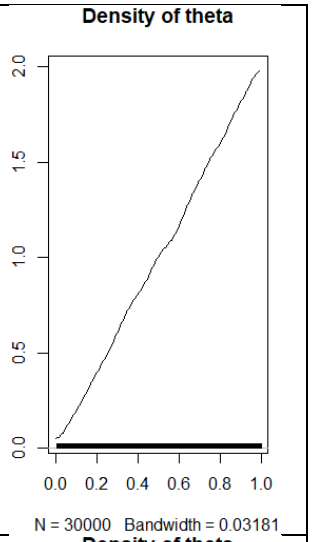
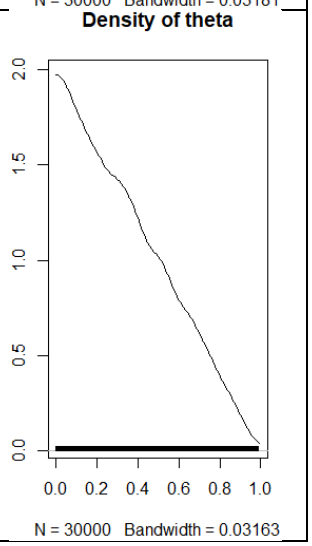
C.10 Pipes service deterioration – group 2

Pipes – Service deterioration group 2 (Other)							
Transition	**Mean**	**Quantiles**					**Posterior Distribution**
		5%	**25%**	**50%**	**75%**	**97.5%**	
P11	9.608e-01	0.9578	0.9598	0.9608	0.9618	0.9637	
P12	1.966e-02	0.01757	0.01890	0.01965	0.02038	0.02185	
P13	1.108e-02	0.009512	0.010511	0.011054	0.011620	0.012756	

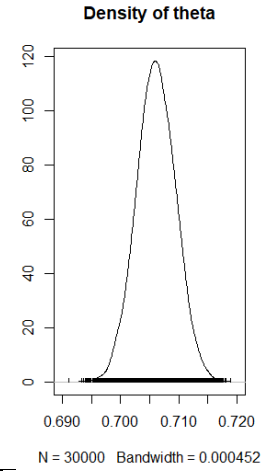
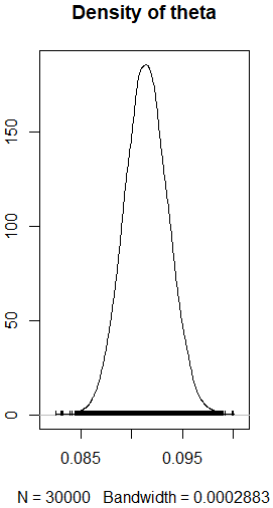
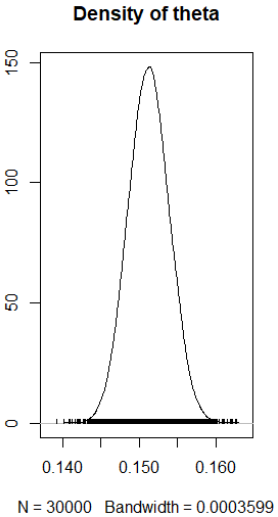
P14	5.908e-03	0.004798	0.005493	0.005889	0.006299	0.007143	
P15	5.007e-03	0.001990	0.002446	0.002715	0.003004	0.003611	
P22	0.3202527	0.1585	0.2542	0.3147	0.3809	0.5124	

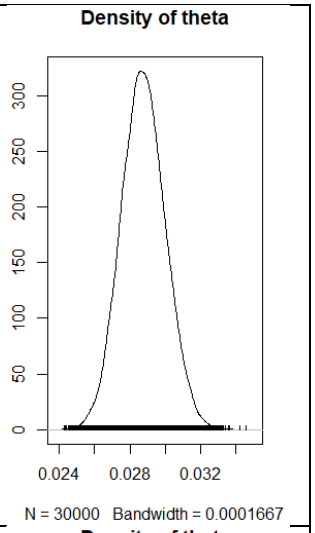
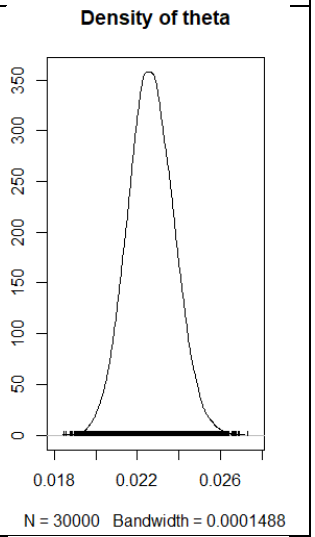
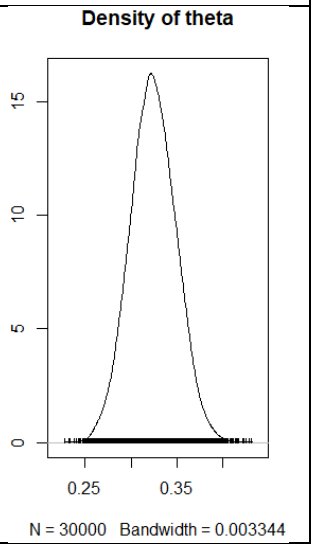
P23	0.3609641	0.1895	0.2941	0.3575	0.4237	0.5528	
P24	0.2011237	0.0715	0.1434	0.1926	0.2510	0.3757	
P25	0.1990095	0.07009	0.14138	0.19081	0.24850	0.37307	

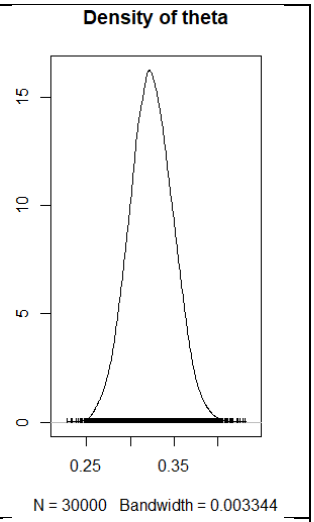
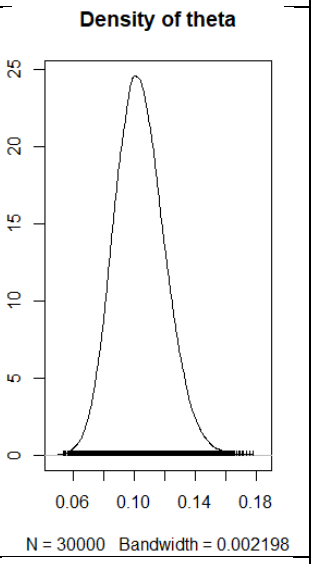
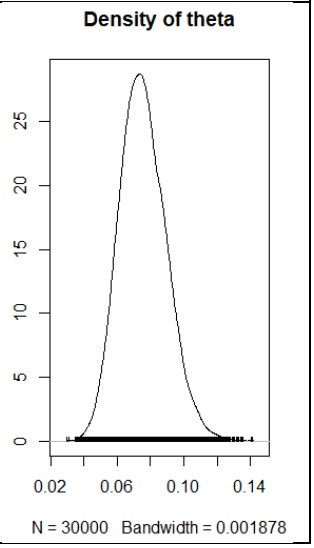
P33	0.4613116	0.2095	0.3658	0.4590	0.5550	0.7273	
P34	0.3842899	0.1490	0.2905	0.3791	0.4727	0.6496	
P35	0.2308471	0.05398	0.14587	0.21672	0.30157	0.48546	

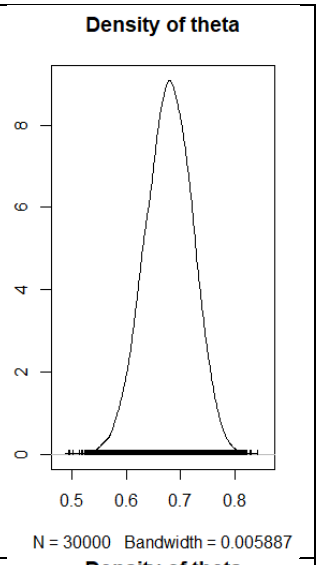
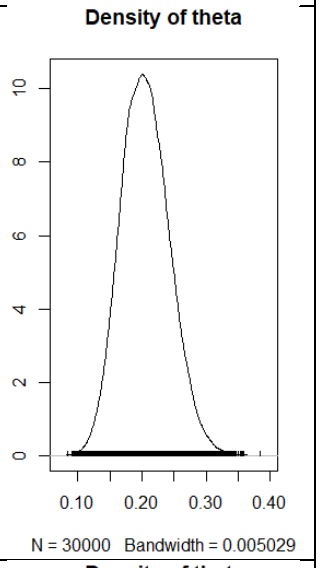
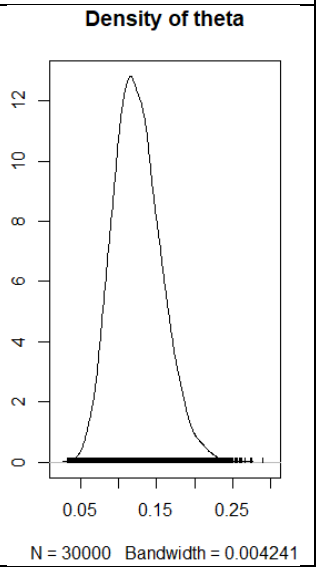
P44	0.667752	0.1615	0.4995	0.7087	0.8674	0.9873	
P45	0.333067	0.01214	0.13364	0.29597	0.50052	0.83711	

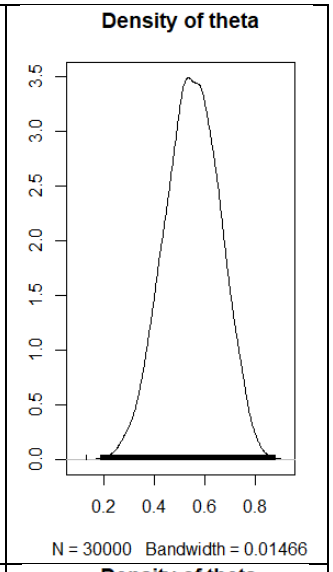
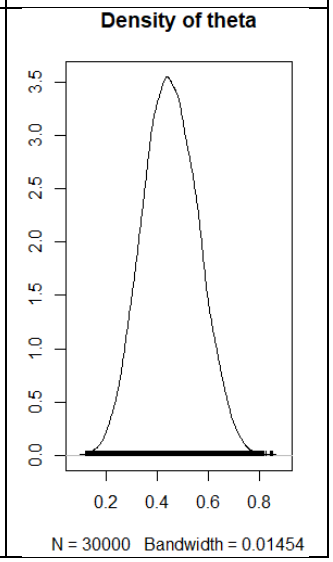
C.11 Channels structural deterioration – group 1

Channels – Structural deterioration group 1 (Masonry– Rectangular– Cess)							
Transition	**Mean**	**Quantiles**					**Posterior Distribution**
		5%	**25%**	**50%**	**75%**	**97.5%**	
P11	0.714824	0.5882	0.6384	0.71824	0.8884	0.9942	
P12	0.097456	0.0145	0.0582	0.09456	0.1634	0.1917	
P13	0.099234	0.0082	0.0966	0.13727	0.2123	0.2682	

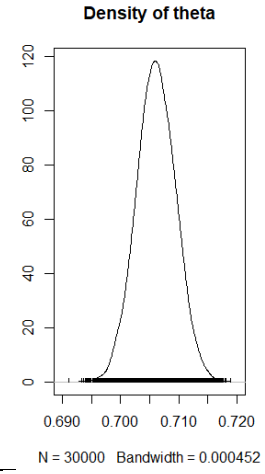
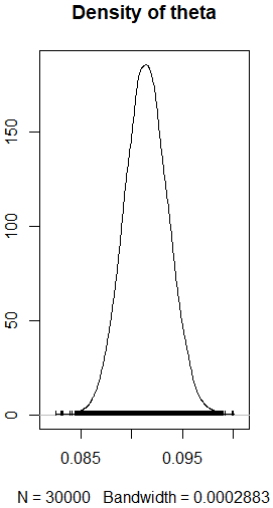
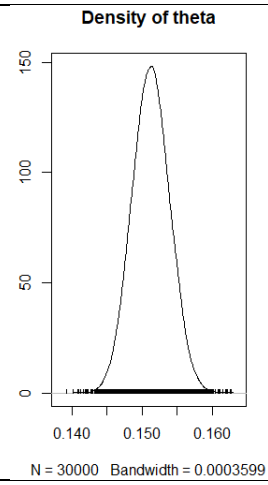
P14	0.012827	0.0042	0.0085	0.01634	0.1163	0.3295	
P15	0.078482	0.0022	0.0183	0.07114	0.1277	0.2379	
P22	0.352483	0.1592	0.2593	0.35456	0.4989	0.5123	

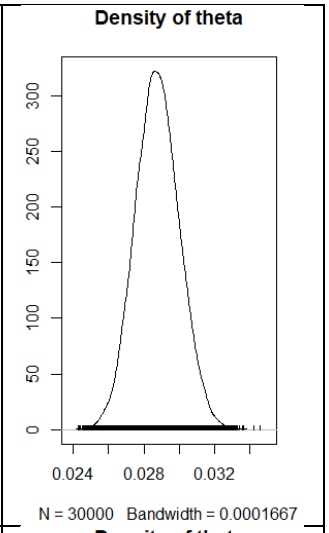
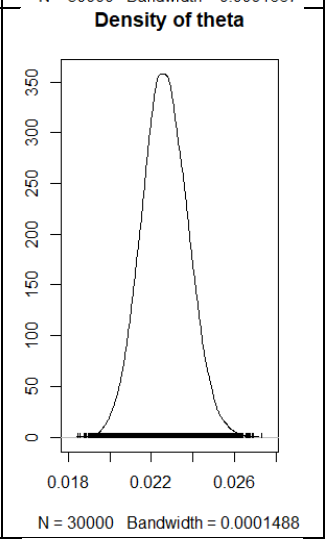
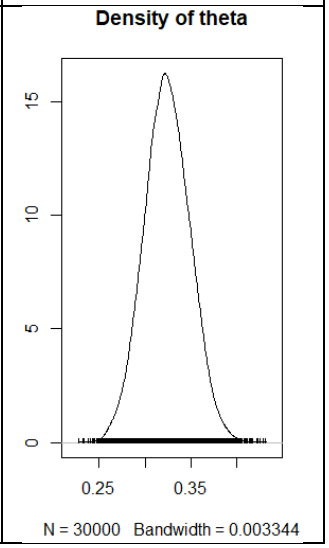
P23	0.476827	0.1839	0.2906	0.47824	0.5334	0.6533	
P24	0.107863	0.0735	0.0903	0.10744	0.2582	0.3763	
P25	0.065777	0.0103	0.0434	0.06482	0.2896	0.3784	

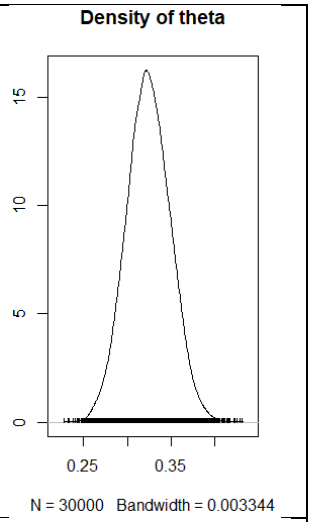
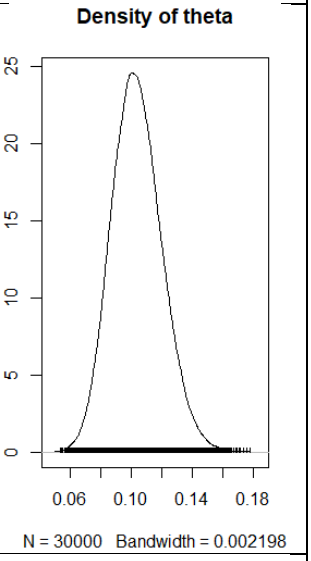
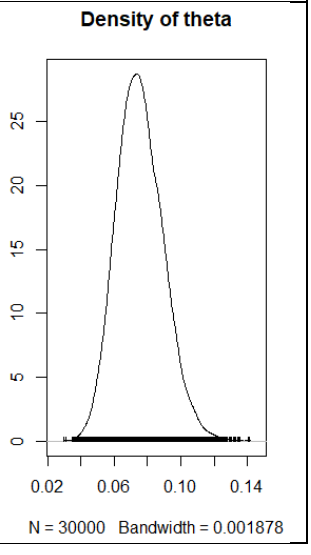
P33	0.735288	0.2063	0.3474	0.73113	0.8739	0.9506	
P34	0.128850	0.0493	0.1006	0.12268	0.3954	0.4201	
P35	0.137698	0.0503	0.0600	0.13922	0.1533	0.2844	

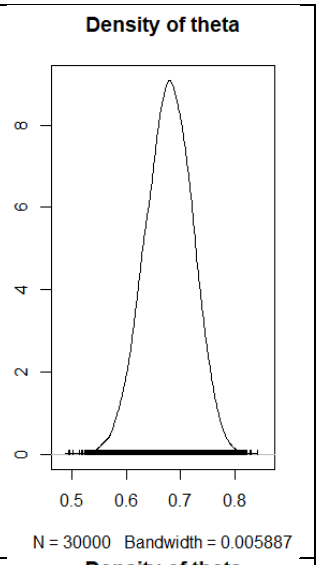
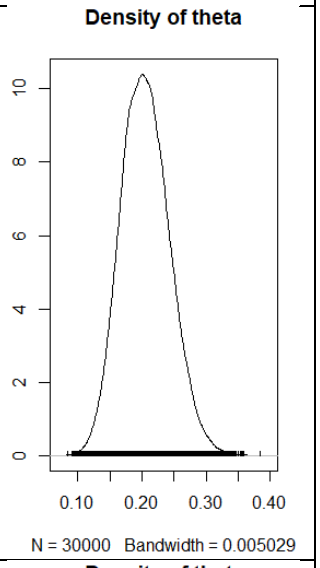
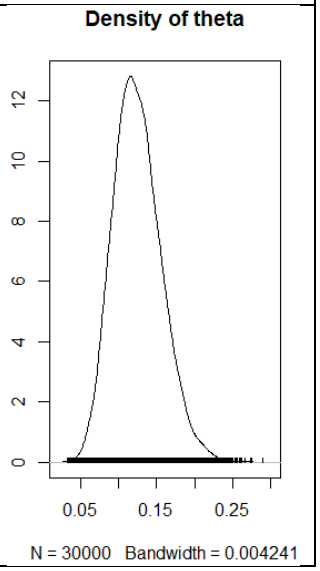
P44	0.643938	0.1634	0.2576	0.64033	0.7612	0.8884	
P45	0.357666	0.0194	0.2351	0.35112	0.6588	0.9368	

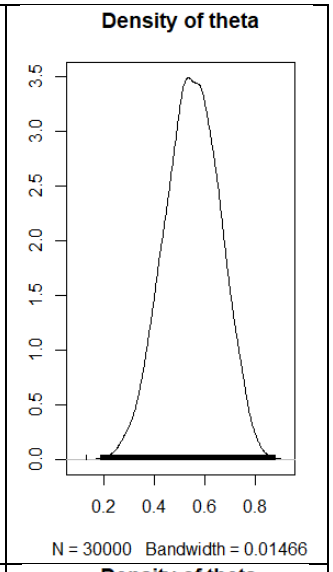
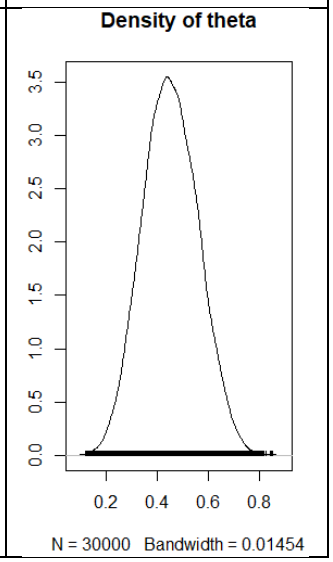
C.12 Channels structural deterioration – group 2

Channels – Structural deterioration group 2 (Masonry– Trapezoidal– Cess)							
Transition	**Mean**	**Quantiles**					**Posterior Distribution**
		5%	**25%**	**50%**	**75%**	**97.5%**	
P11	0.753234	0.5824	0.6334	0.75824	0.8824	0.9937	
P12	0.085345	0.0176	0.0586	0.08456	0.0971	0.0998	
P13	0.131725	0.0089	0.0908	0.13727	0.2118	0.2630	

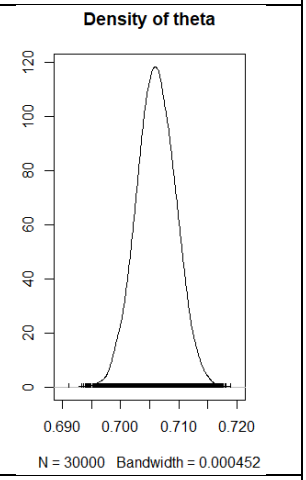
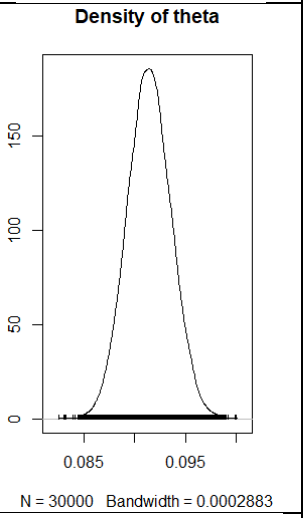
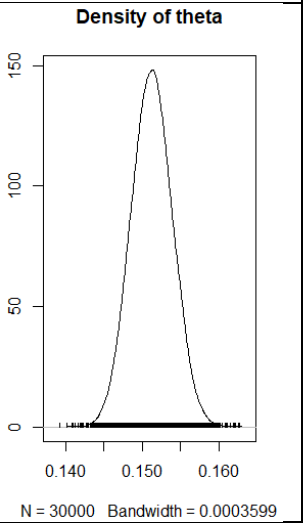
P14	0.010846	0.0049	0.0058	0.01634	0.0262	0.0480	
P15	0.021825	0.0019	0.0126	0.02114	0.0237	0.0336	
P22	0.398856	0.1599	0.2565	0.39456	0.4957	0.5133	

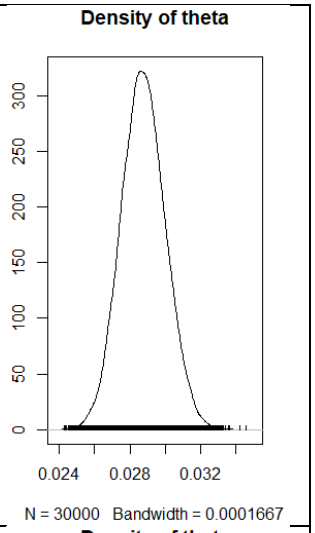
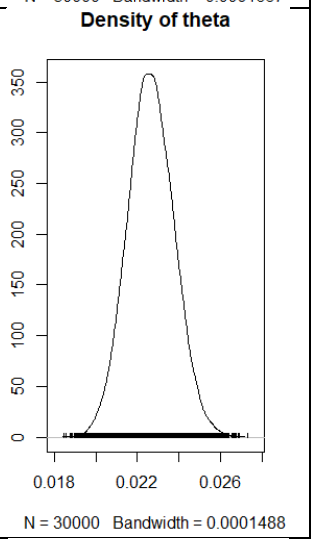
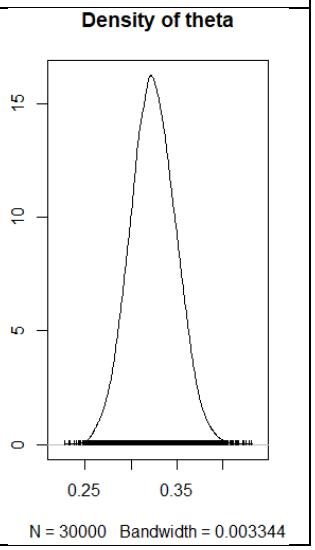
P23	0.411925	0.1872	0.2978	0.41824	0.5385	0.6534	
P24	0.103645	0.0796	0.0995	0.10744	0.2521	0.3734	
P25	0.088445	0.0100	0.0454	0.08482	0.2816	0.3736	

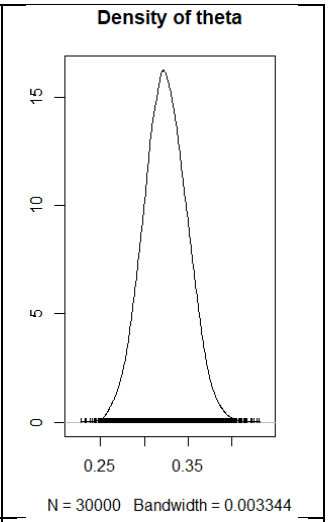
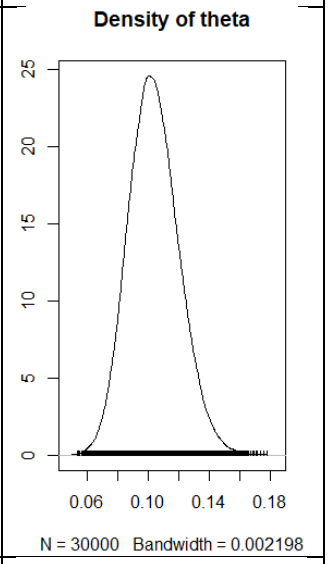
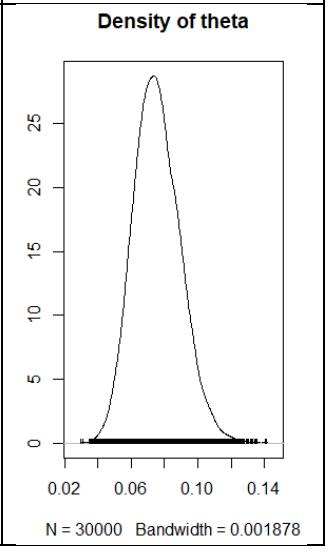
P33	0.704824	0.2086	0.3459	0.70113	0.8782	0.9568	
P34	0.212584	0.1440	0.1944	0.21268	0.3929	0.4234	
P35	0.084592	0.0585	0.0649	0.08922	0.1592	0.2887	

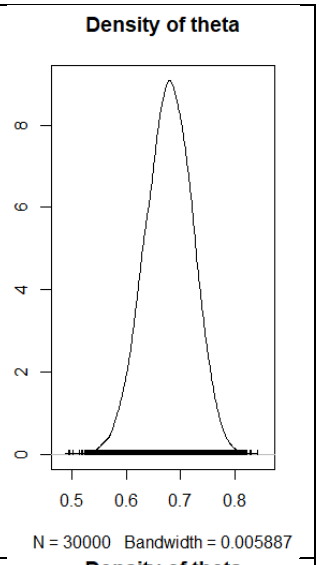
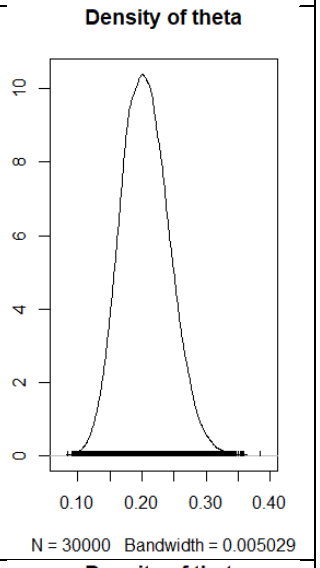
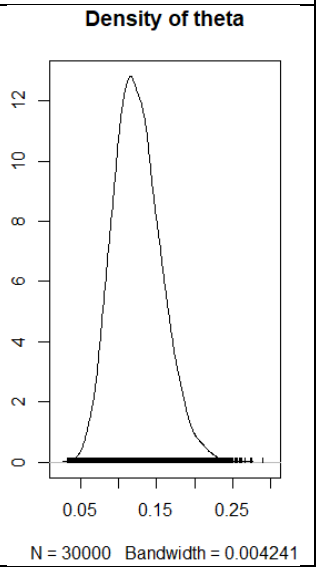
P44	0.493935	0.1665	0.2567	0.49033	0.6674	0.8893	
P45	0.507675	0.0124	0.4354	0.50112	0.6572	0.9392	

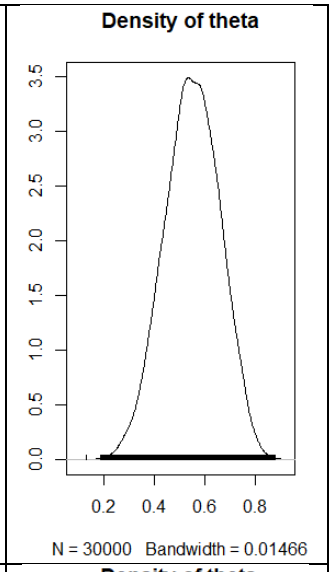
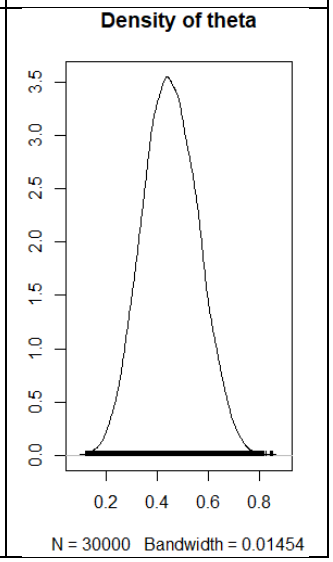
C.13 Channels structural deterioration – group 3

Channels – Structural deterioration group 3 (Others)							
Transition	**Mean**	**Quantiles**					**Posterior Distribution**
		5%	**25%**	**50%**	**75%**	**97.5%**	
P11	0.741105	0.5871	0.6337	0.74824	0.8872	0.9982	
P12	0.093544	0.0145	0.0534	0.09456	0.0974	0.0956	
P13	0.115824	0.0087	0.0972	0.11727	0.2198	0.2685	

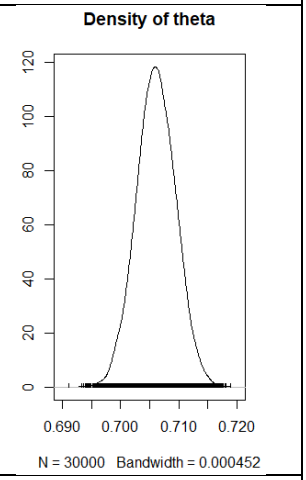
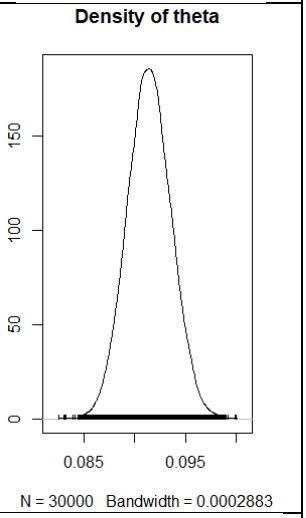
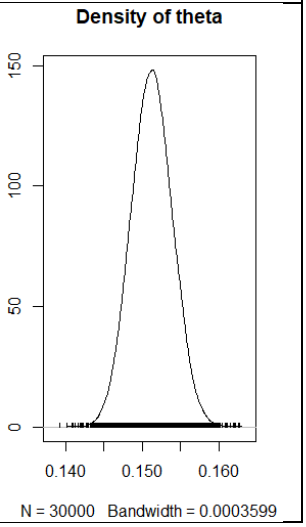
P14	0.012829	0.0045	0.0072	0.01634	0.0172	0.0224	
P15	0.039935	0.0083	0.0134	0.03114	0.0696	0.1055	
P22	0.292922	0.1593	0.2574	0.29456	0.4904	0.5189	

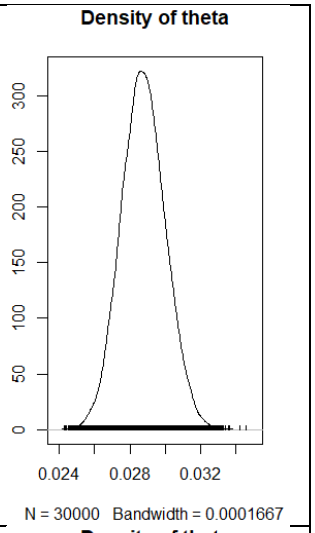
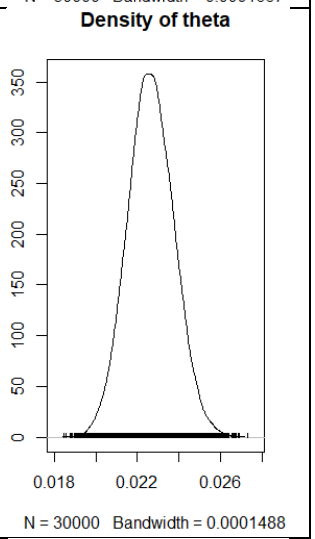
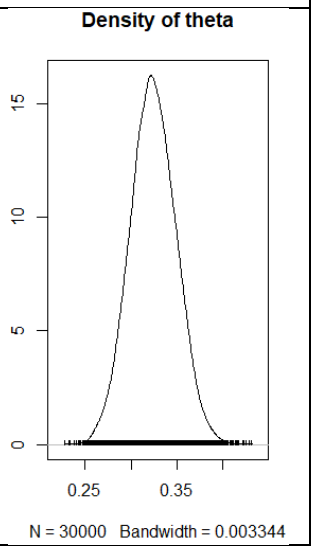
P23	0.527056	0.1834	0.2993	0.52824	0.5824	0.6590	
P24	0.106046	0.0783	0.0905	0.10744	0.2528	0.3744	
P25	0.075807	0.0100	0.0422	0.07482	0.2821	0.3734	

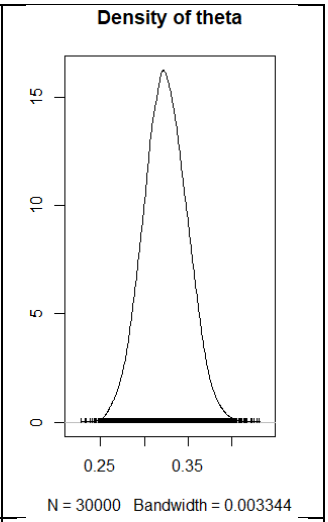
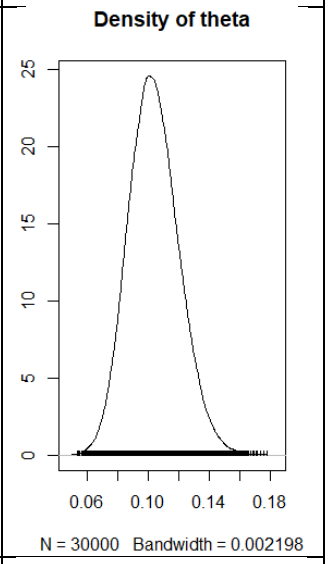
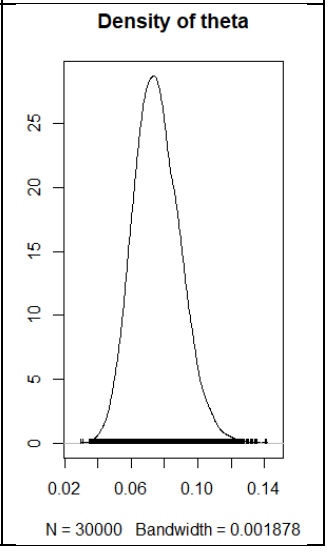
P33	0.618245	0.2087	0.3434	0.61113	0.8748	0.9572	
P34	0.243022	0.0443	0.1078	0.24268	0.3967	0.4296	
P35	0.139856	0.0526	0.0695	0.13922	0.1535	0.2877	

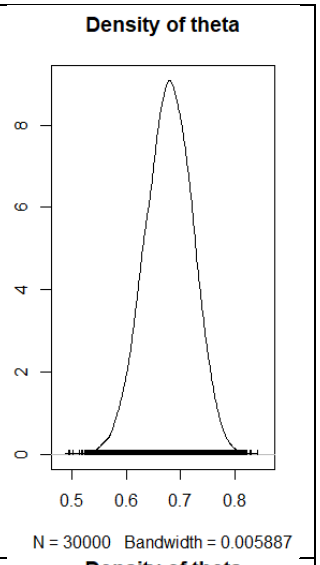
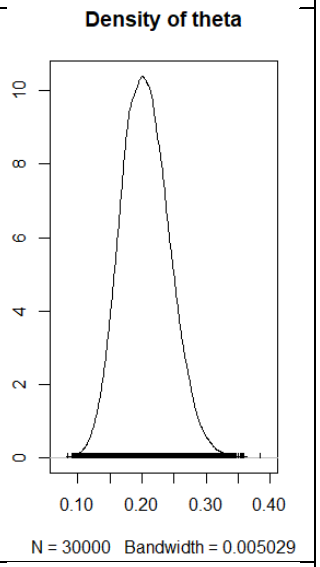
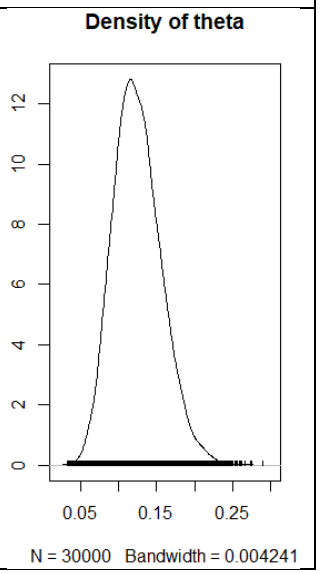
P44	0.605033	0.1682	0.2581	0.60033	0.6670	0.8804	
P45	0.395967	0.0166	0.2303	0.39112	0.6539	0.9312	

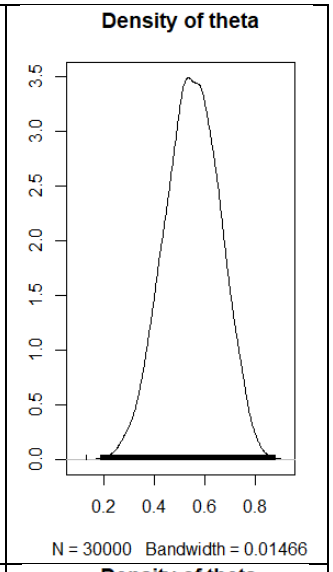
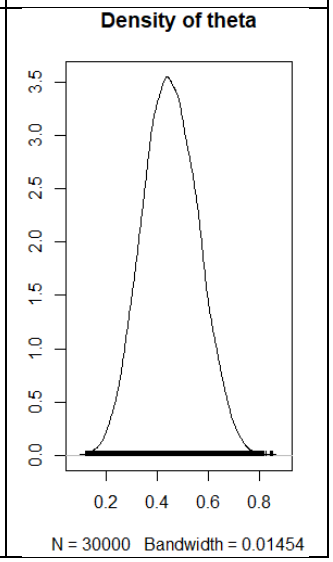
C.14 Channels service deterioration – group 1

Channels – Service deterioration group 1 (PC Concrete– Rectangular)							
Transition	**Mean**	**Quantiles**					**Posterior Distribution**
		5%	**25%**	**50%**	**75%**	**97.5%**	
P11	0.684823	0.5833	0.6392	0.6872	0.8824	0.9927	
P12	0.091824	0.0124	0.0545	0.0956	0.1674	0.2338	
P13	0.196822	0.0057	0.0993	0.1983	0.2114	0.2695	

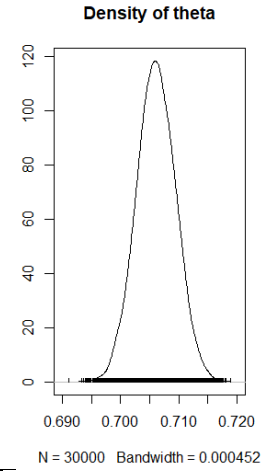
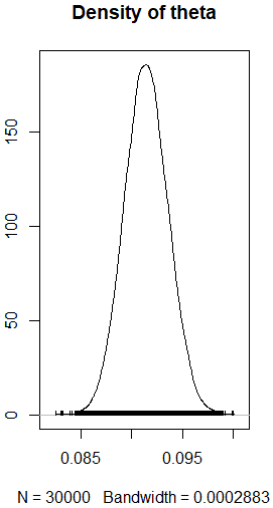
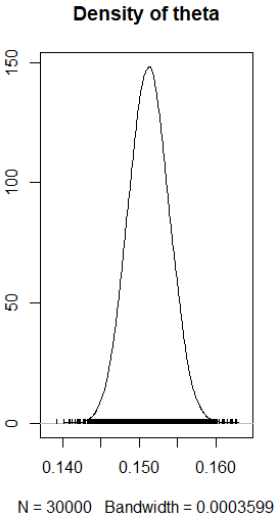
P14	0.019095	0.0069	0.0056	0.0108	0.0185	0.0206	
P15	0.010035	0.0080	0.0193	0.0113	0.0235	0.0373	
P22	0.374645	0.1524	0.2534	0.3757	0.4996	0.5126	

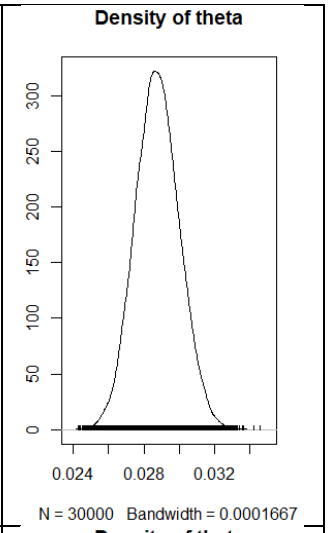
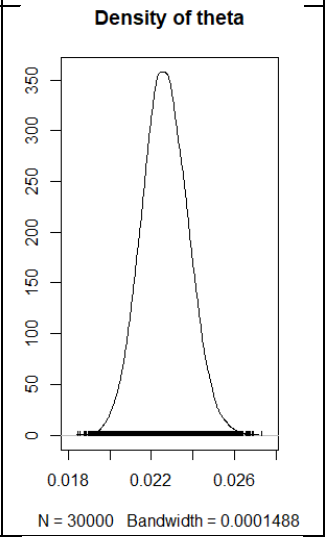
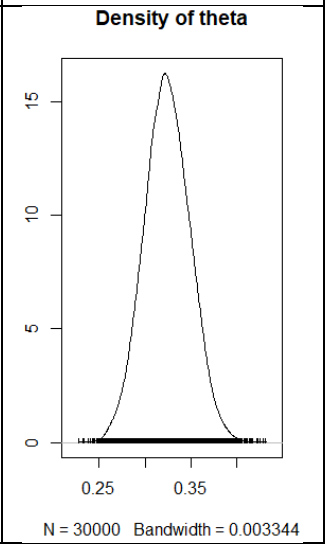
P23	0.502824	0.1875	0.2923	0.5036	0.5308	0.6534	
P24	0.093323	0.0753	0.0993	0.0985	0.2535	0.3767	
P25	0.031174	0.0186	0.0405	0.0625	0.2857	0.3794	

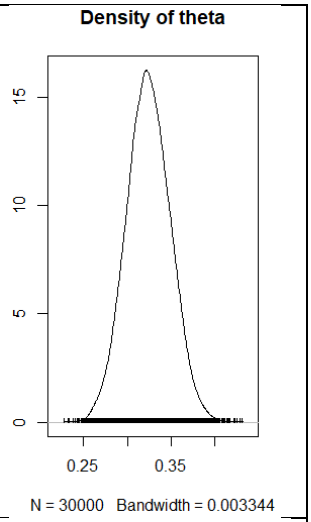
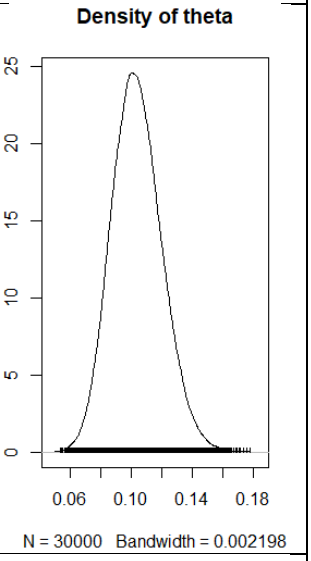
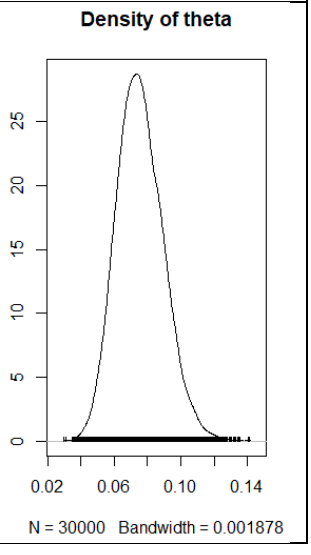
P33	0.675824	0.2008	0.3482	0.6758	0.8714	0.9545	
P34	0.196924	0.0453	0.1045	0.1969	0.3948	0.4238	
P35	0.129453	0.0597	0.0678	0.1280	0.1539	0.2870	

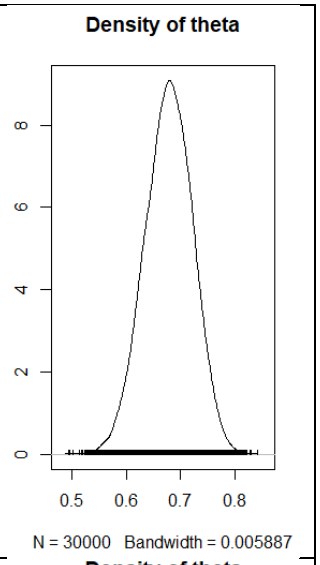
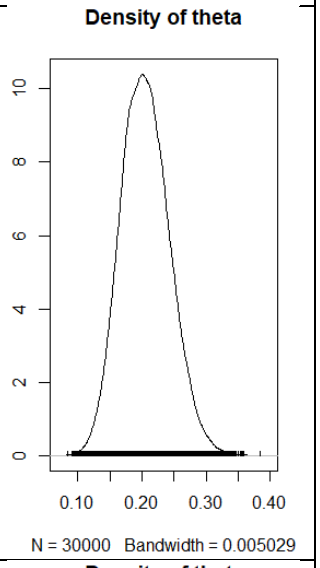
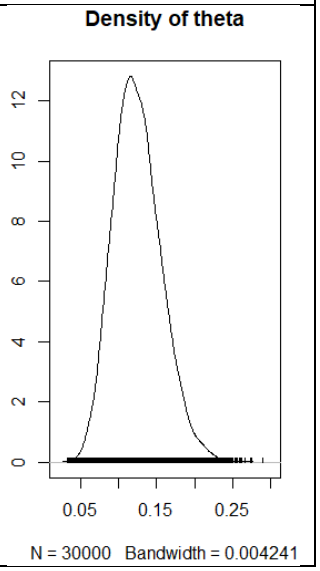
P44	0.540899	0.1635	0.2504	0.5463	0.6640	0.8835	
P45	0.460137	0.0179	0.2324	0.4624	0.6582	0.9393	

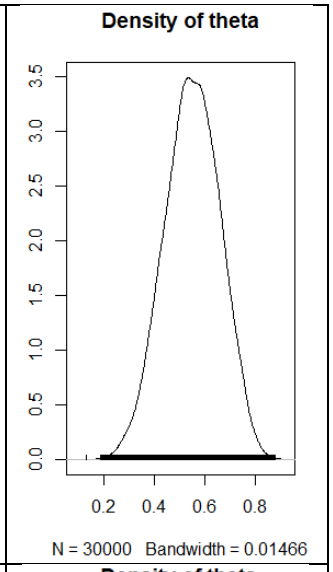
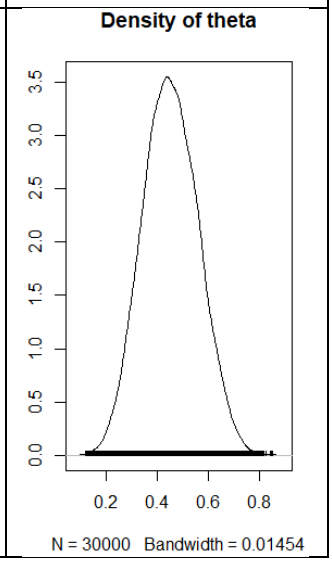
C.15 Channels service deterioration – group 2

Channels – Service deterioration group 2 (Plastic– Rectangular)							
Transition	**Mean**	**Quantiles**					**Posterior Distribution**
		5%	**25%**	**50%**	**75%**	**97.5%**	
P11	0.659824	0.5882	0.6314	0.6582	0.8824	0.9954	
P12	0.098765	0.0145	0.0536	0.0994	0.1982	0.2526	
P13	0.181922	0.0084	0.0984	0.1867	0.2167	0.3693	

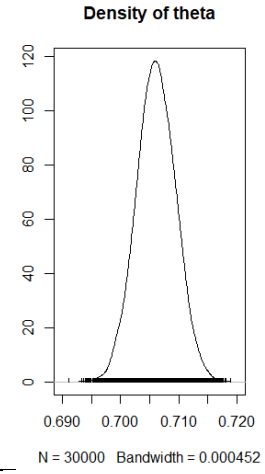
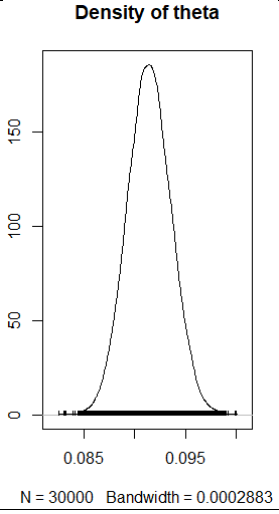
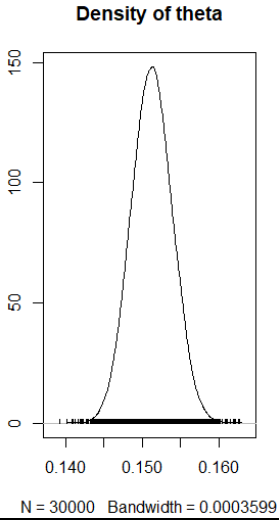
P14	0.021332	0.0034	0.0096	0.0234	0.0344	0.0566	
P15	0.041523	0.0093	0.0134	0.0468	0.0645	0.1393	
P22	0.304536	0.1567	0.2534	0.3069	0.4956	0.5146	

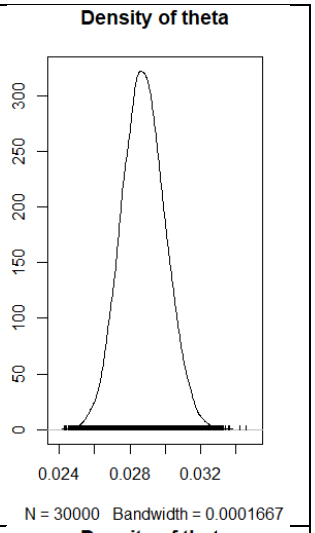
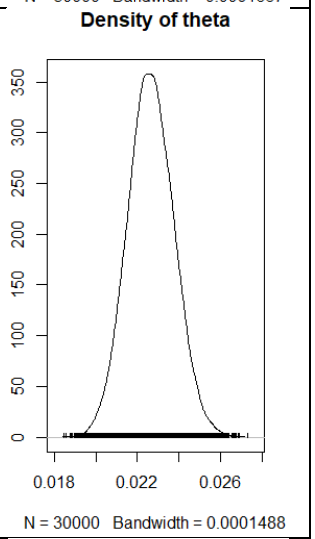
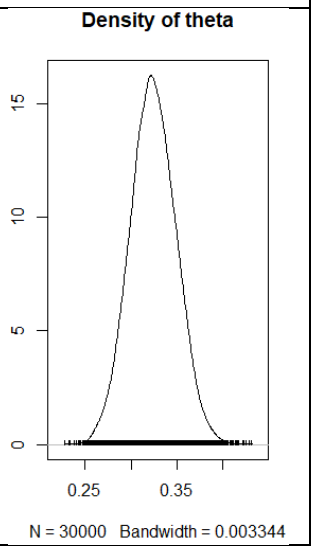
P23	0.494239	0.1804	0.2972	0.4934	0.5326	0.6548	
P24	0.102234	0.0724	0.0993	0.1093	0.2566	0.3769	
P25	0.100237	0.0157	0.0403	0.1005	0.2893	0.3724	

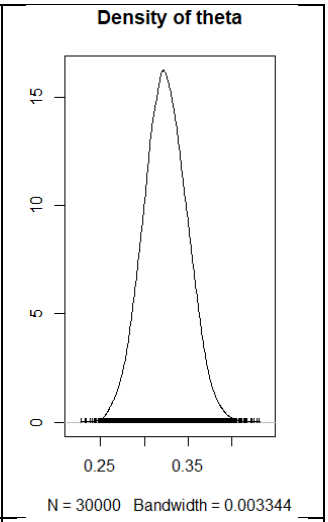
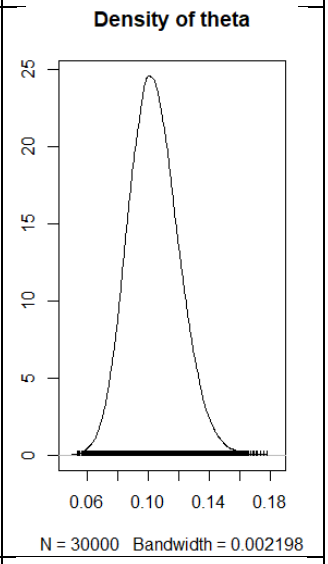
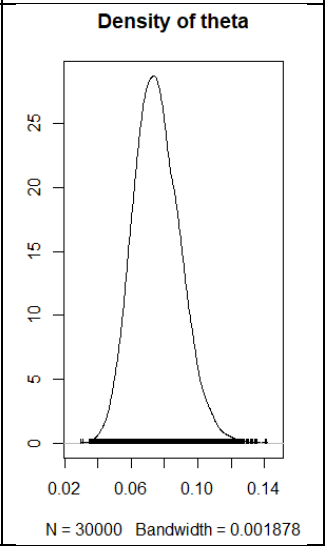
P33	0.626822	0.2004	0.3434	0.6234	0.8765	0.9547	
P34	0.257824	0.0478	0.1092	0.2557	0.3922	0.4259	
P35	0.117566	0.0534	0.0634	0.1104	0.1537	0.2870	

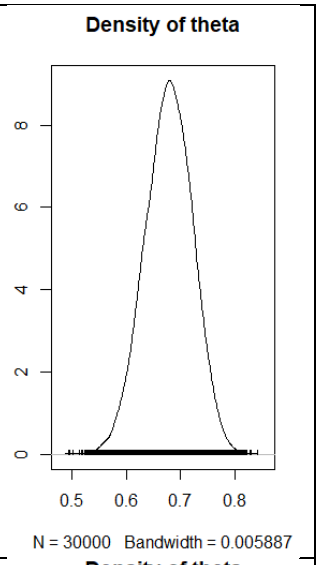
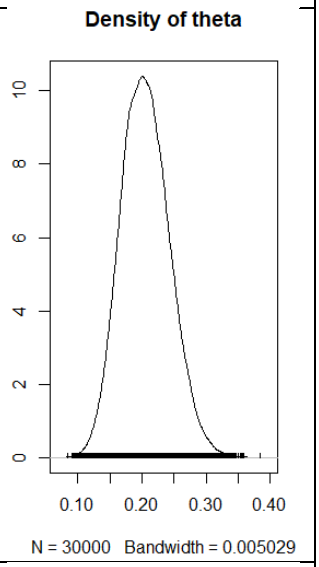
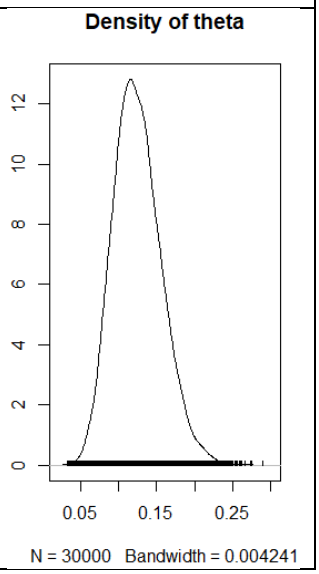
P44	0.585334	0.1696	0.2504	0.5834	0.6691	0.8834	
P45	0.415822	0.0103	0.2312	0.4123	0.6523	0.9344	

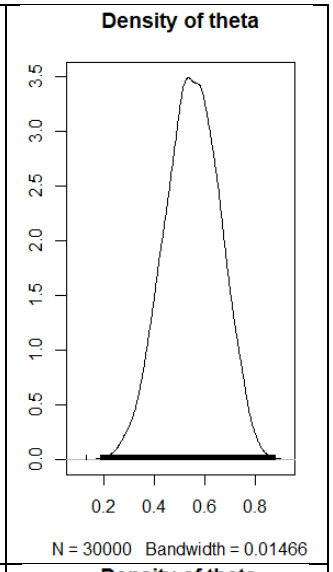
C.16 Channels service deterioration – group 3

Channels – Service deterioration group 3 (Others)							
Transition	**Mean**	**Quantiles**					**Posterior Distribution**
		5%	**25%**	**50%**	**75%**	**97.5%**	
P11	0.702644	0.5872	0.6333	0.7098	0.8824	0.9955	
P12	0.121711	0.0105	0.0543	0.1296	0.2944	0.4964	
P13	0.051854	0.0038	0.0272	0.0507	0.2172	0.4693	

P14	0.023939	0.0038	0.0077	0.0244	0.0456	0.0122	
P15	0.103778	0.0006	0.0104	0.1033	0.2295	0.4363	
P22	0.328334	0.1546	0.2565	0.3282	0.4900	0.5144	

P23	0.513171	0.1894	0.2943	0.5165	0.5368	0.6557	
P24	0.094582	0.0749	0.0937	0.0993	0.2564	0.3782	
P25	0.065233	0.0109	0.0408	0.0613	0.2817	0.3794	

P33	0.590878	0.2077	0.3409	0.5947	0.8718	0.9566	
P34	0.319025	0.0446	0.1087	0.3196	0.3995	0.4243	
P35	0.091933	0.0595	0.0634	0.0923	0.1547	0.2847	

P44	0.504022	0.1604	0.2517	0.5005	0.6603	0.8882	
P45	0.496457	0.0148	0.2394	0.4903	0.6556	0.9388	