`Novel measurement techniques for monitoring particulate matter: development, application and evaluation of a low-cost IoT sensor network

by

Nicole Hannah Cowell



A thesis submitted by the University of Birmingham for the degree of

DOCTOR OF PHILOSOPHY

School of Geography, Earth and Environmental Sciences

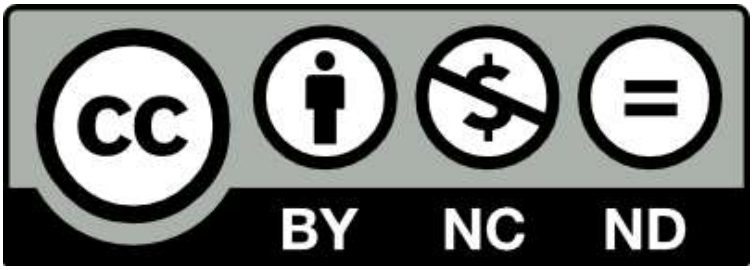
College of Life and Environmental Sciences

University of Birmingham

June 2023

UNIVERSITY OF BIRMINGHAM

University of Birmingham Research Archive
e-theses repository



This unpublished thesis/dissertation is under a Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 International (CC BY-NC-ND 4.0) licence.

You are free to:

Share — copy and redistribute the material in any medium or format

The licensor cannot revoke these freedoms as long as you follow the license terms.

Under the following terms:

Attribution — You must give appropriate credit, provide a link to the license, and indicate if changes were made. You may do so in any reasonable manner, but not in any way that suggests the licensor endorses you or your use.

NonCommercial — You may not use the material for commercial purposes.

NoDerivatives — If you remix, transform, or build upon the material, you may not distribute the modified material.

No additional restrictions — You may not apply legal terms or technological measures that legally restrict others from doing anything the license permits.

Notices:

You do not have to comply with the license for elements of the material in the public domain or where your use is permitted by an applicable exception or limitation.

No warranties are given. The license may not give you all of the permissions necessary for your intended use. For example, other rights such as publicity, privacy, or moral rights may limit how you use the material.

Unless otherwise stated, any material in this thesis/dissertation that is cited to a third-party source is not included in the terms of this licence. Please refer to the original source(s) for licencing conditions of any quotes, images or other material cited to a third party.

Thesis word count:
38406

Abstract

Presented as a collection of articles, this thesis assesses the role of low-cost and Internet-of-Things (IoT) technology in monitoring of ambient particulate matter. Adapting an off-the-shelf low-cost optical particle sensor, an IoT enabled particulate matter sampler was developed, built, and tested in a range of environments. The sampler was designed with field deployment practicality in mind. Completely self-contained, AltasensePM was designed to use battery power and the latest IoT communications technology to enable easy installation onto existing street furniture. Although subject to limitations from covid-19 pandemic, this thesis is able to present exploratory analysis from the use-cases of low-cost sensors for particulate matter monitoring.

Field testing enabled the evaluation of AltasensePM device and the development of a site specific calibration method for tackling the effect of humidity on detected particle concentrations (Cowell et al., 2022). Sensors performed well in co-location with a reference instrument with average correlation coefficients (r^2) between raw device data and reference instrumentation are 0.718, 0.703 and 0.543 for PM_1, $PM_{2.5}$ and PM_{10} respectively, and calibration improving performance. During this testing process, fluctuating performance over time was detected from the sensors. This insight into raw sensors data (which is not always shared when using commercial low-cost sensors), suggest that sensors are best suited to longer term averaging and stable environments. The raw data also suggested that the sensor is not independently monitoring PM_{10}. AltasensePM devices were hosted on the Birmingham Urban Observatory, an open-access online platform for environmental data across the city of Birmingham, UK. The calibration method was automated as an online process, allowing the following work to utilise real-time air quality measurements from the AltasensePM alongside commercial air quality and meteorology sensors.

When deployed in a network, the low-cost PM samplers provided a novel opportunity to study particulate matter concentrations at previously unattainable spatial scales, in both indoor and ambient monitoring settings.

The indoor deployment took place in a typical UK suburban home, during the Covid-19 pandemic, and exposed how activity such as cooking elevated concentrations of PM_1 and

$PM_{2.5}$ in rooms beyond the kitchen (Cowell et al., 2023a). The role of ventilation in reducing extreme peaks in concentrations was highlighted and when extrapolating data from this 7-week study to annual exposure levels, both 2021 and 2004 WHO Air Quality Guidelines were exceeded. The limitations of the sensor highlighted in chapter 2 were also reflected in the indoor performance of the sensor. Novel opportunities for automating indoor monitoring using IoT and Smart home devices could create unprecedented future insight into occupant activity and the impacts on PM, although there are security and privacy risks that will need to be resolved first.

For ambient monitoring, AltasensePM was integrated into an opportunistic nested network of sensors, bringing together commercial low-cost sensors deployed by the University and local authority and AltasensePM onto the Urban Observatory open-access platform. The live-stream of open access $PM_{2.5}$ data from this network gave unprecedented, localised insight into PM concentrations across the city. The network performed very well in longer term regional averaging compared to the regulatory network at estimating city wide annual $PM_{2.5}$ concentrations- with sensor network average for the period within $0.2 \mu g m^{-3}$ of the regulatory average. It is unclear whether sensors are sensitive enough to detect roadside sources, or if other regional sources are more predominant in roadside locations. Sensor performance and local variability highlighted the importance of network design to ensure representative sampling of the city, and the opportunities that collaborations between various low-cost sensing users could provide.

Finally, following from this experience with sensor networks, an evaluation of the future role of IoT, low-cost sensors and live stream data in supporting the management of air quality is presented. Live-stream data from sensors such as the AltasensePM has been shown to have the potential to support digital twin technology, where real time decision making is enhanced by both model and live data streams simultaneously. However, the future of PM in countries such as the UK where there is a modal shift toward electric engine vehicles means that regional sources rather than local traffic sources are likely to become more important in air quality management. Any future digital twins will need to onboard national and international data sets to support such management. Here the best practice in managing data streams for air quality interventions via digital twins is discussed.

COWELL, N. H., CHAPMAN, L., BLOSS, W. & POPE, F. 2022. Field calibration and evaluation of an Internet of Things based particulate matter sensor. Frontiers in Environmental Science, 733.

COWELL, N., CHAPMAN, L., BLOSS, W., SRIVASTAVA, D., BARTINGTON, S. & SINGH, A. 2023a. Particulate matter in a lockdown home: evaluation, calibration, results and health risk from an IoT enabled low-cost sensor network for residential air quality monitoring. Environmental Science: Atmospheres, 3, 65-84.

This thesis is dedicated in loving memory of James Nowshadi, the kindest and most supportive friend whom I miss dearly.

Acknowledgements

This thesis was only possible due to the endless support of my peers.

Firstly, I'd like to offer sincere and heartfelt gratitude to my supervisors, Professor Lee Chapman and Professor William Bloss for their continuous support, invaluable advice and above all patience throughout my PhD. I have greatly enjoyed working with you both. Thank you for challenging and motivating me to be better and for trusting me to steer my research and make my own decisions. Mostly, thank you for offering me this incredible opportunity and allowing me to learn from you both.

I'd also like to thank the wider WM-Air and University of Birmingham team. Thanks to Daniel, Joe, Manna, Yanzhi, David, Vasilis and Andy for your help in the office, field and lab. From climbing lampposts and soldering advice to catching spiders, your help has been greatly appreciated. Thanks to Cat for all your support, organisation and funny chats at our desks. Thanks to all my supportive co-authors Clarissa, Jian, Suzanne, Francis, Ajit and Deep, who's collaborative efforts led to a number of successful publications. I would like to thank my colleagues at BCC, CCC, DfT and all project partners that have engaged in various arms of this research. I am so grateful for all your time and efforts over the past 3 years.

To my wonderful soon-to-be husband, Adam Biggs, I promise to try to be at least 5% less stressed following the submission of this thesis. Thank you for being supportive of all my dreams and achievements. Moving to the midlands, listening to endless manuscript edits, making "it's been a hard day" tacos and bringing a smile to my face every day, none of this would have been possible without you.

This PhD wouldn't have been possible without the unwavering support of my incredible family. To my parents, Lucy and Steven Cowell, thank you for teaching me that nothing is impossible. You are the most hardworking, supportive and inspiring people that I know, and I am so grateful for all you have done for me. I love you both. To my brother, James Cowell, thank you for making regular gig nights a thing, it's been the best way to blow off PhD steam. To my incredible Nan, Sandra Brown, thank you for the endless phone calls on my drives home, always telling me 'you can do it!'. Your strength and independence inspire me, and I am so proud to be your granddaughter.

To my friends, thank you for the pints shared over exhausted, excited and frustrated discussions about my PhD. Becky Crombie, thank you for always being wonderfully silly and supportive over a challenging couple of years (and for baking incredible cookies and figuring out how to post them during the pandemic!).

Finally, thank you to my late friend James Nowshadi. You encouraged me to take the opportunity to do a PhD and believed in me when I didn't believe in myself. You've been my advocate from the day we met, and I'll be forever grateful that you convinced me that I could do this. This thesis is dedicated to you.

Author's contributions

This thesis is formed of 2 edited versions of peer reviewed published manuscripts, one manuscript under review and one viewpoint style paper evaluating the future potential outcomes of this research.

Chapter 1: Introduction

Unique to this thesis

Chapter 2: Field Calibration and Evaluation of an Internet-of-Things-Based Particulate Matter Sensor

Edited from the manuscript published in Frontiers in Environmental Science as

COWELL, N. H., CHAPMAN, L., BLOSS, W. & POPE, F. 2022. Field calibration and evaluation of an Internet of Things based particulate matter sensor. *Frontiers in Environmental Science***,** 733.

Author contributions:

NC was responsible for initial data, analysis, and writing. LC and WB supervised the project, provided guidance for analysis, and supported in editing the paper. FP was a supporting editor and supported with data analysis.

Chapter 3: Particulate matter in a lockdown home: evaluation, calibration, results and health risk from an IoT enabled low-cost sensor network for residential air quality monitoring

Edited from the manuscript published in RSC Environmental Science: Atmospheres as

COWELL, N., CHAPMAN, L., BLOSS, W., SRIVASTAVA, D., BARTINGTON, S. & SINGH, A. 2023. Particulate matter in a lockdown home: evaluation, calibration, results and health risk from an IoT enabled low-cost sensor network for residential air quality monitoring. Environmental Science: Atmospheres.

Author contributions:

Conceptualization NC, LC and WB. Methodology NC, LC, WB, DS. Software NC, DS. Validation NC, LC, WB. Formal analysis NC. Investigation NC. Resources LC, WB, NC. Data curation NC. Writing – Original draft NC, LC, WB. Writing – review & editing – SB, AS, DS. Visualization NC, DS. Supervision LC, WB. Project administration NC. Funding acquisition WJB, LC.

Chapter 4: What can we learn from nested IoT low-cost sensor networks for air quality? A case study of $PM_{2.5}$

COWELL, N., BALDO, C., CHAPMAN, L., BLOSS, W., ZHONG, J. 2023.

Submitted to Special Issue titled "*Unconventional Observations for Meteorological Applications*" as part of the Journal *Meteorological Applications*.

Author contributions:

Conceptualization NC, LC and WB. Methodology NC, LC, WB, CB, JZ. Software NC, CB. Validation NC, CB, LC, WB. Formal analysis NC. Investigation NC. Resources LC, WB, NC. Data curation NC. Writing – Original draft NC, LC, WB. Writing – review & editing – CB, JZ. Visualization NC, JZ. Supervision LC, WB. Project administration NC. Funding acquisition WJB, LC.

Chapter 5: Moving from monitoring to real-time interventions for air quality: the future role of low-cost sensors, IoT and digital twins

Unique to this thesis

This chapter draws information from reports, presentations and other informal outputs from the Economic Data Innovation Fund (EDIF) project which are currently unpublished but are available upon request. The author of this chapter (Nicole Cowell*) contributed to these outputs alongside Lee Chapman*, Philip James†, Daniel Bell†, Jenine Jonczyk†, David Topping‡, Thomas Bannan‡, Ettore Murabito‡, Dustin Carlinoˬ, Alex Gluhakˇ, Sarah Gallacherˇ and DfT colleagues. Reports from this project will eventually be published at:https://www.gov.uk/search/research-and-statistics?content_store_document_type=research&keywords=&organisations%5B%5D=department-for-transport

Chapter 6: Conclusions

Unique to this thesis

Table of contents

Chapter 1 ***Introduction*** **page 1**
1. Particulate Matter page 1
1. 1 Physical properties of particulate matter page 2
1.2 Ambient Particulate Matter Sources page 4
1.2.1 Vehicle emissions: Exhaust emissions page 5
1.2.2 Vehicle emissions: Non-Exhaust Emissions page 6
1.2.3 Solid fuel burning page 6
1.3 Indoor particulate matter page 7
2. Birmingham's air quality context page 7
3. Monitoring of particulate matter page 9
3.1 Monitoring methods page 9
3.2 Low-cost sensors page 12
3.3 Internet of Things (IoT) technology page 15
4. Thesis aims and structure page 17
References page 19

Chapter 2 ***Field Calibration and Evaluation of an Internet-of-Things-Based Particulate Matter Sensor*** **page 30**
Abstract page 30
1. Introduction page 30
2. Methods and Materials page 34
2.1 Instrumentation page 34
2.1.1 Plantower PMS sensor page 34
2.1.2 IoT sensor design page 35
2.2 Sampling method page 37
3 Results and discussion page 38
3.1 Comparison to reference instrumentation page 38
3.2 Device consistency page 41
3.3 Impact of relative humidity and particle composition page 44
3.4 Drift page 45
3.5 Development of a correction factor for RH effects page 47
3.6 Limitations page 50
4 Conclusion page 51
Author contributions page 52
Funding page 52
Acknowledgements page 52
References page 50

Chapter 3 ***Particulate matter in a lockdown home: evaluation, calibration, results and health risk from an IoT enabled low-cost sensor network for residential air quality monitoring*** **page 63**
Abstract page 63
1. Introduction page 63
2. Background page 64
2.1 The problem of Indoor Particulate Matter page 64
2.2 Low-cost sensors, IoT and indoor monitoring page 67
3. Methods & Materials page 69
3.1 Study setting, sensor location and sampling design page 69
3.2 Activity log page 72
3.3 Colocation and correction of low-cost sensors page 73
3.3.1 Indoor sensor correction page 78
3.3.2 Ambient sensor correction page 80
3.4 Data validation page 80
3.5 Novel development in understanding of the Plantower PMS5003 for coarse size fraction page 81
3.6 Data analysis page 82
4. Results & Discussion page 82
4.1 Particulate concentrations and activity page 82
4.1.1 Cooking and downstairs concentrations page 85
4.1.2 External ventilation page 88
4.3 Limitations page 91
5. Conclusions page 91
Author contributions page 92
Conflicts of interest page 92
Acknowledgements page 93
References page 93

Chapter 4 ***What can we learn from nested IoT low-cost sensor networks for air quality? A case study of PM2.5 in a Clean Air Zone*** **page 100**
Abstract page 100
1. Introduction page 100
1.1 Clean Air Zones and air quality management page 101
1.2 IoT and low-cost PM sensors page 101
1.3 Sensor Networks page 102
2 Methods page 103
2.1 Data and instrumentation page 103
2.1.1 AltasensePM page 103

2.1.2 Zephyr page 104
2.1.3 DEFRA AURN page 104
2.2 Sampling locations page 105
2.3 Data validation page 107
2.4 High-resolution air quality model page 108
3 Results and Discussion page 108
3.1 Sensor performance page 108
3.1.1 Data capture page 108
3.1.2 Colocation of sensors page 109
3.1.3 Insights into regional concentrations page 112
3.1.4 Insights into local spatial variability in concentrations page 116
3.2 Comparison with a high-resolution model page 117
3.4 Lessons learned from low-cost sensing network for particulate matter page 119
4. Conclusions page 120
Author Contributions page 121
Acknowledgements page 121
Funding page 121
References page 121
Supplementary information page 125

Chapter 5 ***Moving from monitoring to real-time interventions for air quality: the future role of low-cost sensors, IoT and digital twins*** **page 127**
1.Introduction page 127
1.1 The smart city page 127
1.2 Urban Observatories page 129
1.3 The growth of air quality data sources page 130
1.4 Digital Twins page 131
2. Challenges of achieving large scale digital twins page 132
2.1 National digital twin programme page 132
2.2 Interoperability & metadata of live streams page 134
3. Air quality use cases page 135
3.1 Dynamic messaging page 135
3.2 Traffic routing page 135
3.3 Controlling traffic flow page 138
3.4 Testing interventions page 138
3.5 Feasibility page 138
4. Challenges of sensor data page 139
5. Conclusions page 140
References page 140

Chapter 6 *Conclusions* **page 147**
References page 152

List of figures

Chapter 1 ***Introduction***

Figure 1- PM classification size and diameter comparison adapted from (Acton et al., 2023).

Figure 2- Diagram of ambient PM size distribution of the particle number concentration, surface area concentration and mass concentration (dN/dLog Dp, particle number per cubic millimeter; dS/dLog Dp, particle surface area per cubic millimeter; and dM/dLog Dp, particle mass per cubic millimeter, respectively) separated into 3 subgroups known as the modes of distribution. Taken from (Kwon et al, 2020).

Figure 3- emissions of UK PM2.5 by emission source sector 1990-2021. Data from (DEFRA, 2023b).

Figure 4- location of Birmingham within the UK and the regulatory measurement sites for PM within Birmingham. Map sourced from GoogleMaps.

Figure 5- annual average PM10 (left) and PM2.5 (right) in µgm-3 at 10mx10m resolution from the ADMS-Urban model for the West Midlands region including Birmingham. Taken from (Zhong et al., 2021).

Figure 6- Distribution of the AURN sites across the UK by environment and location type. NB. Traffic refers to stations <10m from a major road kerbside where traffic dominates concentrations. Background refers to areas not significantly influenced by a single source or street. Industrial refers to locations predominately influenced by single industrial sources. Urban environments are completely or predominately built-up street fronts with at least 2 storey buildings. Suburban environments are largely built-up areas that are less dense than urban areas and are mixed in with non-urbanised areas such as lakes/woods/agriculture. Rural environments are areas of vegetation and nature, >20km from cities, >5km from other built up areas/motorways and major roads. (Department of Environmental Food and Rural Affairs, 2023b).

Chapter 2 ***Field Calibration and Evaluation of an Internet-of-Things-Based Particulate Matter Sensor***

Figure 1- A) Fritzing diagram of the breadboard-based prototype for the AltasensePM. This was designed by the Author and passed onto the electronics workshop who converted the circuit into a PCB design. B) A diagram of the custom casing designed in collaboration with the University workshop who had the tools to cut custom plastic shapes. C) An AltasensePM device deployed in the field, showing the casing design and attachments on a lamppost.

Figure 2- Hourly average time plot of low-cost sensors against the Birmingham Air Quality Supersite FIDAS.

Figure 3- Plots of particulate matter concentrations from low-cost sensor vs FIDAS by humidity.

Figure 4- Correlation plot demonstrating inter-sensor correlation and correlation to reference instrument (FIDAS).

Figure 5- Box plot of particulate matter concentrations from low-cost sensors and FIDAS for PM1, PM2.5 and PM10.

Figure 6- Ratio of AltasensePM concentrations/FIDAS PM concentrations vs humidity, with 85% humidity marked in red.

Figure 7- Examples of AltasensePM/reference PM concentrations from sensor A by organic concentrations from ACSM by humidity at different humidity intervals. Linear equation of ratio by organic mass concentration is show on the plot.

Figure 8- Slope of low-cost sensor PM concentrations vs. FIDAS by week, separated by readings that occurred when the sensor recorded <85% humidity and ≥85% humidity for sensor B.

Figure 9- Example of over-correction when using the K-Köhler method stated above for one of the Altasense PM units for PM10 concentrations.

Figure 10- Time plots of hourly averaged PM concentrations for Altasense PM and FIDAS after correction using the multi-linear approach that differentiates correction by humidity.

Chapter 3 ***Particulate matter in a lockdown home: evaluation, calibration, results and health risk from an IoT enabled low-cost sensor network for residential air quality monitoring***

Figure 1- Floor plan of house showing approximate sensor locations with sensor code associated with colocation period.

Figure 2- Kitchen activity for the colocation period. Dots show time when activity was occurring.

Figure 3- Hourly average time series for AltasensePM devices and TSI for colocation week.

Figure 4- TSI : Altasense ratio by sensor concentration demonstrations a logarithmic relationship between the 2 device types where the AltasensePM under-estimates concentrations.

Figure 5- Hourly average data from a colocation with TSI post sensor correction (“cor”) by polynomial model.

Figure 6- Hourly average PM concentrations by room with activity log for each room above. Note kitchen and living room are located next to each other and share a doorway which was often open. Activities are affecting concentrations in other rooms.

Figure 7- Histograms demonstrating the frequent times of day for cooking activity (all cooking types combined) and kitchen extractor fan usage alongside diurnal patterns of PM2.5 concentrations by room. *NB. Frequency here describes the number of minutes the activity was marked as "present" and is separated into bins by hour of day.*

Figure 8- Distribution of PM2.5 concentrations in living room during various activities. Cooking occurred in the adjoining kitchen whilst oil burner and candle were located within the living room itself.

Figure 9- Boxplot of PM1 and PM2.5 concentrations by room for when external windows/doors are open vs. when they are closed. NB. Bedroom only refers to bedroom window, not ensuite bathroom window.

Chapter 4 ***What can we learn from nested IoT low-cost sensor networks for air quality? A case study of PM2.5 in a Clean Air Zone***

Figure 1- map showing Birmingham Clean Air Zone and the location of the various sensors across Birmingham. Figure 1 shows the CAZ area in green- which captures the majority of the city centre attractions, shopping and the CBD. The A38 is a key road that runs through the city joining onto the M6 motorway- a major access route to the region.

Figure 2- colocation daily average time plots of A) urban background Ladywood site, B) urban background BAQS site and C) roadside A4540 site.

Figure 3- hourly average data points of Zephyrs in near-colocation inside the CAZ and city centre of Birmingham. All 3 roadside sites located within ~90-160m of each other across a busy junction on a major road. Holloway Head and Holloway Circus are the closest located at ~90m apart, and the colour of the plot is by Suffolk St Queensway location which is ~160m away.

Figure 4- Polar plot of Holloway Head (hh), Holloway Circus (hc) and Suffolk Street Queensway (SQ) sensor PM2.5 concentrations in µgm-3 by colour, plotted by wind speed and wind direction. Wind speed and wind direction data is from the nearby Elms Cottage weather station on the University of Birmingham campus.

Figure 5- A) weekly average $PM_{2.5}$ by site (Identified by code in appendix). NB. The horizontal black dashed line demonstrates the WHO annual average guideline concentration of 5µgm^{-3} and the red box highlights the peak associated with a regional dust storm B) weekly averages of the mean and the variation between sampling sites (range) of the sensor network and DEFRA AURN network measurements (DEFRA AURN sites Ladywood urban background site

and A4540 Ring road urban traffic site, Sensor network takes into account all sensor sites present at any given time stamp).

Figure 6- DEFRA AURN location vs sensor network mean separated for Urban Background and Urban Traffic sites with coloured by number of sensor observations at each mean point. NB. solid line denotes the 1:1 relationship.

Figure 7- overlaying the average concentration at sensor locations (for sites >75% annual capture) with the ADMS-Urban model (Zhong et al., 2021). Generated using ArcMap and OpenStreetMap. NB. the scale for the model and the sensors is different but scaled to show relative highs and lows of each in the same colour scheme. Bar chart shows the annual average value at the overlayed sensor sites vs the comparative model value for that cell.

Chapter 5 ***Moving from monitoring to real-time interventions for air quality: the future role of low-cost sensors, IoT and digital twins***

Figure 1- An overview of the Gemini Principles taken from (Bolton et al., 2018) under CC BY 3.0 licence.

List of tables

Chapter 1 ***Introduction***

Table 1- Outline of OPC featured within recent literature. Literature listed is non-exhaustive. OPC prices drawn from literature or from online shopping searches for sensors.

Table 2- Outline of low-cost commercial sensing units that are use an OPC for particulate measurements. This is a non-exhaustive list. *Price is the estimated cost of purchasing a unit, not inclusive of any ongoing costs such as subscriptions, communication connection etc. (Earthsense, 2022, PurpleAir, 2023, Schieber, 2020, airly, 2023, Clarity, 2023, Demanega et al., 2021).

Table 3- Outline of the key features, benefits and challenges of 3 types of IoT LPWAN technology.

Table 4- Chapter breakdown of where each research goal and scientific question outlined above is addressed within this thesis.

Chapter 2 ***Field Calibration and Evaluation of an Internet-of-Things-Based Particulate Matter Sensor***

Table 1- Comparison of low-cost sensors vs. traditional monitoring [edited from Kularatna and Sudantha (2008)].

Table 2- Correlation coefficients and statistics for low-cost devices (R, r2 and slope are comparison to Birmingham Air Quality Supersite FIDAS).

Table 3- κ values drawn from Pringle et al. (2010)—column 1 and from Crilley et al.(2018)—columns 2–5.

Table 4- Correlation results for Altasense PM vs. FIDAS for the period 23.04.21–27.04.21 after correction using the multi-linear approach. One device (B) has a tendency to underestimate compared to the other sensors. This device has performed slightly worse than the others in linearity correlations, and this demonstrates some of the concerns about the replicability of data between low-cost sensors due to the unknown manufacturing standards. Despite this, it still generally performs well.

Chapter 3 ***Particulate matter in a lockdown home: evaluation, calibration, results and health risk from an IoT enabled low-cost sensor network for residential air quality monitoring***

Table 1- Description of the correction calibration and data validation methods used by various studies that assessed indoor air particulate concentrations using low-cost sensors. Note that PurpleAir uses the same PMS5003 Plantower sensor that AltasensePM uses, however it has 2 sensors per unit allowing for dual reading and outlier corrections.

Table 2- Description of the sensor location by room and description of potential sources and ventilation by room. NB. *Sensor E was earmarked to be deployed in the ensuite bathroom however it had an issue with the Arduino board in between colocation study and data collection so was unable to be deployed for this study.*

Table 3- Definitions of the various activities recorded in the activity log.

Table 4- Results of AltasensePM colocation with Dusttrak.

Table 5- r^2 values of AltasensePM and Dusttrak from colocation period after correction of sensors with a quadratic model. NB. *Sensor A had significantly less data points (n=14, rather than n=71 for other units) throughout the post correction co-location than other sensors due to a power loss, it's poor performance could be linked to this.*

Table 6- Presence of sensors within study period. All are above the 75% completeness required as part of the data validation steps.

Table 7- Mean concentrations for the whole study period. Mean is colour coded to represent concentrations above and below WHO guidelines for $PM_{2.5}$ and PM_{10}. Green= mean concentration less than WHO 2021 Annual guideline. *Orange= mean concentration falls in between WHO 2021 and WHO 2005 guidelines. Red= mean concentration greater than WHO 2005 annual guideline.*

Chapter 4 ***What can we learn from nested IoT low-cost sensor networks for air quality? A case study of PM2.5 in a Clean Air Zone***

Table 1- $PM_{2.5}$ concentration range and mean for sensor sites with >75% capture over the entire sample period and DEFRA AURN regulatory instruments for the sample period. NB. The 2 regulatory DEFRA AURN sites were chosen because they fall into the ~39km^2 area covered by the sensor network. 1 other regulatory station in Birmingham area (Acocks Green) was not used as this is >2km away from the nearest sensor and is not considered a city centre location.

Table S1- Rationale of sensor locations for University deployed units. **NB.** Site type definitions used (Department of Environmental Food and Rural Affairs, 2023) site classification as guidance.

Chapter 5 ***Moving from monitoring to real-time interventions for air quality: the future role of low-cost sensors, IoT and digital twins***

Table 1- IoT Architecture, information drawn from (Syed et al., 2021, Silva et al., 2018).

Table 2- Outlining the types of AQ monitors used by the UOs.

Table 3- Air quality management techniques in Birmingham which target traffic emissions specifically.

Chapter 6 *Conclusions*

Table 1- Summary of key findings and recommendations from within the thesis chapters.

List of abbreviations

ACSM *Aerosol Chemical Speciation Monitor*

AURN *Automatic Urban and Rural Network*

BAQS *Birmingham Air Quality Supersite*

BCC *Birmingham City Council*

CAZ *Clean Air Zone*

DEFRA *Department for Environment, Food and Rural Affairs*

MCERTS *Monitoring Certification Scheme as issued by the UK Environment Agency*

I:O *Indoor:Outdoor Ratio*

IAQ *Indoor Air Quality*

IoT *Internet of Things*

LEZ *Low Emission Zone*

LoD *Limit of Detection*

LPWAN *Low Power Wide Area Network*

NEE *Non-Exhaust Emission*

OPC *Optical Particle Counter*

PCB *Printed Circuit Board*

PM *Particulate Matter*

RH *Relative Humidity*

UFP *Ultrafine particle*

ULEZ *Ultra Low Emission Zone*

UNB *Ultra-narrow band*

VOC *Volatile Organic Compound*

WHO *World Health Organisation*

WSN *Wireless sensor network*

CBD *Central Business District*

This page is blank

Chapter 1: Introduction

This thesis presents an evaluation of the measurement of particulate matter using low-cost and Internet of Things (IoT) enabled sensing technology. Chapter 1 serves as an introduction to the background of particulate matter monitoring, its importance, sources, and monitoring techniques. It also introduces IoT and low-cost technology in the context of environmental monitoring and its potential use for enhancing air quality observations.

1. Particulate matter

Particulate matter (PM) refers to suspended particles within the air. Ambient particulate matter is either suspended solid or liquid particles and can display a wide range of characteristics, ranging in size, composition and more (Perrino, 2010). Particles are often referred to by their diameter; with PM_1, $PM_{2.5}$ and PM_{10} often used to describe the mass concentration of particles of diameters of <1µm, 2.5µm & 10µm respectively. As particles are rarely perfectly spherical, diameter here is used to describe the diameter of a sphere that would demonstrate physical behaviour the same as the particle, this is commonly referred to as equivalent diameter (Wilson et al., 2002, Friedlander, 2000). There are also particles known as ultrafine or nanoparticles and are smaller in their diameter, often in described in nm (Seigneur, 2019, Coles and Tiwary, 2009). Particulate matter is categorised as primary or secondary PM. Primary PM describes particles that are emitted directly from a source as liquid or solid particles, whereas secondary PM describes particles that are formed in the atmosphere as a result of chemical reactions (United States Environmental Protection Agency, 2023). Examples of primary $PM_{2.5}$ particles are those from combustion, tiny fragments of metal and black carbon, whereas examples of PM_{10} particles are dust and soot (Acton et al., 2023). Ultrafine particles are also linked to combustion; examples of particles of this size are diesel engine combustion particles, and those related to cooking and wood burning activity (Li et al., 2016). Examples of secondary PM is nitrates formed in the atmosphere from gaseous vehicle exhaust emissions. Figure 1 demonstrates some examples of PM by diameter comparison.

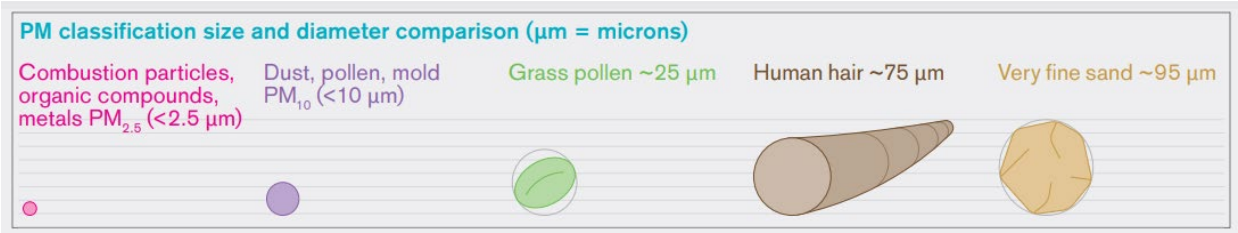


Figure 1- *PM classification size and diameter comparison adapted from (Acton et al., 2023).*

Particulate matter is important due to the heterogenous nature of the problems it presents- alongside public health issues arising from exposure, it can also impact climate, meteorology, environment, building degradation and more (Harrison, 2020). With regards to climate, PM has a number of impacts due to its wide array of sources and properties. PM is vital in cloud formation as airborne aerosols act as condensation nuclei for water vapour to condense on so changes to PM concentrations can affect cloud cover and precipitation patterns (Myhre et al, 2013). Black carbon, a type of $PM_{2.5}$ emitted from the incomplete combustion of fossil fuels absorbs heat in the atmosphere and can alter surface albedo (Fuzzi et al., 2015). Secondary aerosol formation from reduced NO_x emissions may counteract the cooling caused by reduced tropospheric ozone, likely to instead cause climate warming (Myhre et al,

2013) . As such PM remains a big area of uncertainty for radiative forcing, and monitoring during the process of air quality and climate actions will be needed.

Exposure to particulate matter has been associated with a number of health risks- including mental health problems, respiratory and cardiovascular illness, decline in cognitive performance and premature deaths (Cao et al., 2023, Dyer, 2020, Office of Air and Radiation, 2003, Shehab and Pope, 2019). Whilst coarser particles such as PM_{10} have been linked to health issues, exposure to finer particles is generally considered a greater risk. The smaller size of fine particles allows them to penetrate further into the body, including key respiratory organs such as the lungs (World Health Organization, 2013). Further evaluation of health impacts of PM is explored in chapter 3.

1.1 Physical properties of particulate matter

Particulate matter is used to describe particles suspended in the air, however it is important to not oversimplify and consider particles as uniform. There is a diverse array of chemical compounds, including organic and inorganics found within particles and the mixing of these compounds across ambient PM is challenging to define thus there is uncertainty in the quantification of PM components (McFiggans, 2018). These properties are important to understand when monitoring particles, as they affect the way a particle behaves and will be detected in various sampling methods. Particles are comprised of liquid, solid matter, or solid matter encased in a liquid and due to this variation also have a range of shapes, sizes and densities (Wilson et al., 2002). As previously highlighted, diameter is a common metric used to describe particle size; however different definitions of particle diameter will capture different characteristics of particles in their description. A commonly used definition of particle size is aerodynamic diameter (European Commission, 2023, Friedlander, 2000). Aerodynamic diameter is defined as the "*diameter of a spherical particle with a density of 1 gcm^{-3} but with a settling velocity equal to that of the particle in question"* and determines the way a particle is transported, coagulated and deposited on different surfaces (Wilson et al., 2002). As many particles are not uniform in shape and size, this is a useful definition which takes into account density when considering particle diameter (Wilson et al., 2002, Friedlander, 2000). However, this method may lead to oversimplification of the expected motion of particles as the complexity of non-spherical particles will cause irregular movement and some particles with the same aerodynamic diameter may not behave in the same manner in terms of deposition and motion (Friedlander, 2000). A method for classifying equivalent diameter that accounts for particle motion is mobility diameter. Mobility is the ratio of particle velocity to force producing the same motion and mobility diameter is the diameter of a sphere with the same mobility as the irregular size particle (Friedlander, 2000).

Figure 2 outlines the size ranges and classification modes of airborne particles. These modes are known as the nucleation mode, the accumulation mode and the coarse particle mode. Nucleation mode refers to the smallest of particles (referred to in literature as either ≤50nm (AQEG, 2005) or ≤100nm (Wilson et al., 2002, Wallace, 2006) newly formed either by atmospheric nucleation or from high temperature sources that trigger the emission of primary nucleation particles. These particles are impermanent with a short life time, as they quickly undergo condensational growth or deposition due to their tendency for Brownian motion (AQEG, 2005, Kulmala et al., 2001). Accumulation mode refers to slightly larger particles, up to about 1µm in size, which are formed from nucleation mode particles either coagulating or undergoing vapour condensation. Due to their larger size, these particles are less likely to experience Brownian motion so move more slowly but are too small to settle rapidly under

gravitational force thus experience longer lifetimes (unless removed by precipitation processes) (AQEG, 2005). These particles are limited in their ability to grow further by coagulation and condensation so do not tend to grow into coarse particles (Wilson et al., 2002). The coarse mode tends to therefore refer to particles that have been formed from mechanical rather than chemical processes and have a size >1µm (Wilson et al., 2002). These particles are large enough to be subject to gravitational settling to have a shorter life-time than accumulation particles. It is important to distinguish the difference between coarse mode particles and coarse vs fine PM in standard sampling efforts, the latter referring to particles >2.5µm ($PM_{2.5}$) rather than 1µm (AQEG, 2005). The size and movement of particles is important to consider when sampling- methods should be aware of the physics of particles and how it could affect movement and/or deposition of particles within a sampling chamber. As such some sampling methods may be better at detecting certain size fractions than others.

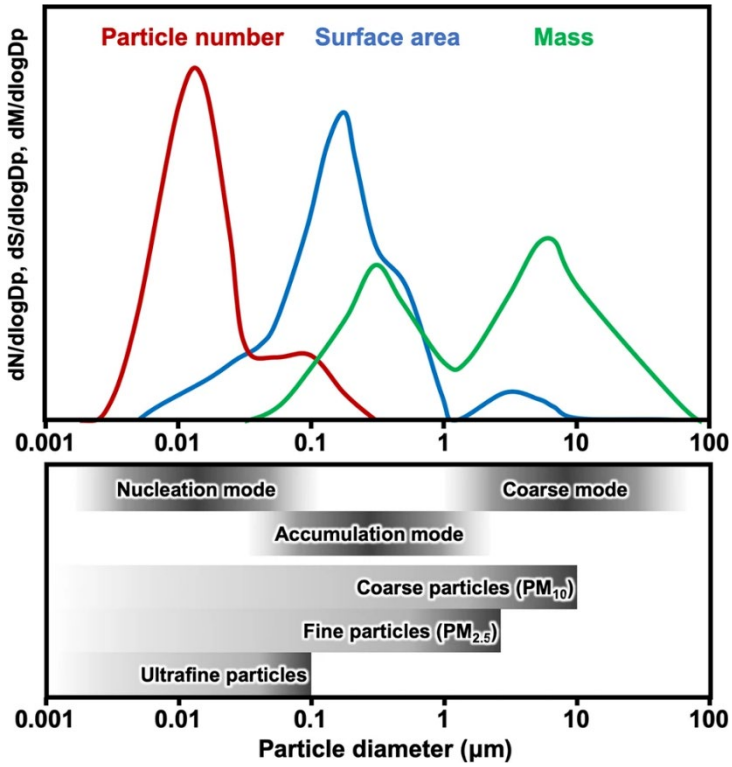


Figure 2- *Diagram of ambient PM size distribution of the particle number concentration, surface area concentration and mass concentration (dN/dLog Dp, particle number per cubic millimeter; dS/dLog Dp, particle surface area per cubic millimeter; and dM/dLog Dp, particle mass per cubic millimeter, respectively) separated into 3 subgroups known as the modes of distribution. Taken from (Kwon et al, 2020).*

Coagulation leads to particles growing across size ranges. As shown in figure 2 as particle numbers decrease, mean particle diameter and mass increases. This can lead to larger size fractions contributing to a significant proportion of the particle mass but only a small proportion of particle numbers (AQEG, 2005, Harrison and Yin, 2000).

Beyond size, composition of particles also effects particle behaviour. Highly water-soluble particles demonstrate better light scattering properties, $PM_{2.5}$ is often be comprised of many water-soluble particles. Hygroscopic particles scatter more light in higher humidity, altering their behaviour in different environments and meteorology (Won et al., 2021). Organic matter, particularly organic

carbon aerosols are associated with high hygroscopicity of particulate matter (Abdul-Razzak, 2012). This again will be important to consider when sampling particulates as it could alter the efficacy of a sampling technique.

1.2 Ambient particulate matter sources

Ambient particulate matter sources can be either natural or anthropogenic. Natural sources of particulate matter include soil dust, salt spray, pollen, volcanic eruptions, wildfires and a range of biological processes (such a bacteria or decay of organisms) (Perrino, 2010, Mukherjee and Agrawal, 2017). As outlined in the introduction there are both primary and secondary sources of PM and these too can be natural or anthropologically driven. Although PM can occur naturally, some of natural sources are exacerbated by human activity. For example, increased frequency of wildfires or increased desertification due to climate change and land management will lead to increased PM emissions. Anthropogenic sources are broad and vary by location and human behaviour, however, include but are not limited to traffic exhaust emissions, traffic non-exhaust emissions, waste disposal, construction, mining and quarry activity, industry, domestic fuel burning and power generation (Karagulian et al., 2015, Guttikunda et al., 2014, Hime et al., 2015, Harrison, 2020). Due to this, the composition and mass concentration of PM may vary between location dependent on natural factors, human activity and management of sources. Figure 3 shows the breakdown of $PM_{2.5}$ emission sources in the UK over time, demonstrating how sources have changed over time with changing societal behaviour.

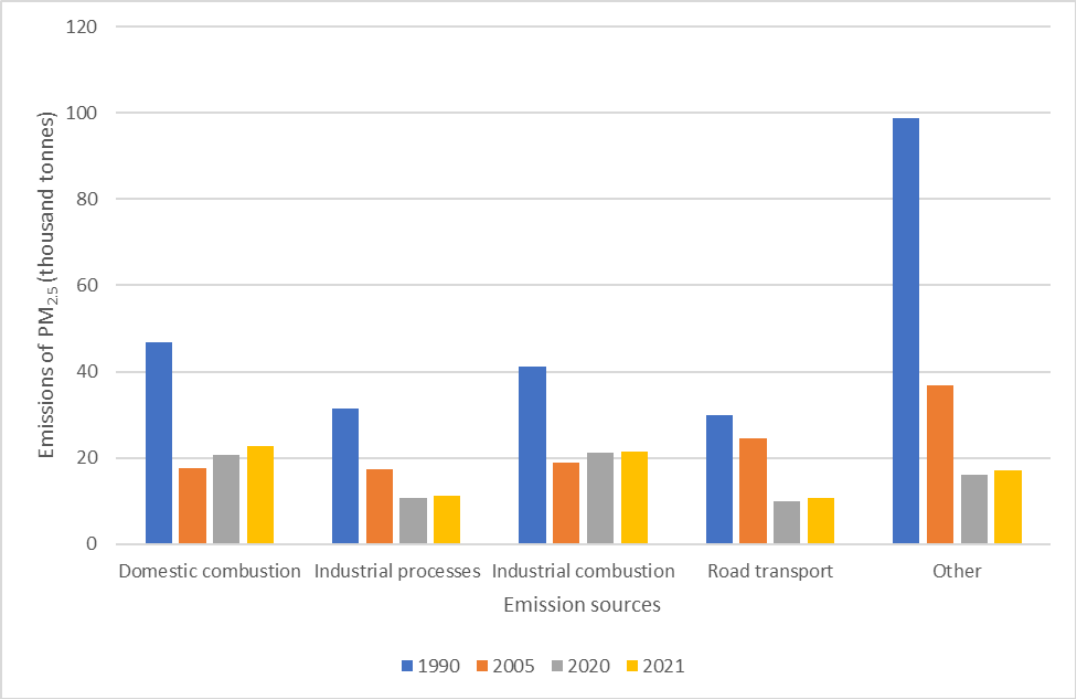


Figure 3- *emissions of UK $PM_{2.5}$ by emission source sector 1990-2021. Data from (DEFRA, 2023c).*

Globally, natural particulate matter emissions (particularly soil dust and sea salt) account for a greater percentage (87%) than anthropogenic, however this does change regionally, and many urban areas see human driven emissions exceeding those of natural source (Hime et al., 2015, Mukherjee and Agrawal, 2017, Querol et al., 2013). An example of a recent attempt at creating a global picture of

$PM_{2.5}$ and PM_{10} sources by compiling results from local studies is (Karagulian et al., 2015) and with (Hopke et al., 2020) updating and expanding on this in 2020. Both studies used article database searches to identify over 400 individual source apportionment records from studies all over the globe, the majority of which were based in urban environments. Whilst Karalugian et al. broke data down into 5 source categories (Traffic, Industry, Domestic fuel burning, Natural sources including soil dust and sea salt and Unspecified sources of human origin), Hopke distinguished groups further by creating 8 source categories (Mixed secondary inorganic aerosol: SIA, Sea Salt, Dust, Traffic, Industry, Biomass burning, Coal/No.6 Oil and Other). Whilst their findings are not directly comparable due to Karagulian et al. grouping sources more coarsely, it is clear from the two studies that anthropogenic sources dominate in most urban regions. The studies agree that traffic and the domestic burning of fuels (biomass, coal, oil or unspecified) are significant contributors in all global regions, however there are disparities on industry contributions between the two studies. This could be due to a change over time of sources contribution between the two studies or due to the alternative methods/different research studies coagulated for use in the studies. Whilst these studies offer comprehensive reviews of the data available, there are significant gaps in the global coverage due to lack of source apportionment studies. Most data focuses on wealthier nations, such as those in North America, Europe and East Asia with a paucity of data in Africa, Eastern Europe and Central and South America. The data is also very urban-centric, with limited datasets coming from rural environments. This chapter will evaluate further some of the key sources relevant to the context of the upcoming chapters and West Midlands region.

1.2.1 Vehicle emissions: Exhaust emissions

Vehicles play a significant role in particulate emissions in urban environments such as Birmingham. Transport contributes to particulate emissions in two ways; exhaust and non-exhaust emissions. Exhaust particulate emissions occur from fuel and oil combustion within the engine (Harrison, 2020). Historically, the majority of transportation has been fuelled by combustion engines burning gasoline or diesel, releasing particulates into the atmosphere as a by-product (Vallero, 2008). These emissions tend to consist of black carbon and organic compounds and are largely found to consist of finer particle sizes(aka $PM_{2.5}$ or smaller) (Charron and Harrison, 2005, Pant and Harrison, 2013, Harrison, 2020).
In 2010, diesel engine vehicles made up the majority of the vehicle fleet in Europe (52%, approx. 35 million vehicles) (Jerzy and Jacek, 2015). Although there has been some shift in vehicle fleet with emerging electric vehicles and a shift to petrol engines over diesel, in the UK only 3.1% of passengers cars were either electric or hybrid electric engines by 2020 (European Automobile Manufacturers Association, 2022) and it has been predicted that by 2050 that internal combustion engines will still make up the majority of the vehicle fleet (Jerzy and Jacek, 2015). The 20th century saw an increase in traffic dominated PM- with particles from combustion engine exhausts dominating ambient particulate concentrations (although this is now in decline in many developed nations) (Harrison, 2020). The reduction of exhaust emissions contribution to ambient PM concentrations is reflective of policies and technological advances that have targeted exhaust emissions over non-exhaust. Many of these interventions targeted reducing gas emissions of NO_2 and CO_2 with PM reductions being a co-benefit. Standards for vehicles emissions have improved engine related emissions of particulate matter, especially in diesel engines. The introduction of the diesel particulate filters has helped reduce primary PM exhaust emissions yet these filters don't reduce non-exhaust emissions or NO_x emissions that can form secondary PM in the form of nitrates (Jerzy and Jacek, 2015).

1.2.2 Vehicle emissions: non-exhaust emissions

Non-exhaust emissions (NEEs) refer to all particles generated by traffic from non-exhaust processes such as brake and tyre wear, road wear and resuspension of road dust (Lewis et al., 2019, Kaddoura et al., 2022). With modernising vehicle fleets, NEEs are a PM source of increasing importance as whilst overall trends are of decreasing PM from traffic due to reduction of exhaust emissions, a greater proportion of traffic related PM will be from NEEs. It is estimated that with modernising vehicles fleets, 90% of total road traffic emissions are non-exhaust related (Pant and Harrison, 2013). Whilst NEE come in a range of size profiles, the majority of emissions are in the coarse PM fraction (Matthaios et al., 2022, Harrison et al., 2021). About 10% of $PM_{2.5}$ and PM_{10} emissions in the UK are sourced from NEE, a contribution that has remained relatively stable since 1996 despite cleaner vehicle fleets (DEFRA, 2023a). The biggest contributor to coarse non-exhaust particles is road dust suspension, whilst finer particles experience the greatest contribution from road tyre abrasion (Matthaios et al., 2022). NEEs are estimated to account for 90% of PM_{10} and 85% of total (both secondary and primary combined) $PM_{2.5}$ from traffic sources and are found to be exceeding primary exhaust emissions in urban areas (Timmers and Achten, 2016, Piscitello et al., 2021, Harrison et al., 2021).

All vehicles contribute NEEs, although there is some controversy around the roles different engine types (electric, combustion) affect NEEs (Lewis et al., 2019, Liu et al., 2022). NEEs are driven by multiple factors; including vehicle weight, braking and driving habits, road cleanliness and the implementation of regenerative braking (Liu et al., 2022). The decarbonisation of vehicle fleets will reduce the emissions of exhaust pollutants such as NO_2 and CO_2, however $PM_{2.5}$ is estimated to only be reduced by 26-31% by transferring to electric vehicles (Kaddoura et al., 2022). Electric vehicles are on average 24% heavier than their combustion engine alternative and there have been links associated with NEEs increasing with increasing vehicle weight (Amato et al., 2014). Previously, there has been a lack of management addressing NEEs although this is starting to change (Amato et al., 2014). The latest Euro VII standards are looking to set limits for non-exhaust particulates starting with particle emissions from brakes (Amato et al., 2014, European Commission, 2022). Methods to reduce NEEs can come from social change (such as reducing mileage and speed limits or increased road cleaning) or from technological improvements (such as lighter vehicles, more efficient brakes/tyres or improved road surfaces). (Kaddoura et al., 2022, Timmers and Achten, 2016, Piscitello et al., 2021). The challenge of the modernising fleet still contributing significantly to particulate concentrations in urban environments suggests the need for continued monitoring of PM, particularly roadside and in areas of traffic management that may encourage modernising fleet uptakes.

1.2.3 Solid fuel burning

Although traffic emissions are often at the heart of air quality management plans, recent reports have highlighted the prominence of residential burning of solid fuels in contribution to ambient PM concentrations. In the UK the reduction in $PM_{2.5}$ emissions from the improving cleanliness of other sectors such as transport is now mostly being offset by burning from industry and residential settings. Domestic wood burning now accounts for 21% of total $PM_{2.5}$ emissions, with emissions up 124% between 2011 and 2021 and 7.5% of homes reporting burning wood for heating in 2016 (DEFRA, 2023a, Waters, 2016). Combustion in homes has been linked to both increased ambient and indoor PM concentrations, generating additional risk to those in wood burning communities as well as for

residents choosing to burn wood in their homes (Ferro et al., 2022). Wood burning fluctuates seasonally- peaks are associated with key holidays such as bonfire night and with cold calm weather when residents turn to wood stoves to heat their homes (Font et al., 2022). However, wood burning drivers are more complex than just seasonal changes- social factors also influence personal choices to use wood burners. Studies have linked increased solid-fuel burning to periods of economic struggle- wood burning or biomass burning can be more affordable than gas heating systems (Wood et al., 2022). This is particularly of concern with the current cost of living crisis across the UK where consumers are facing record high energy prices. Wood burners are also aesthetically and culturally valued, often associated with increasing a homes' desirability as well as providing alternative winter fuel option (Wood et al., 2022). Whilst consumers are shifting towards cleaner, more efficient stoves for burning, these are also likely to be used more frequently than their 'dirtier' predecessor stoves (Font et al., 2022). In urban environments such as Birmingham, with densely population residential regions, emissions from solid fuel burning can affect large numbers of people. Therefore, it is important to ensure urban background measurements are distributed across cities to capture any potential hotspots or areas of concern.

1.3 Indoor particulate matter

Whilst historically ambient PM has been widely researched, indoor air quality research is gaining traction. This is highlighted by the context of a post-covid world where ventilation of indoor spaces, hybrid/remote working and public health concerns have caused modal shifts in various aspects of day-to-day life. Indoor particulate concentrations are driven by 2 source types- internal sources and external sources. Internal sources are particulates generated within the home and include but are not limited too; smoking; cooking; combustion for heating and other human activity such as resuspension and cleaning. External sources are generated outside but have infiltrated into the building via either natural or mechanical ventilation (Li et al., 2017). Past studies have assessed indoor particulate concentrations in home environments (Patel et al., 2020, Semmens et al., 2015, Ojo et al., 2015); office environments (Cocârţă et al., 2021, Küpper et al., 2019, Mandin et al., 2017); schools (Bennett et al., 2019, Mohammadyan et al., 2017); and industry (Bawa et al., 2022, Huang et al., 2007) yet challenges of indoor air study is often the intrusiveness of monitoring technology which is often initially designed to sample in ambient environments. There are also limitations to studies, with a review by Ilacqua et al. (2022) finding that the use of ambient concentrations to estimate indoor concentrations leads to variable results. A detailed assessment of residential indoor air quality sources can be found in chapter 3.

2 Birmingham's air quality context

The original focus of this thesis was going to be framed around Birmingham, UK, using the city and its air quality interventions as a testbed for low-cost sensing technology. Due to interruptions to fieldwork and sensor deployments caused by the coronavirus pandemic, a shift in focus to include indoor assessments and national applications of the low-cost sensors for air quality interventions was adopted. Chapter 2 & 4 are still based within Birmingham, UK, and here additional context is provided to the environment in which ambient sampling occurred.



Figure 4- *location of Birmingham within the UK and the regulatory measurement sites for PM within Birmingham. Map sourced from GoogleMaps.*

Birmingham is located in the West Midlands region of the United Kingdom and is the second largest city in the country. There are 3 regulatory monitoring sites across the city that measure particulate matter (shown in figure 4). The *2019 Air Quality Annual Status Report* from Birmingham City Council reported 2018 annual averages from these sites as 10-12µgm^{-3} and 16-18 µgm^{-3} for $PM_{2.5}$ and PM_{10} respectively (Burns, 2019). In the UK, road transport significantly contributes to $PM_{2.5}$ concentrations with 13.4 kilotons of $PM_{2.5}$ emitted by road transport in 2019 however commercial, industrial and residential combustion was the great emitter of $PM_{2.5}$ (National Atmospheric Emissions Inventory, 2022). This is reflected in Birmingham with road vehicle exhaust emissions being the primary source of $PM_{2.5}$ in the city (Burns, 2019). Figure 5 models the particulate concentrations across the West Midlands region, including Birmingham using 2016 baseline data (Zhong et al., 2021). From this model, high concentrations of particulates coincide with road networks and denser urban environments, with rural areas generally experiencing lower particulate concentrations. Generally, in wealthier nations, road traffic exhaust is declining in its contribution to ambient PM. As vehicle fleets shift to cleaner engine types, non-exhaust emissions are becoming of greater importance (Harrison, 2020) as these are expected to become more important in the context of Birmingham, with traffic management plans such as the Clean Air Zone targeting the most polluting engine types for NO_2 exhaust emissions. Therefore, it will be important to continue to monitor particulates over the periods of changing fleet to assess the real world impact on particulate exposures.

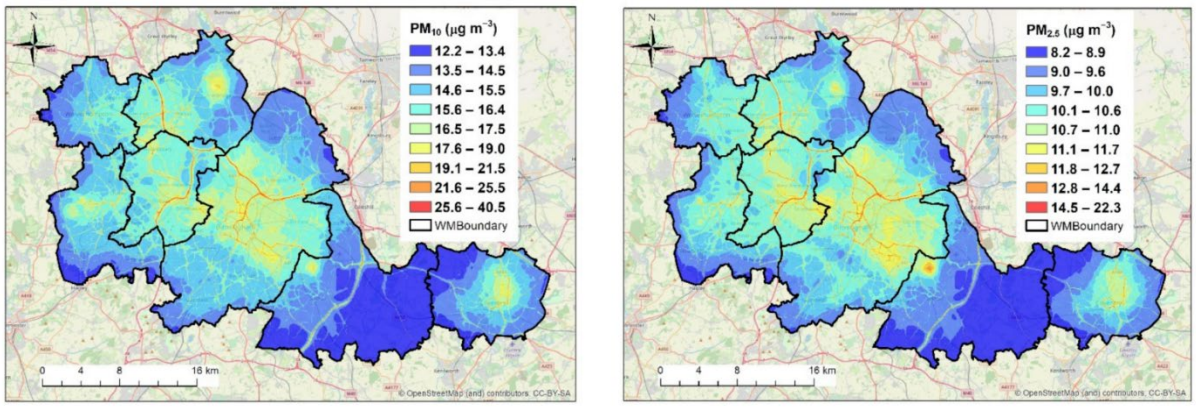


Figure 5- *annual average PM_{10} (left) and $PM_{2.5}$ (right) in µgm^{-3} at 10mx10m resolution from the ADMS-Urban model for the West Midlands region including Birmingham. Taken from (Zhong et al., 2021).*

3 Monitoring of particulate matter

3.1 Monitoring methods

Particulate matter has been monitored using various methods over time. One of the earliest methods for detecting particulates was damage to materials. Reports of soot and particulate build up on buildings, clothes and other infrastructure were used to link particles in the air to anthropogenic activity such as burning and construction. This was referred to as 'darkening' or 'blackening' buildings (Yocom, 1958, McCormick et al., 1971, Brimblecombe and Grossi, 2005). In particular, carbonaceous particles have been reported to have been causing the darkening process on buildings, although the apportionment of the particles to assess this wasn't possible until more recently and historically the building degradation itself was considered as a proxy for assessing pollution concentrations (Ozga et al., 2011). More recently, many studies focused on black smoke measurement using filters. Black smoke is a term used to refer to fine particulate matter that is often dark in colour and emitted from fuel combustion such as diesel engines (or historically coal burning) (DEFRA, 2023b). Black smoke can be sampled by collecting particles on a filter paper using a sampler, assessing the reflectance of the exposed filters against a blank filter. As the filter is exposed to black smoke, it's reflectance decreases as the particles on the filter absorb light rather than reflect it, with higher smoke exposure relating to lower reflectance (Hoek et al., 1997). This reflectance value could be used to convert to a soot mass concentration using a smoke curve or conversion factor (Bloeman et al., 2007, Hoek et al., 1997). These methods have become somewhat outdated, due to their time intensive nature and improved monitoring technology.

Methods using remote sensing to estimate PM concentrations have gained traction (Zhang et al., 2021). These methods utilise data from satellites to calculate aerosol optical thickness or depth, estimating the properties of atmospheric aerosols by quantifying the reduction of solar radiation that reaches a satellite after passing through the atmosphere (Zhang et al., 2021, Gupta et al., 2006). Whilst remote sensing provides opportunity to assess PM concentrations in environments without access to in-situ monitoring and potentially give continuous monitoring, there are still challenges due to the limited samples the statistical correlations used in calculations are based on. This limits how representative calculations may be in different environments (Zhang and Li, 2015).

Current regulatory or reference instrumented in-situ monitoring efforts of particulate matter are often divided into two categories; those which use gravimetric methods such as high volume samplers or those which use alternatives such as optical counters, beta ray attenuation and tapered element oscillation to calculate concentrations (Kelly et al., 2017, Budde et al., 2013). These methods focus on sampling specific size fractions of particulates by diameter (aka UFP, PM_1, $PM_{2.5}$, PM_{10}) and often report a mass concentration or particle number rather than a darkening or change of reflectance of a filter. This reflects the current air quality objectives and guidelines which are often set as mass concentration thresholds over a period of time. Gravimetric methods do not give real time data but use the collection of particles on a filter followed by laboratory analysis to calculate mass concentrations and sometimes source apportionment information. Whilst highly effective and meeting regulatory requirements set by governing bodies, these various equipment cost in the magnitude of USD$10,000+ and have substantial additional costs such as maintenance, staffing, servicing and special housing and storage requirements making them costly investments (Johnson et al., 2018, Sayahi et al., 2019). This equipment is often bulky and due to the housing requirements and costs outlined above are usually stationary. The combination of these factors lead to sparse spatial monitoring, with major urban centres often only having a handful of locations where PM is monitored (Budde et al., 2013). This paucity of data limits understanding and decision making around PM- PM is highly spatio-temporally variable and to identify and understand pollution hotspots and events policy makers and researchers require higher frequency and density of measurements (Kelly et al., 2017, Johnson et al., 2018).

In the UK, the Automatic Urban and Rural Network (AURN) is the largest nationwide network of air quality monitoring stations, managed by the Department of Environment, Food and Rural affairs (DEFRA)(Department of Environmental Food and Rural Affairs, 2022). The network uses traditional monitoring techniques to sample both gaseous pollutants such as NO_x, NO_2, and O_3 as well as particulates and provide open access data (Mead et al., 2013). These sites provide coverage across the UK, but the spread across the country is not uniform. England has significantly more sites than Scotland and Wales, and as shown in figure 6, the majority of sites are based in urban environments. Many cities and towns have only one or a few sites across the entire city, give high resolution measurements at a crude spatial scale. Figure 3 shows the AURN sites in Birmingham. The city has three AURN sites total; with two urban background sites and one urban traffic site.

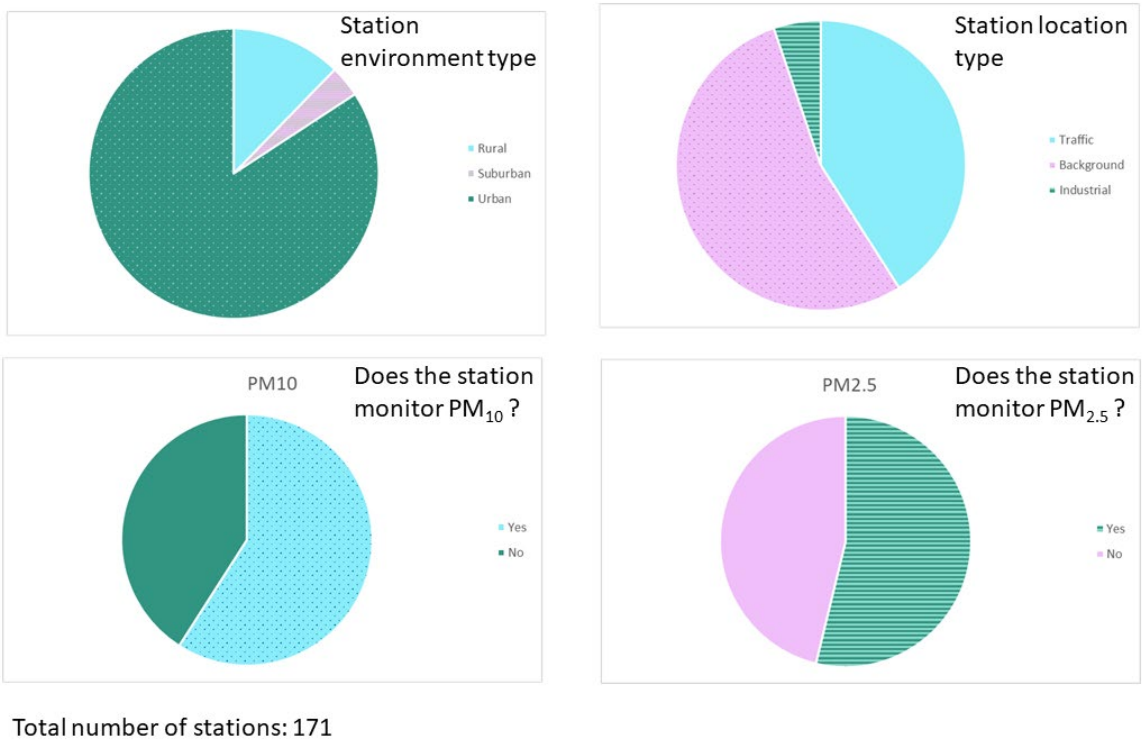


Figure 6- *Distribution of the AURN sites across the UK by environment and location type and number of stations that monitor PM.* ***NB.*** *Traffic refers to stations <10m from a major road kerbside where traffic dominates concentrations. Background refers to areas not significantly influenced by a single source or street. Industrial refers to locations predominately influenced by single industrial sources. Urban environments are completely or predominately built-up street fronts with at least 2 storey buildings. Suburban environments are largely built-up areas that are less dense than urban areas and are mixed in with non-urbanised areas such as lakes/woods/agriculture. Rural environments are areas of vegetation and nature, >20km from cities, >5km from other built up areas/motorways and major roads. (DEFRA, 2023d).*

The AURN network is not the only use of traditional reference instrumentation for air quality measurement; research and local government will often use the same instruments for monitoring campaigns; however, data is often not open-access.

There is a long-standing gap to be addressed in particulate measurements- data capture by government regulatory instruments is coarse and deploying further regulatory instruments is costly and labour intensive. Whilst the regulatory networks provide excellent insight into regional concentrations, localised particulate concentrations are overlooked and require more dense data capture. This is particularly true when wanting to assess interventions for managing air quality such as CAZ's, low-traffic neighbourhoods and wood burning restriction zones. These interventions tend to be localised and may not have a regulatory monitoring site within their bounds restricting the understanding of the full local impact on emissions that the intervention is causing. Further limitations of monitoring methods come from the ability to monitor indoor air quality. Reference grade instrumentation can be installed indoors but there are challenges in doing so. These instruments are labour and power intensive, costly and often invasive into any users of the indoor space, restricting

indoor particulate monitoring. Chapter 3 explores the opportunities to increase indoor monitoring of PM and chapter 4 evaluates spatial distribution of PM measurements in greater detail.

3.2 Low-cost sensors

'Low-cost sensor' is a broad term and for particulate matter encompasses a range of costs and technology. Occasionally, low-cost sensors are also referred to as "small form factor" sensors. This study recognises these terms as interchangeable but focuses on using the language low-cost sensor as this is most consistent with the literature references throughout this work. For this thesis, low-cost sensors are considered to be those of at least one order of magnitude cheaper than traditional monitoring and discuss units costing from approximately £100-£5000. The term 'low-cost sensor' for particulate matter sampling usually refers to some form of modified optical particle counter (OPC), often combining an OPC with power, communications and other sensing technology such as temperature/humidity sensors to create a complete unit. OPC technology uses a light source (often a laser) which is scattered by particles drawn through a sampling chamber by a fan. The scattered light is detected by photodiode which emits electronic pulses dependent on the amount/size of particles in the sampling chamber (Northcross et al., 2013, Zheng et al., 2018, Crilley et al., 2018). Like other modern sampling techniques, this data is then converted into particle count, mass concentration or both. Dependent on the sensor, there are various particle bin sizes that can be reported and some models also have undisclosed algorithms that adjust the data ahead of displaying it (Crilley et al., 2018, Sayahi et al., 2019). Table 1 outlines some commonly featured OPCs from the literature and their costs, whereas table 2 highlights some of the commercially available low-cost sensors that utilise these OPCs and their associated costs.

Light scattering techniques such as those used by OPCs are open to influence from the characteristics of the particles themselves. Particles that are too small (minimum diameter >100nm, although this will vary with OPC manufacturer and is often started as much larger minimum diameter on low-cost instruments) may not be detected by the laser diode within an OPC at all (Amaral et al., 2015). The composition of a particle is also important as it affects the particles' ability to absorb liquid (otherwise known as hygroscopicity). In high humidity, particles prone to high hygroscopicity absorb water from their surroundings causing them to swell and potentially causing erroneous readings in the OPC chamber as the count or size of a particle is misinterpreted (Brattich et al., 2020). Particles composed of nitrates and sulphates are particularly hygroscopic and are likely to cause challenges for OPC measurements (Crilley et al., 2020). Particle size is also important when considering the geometry of the sampling pathway through an OPC, some particles may be too large to navigate the inlet and laser pathway and larger particles can make challenging for sensors to detect all of the scattered light (Ouimette et al., 2022). There is need for investigation into this in a real-world ambient setting ahead of sampling, to ensure only trusted data is being used for analysis.

The low-cost sensing boom offers unprecedented potential to shift the paradigm of environmental monitoring. Whilst regulatory instruments are restricted in deployment numbers by costs, labour intensive management and power/space requirements, low-cost sensors are agile and affordable. There is some contestation around the performance of such devices in both their accuracy and reliability which is discussed and addressed in future chapters of this thesis in detail. The Plantower PMS series of OPC devices is becoming increasingly prominent hardware featured within a number of popular commercial devices (table 2) which are being deployed by a wide range of interested parties,

thus it is important that the sensor is assessed in detail to fully engage with the data outputs. At the initiation of this project, the potential was highlighted to assess and apply this technology to further increase local spatial resolution of particulate sampling in an unprecedented manner and to support open-access data sharing for application of monitoring data.

Table 1- ***Outline of OPC featured within recent literature. Literature listed is non-exhaustive. OPC prices drawn from literature or from online shopping searches for sensors. Detection limits drawn from manufacturer or retailer data sheets.***

OPC model	Price	Particle size detection limits	Examples of featured literature
Plantower PMS5003	~£30 GBP	0.3-10µm	(Zusman et al., 2020, Zamora et al., 2020, Levy Zamora et al., 2019, Feenstra et al., 2019, Tryner et al., 2020b, Ouimette et al., 2022)
Plantower PMS3003	~£30 GBP	0.3-10µm	(Zheng et al., 2018, Zusman et al., 2020, Levy Zamora et al., 2019)
Plantower PMS1003	~£30 GBP	0.3-10µm	(Magi et al., 2020, Zusman et al., 2020, Levy Zamora et al., 2018)
Alphasense OPC-N2	~£150 GBP	0.38-17µm	(Crilley et al., 2018, Mukherjee et al., 2017, Pope et al., 2018, Feenstra et al., 2019)
Alphasense OPC-N3	~£300 GBP	0.35-40µm	(Kaliszewski et al., 2020, Soroka, 2020, Sousan et al., 2021, Harr et al., 2022)
Shinyei PPD20V	<£150 GBP	Approx. >1µm (no upper limit stated)	(Johnson et al., 2018, Borrego et al., 2016)
Shinyei PPD60PV	<£150 GBP	Approx. >0.5µm	(Johnson et al., 2018, Kuula et al., 2017)
Shinyei PPD42NS	<£150 GBP	Approx. >1µm (no upper limit stated)	(Johnson et al., 2018, Kuula et al., 2017, Zusman et al., 2020, Northcross et al., 2013, Feenstra et al., 2019, Borrego et al., 2016)
Dylos	~$260 USD (includes LCD screen)	>0.5µm (upper limit not stated, manufacturer states 2.5µm and beyond)	(Northcross et al., 2013, Pillarisetti et al., 2017, Fishbain et al., 2017)

Syhitech DSM501A	<$100 USD	>1µm (no upper limit stated by manufacturer)	(Zikova et al., 2017, Zamora et al., 2020, Wang et al., 2015)
Sharp GP2Y1010AU0F	~£10 GBP	Not advertised on manufacturer datasheet	(Wang et al., 2015, Sousan et al., 2018)

Table 2- ***Outline of low-cost commercial sensing units that are use an OPC for particulate measurements. This is a non-exhaustive list. *Price is the estimated cost of purchasing a unit, not inclusive of any ongoing costs such as subscriptions, communication connection etc. (Earthsense, 2022, PurpleAir, 2023, Schieber, 2020, airly, 2023, Clarity, 2023, Demanega et al., 2021)***

Low-cost sensing unit	Price * GBP	OPC model used (if known)	Power	Data communication	Examples of use from the literature
Earthsense Zephyr	~£6000	PlantowerPMS5003	Solar, mains or short-term battery (3-7 days)	Wi-Fi, Bluetooth, GSM & 2G	(Schmitz et al., 2021, Ejohwomu et al., 2022, Panchal et al., 2022)
PurpleAir	~£250	PlantowerPMS5003	Mains	Wi-Fi	(Tryner et al., 2020a, Barkjohn et al., 2021, Mousavi and Wu, 2021)
Airly	~£250	Plantower model	Mains	GSM	(Hofman et al., 2022, Rogulski and Badyda, 2019, Zaręba and Danek, 2022)
Clarity	~£1000	Plantower PMS6003	Solar, short-term battery (30 days)	2G, 3G, 4G	(Demanega et al., 2021)

As the demand for environmental data, such as air quality data, grows with the increasing availability of low-cost sensors, there is a need for innovative technology that can support the communication, storage, management and analysis of the subsequent big data that is being generated. Whilst low-cost sensors can support in enhancing the spatial and temporal resolution of data collection, sensors alone do not resolve the issue. Low-cost samplers can have increased agility and sampling rates compared to alternative sampling methods such as gravimetric samplers, supporting the development of high spatio-temporal resolution data and furthering understanding of short-term particulate concentrations in real world environments. Offline sensors can increase spatial resolution but require additional workload in collecting and collating data and delays analysis and decision-making opportunities. Here integrating novel communication technology alongside low-cost sensing technology presents attractive opportunity to further revolutionise the collection and application of air quality data.

3.3 Internet of Things (IoT) technology

The Internet of Things (IoT) is a super network of connected 'things' via the internet, integrating infrastructure, sensors, smart tech and other internet connected devices into an online space where they can communicate without human intervention (Li et al., 2015) – machine-machine. The IoT brings a new dimension to internet technology as it causes a shift from human-human or human-machine internet communication and creates machine-machine communication lines (Tan and Wang, 2010). This global information system is in part comprised of a range of smart infrastructure- sensors embedded into street lamps, train tracks and power grids to provide real time updates on a range of stimuli (Lavric and Popa, 2017). IoT technology is revolutionising the way that infrastructure can be managed- as units can process their own states through sensing and feedback to the user for decision making and management, allowing users to automatically know when infrastructure is experiencing downtime or requires maintenance (Chapman et al., 2016, Zhu et al., 2010).

The low-cost and flexibility of the IoT enables the development of Wireless Sensor Networks (WSNs) which can enhance the monitoring of key environmental issues across a range of contexts (Shah and Mishra, 2016). The wide range of applications for IoT devices create great opportunities in the field of environmental science, particularly for the development of concepts such as "smart cities" in which urban environments are monitored and maintained by IoT devices. The nature of environmental research regularly restricts research of these key areas- harsh environments, difficulty in accessing field sites for ongoing instrument maintenance and costs of instrumentation reduce the availability of data (Lazarescu, 2013). First researched in the 1980's, WSNs are low cost, low power, IoT driven networks of sensors that are now commonplace infrastructure. With the ability to monitor environmental stimuli such as temperature, humidity, pollutant concentrations in a range of different places, WSNs eliminate the issues of wired communication and make data monitoring more cost effective and efficient (Jaladi et al., 2017, Shkurti et al., 2017).

As WSNs have developed, so has the range of applications. Of particular interest to this thesis is the potential role that WSNs could play in air pollution monitoring, particularly in urban environments where they could be the key to attaining the much-needed densification of measurements. WSNs can allow for earlier detection of dangerous pollution levels and real-time data analysis without human intervention- conventional systems do not allow for the high spatio-temporal data nor communications required for this (Ramson and Moni, 2017, Pavani and Rao, 2017). Multiple studies have found that WSNs can support air quality monitoring dependent on performance parameters being met. Boubrima et al. (2019) report that static sensor networks can be successful dependent on the reliability of the sensor hooked onto the WSN controller and that topology may need to be considered for impacts on both communications and sensing results. Sharma et al. (2019) report that both gaseous and particulates can be monitored using WSNs after calibrations of the devices. They also report that the networks have good scalability. Nagaraj and Biradar (2017) found that whilst the accuracy of the sensor can be questioned, the WSNs can provide real time data opportunities. In general, it is reported that WSNs provide great opportunity for real time, high spatio-temporal data but most limitations come from the type of sensor that they use rather than communications protocols themselves (Huang et al., 2020, Pavani and Rao, 2017, Arroyo et al., 2019). Public services such as energy and traffic management can be integrated with IoT technology providing cost effective solutions which enhance urban dwellers lives (Zanella et al., 2014). It can be argued that technology

here enhances the concept of urban space- tasks which used to seem incomprehensible in magnitude and scale can be managed at low costs via IoT devices.

There are many types of internet communication that can enable a device to become part of the IoT. As many IoT applications have specific requirements such as long-range, low power consumption or low costs, Low Power Wide Area Networks (LPWAN) have grown in popularity. LPWAN utilise sub-GHz unlicensed ISM bands to transmit data over low bandwidths, meaning they are most appropriate for sending small size messages over long distances (Patel and Won, 2017). LPWAN are modest in both economic costs and energy requirements, often supporting units to have battery life of magnitude of years and costing <£20/year (Mekki et al., 2019, Song et al., 2017).

There are multiple LPWAN available for use, 3 of the most popular being NB-IoT, LoRa & Sigfox. Each network has its own characteristics and applications and these have been assessed across literature (Mekki et al., 2019, Al-Kashoash and Kemp, 2016, Vejlgaard et al., 2017). Table 3 highlights key features of each.

Table 3- ***outline of the key features, benefits and challenges of 3 types of IoT LPWAN technology***

	Sigfox	LoRa	NB-IoT
Method	Ultra-Narrow Band (UNB) modulation (Vejlgaard et al., 2017).	Proprietary spread spectrum modulation (Vejlgaard et al., 2017).	Simplified version of Long Term Evolution (LTE) technology
Elements	4 key elements: end note, gateway, network service and end user application. (Al-Kashoash and Kemp, 2016)	4 key elements: end note, gateway, network service and end user application. (Al-Kashoash and Kemp, 2016)	3 modes- 2 using simplified LTE and 1 occupying a sublicensed GSM channel (Ratasuk et al., 2016).
Communication	Allows 140 uplink messages per day, with a maximum payload of 12 bytes and 4 downlink messages per day (Mekki et al., 2019)	3 different classes of device depending on power resource. Class A (only allows downlink) to Class C which is constantly listening and communicating. (Montori et al., 2018)	Bidirectional allowance including services such as authentication, policy, tracking and security (Ratasuk et al., 2016).
Benefits	• Due to use of UNB, is very efficient and very low power. • Nodes cannot talk between themselves reducing power needs (Al-Kashoash and Kemp, 2016). • Data can be called by users from Sigfox backend very API. (Mekki et al., 2019)	• Different classes allow for targeting specific user needs. • Spread across a narrow band signal, but wider channel bandwidth means signals have low noise and are hard to interrupt.	• Higher service and data rates than other options. (Sinha et al., 2017, Vejlgaard et al., 2017) • Option for security features (Ratasuk et al., 2016).

Challenges	Limited message size and frequency as a compromise of low power.	Bidirectional messaging means potentially higher power usage than Sigfox.	Higher costs than alternate options Lower coverage (Sinha et al., 2017, Vejlgaard et al., 2017)

Whilst all of these LPWANs aim for similar goals of wide area coverage and low battery consumption and cost, comparisons in the literature demonstrate variations in the suitability of the different network services. NB-IoT generally outperforms compared to Sigfox and LoRa in terms of quality of service and data rates however it is more expensive and has lower coverage than its counterparts (Sinha et al., 2017, Vejlgaard et al., 2017). NB-IoT is more suited to high value IoT networks whilst Sigfox and LoRa perform similarly and are more suitable for those who need infrequent communication of smaller message sizes at greater ranges (Mekki et al., 2019). Therefore, Sigfox and LoRa are more suitable for environmental monitoring networks using low-cost sensors, as they enable power and cost requirements to be kept minimal. This means that if low-cost sensors were able to efficiently utilise LoRa/Sigfox and maintain low-power, they could be turned into highly mobile battery or solar powered sensing units. This would allow for increased spatial coverage of pollution monitoring in locations that were previously unattainable as the requirement for mains power would be removed from the siting requirements of a sensor. There is also room for significant development of sensing networks, these have traditionally required power intensive communication such as WiFi or used SD cards limiting accessibility to real time data. This thesis demonstrates an example of adapting this technology to fit this research gap. In doing so, it enables more fundamental science questions on the spatial variability of air pollution to be explored.

4. Thesis aims and structure

Reviewing air quality sampling in Birmingham, and in more generally particulate matter, there is clear growth in the use of low-cost sensing air quality networks. Real-world application of this technology provides opportunity to enhance understanding of their performance; allowing for the development of standardised methods and best practice to ensure low-cost sensor data can be used to support high-resolution monitoring for decision making.
The overall aim of this thesis is to apply low-cost and IoT technology to particulate matter monitoring. Specific research goals include:

1. Design, build and deploy a low-cost IoT enabled PM sensing device
2. Evaluating the performance of low-cost sensors and IoT adaptability, including the viability of sensor networks
3. Developing scalable calibration methods for low-cost sensors
4. Applying the use of low-cost sensors for meaningful insights into both indoor and ambient PM exposures
5. Evaluating and presenting learnings and best practice for using and future proofing automated sensor data

These research goals highlighted and enabled the following scientific questions to be tested throughout the subsequent chapters of this thesis:

1. How does meteorology and particulate composition affect the performance of an optical based low-cost sensor? What are the methods (and their limitations) of overcoming effects?
2. How does particulate matter in a typical British home vary by room and activity? What potential do IoT sensor networks have at increasing indoor AQ understanding?
3. What effect does ventilation have on indoor particulate exposure?
4. How well does a nested network of various embedded low-cost sensor technology perform in an extended deployment across a city?
5. Does a low-cost embedded sensor network for air quality provided additional insight into spatial variability $PM_{2.5}$ concentrations?
6. How can real-time open access particulate matter measurements be used to enhance and support decision making?

This thesis presents the findings from the development, calibration, application and evaluation of an embedded low-cost IoT air quality sensor network. Table 4 presents how the following chapters of this thesis capture and answer the research goals and questions outlined above. Chapter 2 presents the development of an IoT enabled OPC (called AltasensePM) and results from a colocation at an establish reference site, including a calibration method for ambient monitoring. Chapter 3 presents the application of AltasensePM inside a typical British suburban home, developing a second calibration method suited for indoor sampling and presenting results on activity related PM exposures. Chapter 4 presents the application and evaluation of an ambient sensor network of both AltasensePM and commercial low-cost sensors across the Birmingham conurbation, evaluating the regions PM concentrations and the network itself. Chapter 5 takes a look forward at the role of low-cost sensing in the digital and big data age, evaluating potential application of automated air quality data, particularly within digital twins.

Table 4- ***chapter breakdown of where each research goal and scientific question outlined above is addressed within this thesis.***

Chapter	Research goals	Scientific question
Chapter 2: *Field Calibration and Evaluation of an Internet-of-Things-Based Particulate Matter Sensor*	1, 2,3	1
Chapter 3: *Particulate matter in a lockdown home: evaluation, calibration, results and health risk from an IoT enabled low-cost sensor network for residential air quality monitoring*	1,2,3,	1,2,3,
Chapter 4: *What can we learn from nested IoT low-cost sensor networks for air quality ? A case study of PM2.5 in a Clean Air Zone*	1,2,3,4	4,5
Chapter 5: *Moving from monitoring to real-time*	4	5,6

interventions for air quality: the future role of low-cost sensors, IoT and digital twins		

References

ABDUL-RAZZAK, H. 2012. *Atmospheric Aerosols: Regional Characteristics-Chemistry and Physics*, BoD–Books on Demand.

ACTON, W., ZHONG, J. & BLOSS, W. 2023. What is PM2. 5? An introduction to particulate matter in the atmosphere: a briefing note.

AIR QUALITY EXPERT GROUP 2012. Fine Particulate Matter (PM2.5) in the United Kingdom. *In:* DEFRA (ed.). Online: DEFRA.

AIR QUALITY EXPERT GROUP 2019. Non-Exhaust Emissions from Road Traffic. *In:* DEFRA (ed.). Online: DEFRA.

AIRLY. 2023. *airly* [Online]. Available: https://airly.org/en/ [Accessed 16.01.23].

AL-KASHOASH, H. A. & KEMP, A. H. 2016. Comparison of 6LoWPAN and LPWAN for the Internet of Things. *Australian Journal of Electrical and Electronics Engineering,* 13**,** 268-274.

AMARAL, S. S., DE CARVALHO, J. A., COSTA, M. A. M. & PINHEIRO, C. 2015. An Overview of Particulate Matter Measurement Instruments. *Atmosphere,* 6**,** 1327-1345.

AMATO, F., CASSEE, F. R., DENIER VAN DER GON, H. A., GEHRIG, R., GUSTAFSSON, M., HAFNER, W., HARRISON, R. M., JOZWICKA, M., KELLY, F. J., MORENO, T., PREVOT, A. S., SCHAAP, M., SUNYER, J. & QUEROL, X. 2014. Urban air quality: the challenge of traffic non-exhaust emissions. *J Hazard Mater,* 275**,** 31-6.

AQEG 2005. Particulate Matter in the UK. *In:* DEFRA (ed.). London.

ARDUINO 2020. Arduino Low Power Library. 1.2.0 ed. Online.

ARROYO, P., HERRERO, J. L., SUÁREZ, J. I. & LOZANO, J. 2019. Wireless sensor network combined with cloud computing for air quality monitoring. *Sensors,* 19**,** 691.

BARKJOHN, K. K., GANTT, B. & CLEMENTS, A. L. 2021. Development and application of a United States-wide correction for PM 2.5 data collected with the PurpleAir sensor. *Atmospheric Measurement Techniques,* 14**,** 4617-4637.

BAWA, J., AYUBA, P. & AKANDE, O. Factors Influencing the Performance of Indoor Environmental Quality of Pharmaceutical Factory Buildings in Southwest Nigeria. IOP Conference Series: Earth and Environmental Science, 2022. IOP Publishing, 012023.

BEDDOWS, D. C. S. & HARRISON, R. M. 2021. PM10 and PM2.5 emission factors for non-exhaust particles from road vehicles: Dependence upon vehicle mass and implications for battery electric vehicles. *Atmospheric Environment,* 244**,** 117886.

BENNETT, J., DAVY, P., TROMPETTER, B., WANG, Y., PIERSE, N., BOULIC, M., PHIPPS, R. & HOWDEN-CHAPMAN, P. 2019. Sources of indoor air pollution at a New Zealand urban primary school; a case study. *Atmospheric Pollution Research,* 10**,** 435-444.

BLOEMAN, H., VAN DER MEULEN, A., MOOIBROEK, D. & CASSEE, F. 2007. Monitoring Black Smoke? Monitoring the impact of abatement measures Netherlands: Ministery of Housing, Physical Planning and Environment.

BORREGO, C., COSTA, A. M., GINJA, J., AMORIM, M., COUTINHO, M., KARATZAS, K., SIOUMIS, T., KATSIFARAKIS, N., KONSTANTINIDIS, K., DE VITO, S., ESPOSITO, E., SMITH, P., ANDRÉ, N., GÉRARD, P., FRANCIS, L. A., CASTELL, N., SCHNEIDER, P., VIANA, M., MINGUILLÓN, M. C., REIMRINGER, W., OTJES, R. P., VON SICARD, O., POHLE, R., ELEN, B., SURIANO, D., PFISTER,

V., PRATO, M., DIPINTO, S. & PENZA, M. 2016. Assessment of air quality microsensors versus reference methods: The EuNetAir joint exercise. *Atmospheric Environment,* 147**,** 246-263.
BOUBRIMA, A., BECHKIT, W. & RIVANO, H. 2019. On the deployment of wireless sensor networks for air quality mapping: optimization models and algorithms. *IEEE/ACM Transactions on Networking,* 27**,** 1629-1642.
BRADY, J., NOLAN, K., NOLAN, M. & KELLY, M. 2020. Alert system for internet of things (IoT) devices. Google Patents.
BRATTICH, E., BRACCI, A., ZAPPI, A., MOROZZI, P., DI SABATINO, S., PORCÙ, F., DI NICOLA, F. & TOSITTI, L. 2020. How to Get the Best from Low-Cost Particulate Matter Sensors: Guidelines and Practical Recommendations. *Sensors,* 20**,** 3073.
BRIMBLECOMBE, P. & GROSSI, C. M. 2005. Aesthetic thresholds and blackening of stone buildings. *Science of The Total Environment,* 349**,** 175-189.
BROOK, R. D., RAJAGOPALAN, S., POPE III, C. A., BROOK, J. R., BHATNAGAR, A., DIEZ-ROUX, A. V., HOLGUIN, F., HONG, Y., LUEPKER, R. V. & MITTLEMAN, M. A. 2010. Particulate matter air pollution and cardiovascular disease: an update to the scientific statement from the American Heart Association. *Circulation,* 121**,** 2331-2378.
BUDDE, M., EL MASRI, R., RIEDEL, T. & BEIGL, M. Enabling low-cost particulate matter measurement for participatory sensing scenarios. Proceedings of the 12th international conference on mobile and ubiquitous multimedia, 2013. 1-10.
BULOT, F. M., JOHNSTON, S. J., BASFORD, P. J., EASTON, N. H., APETROAIE-CRISTEA, M., FOSTER, G. L., MORRIS, A. K., COX, S. J. & LOXHAM, M. 2019. Long-term field comparison of multiple low-cost particulate matter sensors in an outdoor urban environment. *Scientific reports,* 9**,** 1-13.
BURNS, P. 2019. 2019 Air Quality Annual Status Report. *In:* HEALTH, E. (ed.). Manor House, Birmingham: Birmingham City Council.
CAO, Z., ZHOU, J., LI, M., HUANG, J. & DOU, D. 2023. Urbanites' mental health undermined by air pollution. *Nature Sustainability*.
CARSLAW, D. & ROPKINS, K. 2012. openair — An R package for air quality data analysis. *Environmental Modelling & Software,* 27–28(0)**,** 52–61.
CASTELL, N., DAUGE, F. R., SCHNEIDER, P., VOGT, M., LERNER, U., FISHBAIN, B., BRODAY, D. & BARTONOVA, A. 2017. Can commercial low-cost sensor platforms contribute to air quality monitoring and exposure estimates? *Environment international,* 99**,** 293-302.
CHAPMAN, L., MULLER, C. L., YOUNG, D. T., WARREN, E. L., GRIMMOND, C. S. B., CAI, X.-M. & FERRANTI, E. J. 2015. The Birmingham urban climate laboratory: An open meteorological test bed and challenges of the smart city. *Bulletin of the American Meteorological Society,* 96**,** 1545-1560.
CHAPMAN, L., WARREN, E. & CHAPMAN, V. Using the internet of things to monitor low adhesion on railways. Proceedings of the Institution of Civil Engineers-Transport, 2016. Thomas Telford Ltd, 321-329.
CHARRON, A. & HARRISON, R. M. 2005. Fine (PM2.5) and Coarse (PM2.5-10) Particulate Matter on A Heavily Trafficked London Highway: Sources and Processes. *Environmental Science & Technology,* 39**,** 7768-7776.
CHONG, C.-Y. & KUMAR, S. 2003. Sensor Networks: Evolution, opportunities, and challenges. *Proceedings of the IEEE,* 91**,** 1247-1256.
CLARITY. 2023. *Node-S Technical Specifications* [Online]. online. Available: https://click.clarity.io/hubfs/Marketing%20Assets%20-%20PDFs/Product%20and%20Specification%20Sheets/Node-S%202%20Specifications%20Sheet%20(October%202021).pdf?_ga=2.178201957.1344132639.1673886395-1714968752.1673886395&_gac=1.209505958.1673886395.EAIaIQobChMIwMih3cDM_AIVRWHmCh0ndwteEAAYASAAEgIIIPD_BwE [Accessed 16.01.23].

COCÂRŢĂ, D. M., PRODANA, M., DEMETRESCU, I., LUNGU, P. E. M. & DIDILESCU, A. C. 2021. Indoor Air Pollution with Fine Particles and Implications for Workers' Health in Dental Offices: A Brief Review. *Sustainability,* 13**,** 599.

COLES, J. & TIWARY, A. 2009. *Air Pollution : Measurement, Modelling and Mitigation,* London, CRC Press LLC.

CRILLEY, L. R., SHAW, M., POUND, R., KRAMER, L. J., PRICE, R., YOUNG, S., LEWIS, A. C. & POPE, F. D. 2018. Evaluation of a low-cost optical particle counter (Alphasense OPC-N2) for ambient air monitoring. *Atmospheric Measurement Techniques***,** 709-720.

CRILLEY, L. R., SINGH, A., KRAMER, L. J., SHAW, M. D., ALAM, M. S., APTE, J. S., BLOSS, W. J., HILDEBRANDT RUIZ, L., FU, P., FU, W., GANI, S., GATARI, M., ILYINSKAYA, E., LEWIS, A. C., NG'ANG'A, D., SUN, Y., WHITTY, R. C. W., YUE, S., YOUNG, S. & POPE, F. D. 2020. Effect of aerosol composition on the performance of low-cost optical particle counter correction factors. *Atmos. Meas. Tech.,* 13**,** 1181-1193.

DE NAZELLE, A., BODE, O. & ORJUELA, J. P. 2017. Comparison of air pollution exposures in active vs. passive travel modes in European cities: A quantitative review. *Environment international,* 99**,** 151-160.

DEFRA. 2023a. *Glossary* [Online]. online. Available: https://uk-air.defra.gov.uk/air-pollution/glossary.php?glossary_id=16#:~:text=Black%20Smoke,emitted%20mainly%20from%20fuel%20combustion. [Accessed 20.03.23].

DEFRA 2023b. National statistics Emissions of air pollutants in the UK – Particulate matter (PM10 and PM2.5). online.

DEMANEGA, I., MUJAN, I., SINGER, B. C., ANĐELKOVIĆ, A. S., BABICH, F. & LICINA, D. 2021. Performance assessment of low-cost environmental monitors and single sensors under variable indoor air quality and thermal conditions. *Building and Environment,* 187**,** 107415.

DEPARTMENT OF ENVIRONMENTAL FOOD AND RURAL AFFAIRS. 2022. *Interactive monitoring networks map* [Online]. Available: https://uk-air.defra.gov.uk/interactive-map [Accessed 12/01/2023].

DEPARTMENT OF ENVIRONMENTAL FOOD AND RURAL AFFAIRS 2023a. Emissions of air pollutants in the UK – Particulate matter (PM10 and PM2.5). *In:* STATISTICS, N. (ed.). online.

DEPARTMENT OF ENVIRONMENTAL FOOD AND RURAL AFFAIRS. 2023b. *Site Environment Types* [Online]. Available: https://uk-air.defra.gov.uk/networks/site-types [Accessed 11/01/2023].

DI ANTONIO, A., POPOOLA, O. A., OUYANG, B., SAFFELL, J. & JONES, R. L. 2018. Developing a relative humidity correction for low-cost sensors measuring ambient particulate matter. *Sensors,* 18**,** 2790.

DOGEANU, A., NASTASE, I., URSU, I., ENCIU, D., BODE, F., SANDU, M., CROITORU, C., ZAHARIA, S. & IANA, G. Real time monitoring network demonstrator for air quality management. 2019 International Conference on ENERGY and ENVIRONMENT (CIEM), 2019. IEEE, 459-463.

DYER, C. 2020. Air pollution from road traffic contributed to girl's death from asthma, coroner concludes. British Medical Journal Publishing Group.

EARTHSENSE 2022. Zephyr Air Quality Monitor Specification Sheet. online.

EJOHWOMU, O. A., OLADOKUN, M., OSHODI, O. S., BUKOYE, O. T., EDWARDS, D. J., EMEKWURU, N., ADENUGA, O., SOTUNBO, A., UDUKU, O. & BALOGUN, M. 2022. The Exposure of Workers at a Busy Road Node to PM2. 5: Occupational Risk Characterisation and Mitigation Measures. *International Journal of Environmental Research and Public Health,* 19**,** 4636.

ENVIRONMENT PROTECTION AUTHORITY 2004. Photochemical smog

—what it means for us Adelaide.

EU-DIRECTIVE 2008. 2008/50/EC of the European Parliament and the Council of 21 May 2008 on Ambient Air Quality and Cleaner Air for Europe.

EUROPEAN AUTOMOBILE MANUFACTURERS ASSOCIATION 2022. Vehicles in use Europe 2022. online.

EUROPEAN COMMISSION. 2022. *Questions and Answers: Commission proposal on the new Euro 7 standards* [Online]. Brussels. Available: https://ec.europa.eu/commission/presscorner/detail/en/qanda_22_6496 [Accessed 20.03.23].

EUROPEAN COMMISSION. 2023. *Coarse particles* [Online]. online. Available: https://ec.europa.eu/health/scientific_committees/opinions_layman/en/indoor-air-pollution/glossary/abc/coarse-particles.htm#:~:text=Coarse%20particles%20have%20an%20aerodynamic,1). [Accessed 08.05.23].

EUROPEAN UNION 2008. Directive 2008/50/EC of the European Parliament and of the Council of 21 May 2008 on ambient air quality and cleaner air for Europe. Official Journal of the European Union.

FEENSTRA, B., PAPAPOSTOLOU, V., HASHEMINASSAB, S., ZHANG, H., BOGHOSSIAN, B. D., COCKER, D. & POLIDORI, A. 2019. Performance evaluation of twelve low-cost PM2.5 sensors at an ambient air monitoring site. *Atmospheric Environment,* 216**,** 116946.

FERRO, A. R., ZÍKOVÁ, N., MASIOL, M., SATSANGI, G. P., TWOMEY, T., CHALUPA, D. C., RICH, D. Q. & HOPKE, P. K. 2022. Residential Indoor and Outdoor PM Measured Using Low-cost Monitors during the Heating Season in Monroe County, NY. *Aerosol and Air Quality Research,* 22**,** 220210.

FISHBAIN, B., LERNER, U., CASTELL, N., COLE-HUNTER, T., POPOOLA, O., BRODAY, D. M., IÑIGUEZ, T. M., NIEUWENHUIJSEN, M., JOVASEVIC-STOJANOVIC, M. & TOPALOVIC, D. 2017. An evaluation tool kit of air quality micro-sensing units. *Science of the total environment,* 575**,** 639-648.

FONT, A., CIUPEK, K., BUTTERFIELD, D. & FULLER, G. W. 2022. Long-term trends in particulate matter from wood burning in the United Kingdom: Dependence on weather and social factors. *Environmental Pollution,* 314**,** 120105.

FRIEDLANDER, S. 2000. *Smoke, Dust and Haze Fundamentals of Aerosol Dynamics,* New York, Oxford University Press.

FUZZI, S., BALTENSPERGER, U., CARSLAW, K., DECESARI, S., DENIER VAN DER GON, H., FACCHINI, M. C., FOWLER, D., KOREN, I., LANGFORD, B., LOHMANN, U., NEMITZ, E., PANDIS, S., RIIPINEN, I., RUDICH, Y., SCHAAP, M., SLOWIK, J. G., SPRACKLEN, D. V., VIGNATI, E., WILD, M., WILLIAMS, M. & GILARDONI, S. 2015. Particulate matter, air quality and climate: lessons learned and future needs. *Atmos. Chem. Phys.,* 15**,** 8217-8299.

GOMEZ, C., VERAS, J. C., VIDAL, R., CASALS, L. & PARADELLS, J. 2019. A sigfox energy consumption model. *Sensors,* 19**,** 681.

GORAI, A. K., TCHOUNWOU, P. B., BISWAL, S. S. & TULURI, F. 2018. Spatio-Temporal Variation of Particulate Matter(PM2.5) Concentrations and Its Health Impacts in a Mega City, Delhi in India. *Environmental Health Insights,* 12**,** 1178630218792861.

GREATER LONDON AUTHORITY 2019. PM2.5 in London:Roadmap to meeting World Health Organization guidelines by 2030. City Hall, London.

GULIA, S., KHANNA, I., SHUKLA, K. & KHARE, M. 2020. Ambient air pollutant monitoring and analysis protocol for low and middle income countries: An element of comprehensive urban air quality management framework. *Atmospheric Environment,* 222**,** 117120.

GUPTA, P., CHRISTOPHER, S. A., WANG, J., GEHRIG, R., LEE, Y. & KUMAR, N. 2006. Satellite remote sensing of particulate matter and air quality assessment over global cities. *Atmospheric Environment,* 40**,** 5880-5892.

GUTTIKUNDA, S. K., GOEL, R. & PANT, P. 2014. Nature of air pollution, emission sources, and management in the Indian cities. *Atmospheric Environment,* 95**,** 501-510.

HARR, L., SINSEL, T., SIMON, H. & ESPER, J. 2022. Seasonal Changes in Urban PM2. 5 Hotspots and Sources from Low-Cost Sensors. *Atmosphere,* 13**,** 694.

HARRISON, R. M. 2020. Airborne particulate matter. *Philosophical Transactions of the Royal Society A,* 378**,** 20190319.
HARRISON, R. M., ALLAN, J., CARRUTHERS, D., HEAL, M. R., LEWIS, A. C., MARNER, B., MURRELLS, T. & WILLIAMS, A. 2021. Non-exhaust vehicle emissions of particulate matter and VOC from road traffic: A review. *Atmospheric Environment,* 262**,** 118592.
HARRISON, R. M. & YIN, J. 2000. Particulate matter in the atmosphere: which particle properties are important for its effects on health? *Science of The Total Environment,* 249**,** 85-101.
HE, M., KUERBANJIANG, N. & DHANIYALA, S. 2020. Performance characteristics of the low-cost Plantower PMS optical sensor. *Aerosol Science and Technology,* 54**,** 232-241.
HIME, N., COWIE, C. & MARKS, G. 2015. *Review of the health impacts of emission sources, types and levels of particulate matter air pollution in ambient air in NSW*.
HOEK, G., WELINDER, H., VASKOVI, E., CIACCHINI, G., MANALIS, N., RØYSET, O., REPONEN, A., CYRYS, J. & BRUNEKREEF, B. 1997. Interlaboratory comparison of PM10 and black smoke measurements in the PEACE study. *Atmospheric Environment,* 31**,** 3341-3349.
HOFMAN, J., PETERS, J., STROOBANTS, C., ELST, E., BAEYENS, B., VAN LAER, J., SPRUYT, M., VAN ESSCHE, W., DELBARE, E. & ROELS, B. 2022. Air Quality Sensor Networks for Evidence-Based Policy Making: Best Practices for Actionable Insights. *Atmosphere,* 13**,** 944.
HOPKE, P. K., DAI, Q., LI, L. & FENG, Y. 2020. Global review of recent source apportionments for airborne particulate matter. *Science of The Total Environment,* 740**,** 140091.
HUANG, H., LEE, S.-C., CAO, J.-J., ZOU, C.-W., CHEN, X.-G. & FAN, S.-J. 2007. Characteristics of indoor/outdoor PM2.5 and elemental components in generic urban, roadside and industrial plant areas of Guangzhou City, China. *Journal of Environmental Sciences,* 19**,** 35-43.
HUANG, T.-H., TSAI, C.-H. & SHAN, M.-K. Key sensor discovery for quality audit of air sensor networks. Proceedings of the 18th International Conference on Mobile Systems, Applications, and Services, 2020. 474-475.
IAQM, I. O. A. Q. M. 2018. IAQM Guidance On Air Quality Monitoring In The Vicinity Of Demolition And Construction Sites.
ILACQUA, V., SCHARKO, N., ZAMBRANA, J. & MALASHOCK, D. 2022. Survey of residential indoor particulate matter measurements 1990–2019. *Indoor air,* 32**,** e13057.
JALADI, A. R., KHITHANI, K., PAWAR, P., MALVI, K. & SAHOO, G. 2017. Environmental monitoring using wireless sensor networks (WSN) based on IOT. *Int. Res. J. Eng. Technol,* 4**,** 1371-1378.
JERZY, M. & JACEK, P. 2015. *Nanoparticle Emissions From Combustion Engines,* Cham, Springer.
JOHNSON, K. K., BERGIN, M. H., RUSSELL, A. G. & HAGLER, G. S. 2018. Field test of several low-cost particulate matter sensors in high and low concentration urban environments. *Aerosol and Air Quality Research,* 18**,** 565.
JORIS, L., DUPONT, F., LAURENT, P., BELLIER, P., STOUKATCH, S. & REDOUTÉ, J.-M. 2019. An autonomous sigfox wireless sensor node for environmental monitoring. *IEEE Sensors Letters,* 3**,** 01-04.
KADDOURA, I., EWERT, R. & MARTINS-TURNER, K. 2022. Exhaust and non-exhaust emissions from today's and future road transport: A simulation-based quantification for Berlin. *Transportation Research Procedia,* 62**,** 696-702.
KAISER, H. & SPECKER, H. 1956. Evaluation and comparison of methods of analysis. *Z. anal. Chem,* 149**,** 46.
KALISZEWSKI, M., WŁODARSKI, M., MŁYŃCZAK, J. & KOPCZYŃSKI, K. 2020. Comparison of Low-Cost Particulate Matter Sensors for Indoor Air Monitoring during COVID-19 Lockdown. *Sensors,* 20.
KARAGULIAN, F., BELIS, C. A., DORA, C. F. C., PRÜSS-USTÜN, A. M., BONJOUR, S., ADAIR-ROHANI, H. & AMANN, M. 2015. Contributions to cities' ambient particulate matter (PM): A systematic review of local source contributions at global level. *Atmospheric environment,* 120**,** 475-483.

KELLY, K., WHITAKER, J., PETTY, A., WIDMER, C., DYBWAD, A., SLEETH, D., MARTIN, R. & BUTTERFIELD, A. 2017. Ambient and laboratory evaluation of a low-cost particulate matter sensor. *Environmental Pollution,* 221**,** 491-500.

KNOLL, M., BREITEGGER, P. & BERGMANN, A. 2018. Low-Power Wide-Area technologies as building block for smart sensors in air quality measurements. *e & i Elektrotechnik und Informationstechnik,* 135**,** 416-422.

KULARATNA, N. & SUDANTHA, B. 2008. An environmental air pollution monitoring system based on the IEEE 1451 standard for low cost requirements. *IEEE Sensors Journal,* 8**,** 415-422.

KULMALA, M., MASO, M. D., MÄKELÄ, J., PIRJOLA, L., VÄKEVÄ, M., AALTO, P., MIIKKULAINEN, P., HÄMERI, K. & O'DOWD, C. 2001. On the formation, growth and composition of nucleation mode particles. *Tellus B,* 53**,** 479-490.

KÜPPER, M., ASBACH, C., SCHNEIDERWIND, U., FINGER, H., SPIEGELHOFF, D. & SCHUMACHER, S. 2019. Testing of an indoor air cleaner for particulate pollutants under realistic conditions in an office room. *Aerosol and Air Quality Research,* 19**,** 1655-1665.

KUULA, J., MÄKELÄ, T., HILLAMO, R. & TIMONEN, H. 2017. Response Characterization of an Inexpensive Aerosol Sensor. *Sensors (Basel, Switzerland),* 17**,** 2915.

KWON, H.S., RYU, M.H. AND CARLSTEN, C., 2020. Ultrafine particles: unique physicochemical properties relevant to health and disease. *Experimental & molecular medicine*, *52*(3), pp.318-328.

LAVRIC, A. & POPA, V. Internet of things and LoRa™ low-power wide-area networks: a survey. 2017 International Symposium on Signals, Circuits and Systems (ISSCS), 2017. IEEE, 1-5.

LAZARESCU, M. T. 2013. Design of a WSN platform for long-term environmental monitoring for IoT applications. *IEEE Journal on emerging and selected topics in circuits and systems,* 3**,** 45-54.

LEVY ZAMORA, M., XIONG, F., GENTNER, D., KERKEZ, B., KOHRMAN-GLASER, J. & KOEHLER, K. 2018. Field and laboratory evaluations of the low-cost plantower particulate matter sensor. *Environmental science & technology,* 53**,** 838-849.

LEVY ZAMORA, M., XIONG, F., GENTNER, D., KERKEZ, B., KOHRMAN-GLASER, J. & KOEHLER, K. 2019. Field and Laboratory Evaluations of the Low-Cost Plantower Particulate Matter Sensor. *Environmental Science & Technology,* 53**,** 838-849.

LEWIS, A., MOLLER, S. J. & CARSLAW, D. 2019. Non-exhaust emissions from road traffic.

LEWIS, A., PELTIER, W. R. & VON SCHNEIDEMESSER, E. 2018. Low-cost sensors for the measurement of atmospheric composition: overview of topic and future applications.

LEWIS, A. C., LEE, J. D., EDWARDS, P. M., SHAW, M. D., EVANS, M. J., MOLLER, S. J., SMITH, K. R., BUCKLEY, J. W., ELLIS, M., GILLOT, S. R. & WHITE, A. 2016. Evaluating the performance of low cost chemical sensors for air pollution research. *Faraday Discussions,* 189**,** 85-103.

LI, N., GEORAS, S., ALEXIS, N., FRITZ, P., XIA, T., WILLIAMS, M. A., HORNER, E. & NEL, A. 2016. A work group report on ultrafine particles (AAAAI) why ambient ultrafine and engineered nanoparticles should receive special attention for possible adverse health outcomes in humans. *The Journal of allergy and clinical immunology,* 138**,** 386.

LI, S., XU, L. D. & ZHAO, S. 2015. The internet of things: a survey. *Information Systems Frontiers,* 17**,** 243-259.

LI, Z., WEN, Q. & ZHANG, R. 2017. Sources, health effects and control strategies of indoor fine particulate matter (PM2.5): A review. *Science of The Total Environment,* 586**,** 610-622.

LIU, Y., CHEN, H., LI, Y., GAO, J., DAVE, K., CHEN, J., LI, T. & TU, R. 2022. Exhaust and non-exhaust emissions from conventional and electric vehicles: A comparison of monetary impact values. *Journal of Cleaner Production,* 331**,** 129965.

MAGI, B. I., CUPINI, C., FRANCIS, J., GREEN, M. & HAUSER, C. 2020. Evaluation of PM2. 5 measured in an urban setting using a low-cost optical particle counter and a Federal Equivalent Method Beta Attenuation Monitor. *Aerosol Science and Technology,* 54**,** 147-159.

MANDIN, C., TRANTALLIDI, M., CATTANEO, A., CANHA, N., MIHUCZ, V. G., SZIGETI, T., MABILIA, R., PERRECA, E., SPINAZZÈ, A., FOSSATI, S., DE KLUIZENAAR, Y., CORNELISSEN, E., SAKELLARIS, I.,

SARAGA, D., HÄNNINEN, O., DE OLIVEIRA FERNANDES, E., VENTURA, G., WOLKOFF, P., CARRER, P. & BARTZIS, J. 2017. Assessment of indoor air quality in office buildings across Europe – The OFFICAIR study. *Science of The Total Environment,* 579**,** 169-178.

MATTHAIOS, V. N., LAWRENCE, J., MARTINS, M. A. G., FERGUSON, S. T., WOLFSON, J. M., HARRISON, R. M. & KOUTRAKIS, P. 2022. Quantifying factors affecting contributions of roadway exhaust and non-exhaust emissions to ambient PM10–2.5 and PM2.5–0.2 particles. *Science of The Total Environment,* 835**,** 155368.

MCCORMICK, R. A., LIGHTHILL, M. J. & SILVERLEAF, A. 1971. Air pollution in the locality of buildings. *Philosophical Transactions of the Royal Society of London. Series A, Mathematical and Physical Sciences,* 269**,** 515-526.

MCFIGGANS, G. (2018). "Readily Mixed Atmospheric Organic Particles." Chem **4**(3): 399-401.

MEAD, M., POPOOLA, O., STEWART, G., LANDSHOFF, P., CALLEJA, M., HAYES, M., BALDOVI, J., MCLEOD, M., HODGSON, T. & DICKS, J. 2013. The use of electrochemical sensors for monitoring urban air quality in low-cost, high-density networks. *Atmospheric Environment,* 70**,** 186-203.

MEKKI, K., BAJIC, E., CHAXEL, F. & MEYER, F. Overview of cellular LPWAN technologies for IoT deployment: Sigfox, LoRaWAN, and NB-IoT. 2018 ieee international conference on pervasive computing and communications workshops (percom workshops), 2018. IEEE, 197-202.

MEKKI, K., BAJIC, E., CHAXEL, F. & MEYER, F. 2019. A comparative study of LPWAN technologies for large-scale IoT deployment. *ICT express,* 5**,** 1-7.

MOHAMMADYAN, M., ALIZADEH-LARIMI, A., ETEMADINEJAD, S., LATIF, M. T., HEIBATI, B., YETILMEZSOY, K., ABDUL-WAHAB, S. A. & DADVAND, P. 2017. Particulate air pollution at schools: Indoor-outdoor relationship and determinants of indoor concentrations. *Aerosol and Air Quality Research,* 17**,** 857-864.

MOUSAVI, A. & WU, J. 2021. Indoor-Generated PM2.5 During COVID-19 Shutdowns Across California: Application of the PurpleAir Indoor–Outdoor Low-Cost Sensor Network. *Environmental Science & Technology,* 55**,** 5648-5656.

MUKHERJEE, A. & AGRAWAL, M. 2017. World air particulate matter: sources, distribution and health effects. *Environmental Chemistry Letters,* 15**,** 283-309.

MUKHERJEE, A., STANTON, L. G., GRAHAM, A. R. & ROBERTS, P. T. 2017. Assessing the utility of low-cost particulate matter sensors over a 12-week period in the Cuyama valley of California. *Sensors,* 17**,** 1805.

MYHRE, G., D. SHINDELL, F.-M. BRÉON, W. COLLINS, J. FUGLESTVEDT, J. HUANG, D. KOCH, J.-F. LAMARQUE, D. LEE, B. MENDOZA, T. NAKAJIMA, A. ROBOCK, G. STEPHENS, T. TAKEMURA AND H. ZHANG, 2013. Anthropogenic and Natural Radiative Forcing. In: *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* [Stocker, T.F., D. Qin, G.-K. Plattner, M. Tignor, S.K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex and P.M. Midgley (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York,NY, USA, pp. 659–740, doi:10.1017/ CBO9781107415324.018.

NAGARAJ, S. & BIRADAR, R. V. Applications of wireless sensor networks in the real-time ambient air pollution monitoring and air quality in metropolitan cities—a survey. 2017 International Conference On Smart Technologies For Smart Nation (SmartTechCon), 2017. IEEE, 1393-1398.

NATIONAL ATMOSPHERIC EMISSIONS INVENTORY 2022. Pollutant Information: PM2.5.

NORTHCROSS, A. L., EDWARDS, R. J., JOHNSON, M. A., WANG, Z.-M., ZHU, K., ALLEN, T. & SMITH, K. R. 2013. A low-cost particle counter as a realtime fine-particle mass monitor. *Environmental Science: Processes & Impacts,* 15**,** 433-439.

OFFICE OF AIR AND RADIATION. 2003. *Particle Pollution and Your Health* [Online]. Online/USA: Environmental Protection Agency. Available: https://nepis.epa.gov/Exe/ZyPDF.cgi?Dockey=P1001EX6.txt [Accessed 14/03/2023].

OJO, K. D., SONEJA, S. I., SCRAFFORD, C. G., KHATRY, S. K., LECLERQ, S. C., CHECKLEY, W., KATZ, J., BREYSSE, P. N. & TIELSCH, J. M. 2015. Indoor particulate matter concentration, water boiling time, and fuel use of selected alternative cookstoves in a home-like setting in rural Nepal. *International journal of environmental research and public health,* 12**,** 7558-7581.

OUIMETTE, J. R., MALM, W. C., SCHICHTEL, B. A., SHERIDAN, P. J., ANDREWS, E., OGREN, J. A. & ARNOTT, W. P. 2022. Evaluating the PurpleAir monitor as an aerosol light scattering instrument. *Atmos. Meas. Tech.,* 15**,** 655-676.

OZGA, I., BONAZZA, A., BERNARDI, E., TITTARELLI, F., FAVONI, O., GHEDINI, N., MORSELLI, L. & SABBIONI, C. 2011. Diagnosis of surface damage induced by air pollution on 20th-century concrete buildings. *Atmospheric Environment,* 45**,** 4986-4995.

PANCHAL, R., PANAGI, M., MAY, H. R., OBSZYNSKA, J. A., EVANS, M. S., HANSELL, A. L., GULLIVER, J. & HEY, J. D. V. 2022. Personal air pollution exposure during morning commute car and active transport journeys. *Journal of Transport & Health***,** 101365.

PANT, P. & HARRISON, R. M. 2013. Estimation of the contribution of road traffic emissions to particulate matter concentrations from field measurements: A review. *Atmospheric Environment,* 77**,** 78-97.

PATEL, D. & WON, M. Experimental study on low power wide area networks (LPWAN) for mobile Internet of Things. 2017 IEEE 85th vehicular technology conference (VTC Spring), 2017. IEEE, 1-5.

PATEL, S., SANKHYAN, S., BOEDICKER, E. K., DECARLO, P. F., FARMER, D. K., GOLDSTEIN, A. H., KATZ, E. F., NAZAROFF, W. W., TIAN, Y., VANHANEN, J. & VANCE, M. E. 2020. Indoor Particulate Matter during HOMEChem: Concentrations, Size Distributions, and Exposures. *Environmental Science & Technology,* 54**,** 7107-7116.

PAVANI, M. & RAO, P. T. 2017. Urban air pollution monitoring using wireless sensor networks: a comprehensive review. *International Journal of Communication Networks and Information Security,* 9**,** 439-449.

PERRINO, C. 2010. Atmospheric particulate matter. *Biophysics and Bioengineering Letters,* 3.

PILLARISETTI, A., ALLEN, T., RUIZ-MERCADO, I., EDWARDS, R., CHOWDHURY, Z., GARLAND, C., HILL, L. D., JOHNSON, M., LITTON, C. D. & LAM, N. L. 2017. Small, smart, fast, and cheap: microchip-based sensors to estimate air pollution exposures in rural households. *Sensors,* 17**,** 1879.

PISCITELLO, A., BIANCO, C., CASASSO, A. & SETHI, R. 2021. Non-exhaust traffic emissions: Sources, characterization, and mitigation measures. *Science of The Total Environment,* 766**,** 144440.

PISONI, E., CHRISTIDIS, P., THUNIS, P. & TROMBETTI, M. 2019. Evaluating the impact of "Sustainable Urban Mobility Plans" on urban background air quality. *Journal of environmental management,* 231**,** 249-255.

POPE, F. D., GATARI, M., NG'ANG'A, D., POYNTER, A. & BLAKE, R. 2018. Airborne particulate matter monitoring in Kenya using calibrated low-cost sensors. *Atmospheric Chemistry and Physics,* 18**,** 15403-15418.

PÖSCHL, U. 2005. Atmospheric aerosols: composition, transformation, climate and health effects. *Angewandte Chemie International Edition,* 44**,** 7520-7540.

PRINGLE, K. J., TOST, H., POZZER, A., PÖSCHL, U. & LELIEVELD, J. 2010. Global distribution of the effective aerosol hygroscopicity parameter for CCN activation. *Atmos. Chem. Phys.,* 10**,** 5241-5255.

PURPLEAIR. 2023. *https://www2.purpleair.com/* [Online]. [Accessed 16.01.2023].

QUARMBY, S., SANTOS, G. & MATHIAS, M. 2019. Air quality strategies and technologies: A rapid review of the international evidence. *Sustainability,* 11**,** 2757.

QUEROL, X., MINGUILLÓN, M.-C. & VIANA, M. 2013. *Particulate Matter,* London, London: Future Science Ltd.

RAI, A. C., KUMAR, P., PILLA, F., SKOULOUDIS, A. N., DI SABATINO, S., RATTI, C., YASAR, A. & RICKERBY, D. 2017. End-user perspective of low-cost sensors for outdoor air pollution monitoring. *Science of The Total Environment,* 607**,** 691-705.

RAMSON, S. J. & MONI, D. J. Applications of wireless sensor networks—A survey. 2017 international conference on innovations in electrical, electronics, instrumentation and media technology (ICEEIMT), 2017. IEEE, 325-329.
RATASUK, R., VEJLGAARD, B., MANGALVEDHE, N. & GHOSH, A. NB-IoT system for M2M communication. 2016 IEEE wireless communications and networking conference, 2016. IEEE, 1-5.
ROGULSKI, M. & BADYDA, A. Current trends in network based air quality monitoring systems. IOP Conference Series: Earth and Environmental Science, 2019. IOP Publishing, 012085.
SAYAHI, T., BUTTERFIELD, A. & KELLY, K. 2019. Long-term field evaluation of the Plantower PMS low-cost particulate matter sensors. *Environmental Pollution,* 245**,** 932-940.
SCHIEBER, J. 2020. Air quality monitoring service Airly raises $2 million as fires, pollution force consumers to take note. *TechCrunch.* online.
SCHMITZ, S., CASEIRO, A., KERSCHBAUMER, A. & VON SCHNEIDEMESSER, E. 2021. Do new bike lanes impact air pollution exposure for cyclists?—a case study from Berlin. *Environmental Research Letters,* 16**,** 084031.
SEIGNEUR, C. 2019. Atmospheric Particles. *Air Pollution: Concepts, Theory, and Applications. Cambridge University Press***,** 190-238.
SEMMENS, E. O., NOONAN, C. W., ALLEN, R. W., WEILER, E. C. & WARD, T. J. 2015. Indoor particulate matter in rural, wood stove heated homes. *Environmental research,* 138**,** 93-100.
SHAH, J. & MISHRA, B. IoT enabled environmental monitoring system for smart cities. 2016 international conference on internet of things and applications (IOTA), 2016. IEEE, 383-388.
SHARMA, A., MISHRA, B., SUTARIA, R. & ZELE, R. Design and Development of Low-cost Wireless Sensor Device for Air Quality Networks. TENCON 2019-2019 IEEE Region 10 Conference (TENCON), 2019. IEEE, 2345-2350.
SHEHAB, M. A. & POPE, F. D. 2019. Effects of short-term exposure to particulate matter air pollution on cognitive performance. *Scientific Reports,* 9**,** 8237.
SHENG, Z., MAHAPATRA, C., ZHU, C. & LEUNG, V. C. 2015. Recent advances in industrial wireless sensor networks toward efficient management in IoT. *IEEE access,* 3**,** 622-637.
SHKURTI, L., BAJRAMI, X., CANHASI, E., LIMANI, B., KRRABAJ, S. & HULAJ, A. Development of ambient environmental monitoring system through wireless sensor network (WSN) using NodeMCU and "WSN monitoring". 2017 6th Mediterranean Conference on Embedded Computing (MECO), 2017. IEEE, 1-5.
SIGFOX. 2020. *What Is Sigfox? | Sigfox Build* [Online]. Available: https://build.sigfox.com/sigfox [Accessed 4 June 2020].
SINHA, R. S., WEI, Y. & HWANG, S.-H. 2017. A survey on LPWA technology: LoRa and NB-IoT. *Ict Express,* 3**,** 14-21.
SNYDER, E. G., WATKINS, T. H., SOLOMON, P. A., THOMA, E. D., WILLIAMS, R. W., HAGLER, G. S., SHELOW, D., HINDIN, D. A., KILARU, V. J. & PREUSS, P. W. 2013. The changing paradigm of air pollution monitoring. *Environmental science & technology,* 47**,** 11369-11377.
SONG, Y., LIN, J., TANG, M. & DONG, S. 2017. An Internet of energy things based on wireless LPWAN. *Engineering,* 3**,** 460-466.
SOROKA, E. G. 2020. Indoor and Outdoor Measurements of Particulate Matter with the Low-Cost Optical Sensor OPC-N3.
SOUSAN, S., GRAY, A., ZUIDEMA, C., STEBOUNOVA, L., THOMAS, G., KOEHLER, K. & PETERS, T. 2018. Sensor selection to improve estimates of particulate matter concentration from a low-cost network. *Sensors,* 18**,** 3008.
SOUSAN, S., REGMI, S. & PARK, Y. M. 2021. Laboratory evaluation of low-cost optical particle counters for environmental and occupational exposures. *Sensors,* 21**,** 4146.
TIMMERS, V. R. & ACHTEN, P. A. 2016. Non-exhaust PM emissions from electric vehicles. *Atmospheric Environment,* 134**,** 10-17.

TRYNER, J., L'ORANGE, C., MEHAFFY, J., MILLER-LIONBERG, D., HOFSTETTER, J. C., WILSON, A. & VOLCKENS, J. 2020a. Laboratory evaluation of low-cost PurpleAir PM monitors and in-field correction using co-located portable filter samplers. *Atmospheric Environment,* 220**,** 117067.

TRYNER, J., MEHAFFY, J., MILLER-LIONBERG, D. & VOLCKENS, J. 2020b. Effects of aerosol type and simulated aging on performance of low-cost PM sensors. *Journal of Aerosol Science,* 150**,** 105654.

UNITED STATES ENVIRONMENTAL PROTECTION AGENCY. 2023. *What is PM?* [Online]. online. Available: https://www3.epa.gov/region1/airquality/pm-what-is.html [Accessed 29.05.23].

VALLERO, D. A. 2008. 10 - Sources of Air Pollution. *In:* VALLERO, D. A. (ed.) *Fundamentals of Air Pollution (Fourth Edition).* Burlington: Academic Press.

VEJLGAARD, B., LAURIDSEN, M., NGUYEN, H., KOVÁCS, I. Z., MOGENSEN, P. & SORENSEN, M. Coverage and capacity analysis of sigfox, lora, gprs, and nb-iot. 2017 IEEE 85th vehicular technology conference (VTC Spring), 2017. IEEE, 1-5.

WALLACE, L. 2006. Indoor Sources of Ultrafine and Accumulation Mode Particles: Size Distributions, Size-Resolved Concentrations, and Source Strengths. *Aerosol Science and Technology,* 40**,** 348-360.

WANG, Y., LI, J., JING, H., ZHANG, Q., JIANG, J. & BISWAS, P. 2015. Laboratory evaluation and calibration of three low-cost particle sensors for particulate matter measurement. *Aerosol Science and Technology,* 49**,** 1063-1077.

WATERS, L. 2016. Summary results of the domestic wood use survery. Tech. rep., Renewable Energy Statistics, available at: https://www. gov. uk ….

WHO 2018. Ambient (outdoor) air pollution. online: World Health Organisation.

WHO. 2019. *Air Pollution* [Online]. Available: https://www.who.int/health-topics/air-pollution#tab=tab_1 [Accessed 24 March 2020].

WILLIAMS, R., KAUFMAN, A., HANLEY, T., RICE, J. & GARVEY, S. 2014a. Evaluation of field-deployed low cost PM sensors. *US Environmental Protection Agency*.

WILLIAMS, R., KILARU, V., SNYDER, E., KAUFMAN, A., DYE, T., RUTTER, A. & HAFNER, H. 2014b. Air Sensor Guidebook. *In:* AGENCY, U. S. E. P. (ed.). Washington DC.

WILSON, W. E., CHOW, J. C., CLAIBORN, C., FUSHENG, W., ENGELBRECHT, J. & WATSON, J. G. 2002. Monitoring of particulate matter outdoors. *Chemosphere,* 49**,** 1009-1043.

WON, W.-S., OH, R., LEE, W., KU, S., SU, P.-C. & YOON, Y.-J. 2021. Hygroscopic properties of particulate matter and effects of their interactions with weather on visibility. *Scientific Reports,* 11**,** 16401.

WOOD, M., WOOD, C., STYRING, P., JONES, C. R., SMITH, J., DAY, M., CHAKRABORTY, R. & MENSAH, G. 2022. Perceptions of Accountability and Trust in the Regulatory Governance of Wood Burning Stove Sustainability: Survey Evidence from the Post-Brexit UK. *Available at SSRN 4233888*.

WORLD HEALTH ORGANIZATION 2013. Health Effects of Particulate Matter: Policy implications for countries in eastern Europe, Caucasus and central Asia.

YOCOM, J. E. 1958. The deterioration of materials in polluted atmospheres. *Journal of the Air Pollution Control Association,* 8**,** 203-208.

YOUNG, D. T., CHAPMAN, L., MULLER, C. L., CAI, X.-M. & GRIMMOND, C. 2014. A low-cost wireless temperature sensor: Evaluation for use in environmental monitoring applications. *Journal of Atmospheric and Oceanic Technology,* 31**,** 938-944.

ZAMORA, M. L., RICE, J. & KOEHLER, K. 2020. One year evaluation of three low-cost PM2. 5 monitors. *Atmospheric Environment***,** 117615.

ZANELLA, A., BUI, N., CASTELLANI, A., VANGELISTA, L. & ZORZI, M. 2014. Internet of things for smart cities. *IEEE Internet of Things journal,* 1**,** 22-32.

ZARĘBA, M. & DANEK, T. 2022. Analysis of Air Pollution Migration during COVID-19 Lockdown in Krakow, Poland. *Aerosol and Air Quality Research,* 22**,** 210275.

ZHANG, Y. & LI, Z. 2015. Remote sensing of atmospheric fine particulate matter (PM2.5) mass concentration near the ground from satellite observation. *Remote Sensing of Environment,* 160**,** 252-262.

ZHANG, Y., LI, Z., BAI, K., WEI, Y., XIE, Y., ZHANG, Y., OU, Y., COHEN, J., ZHANG, Y., PENG, Z., ZHANG, X., CHEN, C., HONG, J., XU, H., GUANG, J., LV, Y., LI, K. & LI, D. 2021. Satellite remote sensing of atmospheric particulate matter mass concentration: Advances, challenges, and perspectives. *Fundamental Research,* 1**,** 240-258.

ZHENG, T., BERGIN, M. H., JOHNSON, K. K., TRIPATHI, S. N., SHIRODKAR, S., LANDIS, M. S., SUTARIA, R. & CARLSON, D. E. 2018. Field evaluation of low-cost particulate matter sensors in high-and low-concentration environments. *Atmospheric Measurement Techniques,* 11**,** 4823-4846.

ZHONG, J., HOOD, C., JOHNSON, K., STOCKER, J., HANDLEY, J., WOLSTENCROFT, M., MAZZEO, A., CAI, X. & BLOSS, W. J. 2021. Using Task Farming to Optimise a Street-Scale Resolution Air Quality Model of the West Midlands (UK). *Atmosphere,* 12**,** 983.

ZHU, Q., WANG, R., CHEN, Q., LIU, Y. & QIN, W. Iot gateway: Bridgingwireless sensor networks into internet of things. 2010 IEEE/IFIP International Conference on Embedded and Ubiquitous Computing, 2010. Ieee, 347-352.

ZIKOVA, N., MASIOL, M., CHALUPA, D. C., RICH, D. Q., FERRO, A. R. & HOPKE, P. K. 2017. Estimating hourly concentrations of PM2. 5 across a metropolitan area using low-cost particle monitors. *Sensors,* 17**,** 1922.

ZOU, Y., CLARK, J. D. & MAY, A. A. 2021. Laboratory evaluation of the effects of particle size and composition on the performance of integrated devices containing Plantower particle sensors. *Aerosol Science and Technology***,** 1-14.

ZUSMAN, M., SCHUMACHER, C. S., GASSETT, A. J., SPALT, E. W., AUSTIN, E., LARSON, T. V., CARVLIN, G., SETO, E., KAUFMAN, J. D. & SHEPPARD, L. 2020. Calibration of low-cost particulate matter sensors: Model development for a multi-city epidemiological study. *Environment International,* 134**,** 105329.

Chapter 2: Field Calibration and Evaluation of an Internet-of-Things-Based Particulate Matter Sensor

This chapter is published and can be found under the following citation:

Cowell, N., Chapman, L., Bloss, W. and Pope, F., 2022. Field Calibration and Evaluation of an Internet-of-Things-Based Particulate Matter Sensor. Frontiers in Environmental Science, 9, p.798485.

Or at the following doi:

https://doi.org/10.3389/fenvs.2021.798485

Abstract

This paper presents a field evaluation of IoT enabled Plantower PMS5003 particulate matter sensors in Birmingham, United Kingdom. Sensors were adapted to become battery powered devices, and by utilizing the low power draw of the devices with the low power demand of Low Power Wide Area Network (LPWAN) IoT technology, were capable of measuring and communicating data to an online platform with a battery life of ~2 months, allowing for automated air quality monitoring for extended periods at high density. The sensors demonstrate success at being integrated into a wireless sensor network, with a high presence of readings. The average correlation coefficients (r^2) between raw PMS device data and reference instrumentation are 0.718, 0.703 and 0.543 for PM_1, $PM_{2.5}$ and PM_{10} respectively. The devices also demonstrate good inter-sensor consistency, with Pearson's r values between pairs ranging from 0.92-0.99 across all size ranges. Relative Humidity (RH) clearly influences the response of the sensors, especially for RH > 85%, in keeping with previous laboratory evaluations and evaluations of similar devices. The development of a multi-linear correction factor that accounts for humidity effects on performance of the sensors is described; using this model, Pearson's r values range from 0.81-0.91 compared to 0.73-0.85 from uncorrected values. There is some inconsistency in sensor performance over time, suggesting that sensors are best suited for longer term average measurements or measuring in more stable environments (such as indoor monitoring).

1 Introduction

There are estimated to be 4.2 million premature global deaths as a result of exposure to ambient air pollution, specifically Particulate Matter (PM). PM is a major concern due to the adverse effects it has on the respiratory, cardiovascular and cognitive functions of exposed populations (WHO, 2019, Brook et al., 2010). Sources of particulate matter pollution and particle concentrations are spatio-temporally variable leading and the limited data available for PM (particularly away from urban centres due to the high financial cost of running monitoring sites as well as a lack of space, security and availability of trained staff (Young et al., 2014) makes drawing clear understanding from data challenging. Although high income countries often have small networks of monitoring sites across the larger cities

and conurbations, many low & middle income countries are still developing air quality management and monitoring plans (Gulia et al., 2020, Castell et al., 2017). Overall, large areas of urban and rural environments are not covered by traditional, reference-grade air quality monitors, and this increases the challenge of measuring and hence managing human exposure (De Nazelle et al., 2017).

With 80% of Europe's population living within urban areas, urban air quality policy and management is key to reducing human exposure to pollutants (Dogeanu et al., 2019). Motor vehicles are a both a prominent primary source of particulate matter from exhaust emission and mechanical wear, but also contribute to secondary particulate sources such as photochemical smog, as the nitrous oxides and VOCs released in combustion can contribute to photochemical smog in locations of favorable meteorology(Environment Protection Authority, 2004). Air quality management often has a multifaceted approach including a range of hard and soft measures; active and public transport initiatives, wood/coal burning bans, green infrastructure, road/industry pollution barriers, reduced road speed limits, car sharing schemes and low emission zones. Clean air or low emission zones are becoming increasingly popular as an air quality management technique; with cities across the UK and further afield introducing charges and restrictions for combustion engine vehicles driving within city centres (Quarmby et al., 2019, Pisoni et al., 2019). Whilst low emission zones, frequently mandated by exceedances of NO_2 air quality standards, may reduce gaseous and aerosol exhaust emissions, constraints by vehicle age / EURO classification may have limited impacts on non-exhaust particulates despite research demonstrating non-exhaust emissions contributed 60% and 73% of primary road traffic emissions in the UK for $PM_{2.5}$ and PM_{10} respectively (Air Quality Expert Group, 2019). WHO guidelines estimate that by reducing potential $PM_{2.5}$ concentrations from an annual average of 35μgm^{-3} to a total of 10μgm^{-3} could reduce deaths related to poor air quality by ~15% globally (WHO, 2018). Therefore, as policies evolve to encourage the uptake of lower emission combustion engine vehicles as well as electric and hybrid power, there is potential for PM emissions to become increasingly important as gaseous emissions are reduced. Electric vehicles tend to be heavier and thus generate greater non-exhaust emissions due to increased mechanical wear, which may only be partially offset by reduced brake wear through regenerative braking. (Timmers and Achten, 2016, Amato et al., 2014). Beddows and Harrison (2021) found that without the uptake of regenerative braking, there would be no reduction to PM_{10} when changing from a Euro6 fleet to a fully electric drive chain. Thus, it is becoming increasingly important to focus on improving monitoring capabilities of PM, especially in heavily trafficked urban environments. Moreover, road vehicles are not the only anthropogenic source of PM, with combustion in homes, industry and energy production, agriculture, metalworks, quarries and waste burning are just some of the other activities contributing to particulate concentrations (Air Quality Expert Group, 2012). All of these sources will be contributing regional and wider PM concentrations, highlighting the need for wider PM monitoring.

There has been a paradigm shift in pollutant monitoring in the past decade, with low cost (defined here as ~>£30-500) sensors becoming increasingly prevalent (Lewis et al., 2016). The decreased size and cost, compared to traditional monitoring instrumentation, provides the potential to dramatically increase the density of monitoring sites as well providing increasingly portable monitoring solutions (Chong and Kumar, 2003, Snyder et al., 2013). However, the decreasing cost of sensing capabilities is only one part of the solution and deployments are still often limited by the availability of a reliable power source needed to run both the sensor and communications, often significantly adding to the cost of the device.

It is here where the IoT (Internet of Things) is potentially revolutionary. The IoT refers to sensors or devices that are connected via low-power, internet based, communication protocols. Representing a global information system comprised of hundreds of millions of objects, IoT creates smart infrastructure by embedding sensors into objects such as power grids, train lines and buildings (Brady et al., 2020, Lavric and Popa, 2017). These "things" are becoming increasingly critical to modern technological infrastructure and the IoT ecosystem can allow for processing of a "things" state thus providing decision making and management opportunities (Chapman et al., 2015, Zhu et al., 2010). As the IoT rapidly grows, wireless sensor networks are becoming increasingly prominent in advancing monitoring approaches in a range of applications. Importantly, most sensors can be run on battery power alone, which can constrain the choice of sensor (Sheng et al., 2015), but enable sensors to effectively be positioned anywhere with sufficient mobile data coverage. Furthermore, the use of Low Power Wide Area Networks (LPWANs) has become a significant enabling technology, allowing for bidirectional communication on limited battery consumption, often at low subscription costs by limiting message size and frequency. This can allow for battery life to now extend for months-years, dependent on device (Mekki et al., 2018) which is more than adequate for the calibration cycle of instrumentation.

However, although increasingly technologically feasible, the scientific credibility of data from low cost sensors has been debated with multiple studies into their success varying in findings (Crilley et al., 2018, Sayahi et al., 2019, Wang et al., 2015, Zou et al., 2021). Current standards for monitoring equipment are often not met by low-cost sensors as these standards were created based on the high performance of reference instrumentation. There is an increasing need for further indicative standards for devices of low-cost calibre to ensure quality when measuring with less consistent equipment. The 2008 European Air Quality directive has data quality objectives for both fixed and indicative measurements, of 25% and 50% uncertainty respectively with all measurements being expected to capture at least 90% of data for particulates. The directive suggests reference grade instruments as standard- however permits the use of other methods if they can demonstrate equivalence with reference methods (European Union, 2008). Conclusions of low-cost sensors are often based on precision alone and ability to meet equivalence standards; with many studies failing to acknowledge the potential benefits of a spatial cloud of data, even if it is of lower precision (Chapman et al., 2017). Table 1 presents an updated key comparisons between traditional monitoring and low-cost IoT sensors from (Kularatna and Sudantha, 2008).

Table 1- Comparison of low-cost sensors vs. traditional monitoring [edited from Kularatna and Sudantha (2008)].

Feature	Traditional monitoring equipment	Low-cost IoT sensors
Spatial resolution	Low	Dense
Cost	High (capital purchase)	Moderate-low (consumable)
Response	Varies with instrument	Quick
Rigidity	Fragile	Rigid
Mass production	Difficult and costly	Easy
Power requirements	Mains or specialized power outlets	Mains/USB/battery
Deployment	Permanent	Semi-mobile
Technical staff requirements for maintenance/installation	High	Not required
Unit maintenance	Servicing, filter replacement, calibration	Calibration with reference instrument, drift checks

Guidance in what is to be expected and how to evaluate the results from low-cost sensors has a wide range of advice covering a range of potential issues from carefully considering siting, evaluating the impact of meteorology and evaluating results via linearity (Williams et al., 2014b) (Williams et al., 2014a). It is recommended that reference instruments and low-cost sensors could share quality assurance frameworks and standards, such as the Air Quality Directive 2008/50/EC (Lewis et al., 2018, EU-Directive, 2008, Castell et al., 2017). However, it is argued that basic correlation evaluative measures fail to represent all of the variability of performance between low-cost sensors and reference instruments, or potential temporal changes in performance (Fishbain et al., 2017). Fishbain et al. (2017), present a toolkit for evaluating low-cost pollution sensors and suggest 8 performance measures which include a range of classic assessments such as correlations, alongside novel measures such as percentage of data that a sensor successfully captures (presence), which has been drawn from in this paper.

It is clear from the literature that, in particular, the monitoring capability of gaseous low-cost sensors is of the most concern (e.g. (Lewis et al., 2018), however studies involving PM sensors are more encouraging (e.g.(Crilley et al., 2018, Sayahi et al., 2019). Past evaluations of a range of sensor models have exposed both varying correlation strengths with reference instrumentation as well as contrasting relationships with meteorology- relative humidity impact being widely studied for optical particle counters in particular (Zheng et al., 2018). It is suspected that measurements of the mass concentration of hygroscopic particles by light scattering instruments are influenced by relative humidity, particularly in instances of high humidity when particles will swell significantly as they absorb water. Some optical particle counter studies have demonstrated over-reading due to this process. Lasers within the OPCs struggle to distinguish the larger particles indiviudally and record greater particle concentration values (Crilley et al., 2018, Sayahi et al., 2019, Levy Zamora et al., 2019). Hygroscopicity is determined by the chemical composition of particles and hence PM composition influences the ability of an OPC to accurately measure- especially in the presence of more hygroscopic particles such as nitrate and sulphate (Crilley et al., 2020, Zou et al., 2021).

Despite these challenges, early scientific results indicate low-cost instrumentation for PM to be consistent with reference instruments and feasible for wider deployment with available sensors being sufficiently low powered to be embedded into an IoT solution (Crilley et al., 2018, Levy Zamora et al., 2018, Tryner et al., 2020a). This makes PM appear to be an ideal target for a preliminary study into IoT enabled AQ devices. This paper presents a methodology to IoT enable the Plantower PMS 5003

sensor, a popular optical particle counter that retails at <£30, along with a field evaluation of its performance based on methods drawn from across this literature.

2 Methods and Materials

2.1 Instrumentation

2.1.1 Plantower PMS sensor

The Plantower PMS5003 is an optical particle counter that uses a light scattering technique to determine particle count and size. A photo-diode detector converts light scattered by the particles to a voltage pulse which in-turn is converted into a particle count using an undisclosed algorithm from the manufacturer (Sayahi et al., 2019, He et al., 2020). The laser in the PMS5003 operates at a wavelength of 680±10 nm and the fan draws air through the sensor at 0.1Lm^{-1}. The specification states uncertainty of ±10μgm^{-3} for ranges of 0-100μgm^{-3} and ±10% for ranges 100-500μgm^{-3} for PM_1, $PM_{2.5}$ and PM_{10} with 2 default correction factors available for mass concentration; standard particles (indoor) or atmospheric environment (Sayahi et al., 2019). Particles with diameters less than 0.3 µm do not scatter the 680 nm laser light efficiently and particles with diameters >10 µm are too large to draw into the sensor easily, thus sensor detection efficiency falls outside of this range (Bulot et al., 2019). The PMS5003 is specified to sense particles of >0.5 µm diameter.

There are commercial adaptations of the Plantower PMS OPC series into low-cost sensing units which are becoming increasingly popular- such as the Earthsense Zephyr, PurpleAir, Airly and Clarity models. Whilst these units offer convenience in terms of a complete sensing unit with inbuilt data storage, communication and online data services, they all use WiFi, Bluetooth or cellular signal such as GSM/3G to communicate and as such require mains or solar power (or face limited battery lifetimes <30 days max) (Earthsense., 2022, PurpleAir., 2023, Schieber., 2020, Airly., 2023, Clarity., 2023., Demanega et al., 2021). This can limit the deployment of units. Mains power isn't always available in the field (as is the case for our planned sensor deployments), and reliable solar insolation is not always feasible in city centres with building shadow, or in environments that experience short sunlight hours or high cloud cover. The reliance on Wi-Fi and cellular networks can also limit where units can be deployed, as well as reduce the battery life of a sensor. As such, there is scope to adapt a Plantower device using LPWAN technology such as Sigfox to test the suitability of such communication technology in enhancing the locations available for the deployment of low-cost sensors.

Whilst there are recent laboratory evaluations of Plantower devices (Levy Zamora et al., 2018, Tryner et al., 2020a, Zou et al., 2021), recent in-field studies have used limited numbers of sensors or have sensors spread widely across a study area, limiting the ability to assess suitability for large scale network deployment (Sayahi et al., 2019, Bulot et al., 2019, Zou et al., 2021). Furthermore, previous studies with older Plantower models do not fit the environmental/meteorological context of which these sensors will be placed long term (Zheng et al., 2018). Results from recent studies on sensor performance can be contrasting in its findings. Some suggest the existence of a correlation between PM levels recorded by the PMS device and relative humidity (RH), whilst others suggest that any correlations are not significant (Levy Zamora et al., 2019, Bulot et al., 2019). For example, one laboratory test demonstrated that performance of the PMS5003 for $PM_{2.5}$ weakened at >74-80% humidity dependent on particulate composition (Tryner et al., 2020b). It is unclear as to why this contrast of findings exists although the results could be impacted by the environment in which they

are sampling. Variance in error at high PM concentrations has also been recorded at a different level to the error reported by the manufacturer (Zheng et al., 2018).

The impact of the source of PM on accuracy has also been discussed with laboratory results demonstrating that different sources (and hence PM composition and morphology) can impact the ability of the device to correctly measure particulate concentrations (Zou et al., 2021). Whilst this could be due to varying chemical composition affecting the refractive index of particles, and thus the sensors ability to detect them using the light scattering techniques, composition of the particulates was not measured. Laboratory tests have shown that the PMS5003 underestimate PM mass concentrations where PM primarily comprises ammonium sulphate and Arizona road dust, but correctly record "urban" PM concentrations and over-estimate woodsmoke (Tryner et al., 2020b). There have been suggestions the size variation of particulates from various sources can also impact the ability of the light scattering measurement, with Plantower sensors generally detecting particles of larger diameters with better accuracy (Zou et al., 2021, He et al., 2020, Tryner et al., 2020a). There is contrast in the settings used on the PMS sensor, with Bulot et al. (2019) focusing on the conversion process from particle count to mass concentration and Sayahi et al. (2019) using the standard particles correction factor setting, rather than the atmospheric environment setting designed for field use. Literature also reports that this sensor may not be appropriate for monitoring at >1 year of use, with laboratory simulated aging of conditions equivalent to continuous exposure of 15µgm^{-3} of $PM_{2.5}$ for 1 year causing the PMS5003 to report more extremely high concentrations than at the beginning of the "year" despite median values remaining similar, with $\frac{Interquartile\ range}{Median}$ increasing from ~0.1 on day 1 to ~2 by day 365. This decrease in performance starts to appear at around the 3-4 month stage of simulated aging and worsens over the year period (Tryner et al., 2020b).

This paper extends upon the research by performing an assessment of 4 PMS5003 sensors for ~12 weeks co-located at an urban background monitoring site against a PALAS FIDAS 200e Dust Aerosol Spectrometer, recording data using the "Atmospheric Environment" setting of the PMS. Data are evaluated using a range of methods including traditional correlations and novel measures drawn from the literature(Crilley et al., 2018, Fishbain et al., 2017). An evaluation of external factors such as humidity and particulate composition is also be conducted and a calibration method developed for the sensors to ensure they are suitable for deployment in an ambient air quality network. This analysis is performed in the context of Birmingham's urban background, as it is important to assess the applicability of and calibrate these devices within realistic conditions which are similar to the planned deployment conditions (Sayahi et al., 2019).

2.1.2 IoT Sensor design

In this study, the PMS5003 was adapted into a battery powered IoT enabled device (hereafter referred to as AltasensePM). This was achieved by using an Arduino MKRFox1200, alongside a custom PCB and an SHT85 sensor for temperature and humidity. All AltasensePM devices were built in-house, meaning that individual components were soldered together and then programmed by the Author using information from the product data sheets and Arduino open-source libraries. Breadboards, Arduino boards and the Arduino IDE were used to trial and error design until a successful circuit was made, after which a custom PCB was designed to replace the breadboard and wires for ease of build when creating many sensing units. Figure 1A shows a schematic of the breadboard design for the Plantower device, which was passed onto the electronics workshop at the University to design a custom PCB.

After the custom PCBs were produced, AltasensePM devices were constructed by the author using a soldering iron.

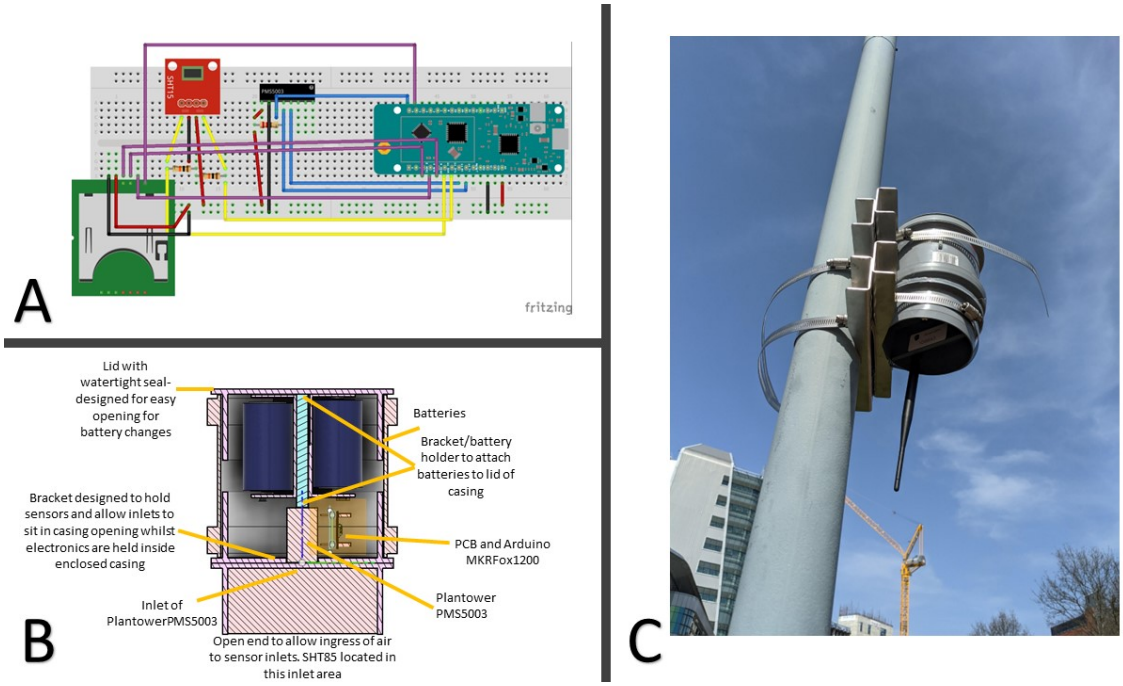


Figure 1- *A) Fritzing diagram of the breadboard-based prototype for the AltasensePM. This was designed by the Author and passed onto the electronics workshop who converted the circuit into a PCB design. B) A diagram of the custom casing designed in collaboration with the University workshop who had the tools to cut custom plastic shapes. C) An AltasensePM device deployed in the field, showing the casing design and attachments on a lamppost.*

Arduino is an open-source platform which offers entry level access into microcontrollers and programming. The ArduinoMKRFox1200 board is a microcontroller with connectivity via Sigfox, an IoT network with very low power consumption making it suitable for the goal developing a battery powered device that could sample for the duration of ~months. The Arduino MKRFox1200 utilises the Sigfox network to send messages of up to 12 bytes to a backend. Sigfox is a radio-based global network specialising in IoT data transmission, which is operated by WND in the UK (Sigfox, 2020). Previous studies suggests that Sigfox communications could be suitable for air quality monitoring- if message sizes are small and do not breach the daily transmission limits set by the level of subscription (Knoll et al., 2018). The hex string message was programmed to contain the temperature, humidity, PM_1, $PM_{2.5}$ and PM_{10} data with a timestamp being called from when the message was received (due to message transmission being almost instantaneous when the values were recorded and the limited message size). Messages are sent to the Sigfox backend before being called by an API key to the Birmingham Urban Observatory online platform (https://birminghamurbanobservatory.com/). A protocol was programmed which decoded the hex message and turned it into readable data for the Urban Observatory platform. Data and metadata are translated into the format of the SSN/SOSA ontology used by the Urban Observatory to organise data. Metadata (location/platform/features of interest) around the sensors is manually input, a compromise of the small message sizes of the Sigfox network. The platform displays data in real-time on the Urban Observatory open-access website (which at the time of submitting this thesis, is unfortunately no longer live due to funding closure). Tests of Sigfox in an environmental monitoring context demonstrate extremely low power consumption, with a small

90mAh coin battery capable of sending >1000 Sigfox transmissions (Joris et al., 2019). Further study shows that the MKRFox1200 device has a battery life of 0.87 years when transmitting 12byte messages every 10 minutes when powered by a 2400mAh battery with a presumed self-discharge rate of 1%/year (Gomez et al., 2019). The battery life will be dependent on the other components/sensors which are connected to the MKRFox1200 however there is clear potential for mid-long term field sampling campaigns as it could be self-sufficient in the (seasonal) scale of 2-3 months in ideal conditions. To further reduce the power consumption of the MKRFox1200, the additional LED was removed from the board during the build process of the AltasensePM device leaving only a single LED for notifying of device power. Altasense is programmed to turn on every 15 minutes and operate for 1 minute, with the minute run time suggested by the manufacturer to allow for the fan to stabilize ahead of taking the reading. This sampling frequency utilises nearly the entire allocation of Sigfox messages allowed per day by the Sigfox network and created the best compromise of data frequency and power consumption. To maximise battery life, the shutdown period between readings is programmed to utilizes the low power aspect of the Arduino MKRFox1200 board via the Arduino Low Power Library deep sleep function, completely powering down not only the Plantower PMS but also all unnecessary function on the board for a set period until power up is required allowing for a prolonged battery life (Arduino, 2020).

The AltasensePM device was housed in a waterproof enclosure with the PMS device inlets drawing in from the base of the enclosure. To allow for the various inlets of the AltasensePM device, a custom housing was designed using readily available plastics designed for plumbing and waterproof housings. The PMS5003 inlet was designed to sample from underneath the device, making it suitable for the end goal of deploying on existing street furniture with out being obstructed by the furniture itself. Custom brackets to secure the battery packs and sensors in place were designed in collaboration with the University of Birmingham workshop and cut from sheet plastic. The author then put the waterproof enclosures together manually using the pipe, caps and custom plastic parts. Figure 1B & 1C demonstrate the casing for the AltasensePM. The PMS5003 intake inlet comprises of 4 small round holes, arranged in a straight line and air is pulled through by the fan which is located at the exhaust outlet. As the intake and exhaust are on the same side of the PMS5003, the enclosure was designed to feature a divider between the two, to limit mixing of the exhaust into the intake. To facilitate any needed corrections for RH, a low-cost temperature and humidity sensor (Sensiron SHT85) was attached near the air intake to ensure humidity readings reflected the air being measured within the sensor. This was to ensure that any humidity corrections replicate the condition of the monitored air, not ambient, which may be different due to warming of air from the mechanics of the PMS of the casing in various weather conditions (Crilley et al., 2018). The SHT85 is housed within a protective mesh (purchased with the SHT85 devices from the manufacturer) which protects the sensor from water damage. Whilst the separate inlet should limit the mixing of the intake and exhaust, some mixing still may occur as the inlet and exhaust are situated close together on the device.

The openair package in R assisted with data analysis (Carslaw and Ropkins, 2012).

2.2 Sampling method

Data collection took place at the Birmingham Air Quality Supersite (BAQS) which is based on the University of Birmingham campus, UK. This is an urban background monitoring site for the city of Birmingham, which houses a state-of-the-art array of pollutant monitoring equipment as well as meteorology equipment. The research grade instrument co-located with the AltasensePM devices

consisted of a MCERTS (Monitoring Certification Scheme as issued by the UK Environment Agency) certified PALAS, FIDAS 200E Dust Aerosol Spectrometer. The FIDAS draws ambient air through an inlet and dryer system and uses light scattering techniques to detect PM. A LED light source and detector measures pulses from light scattered at a 90 degree angle to the source. Particle number concentration is calculated from the number of scattered light impulses and particle size diameter is inferred by the intensity of the scattered light. A proprietary algorithm converts signal into particle counts (spectra) and thus into mass concentrations. The FIDAS samples air from approx. 2.5m above ground level and operates with a flow of 0.3 m^3/h and uses a drying line to prevent condensation affecting measurement. The drying system removes volatile particles and compensates for the condensation of water and the related particle growth if the relative humidity is larger than 60%. It has a detection range of 0.18-100µm and has accuracy defined as 9.7% and 7.5% for $PM_{2.5}$ and PM_{10} respectively (PALAS., 2020). Whilst this is research grade instrumentation, local authority air quality guidance suggests that results for unusually heavy or light particles may differ to results from monitoring equipment with size selective inlets (IAQM, 2018). An Aerodyne Aerosol Chemical Speciation Monitor (ACSM) with a $PM_{2.5}$ inlet is also located at BAQS and was used to collect organic particulate concentrations for assessing for the impact of particulate composition on sensor performance. The ACSM analysis determines NH_4, SO_4, NO_3, Chl and Organic mass loadings and has a volumetric sample flow of 85 cc min^{-1} and has a detection limit of <0.2 μgm^{-3} for 30 min of signal averaging.

Four AltasensePM devices were located at the BAQS site, labelled A, B, C & D within analysis to differentiate between devices. They were installed at a height of ~1.5m and attached to an open mesh fence. 8 weeks of measurement were obtained and used for calibration, from 24th of February 2021 to 22nd April 2021. There were 2 calibrations performed on the FIDAS during this period, each lasting a few hours. Data from these have been removed from the data set. The measurement campaign was constrained by the battery life of the sensor, which was found to be limited to around 9-10 weeks. The ACSM data were obtained from 1st March 2021 onwards.

3 Results & Discussion

3.1 Comparison to reference instrumentation

Data presence can be an issue for low-cost sensors (Crilley et al., 2018, Rai et al., 2017, Fishbain et al., 2017). However, the AltasensePM devices performed well capturing at least 95% of total expected measurement for the 8 week period of monitoring. Data outages occurred due to a combination of power and comms failures.

Time series plots in figure 2 demonstrate the capability of AltasensePM sensors in recording the broad trends in PM mass concentration detected by the FIDAS. Values from a linear regression model (figure 3) are presented in Table 2. The average correlation coefficients (r^2) between PMS devices and BAQS are 0.718, 0.703 and 0.543 for PM_1, $PM_{2.5}$ and PM_{10} respectively. Slope varies from 0.98-1.2, 1.7-2 and 1.5-1.9 for PM_1, $PM_{2.5}$ and PM_{10} respectively. Y intercept varies from 1.4-1.8μgm^{-3}, -0.23-0.61μgm^{-3}, and -2.1- -1.2μgm^{-3} for PM_1, $PM_{2.5}$ and PM_{10} respectively sitting within the ±10μgm^{-3} uncertainty suggested by Plantower at the PM levels encountered during these measurements (mean PM2.5 concentration detected by PMS5003 devices=18.79-22.18). PM_{10} fits this model the least with low R and r^2. There is some variation that cannot be accounted for by the linear model. For example, all

sensors have periods of over-reading, more so for $PM_{2.5}$ and PM_{10}. It is unclear exactly why this occurs, but it is hypothesised that this is due to the challenges of larger particles navigating the 90º angles at the entrance and exit the PMS sampling chamber effectively (Sayahi et al., 2019). Another cause of over-reading of larger size particle concentrations could be due to multiple smaller particles being detected as one larger particle, thus causing variation from the reference instrument. Both hypotheses could vary temporally with changes in humidity and particle composition. Both reference instrument and low-cost sensor measure concentration based on light scattering principle, thus whilst external factors (such as temperature/humidity) may correlate to the deviation between devices, the differences are due to an unidentified instrumental factor reacting to them, rather than particles reacting differently to various measurement principles.

Table 2- Correlation coefficients and statistics for low-cost devices (R, r^2 and slope are comparison to Birmingham Air Quality Supersite FIDAS).

Device	Species	Pearson's *r*	Slope	r^2	LoD (µg m^{-3})	Mean	y-intercept
A	PM_1	0.85	1.20	0.72	1.25	11.86	1.40
	$PM_{2.5}$	0.84	2.0	0.70	1.15	22.18	–0.23
	PM_{10}	0.74	1.90	0.54	1.75	27.49	–2.10
B	PM_1	0.84	1.0	0.71	2.60	11.14	1.70
	$PM_{2.5}$	0.84	1.70	0.70	2.47	19.84	0.61
	PM_{10}	0.74	1.50	0.55	2.22	23.31	–1.50
C	PM_1	0.85	0.98	0.72	2.22	10.34	1.50
	$PM_{2.5}$	0.83	1.70	0.71	1.59	18.79	0.20
	PM_{10}	0.73	1.50	0.55	1.73	22.96	–1.70
D	PM_1	0.85	1.10	0.72	1.50	11.26	1.80
	$PM_{2.5}$	0.84	1.70	0.70	1.46	19.97	0.40
	PM_{10}	0.74	1.50	0.53	1.46	23.36	–1.20

The Plantowers inability to monitor particles with equivalent diameter <0.3µm means that there will be a number of smaller particles not being counted in the PM_1 fraction. There is a moderately strong correlation (slope 0.65-0.78, r^2 0.67-0.68) between Altasense PM_1 and FIDAS $PM_{2.5}$ measurements suggesting that the larger PM_1 mass is dominating what is being detected by the sensor. From comparison with the reference data, we can also determine that the AltasensePM is likely attributing $PM_{2.5}$ as $PM_{10.}$ Correlations between PM_{10} measurements from the sensor are strongly correlated with $PM_{2.5}$ measurements from FIDAS (r^2 0.7-0.72) although this may be because PM_{10} and $PM_{2.5}$ concentrations are well correlated during this study period (FIDAS PM_{10}:$PM_{2.5}$ has a slope of 0.75 and a r^2 of 0.88). By making a control quantity for the larger fractions of PM_{10} from the reference instrument (PM_{10} measurement minus $PM_{2.5}$ measurement) we can create a PMcontrol which only shows the mass concentration from the larger PM_{10} particles (Hagan and Cross., 2022). If PM_{10} measurements were independent from $PM_{2.5}$ we'd expect a correlation between PMcontrol and PM_{10} however our results show that the correlation between PMControl and PM10 is weak (r^2 0.24-0.47).

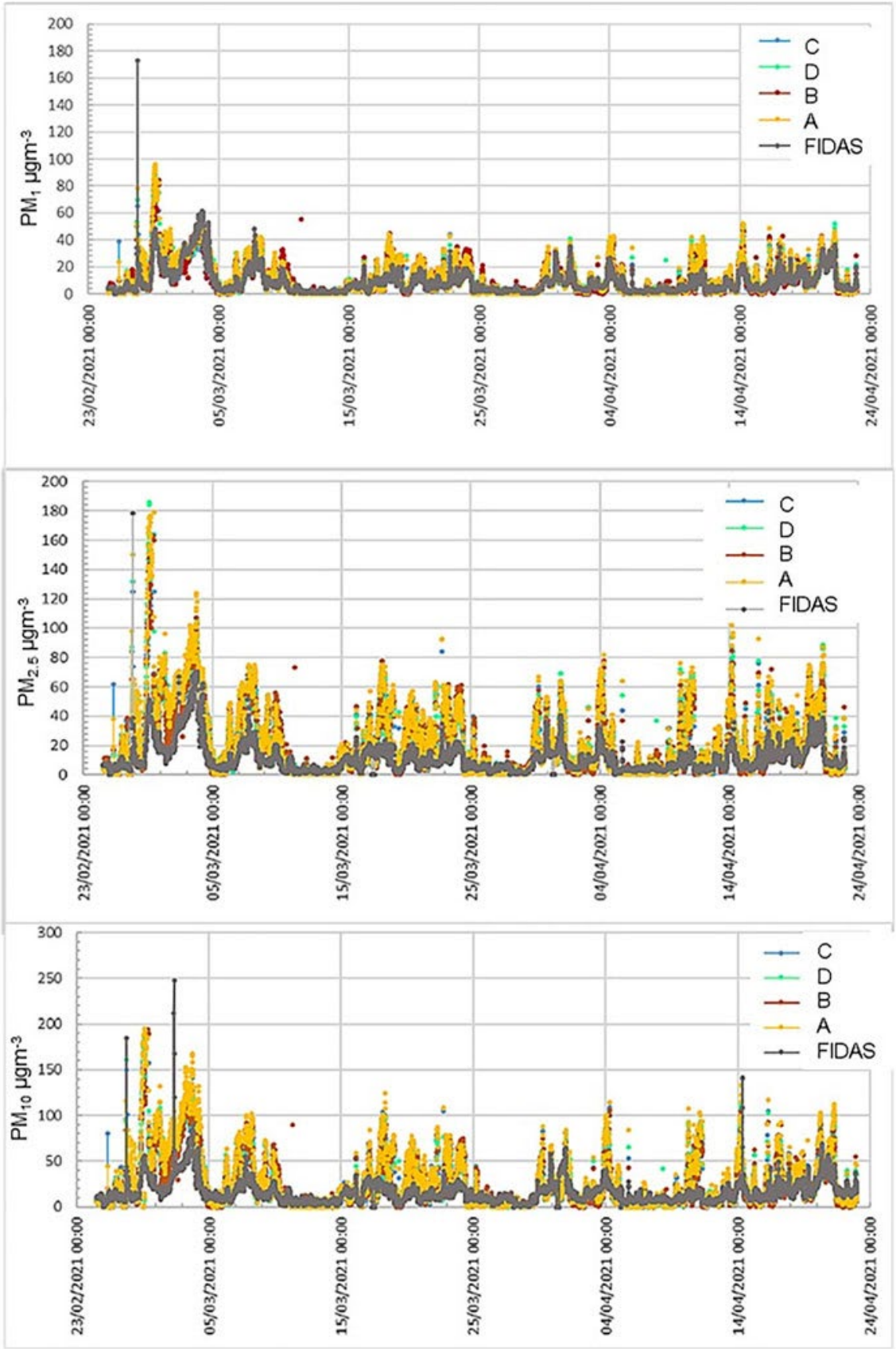


Figure 2 *Hourly average time plot of low-cost sensors against the Birmingham Air Quality Supersite FIDAS*

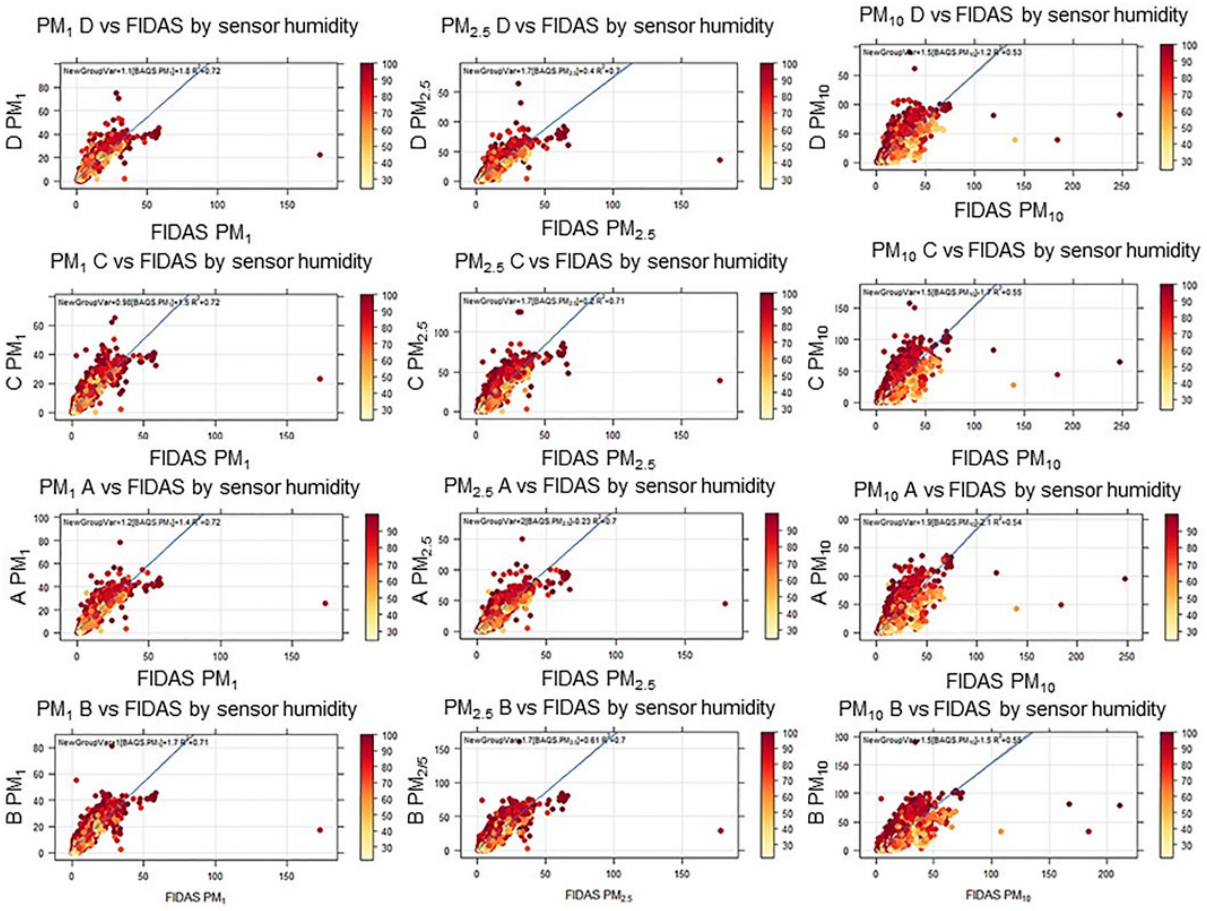


Figure 3 *Plots of particulate matter concentrations from low-cost sensor vs FIDAS by humidity.*

3.2 Device consistency

An intercomparison between the low-cost devices demonstrates a positive relationship with all measuring similar concentrations. Good linearity between the devices is also demonstrated (Figure 5) with Pearson's r values between pairs ranging from 0.92-0.99 across all species (size ranges) and devices. The range in mean concentration recorded by devices is 1.52µgm^{-3}, 3.39µgm^{-3} and 4.53µgm^{-3} for PM_1, $PM_{2.5}$ and PM_{10} respectively. Low-cost devices experience some extreme variations from the mean, especially for PM_1 and $PM_{2.5}$ species as seen in figure 4. The greatest variations in performance were related to $PM_{2.5}$, with a difference of maximum concentration recorded between sensors of 47µgm^{-3}, which is greater than the manufacturer specification of ±10 µgm^{-}3 at <100µgm^{-3} and ±10% at >100µgm^{-3} . The range in mean concentration recorded by devices is 1.52µgm^{-3}, 3.39µgm^{-3} and 4.53µgm^{-3} for PM_1, $PM_{2.5}$ and PM_{10} respectively. Overall, although all size ranges show good inter-device concentration agreement, this generally decreases with size suggesting a size-dependent impact on sensor performance. In contrast to Zou et al. (2021), it was found that performance decreased with particle size, in terms of both inter-sensor precision and linearity with respect to the reference instrument.

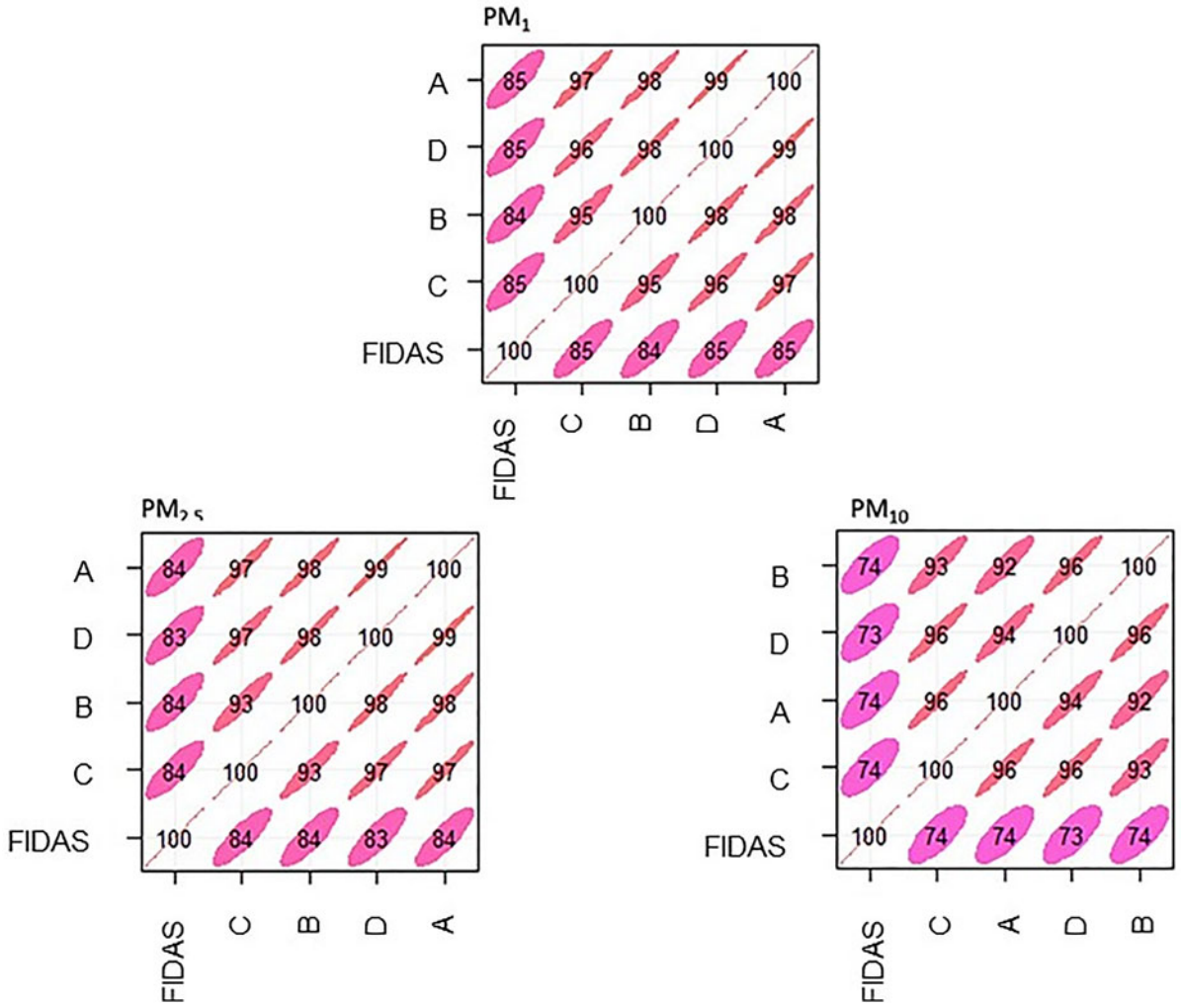


Figure 4 *Correlation plot demonstrating inter-sensor correlation and correlation to reference instrument (FIDAS)*

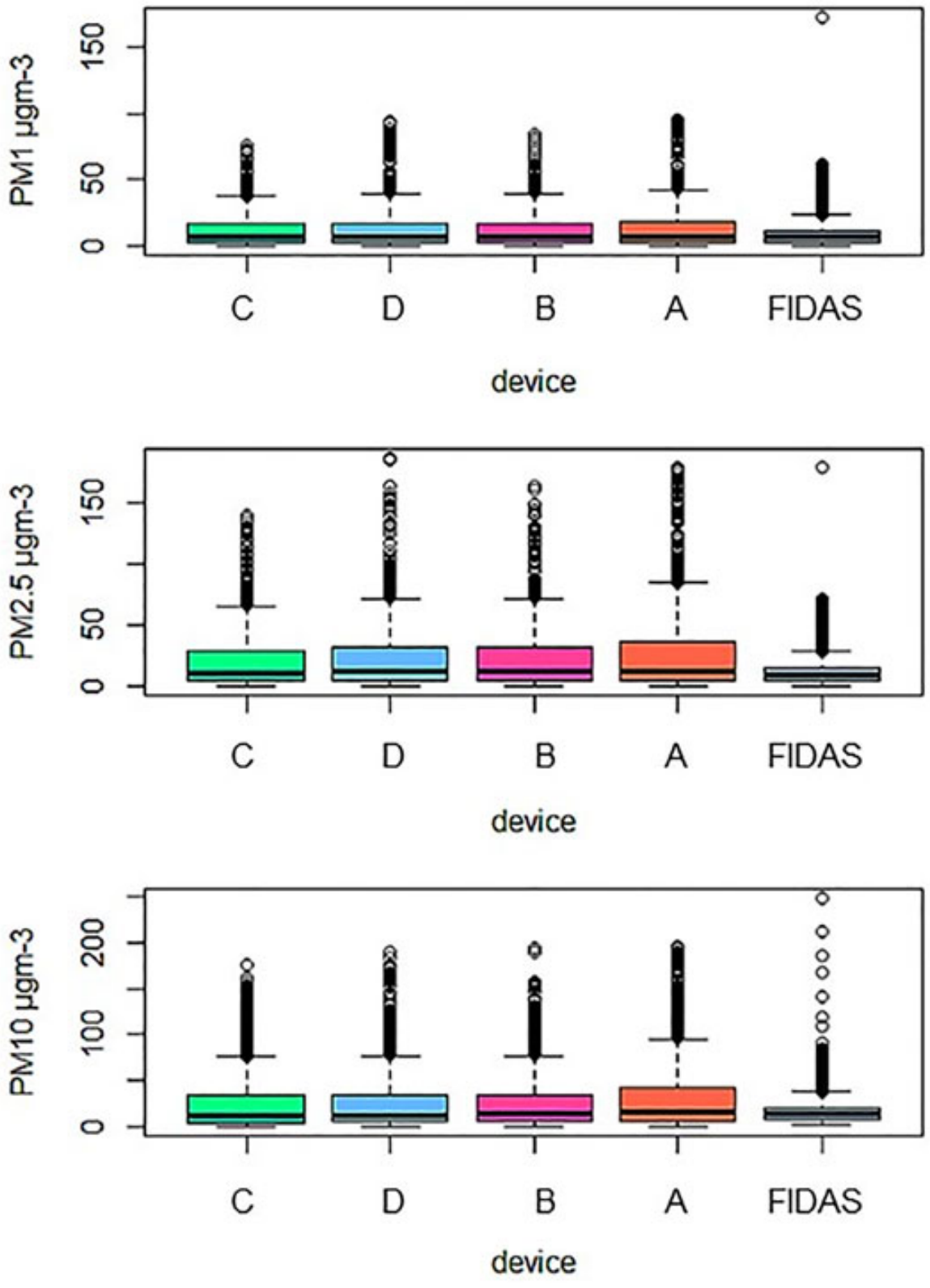


Figure 5 *Box plot of particulate matter concentrations from low-cost sensors and FIDAS for PM_1, $PM_{2.5}$ and PM_{10}.*

3.3 Impact of relative humidity and particle composition

The relationship between PMS sensors and relative humidity was investigated to see if the PMS data showed significant dependencies upon humidity, especially during high humidity episodes, as suggested by prior literature (Crilley et al., 2018, Sayahi et al., 2019, Levy Zamora et al., 2019). It is important to note that particulate composition determines the hygroscopic characteristics of PM and this will vary between studies and between deployment locations (Crilley et al., 2018).

From inspection of the ratio of AltasensePM device:FIDAS PM mass concentration versus humidity in figure 6, it appears that there is a non-linear response at high relative humidity values (~85%+). This behaviour was also seen in other studies which used an alternative low cost PM-Sensor, Alphasense OPC-N2 and is consistent with is the trend expected from hygroscopic particle growth curves (Crilley et al., 2018, Pöschl, 2005). However, the point of inflection appears higher than laboratory studies of the PMS5003, where humidity impacted the ratio of PMS:reference at values of 74-80% dependent on composition of the particulate used (Tryner et al., 2020b). The higher humidity threshold may be due to composition differences between the literature lab assessments vs this field evaluation, or due to differences in the reference instrument used. For information, the ACSM at this study site during March and April 2021 recorded average total organic mass of 1.71µgm^{-3} with average NH_4, SO_4 and NO_3 measured at 0.8µgm^{-3}, 0.47µgm^{-3} and 1.23µgm^{-3} respectively.

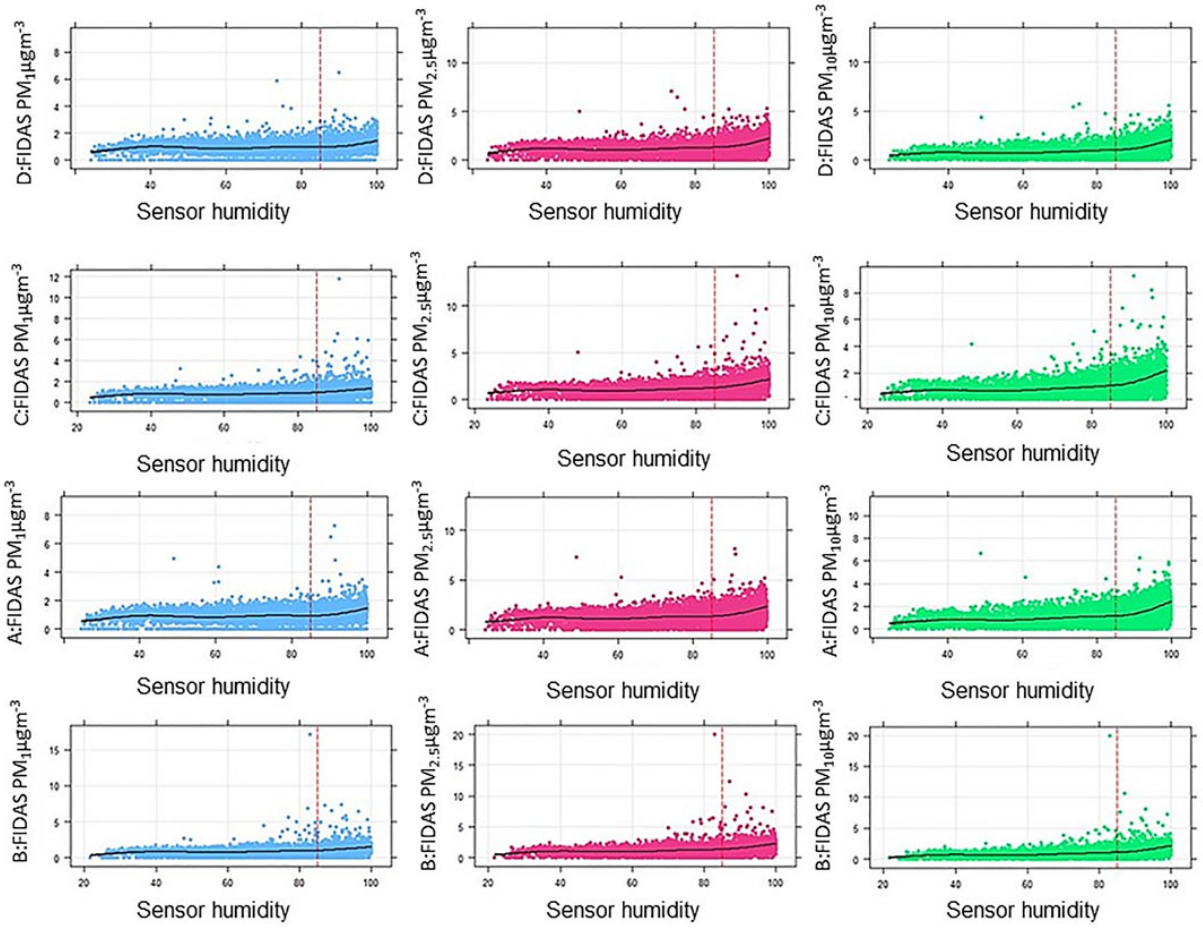


Figure 6 *Ratio of AltasensePM concentrations/FIDAS PM concentrations vs humidity, with 85% humidity marked in red.*

As the composition of PM will determine the hygroscopicity of particles and therefore the relationship between PM levels recorded and humidity, the impact of composition was also assessed (Figure 7).

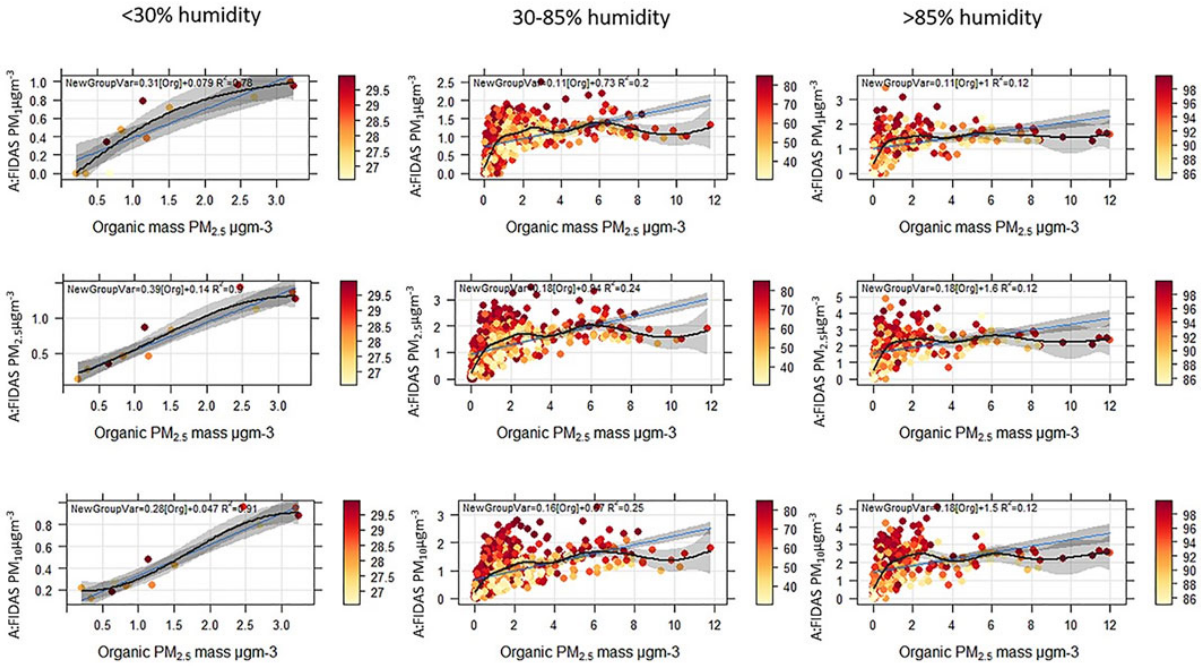


Figure 7 *Examples of AltasensePM/reference PM concentrations from sensor A by organic concentrations from ACSM by humidity at different humidity intervals. Linear equation of ratio by organic mass concentration is show on the plot.*

At lower humidity, the ratio of AltasensePM:reference increases rapidly with increased organic content, but this increase slows at moderate and high humidity. There is some indication that RH dominates over organic content in controlling the ratio, particularly at higher humidity. When plotting the ratio of AltasensePM:reference vs total organic mass from the ACSM by humidity, it becomes clear that at there is large variation in AltasensePM:reference for similar organic concentrations. This suggests the importance of correcting for humidity.

Whilst it is expected that as the reference instrument and PMS5003 should react similarly to varying particle composition due to their mutual basis on light scattering techniques, these findings further confirm the results of the previous laboratory study of the PMS5003 where varying composition of particulates changed the relationship with the reference instrument (Tryner et al., 2020b).

3.4 Drift

It is suggested in the literature that some particles may struggle to leave the chamber of the low cost sensor due to the 90º angles of the particle path (Sayahi et al., 2019). This may result in drift in the form of an increased ratio over time at higher humidity as particle build up in the sensor may swell at higher humidity thus leading to further over reading. As particle build up increases over time, so could the amount of over-reading that occurs. Previous research indicates that the low cost sensor used will experience significant drift after 1 year of monitoring 15 µgm^{-3}, with performance starting to decrease from around 120 days at this concentration and significantly worsening by 20x by the end of a year window, with drift being measured as increase in variation from a median in a simulated aging scenario (Tryner et al., 2020b). However, with the battery life of the AltasensePM sensor presently limited to just over 8 weeks, this would indicate that drift should not be a significant problem during

this time frame. This study is limited in its sampling period and therefore there is not enough data to assess drift on a longer time scale such as 1 year as within the literature. Therefore, to overcome this limitation when an Altasense PM has a battery change, it should be collocated again with reference instrumentation, to not only update calibration equations but to allow for further assessment of sensor performance.

The results of the weekly breakdown on the ratio of AltasensePM:Reference are shown in Figure 8. It is unclear whether the sensor experiences drift during this study as there is not a consistent pattern of decline in performance. Statistical test for difference between the PM sensor: reference slope datasets from each week (Kruskal-Wallis) show that for PM_1, $PM_{2.5}$, PM_{10} ($p<2.2e^{-16}$) the weekly datasets are significantly different for the sensor shown in figure 8. The changes in slope by week suggest that the correction performs differently over short time periods- this could be due to changes in sources, as well as meteorology affecting sensor performance. This suggests that detecting short term fluctuations in concentrations with these sensors will be limited by sensor performance.

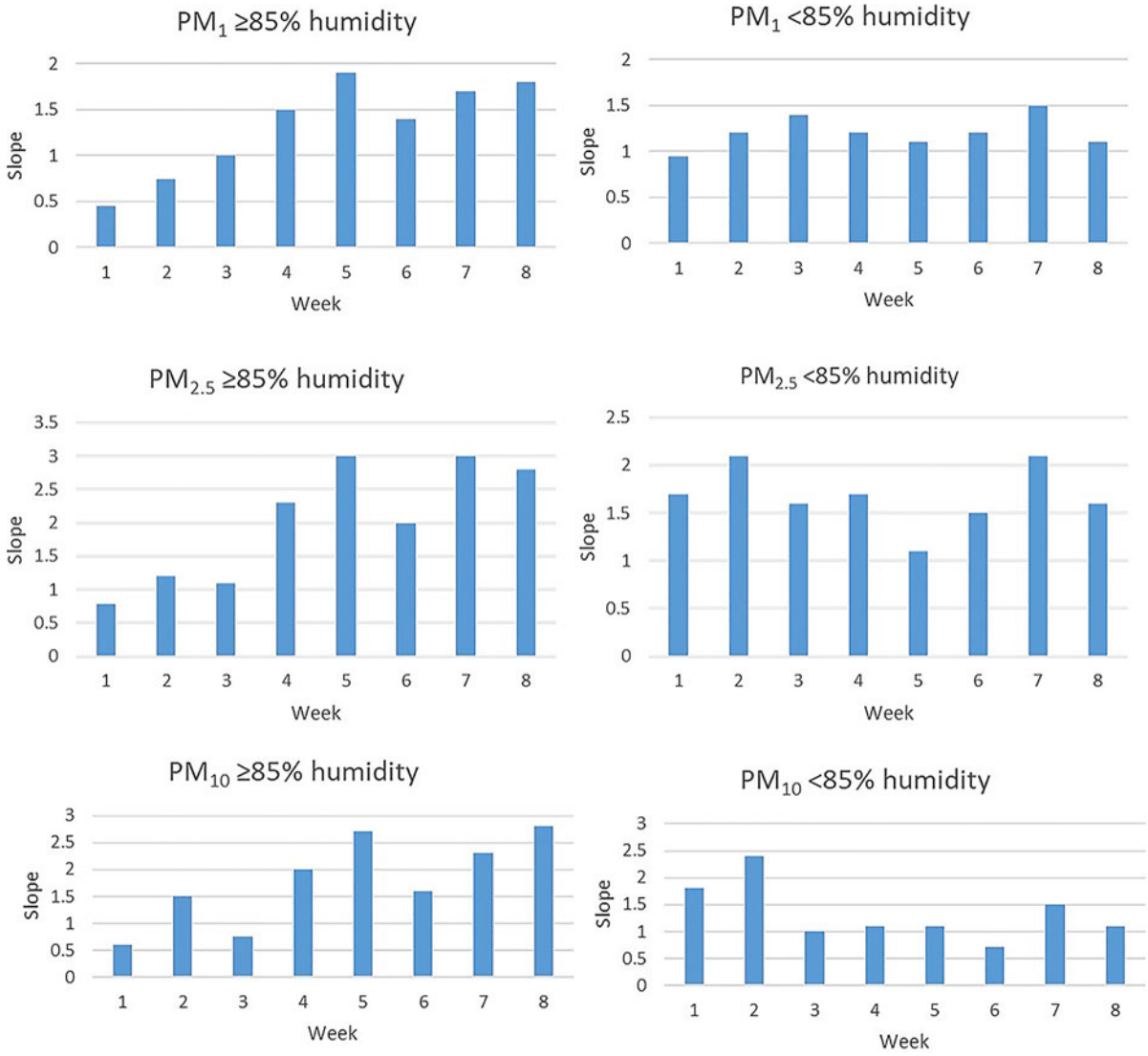


Figure 8 *Slope of low-cost sensor PM concentrations vs. FIDAS by week, separated by readings that occurred when the sensor recorded <85% humidity and ≥85% humidity for sensor B.*

However, when slopes are averaged over a longer period (such as the 8 weeks) they fall closer to one suggesting sensors could be suitable for longer term monitoring and averaging where the varying performance due to source or meteorology changes are averaged out. The sensors are more suited to environments with stable meteorology/sources to reduce the impact of fluctuating performance- such as indoor sampling environments.

3.5 Development of a correction factor for RH effects

These analyses highlight that the PMS5003 cannot be corrected by a singular linear model alone and requires a more comprehensive correction for the impact of humidity. Sensors will be best calibrated in field sites near to their deployment so that corrections are developed in areas with similar particulate composition as future deployment sites to take into effect the role of hygroscopic particles in influencing readings in different meteorological environments (Zusman et al., 2020, Crilley et al., 2018). It is also sensible to suggest re-assessing calibration models over time, not just due to potential drift but also as atmospheric composition is unlikely to remain stable across seasons and thus models may change to reflect the altered chemical composition and hygroscopic properties of particulates (Sayahi et al., 2019).

There has been development of correction factors in the literature founded onκ-Köhler theory for the Alphasense OPC-N2 sensor that require either a reference instrument that can measure dry particle mass or failing that, to draw a generic κ value for the environment sampled from the literature (Crilley et al., 2018, Di Antonio et al., 2018). The method from the Crilley et al (2018) OPC evaluation suggests using a linear corrections for when humidity is <85% and a correction factor derived below when humidity is ≥85%:

$$C = 1 + \frac{\frac{\kappa}{1.65}}{-1 + \frac{1}{aw}} \quad (1)$$

$$PM_{Corrected} = \frac{PM_{Raw}}{C} \quad (2)$$

Where aw(water activity) is defined as RH/100 and with κ = 0.36 (expected κ for Europe as drawn from (Crilley et al., 2018, Pringle et al., 2010)).

However, when applying this method using either Europe or Birmingham specific κ values drawn from the literature (Table 3), the AltasensePM data becomes overcorrected and loses the trends from the FIDAS (figure 9). This method may not work as it was developed using ambient RH but this study uses humidity values from the inlet of the sensor as this reflects the air being sampled more closely. This is similar to results found by (Tryner et al., 2020b) where Köhler based corrections for the Plantower cause underestimation of results- they suggest that past literature with linear correction models demonstrate better performance relative to reference instrumentation (Zusman et al., 2020).

Table 3- κ values drawn from Pringle et al. (2010)—column 1 and from Crilley et al.(2018)—columns 2–5.

Europe	Birmingham $PM_{2.5}$ TEOM	Birmingham $PM_{2.5}$ GRIMM	Birmingham PM_{10} TEOM	Birmingham PM_{10} GRIMM
0.36 ± 0.16	0.38–0.41	0.41–0.44	0.48–0.51	0.38–0.41

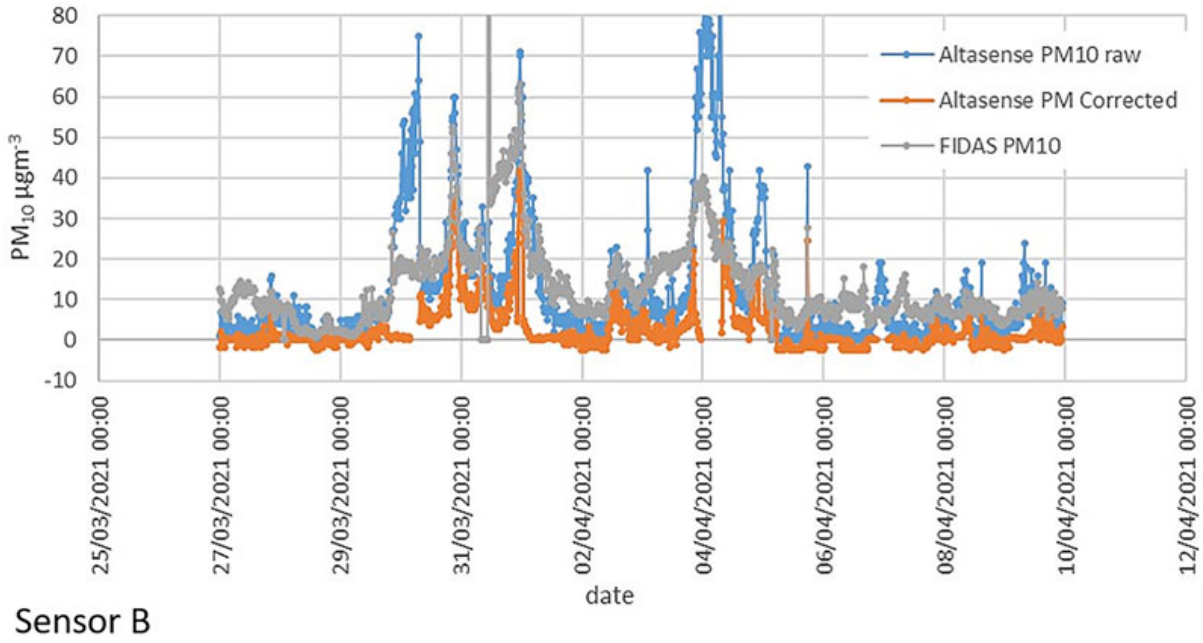


Figure 9 *Example of over-correction when using the K-Köhler method stated above for one of the Altasense PM units for PM_{10} concentrations.*

The final model uses one linear correction equation per PM species (PM_1, $PM_{2.5}$, PM_{10}) for values when humidity is recorded at <85% and another when humidity is ≥85% (as per Figure 10 and Table 4). 85% was selected as not only is this the value at which hygroscopic growth curves suggest changes to response should be seen, but it also reflective of our data as slope of AltasensePM vs FIDAS varies by an average of 0.25, 0.2 and 0.15 for PM_1, $PM_{2.5}$ and PM_{10} respectively when plotting data from ≥85% humidity compared to <85% (Pöschl, 2005). Using this model, Pearson's r values range from 0.81-0.91 from 0.73-0.85 from uncorrected values. Time series plots also demonstrate sensor ability to detect trends well after these corrections- there are no longer large periods of over reading, with the majority of concentrations sitting very close to the reference instrument values. It is expected that due to the drift indicators discussed above that these linear models will need recalculating as part of the 8 week service when batteries are changed. Overall, this method has promising results as well as reducing the need for environment-specific composition data, making the low-cost sensors more deployable in low/middle income environments.

Table 4 Correlation results for Altasense PM vs. FIDAS for the period 23.04.21–27.04.21 after correction using the multi-linear approach. One device (B) has a tendency to underestimate compared to the other sensors. This device has performed slightly worse than the others in linearity correlations, and this demonstrates some of the concerns about the replicability of data between low-cost sensors due to the unknown manufacturing standards. Despite this, it still generally performs well.

Device	Species	*R*	Slope	r^2
A	PM_1	0.90	0.64	0.80
	$PM_{2.5}$	0.87	0.70	0.76
	PM_{10}	0.81	0.53	0.66
B	PM_1	0.86	0.74	0.74
	$PM_{2.5}$	0.84	0.74	0.71
	PM_{10}	0.83	0.57	0.68
C	PM_1	0.91	0.75	0.84
	$PM_{2.5}$	0.90	0.79	0.80
	PM_{10}	0.86	0.59	0.74
D	PM_1	0.91	0.94	0.83
	$PM_{2.5}$	0.88	0.89	0.78
	PM_{10}	0.82	0.68	0.67

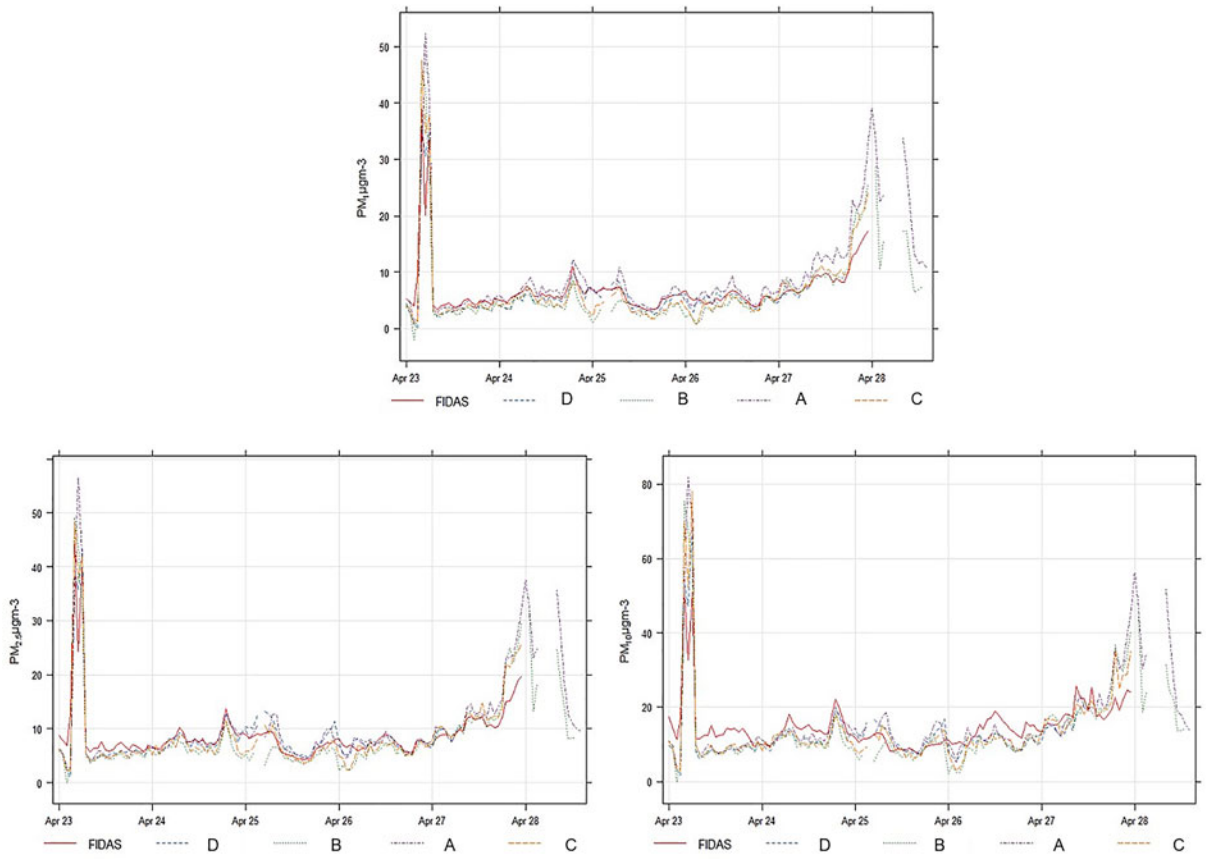


Figure 10 *Time plots of hourly averaged PM concentrations for Altasense PM and FIDAS after correction using the multi-linear approach that differentiates correction by humidity.*

3.6 Limitations

Whilst this paper demonstrates the feasibility and potential of low-cost sensors and IoT technology for particulate matter monitoring, there are some limitations of the study. The Plantowers inability to monitor particles <0.3µm means that there are some particles that are not being counted by the sensor in the PM_1 fraction (although with smaller size fractions they are less likely to be contributing significantly to the total mass concentration).

Limitations also arise from the methodology for developing a calibration method- it is important to recognise that this calibration is site specific, subject to the meteorology and particle composition and sources experienced during the calibration period. This means that although sensors perform well during this period, calibrations may not translate to periods of different meteorology or spaces with different PM composition and sources. However, the design of our sampling strategy for ambient monitoring can be adapted to reflect this. Sensors are to be deployed immediately following their calibration period so that seasonal meteorology should be as similar as possible to the calibration period (although recognising the difference between seasons weather and daily fluctuations in weather). Sensors are planned to be deployed close to the reference station, in the West Midlands so that regional PM sources will be as similar as possible to those in the calibration period. We do recognise however that there may be some near source differences, as the calibration site in this paper is an urban background site and sensors may be deployed at road-side or other near source sites.

Further limitation from the calibration is that it is instrument specific, the FIDAS is also an optical based sampler and as such, the calibration method may not perform as well against gravimetric or other reference instrumentation. Unfortunately, the scope of this research, during a pandemic and with limited access to roadside reference equipment to install sensors near, or alternate reference monitors means that these limitations cannot assessed further at this stage. Ongoing research should consider these limitations, and colocations with various reference instruments in different site types would give further insight into sensor performance.

4 Conclusion

The Plantower PMS5003 modified as an IoT capable device provides the opportunity to monitor air quality at a low cost. The underpinning IoT philosophy enables this device to be deployed in large networks and provides an opportunity to monitor particulates at unprecedented spatial resolution. The sensors simple design allows for a semi-permanent approach, with sensors easily being able to be moved and networks adjusted according to end-user requirements. The low power aspect of the IoT Sigfox integration and ability to limit power draw from the PMS5003 with shutdown time allows for frequent communication of near real-time data to an online platform, without compromising location by requiring mains power. Data can be accessed and assessed remotely and instantly, without the need for staff at an air quality station. This means that with the correct data contract, units can be deployed anywhere with a Sigfox connection- currently over 80 countries worldwide, including low, middle and high income countries enabling low cost PM monitoring in many different environmental and anthropogenic contexts.

The results from this study demonstrates the ability of the Plantower PMS5003 to detect PM trends and concentrations relative to the research grade PALAS FIDAS instrumentation over an 8 week period and with improvements after applying a correction factor. Inter-sensor variability is low and there are strong correlations between the reference instrument and low-cost units, as expected from instruments based on the same light scattering principle. It has been demonstrated that humidity and particulate composition play a role in sensor performance but the results can be improved by minimal calibration efforts. After correction, low-cost devices perform well; particularly at recording peaks in particulate concentrations when they match extremely well with reference measurements. This may be because the data used to train the model experienced several periods of higher concentrations (>20μgm^{-3}) generating a correction that is favourable to these conditions. This is a limitation of the study- these sensors are calibration against a specific instrument in one location and one season and therefore would be expected to perform differently when monitoring other sources, or if the meteorology is different. There is some suggestion that the sensors are not able to independently monitor the difference size fractions- with some PM_1 and PM_{10} particles falling outside of the monitoring capabilities of the sensor.

Future work designing a custom PCB to increase the durability and replicability of the unit will allow for easier deployment of large numbers of sensing units. Extending battery life will also be a key priority, after which it will be imperative to revisit drift assessments to take into account extended monitoring periods (Sayahi et al., 2019). From our initial drift assessments, it is suggested that these sensors will perform well in environments with stable meteorology and may be well suited to support indoor air quality monitoring. Overall, this study has highlighted the feasibility of using the IoT for dense sensor networks to monitor PM.

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Author contributions

NC was responsible for initial data and analysis and writing

LC and WB supervised the project, provided guidance for analysis and supported in editing the paper

FP was a supporting editor and supported with data analysis

Funding

This work was funded as part of the NERC RISE WM-Air project (NE/S003487/1), EPSRC UKCRIC Urban Observatories project (EP/P016782/1), and EPSRC IAA funding which helped support translation. BAQS is supported through the NERC project OSCA (NE/T001976/1)

Acknowledgments

The assistance of Dr Siqi Hou and colleagues at the Birmingham Air Quality Supersite at the University of Birmingham for supporting in the colocation of sensors as part of this project. The University of Birmingham workshop team who supported the sensor build.

References

ABDUL-RAZZAK, H. 2012. *Atmospheric Aerosols: Regional Characteristics-Chemistry and Physics*, BoD–Books on Demand.

ACTON, W., ZHONG, J. & BLOSS, W. 2023. What is PM2. 5? An introduction to particulate matter in the atmosphere: a briefing note.

AIR QUALITY EXPERT GROUP 2012. Fine Particulate Matter (PM2.5) in the United Kingdom. *In:* DEFRA (ed.). Online: DEFRA.

AIR QUALITY EXPERT GROUP 2019. Non-Exhaust Emissions from Road Traffic. *In:* DEFRA (ed.). Online: DEFRA.

AIRLY. 2023. *airly* [Online]. Available: https://airly.org/en/ [Accessed 16.01.23].

AL-KASHOASH, H. A. & KEMP, A. H. 2016. Comparison of 6LoWPAN and LPWAN for the Internet of Things. *Australian Journal of Electrical and Electronics Engineering,* 13**,** 268-274.

AMARAL, S. S., DE CARVALHO, J. A., COSTA, M. A. M. & PINHEIRO, C. 2015. An Overview of Particulate Matter Measurement Instruments. *Atmosphere,* 6**,** 1327-1345.

AMATO, F., CASSEE, F. R., DENIER VAN DER GON, H. A., GEHRIG, R., GUSTAFSSON, M., HAFNER, W., HARRISON, R. M., JOZWICKA, M., KELLY, F. J., MORENO, T., PREVOT, A. S., SCHAAP, M., SUNYER, J. & QUEROL, X. 2014. Urban air quality: the challenge of traffic non-exhaust emissions. *J Hazard Mater,* 275**,** 31-6.

AQEG 2005. Particulate Matter in the UK. *In:* DEFRA (ed.). London.

ARDUINO 2020. Arduino Low Power Library. 1.2.0 ed. Online.

ARROYO, P., HERRERO, J. L., SUÁREZ, J. I. & LOZANO, J. 2019. Wireless sensor network combined with cloud computing for air quality monitoring. *Sensors,* 19**,** 691.

BARKJOHN, K. K., GANTT, B. & CLEMENTS, A. L. 2021. Development and application of a United States-wide correction for PM 2.5 data collected with the PurpleAir sensor. *Atmospheric Measurement Techniques,* 14**,** 4617-4637.

BAWA, J., AYUBA, P. & AKANDE, O. Factors Influencing the Performance of Indoor Environmental Quality of Pharmaceutical Factory Buildings in Southwest Nigeria. IOP Conference Series: Earth and Environmental Science, 2022. IOP Publishing, 012023.

BEDDOWS, D. C. S. & HARRISON, R. M. 2021. PM10 and PM2.5 emission factors for non-exhaust particles from road vehicles: Dependence upon vehicle mass and implications for battery electric vehicles. *Atmospheric Environment,* 244**,** 117886.

BENNETT, J., DAVY, P., TROMPETTER, B., WANG, Y., PIERSE, N., BOULIC, M., PHIPPS, R. & HOWDEN-CHAPMAN, P. 2019. Sources of indoor air pollution at a New Zealand urban primary school; a case study. *Atmospheric Pollution Research,* 10**,** 435-444.

BLOEMAN, H., VAN DER MEULEN, A., MOOIBROEK, D. & CASSEE, F. 2007. Monitoring Black Smoke? Monitoring the impact of abatement measures Netherlands: Ministery of Housing, Physical Planning and Environment.

BORREGO, C., COSTA, A. M., GINJA, J., AMORIM, M., COUTINHO, M., KARATZAS, K., SIOUMIS, T., KATSIFARAKIS, N., KONSTANTINIDIS, K., DE VITO, S., ESPOSITO, E., SMITH, P., ANDRÉ, N., GÉRARD, P., FRANCIS, L. A., CASTELL, N., SCHNEIDER, P., VIANA, M., MINGUILLÓN, M. C., REIMRINGER, W., OTJES, R. P., VON SICARD, O., POHLE, R., ELEN, B., SURIANO, D., PFISTER, V., PRATO, M., DIPINTO, S. & PENZA, M. 2016. Assessment of air quality microsensors versus reference methods: The EuNetAir joint exercise. *Atmospheric Environment,* 147**,** 246-263.

BOUBRIMA, A., BECHKIT, W. & RIVANO, H. 2019. On the deployment of wireless sensor networks for air quality mapping: optimization models and algorithms. *IEEE/ACM Transactions on Networking,* 27**,** 1629-1642.

BRADY, J., NOLAN, K., NOLAN, M. & KELLY, M. 2020. Alert system for internet of things (IoT) devices. Google Patents.

BRATTICH, E., BRACCI, A., ZAPPI, A., MOROZZI, P., DI SABATINO, S., PORCÙ, F., DI NICOLA, F. & TOSITTI, L. 2020. How to Get the Best from Low-Cost Particulate Matter Sensors: Guidelines and Practical Recommendations. *Sensors,* 20**,** 3073.

BRIMBLECOMBE, P. & GROSSI, C. M. 2005. Aesthetic thresholds and blackening of stone buildings. *Science of The Total Environment,* 349**,** 175-189.

BROOK, R. D., RAJAGOPALAN, S., POPE III, C. A., BROOK, J. R., BHATNAGAR, A., DIEZ-ROUX, A. V., HOLGUIN, F., HONG, Y., LUEPKER, R. V. & MITTLEMAN, M. A. 2010. Particulate matter air pollution and cardiovascular disease: an update to the scientific statement from the American Heart Association. *Circulation,* 121**,** 2331-2378.

BUDDE, M., EL MASRI, R., RIEDEL, T. & BEIGL, M. Enabling low-cost particulate matter measurement for participatory sensing scenarios. Proceedings of the 12th international conference on mobile and ubiquitous multimedia, 2013. 1-10.

BULOT, F. M., JOHNSTON, S. J., BASFORD, P. J., EASTON, N. H., APETROAIE-CRISTEA, M., FOSTER, G. L., MORRIS, A. K., COX, S. J. & LOXHAM, M. 2019. Long-term field comparison of multiple low-cost particulate matter sensors in an outdoor urban environment. *Scientific reports,* 9**,** 1-13.

BURNS, P. 2019. 2019 Air Quality Annual Status Report. *In:* HEALTH, E. (ed.). Manor House, Birmingham: Birmingham City Council.

CAO, Z., ZHOU, J., LI, M., HUANG, J. & DOU, D. 2023. Urbanites' mental health undermined by air pollution. *Nature Sustainability*.

CARSLAW, D. & ROPKINS, K. 2012. openair — An R package for air quality data analysis. *Environmental Modelling & Software,* 27–28(0)**,** 52–61.

CASTELL, N., DAUGE, F. R., SCHNEIDER, P., VOGT, M., LERNER, U., FISHBAIN, B., BRODAY, D. & BARTONOVA, A. 2017. Can commercial low-cost sensor platforms contribute to air quality monitoring and exposure estimates? *Environment international,* 99**,** 293-302.

CHAPMAN, L., MULLER, C. L., YOUNG, D. T., WARREN, E. L., GRIMMOND, C. S. B., CAI, X.-M. & FERRANTI, E. J. 2015. The Birmingham urban climate laboratory: An open meteorological

test bed and challenges of the smart city. *Bulletin of the American Meteorological Society,* 96**,** 1545-1560.
CHAPMAN, L., WARREN, E. & CHAPMAN, V. Using the internet of things to monitor low adhesion on railways. Proceedings of the Institution of Civil Engineers-Transport, 2016. Thomas Telford Ltd, 321-329.
CHARRON, A. & HARRISON, R. M. 2005. Fine (PM2.5) and Coarse (PM2.5-10) Particulate Matter on A Heavily Trafficked London Highway: Sources and Processes. *Environmental Science & Technology,* 39**,** 7768-7776.
CHONG, C.-Y. & KUMAR, S. 2003. Sensor Networks: Evolution, opportunities, and challenges. *Proceedings of the IEEE,* 91**,** 1247-1256.
CLARITY. 2023. *Node-S Technical Specifications* [Online]. online. Available: https://click.clarity.io/hubfs/Marketing%20Assets%20-%20PDFs/Product%20and%20Specification%20Sheets/Node-S%202%20Specifications%20Sheet%20(October%202021).pdf?_ga=2.178201957.1344132639.1673886395-1714968752.1673886395&_gac=1.209505958.1673886395.EAIaIQobChMIwMih3cDM_AIVRWHmCh0ndwteEAAYASAAEgIIIPD_BwE [Accessed 16.01.23].
COCÂRŢĂ, D. M., PRODANA, M., DEMETRESCU, I., LUNGU, P. E. M. & DIDILESCU, A. C. 2021. Indoor Air Pollution with Fine Particles and Implications for Workers' Health in Dental Offices: A Brief Review. *Sustainability,* 13**,** 599.
COLES, J. & TIWARY, A. 2009. *Air Pollution : Measurement, Modelling and Mitigation,* London, CRC Press LLC.
CRILLEY, L. R., SHAW, M., POUND, R., KRAMER, L. J., PRICE, R., YOUNG, S., LEWIS, A. C. & POPE, F. D. 2018. Evaluation of a low-cost optical particle counter (Alphasense OPC-N2) for ambient air monitoring. *Atmospheric Measurement Techniques***,** 709-720.
CRILLEY, L. R., SINGH, A., KRAMER, L. J., SHAW, M. D., ALAM, M. S., APTE, J. S., BLOSS, W. J., HILDEBRANDT RUIZ, L., FU, P., FU, W., GANI, S., GATARI, M., ILYINSKAYA, E., LEWIS, A. C., NG'ANG'A, D., SUN, Y., WHITTY, R. C. W., YUE, S., YOUNG, S. & POPE, F. D. 2020. Effect of aerosol composition on the performance of low-cost optical particle counter correction factors. *Atmos. Meas. Tech.,* 13**,** 1181-1193.
DE NAZELLE, A., BODE, O. & ORJUELA, J. P. 2017. Comparison of air pollution exposures in active vs. passive travel modes in European cities: A quantitative review. *Environment international,* 99**,** 151-160.
DEFRA 2023a. Emissions of air pollutants in the UK – Particulate matter (PM10 and PM2.5). *In:* STATISTICS, N. (ed.). online.
DEFRA. 2023b. *Glossary* [Online]. online. Available: https://uk-air.defra.gov.uk/air-pollution/glossary.php?glossary_id=16#:~:text=Black%20Smoke,emitted%20mainly%20from%20fuel%20combustion. [Accessed 20.03.23].
DEFRA 2023c. National statistics Emissions of air pollutants in the UK – Particulate matter (PM10 and PM2.5). online.
DEFRA. 2023d. *Site Environment Types* [Online]. Available: https://uk-air.defra.gov.uk/networks/site-types [Accessed 11/01/2023].
DEMANEGA, I., MUJAN, I., SINGER, B. C., ANĐELKOVIĆ, A. S., BABICH, F. & LICINA, D. 2021. Performance assessment of low-cost environmental monitors and single sensors under variable indoor air quality and thermal conditions. *Building and Environment,* 187**,** 107415.
DEPARTMENT OF ENVIRONMENTAL FOOD AND RURAL AFFAIRS. 2022. *Interactive monitoring networks map* [Online]. Available: https://uk-air.defra.gov.uk/interactive-map [Accessed 12/01/2023].
DI ANTONIO, A., POPOOLA, O. A., OUYANG, B., SAFFELL, J. & JONES, R. L. 2018. Developing a relative humidity correction for low-cost sensors measuring ambient particulate matter. *Sensors,* 18**,** 2790.

DOGEANU, A., NASTASE, I., URSU, I., ENCIU, D., BODE, F., SANDU, M., CROITORU, C., ZAHARIA, S. & IANA, G. Real time monitoring network demonstrator for air quality management. 2019 International Conference on ENERGY and ENVIRONMENT (CIEM), 2019. IEEE, 459-463.

DYER, C. 2020. Air pollution from road traffic contributed to girl's death from asthma, coroner concludes. British Medical Journal Publishing Group.

EARTHSENSE 2022. Zephyr Air Quality Monitor Specification Sheet. online.

EJOHWOMU, O. A., OLADOKUN, M., OSHODI, O. S., BUKOYE, O. T., EDWARDS, D. J., EMEKWURU, N., ADENUGA, O., SOTUNBO, A., UDUKU, O. & BALOGUN, M. 2022. The Exposure of Workers at a Busy Road Node to PM2. 5: Occupational Risk Characterisation and Mitigation Measures. *International Journal of Environmental Research and Public Health,* 19**,** 4636.

ENVIRONMENT PROTECTION AUTHORITY 2004. Photochemical smog

—what it means for us Adelaide.

EU-DIRECTIVE 2008. 2008/50/EC of the European Parliament and the Council of 21 May 2008 on Ambient Air Quality and Cleaner Air for Europe.

EUROPEAN AUTOMOBILE MANUFACTURERS ASSOCIATION 2022. Vehicles in use Europe 2022. online.

EUROPEAN COMMISSION. 2022. *Questions and Answers: Commission proposal on the new Euro 7 standards* [Online]. Brussels. Available: https://ec.europa.eu/commission/presscorner/detail/en/qanda_22_6496 [Accessed 20.03.23].

EUROPEAN COMMISSION. 2023. *Coarse particles* [Online]. online. Available: https://ec.europa.eu/health/scientific_committees/opinions_layman/en/indoor-air-pollution/glossary/abc/coarse-particles.htm#:~:text=Coarse%20particles%20have%20an%20aerodynamic,1). [Accessed 08.05.23].

EUROPEAN UNION 2008. Directive 2008/50/EC of the European Parliament and of the Council

of 21 May 2008

on ambient air quality and cleaner air for Europe. Official Journal of the European Union.

FEENSTRA, B., PAPAPOSTOLOU, V., HASHEMINASSAB, S., ZHANG, H., BOGHOSSIAN, B. D., COCKER, D. & POLIDORI, A. 2019. Performance evaluation of twelve low-cost PM2.5 sensors at an ambient air monitoring site. *Atmospheric Environment,* 216**,** 116946.

FERRO, A. R., ZÍKOVÁ, N., MASIOL, M., SATSANGI, G. P., TWOMEY, T., CHALUPA, D. C., RICH, D. Q. & HOPKE, P. K. 2022. Residential Indoor and Outdoor PM Measured Using Low-cost Monitors during the Heating Season in Monroe County, NY. *Aerosol and Air Quality Research,* 22**,** 220210.

FISHBAIN, B., LERNER, U., CASTELL, N., COLE-HUNTER, T., POPOOLA, O., BRODAY, D. M., IÑIGUEZ, T. M., NIEUWENHUIJSEN, M., JOVASEVIC-STOJANOVIC, M. & TOPALOVIC, D. 2017. An evaluation tool kit of air quality micro-sensing units. *Science of the total environment,* 575**,** 639-648.

FONT, A., CIUPEK, K., BUTTERFIELD, D. & FULLER, G. W. 2022. Long-term trends in particulate matter from wood burning in the United Kingdom: Dependence on weather and social factors. *Environmental Pollution,* 314**,** 120105.

FRIEDLANDER, S. 2000. *Smoke, Dust and Haze Fundamentals of Aerosol Dynamics,* New York, Oxford University Press.

FUZZI, S., BALTENSPERGER, U., CARSLAW, K., DECESARI, S., DENIER VAN DER GON, H., FACCHINI, M. C., FOWLER, D., KOREN, I., LANGFORD, B., LOHMANN, U., NEMITZ, E., PANDIS, S., RIIPINEN, I., RUDICH, Y., SCHAAP, M., SLOWIK, J. G., SPRACKLEN, D. V., VIGNATI, E., WILD, M., WILLIAMS, M. & GILARDONI, S. 2015. Particulate matter, air quality and climate: lessons learned and future needs. *Atmos. Chem. Phys.,* 15**,** 8217-8299.

GOMEZ, C., VERAS, J. C., VIDAL, R., CASALS, L. & PARADELLS, J. 2019. A sigfox energy consumption model. *Sensors,* 19**,** 681.
GORAI, A. K., TCHOUNWOU, P. B., BISWAL, S. S. & TULURI, F. 2018. Spatio-Temporal Variation of Particulate Matter(PM2.5) Concentrations and Its Health Impacts in a Mega City, Delhi in India. *Environmental Health Insights,* 12**,** 1178630218792861.
GREATER LONDON AUTHORITY 2019. PM2.5 in London:Roadmap to meeting World Health Organization guidelines by 2030. City Hall, London.
GULIA, S., KHANNA, I., SHUKLA, K. & KHARE, M. 2020. Ambient air pollutant monitoring and analysis protocol for low and middle income countries: An element of comprehensive urban air quality management framework. *Atmospheric Environment,* 222**,** 117120.
GUPTA, P., CHRISTOPHER, S. A., WANG, J., GEHRIG, R., LEE, Y. & KUMAR, N. 2006. Satellite remote sensing of particulate matter and air quality assessment over global cities. *Atmospheric Environment,* 40**,** 5880-5892.
GUTTIKUNDA, S. K., GOEL, R. & PANT, P. 2014. Nature of air pollution, emission sources, and management in the Indian cities. *Atmospheric Environment,* 95**,** 501-510.
HAGAN, D. & CROSS, E. 2022. Can your Plantower PMS5003-based Air Quality Sensor Measure PM10? Available from: https://blog.quant-aq.com/can-your-plantower-pms5003-based-air-quality-sensor-measure-pm10/?s=03 2022].
HARR, L., SINSEL, T., SIMON, H. & ESPER, J. 2022. Seasonal Changes in Urban PM2. 5 Hotspots and Sources from Low-Cost Sensors. *Atmosphere,* 13**,** 694.
HARRISON, R. M. 2020. Airborne particulate matter. *Philosophical Transactions of the Royal Society A,* 378**,** 20190319.
HARRISON, R. M., ALLAN, J., CARRUTHERS, D., HEAL, M. R., LEWIS, A. C., MARNER, B., MURRELLS, T. & WILLIAMS, A. 2021. Non-exhaust vehicle emissions of particulate matter and VOC from road traffic: A review. *Atmospheric Environment,* 262**,** 118592.
HARRISON, R. M. & YIN, J. 2000. Particulate matter in the atmosphere: which particle properties are important for its effects on health? *Science of The Total Environment,* 249**,** 85-101.
HE, M., KUERBANJIANG, N. & DHANIYALA, S. 2020. Performance characteristics of the low-cost Plantower PMS optical sensor. *Aerosol Science and Technology,* 54**,** 232-241.
HIME, N., COWIE, C. & MARKS, G. 2015. *Review of the health impacts of emission sources, types and levels of particulate matter air pollution in ambient air in NSW*.
HOEK, G., WELINDER, H., VASKOVI, E., CIACCHINI, G., MANALIS, N., RØYSET, O., REPONEN, A., CYRYS, J. & BRUNEKREEF, B. 1997. Interlaboratory comparison of PM10 and black smoke measurements in the PEACE study. *Atmospheric Environment,* 31**,** 3341-3349.
HOFMAN, J., PETERS, J., STROOBANTS, C., ELST, E., BAEYENS, B., VAN LAER, J., SPRUYT, M., VAN ESSCHE, W., DELBARE, E. & ROELS, B. 2022. Air Quality Sensor Networks for Evidence-Based Policy Making: Best Practices for Actionable Insights. *Atmosphere,* 13**,** 944.
HOPKE, P. K., DAI, Q., LI, L. & FENG, Y. 2020. Global review of recent source apportionments for airborne particulate matter. *Science of The Total Environment,* 740**,** 140091.
HUANG, H., LEE, S.-C., CAO, J.-J., ZOU, C.-W., CHEN, X.-G. & FAN, S.-J. 2007. Characteristics of indoor/outdoor PM2.5 and elemental components in generic urban, roadside and industrial plant areas of Guangzhou City, China. *Journal of Environmental Sciences,* 19**,** 35-43.
HUANG, T.-H., TSAI, C.-H. & SHAN, M.-K. Key sensor discovery for quality audit of air sensor networks. Proceedings of the 18th International Conference on Mobile Systems, Applications, and Services, 2020. 474-475.
IAQM, I. O. A. Q. M. 2018. IAQM Guidance On Air Quality Monitoring In The Vicinity Of Demolition And Construction Sites.
ILACQUA, V., SCHARKO, N., ZAMBRANA, J. & MALASHOCK, D. 2022. Survey of residential indoor particulate matter measurements 1990–2019. *Indoor air,* 32**,** e13057.

JALADI, A. R., KHITHANI, K., PAWAR, P., MALVI, K. & SAHOO, G. 2017. Environmental monitoring using wireless sensor networks (WSN) based on IOT. *Int. Res. J. Eng. Technol,* 4**,** 1371-1378.
JERZY, M. & JACEK, P. 2015. *Nanoparticle Emissions From Combustion Engines,* Cham, Springer.
JOHNSON, K. K., BERGIN, M. H., RUSSELL, A. G. & HAGLER, G. S. 2018. Field test of several low-cost particulate matter sensors in high and low concentration urban environments. *Aerosol and Air Quality Research,* 18**,** 565.
JORIS, L., DUPONT, F., LAURENT, P., BELLIER, P., STOUKATCH, S. & REDOUTÉ, J.-M. 2019. An autonomous sigfox wireless sensor node for environmental monitoring. *IEEE Sensors Letters,* 3**,** 01-04.
KADDOURA, I., EWERT, R. & MARTINS-TURNER, K. 2022. Exhaust and non-exhaust emissions from today's and future road transport: A simulation-based quantification for Berlin. *Transportation Research Procedia,* 62**,** 696-702.
KAISER, H. & SPECKER, H. 1956. Evaluation and comparison of methods of analysis. *Z. anal. Chem,* 149**,** 46.
KALISZEWSKI, M., WŁODARSKI, M., MŁYŃCZAK, J. & KOPCZYŃSKI, K. 2020. Comparison of Low-Cost Particulate Matter Sensors for Indoor Air Monitoring during COVID-19 Lockdown. *Sensors,* 20.
KARAGULIAN, F., BELIS, C. A., DORA, C. F. C., PRÜSS-USTÜN, A. M., BONJOUR, S., ADAIR-ROHANI, H. & AMANN, M. 2015. Contributions to cities' ambient particulate matter (PM): A systematic review of local source contributions at global level. *Atmospheric environment,* 120**,** 475-483.
KELLY, K., WHITAKER, J., PETTY, A., WIDMER, C., DYBWAD, A., SLEETH, D., MARTIN, R. & BUTTERFIELD, A. 2017. Ambient and laboratory evaluation of a low-cost particulate matter sensor. *Environmental Pollution,* 221**,** 491-500.
KIM, S., PARK, S. & LEE, J. 2019. Evaluation of Performance of Inexpensive Laser Based PM2.5 Sensor Monitors for Typical Indoor and Outdoor Hotspots of South Korea. *Applied Sciences,* 9**,** 1947.
KNOLL, M., BREITEGGER, P. & BERGMANN, A. 2018. Low-Power Wide-Area technologies as building block for smart sensors in air quality measurements. *e & i Elektrotechnik und Informationstechnik,* 135**,** 416-422.
KULARATNA, N. & SUDANTHA, B. 2008. An environmental air pollution monitoring system based on the IEEE 1451 standard for low cost requirements. *IEEE Sensors Journal,* 8**,** 415-422.
KULMALA, M., MASO, M. D., MÄKELÄ, J., PIRJOLA, L., VÄKEVÄ, M., AALTO, P., MIIKKULAINEN, P., HÄMERI, K. & O'DOWD, C. 2001. On the formation, growth and composition of nucleation mode particles. *Tellus B,* 53**,** 479-490.
KÜPPER, M., ASBACH, C., SCHNEIDERWIND, U., FINGER, H., SPIEGELHOFF, D. & SCHUMACHER, S. 2019. Testing of an indoor air cleaner for particulate pollutants under realistic conditions in an office room. *Aerosol and Air Quality Research,* 19**,** 1655-1665.
KUULA, J., MÄKELÄ, T., HILLAMO, R. & TIMONEN, H. 2017. Response Characterization of an Inexpensive Aerosol Sensor. *Sensors (Basel, Switzerland),* 17**,** 2915.
LAVRIC, A. & POPA, V. Internet of things and LoRa™ low-power wide-area networks: a survey. 2017 International Symposium on Signals, Circuits and Systems (ISSCS), 2017. IEEE, 1-5.
LAZARESCU, M. T. 2013. Design of a WSN platform for long-term environmental monitoring for IoT applications. *IEEE Journal on emerging and selected topics in circuits and systems,* 3**,** 45-54.
LEVY ZAMORA, M., XIONG, F., GENTNER, D., KERKEZ, B., KOHRMAN-GLASER, J. & KOEHLER, K. 2018. Field and laboratory evaluations of the low-cost plantower particulate matter sensor. *Environmental science & technology,* 53**,** 838-849.
LEVY ZAMORA, M., XIONG, F., GENTNER, D., KERKEZ, B., KOHRMAN-GLASER, J. & KOEHLER, K. 2019. Field and Laboratory Evaluations of the Low-Cost Plantower Particulate Matter Sensor. *Environmental Science & Technology,* 53**,** 838-849.
LEWIS, A., MOLLER, S. J. & CARSLAW, D. 2019. Non-exhaust emissions from road traffic.
LEWIS, A., PELTIER, W. R. & VON SCHNEIDEMESSER, E. 2018. Low-cost sensors for the measurement of atmospheric composition: overview of topic and future applications.

LEWIS, A. C., LEE, J. D., EDWARDS, P. M., SHAW, M. D., EVANS, M. J., MOLLER, S. J., SMITH, K. R., BUCKLEY, J. W., ELLIS, M., GILLOT, S. R. & WHITE, A. 2016. Evaluating the performance of low cost chemical sensors for air pollution research. *Faraday Discussions,* 189**,** 85-103.

LI, N., GEORAS, S., ALEXIS, N., FRITZ, P., XIA, T., WILLIAMS, M. A., HORNER, E. & NEL, A. 2016. A work group report on ultrafine particles (AAAAI) why ambient ultrafine and engineered nanoparticles should receive special attention for possible adverse health outcomes in humans. *The Journal of allergy and clinical immunology,* 138**,** 386.

LI, S., XU, L. D. & ZHAO, S. 2015. The internet of things: a survey. *Information Systems Frontiers,* 17**,** 243-259.

LI, Z., WEN, Q. & ZHANG, R. 2017. Sources, health effects and control strategies of indoor fine particulate matter (PM2.5): A review. *Science of The Total Environment,* 586**,** 610-622.

LIU, Y., CHEN, H., LI, Y., GAO, J., DAVE, K., CHEN, J., LI, T. & TU, R. 2022. Exhaust and non-exhaust emissions from conventional and electric vehicles: A comparison of monetary impact values. *Journal of Cleaner Production,* 331**,** 129965.

MAGI, B. I., CUPINI, C., FRANCIS, J., GREEN, M. & HAUSER, C. 2020. Evaluation of PM2. 5 measured in an urban setting using a low-cost optical particle counter and a Federal Equivalent Method Beta Attenuation Monitor. *Aerosol Science and Technology,* 54**,** 147-159.

MANDIN, C., TRANTALLIDI, M., CATTANEO, A., CANHA, N., MIHUCZ, V. G., SZIGETI, T., MABILIA, R., PERRECA, E., SPINAZZÈ, A., FOSSATI, S., DE KLUIZENAAR, Y., CORNELISSEN, E., SAKELLARIS, I., SARAGA, D., HÄNNINEN, O., DE OLIVEIRA FERNANDES, E., VENTURA, G., WOLKOFF, P., CARRER, P. & BARTZIS, J. 2017. Assessment of indoor air quality in office buildings across Europe – The OFFICAIR study. *Science of The Total Environment,* 579**,** 169-178.

MATTHAIOS, V. N., LAWRENCE, J., MARTINS, M. A. G., FERGUSON, S. T., WOLFSON, J. M., HARRISON, R. M. & KOUTRAKIS, P. 2022. Quantifying factors affecting contributions of roadway exhaust and non-exhaust emissions to ambient PM10–2.5 and PM2.5–0.2 particles. *Science of The Total Environment,* 835**,** 155368.

MCCORMICK, R. A., LIGHTHILL, M. J. & SILVERLEAF, A. 1971. Air pollution in the locality of buildings. *Philosophical Transactions of the Royal Society of London. Series A, Mathematical and Physical Sciences,* 269**,** 515-526.

MEAD, M., POPOOLA, O., STEWART, G., LANDSHOFF, P., CALLEJA, M., HAYES, M., BALDOVI, J., MCLEOD, M., HODGSON, T. & DICKS, J. 2013. The use of electrochemical sensors for monitoring urban air quality in low-cost, high-density networks. *Atmospheric Environment,* 70**,** 186-203.

MEKKI, K., BAJIC, E., CHAXEL, F. & MEYER, F. Overview of cellular LPWAN technologies for IoT deployment: Sigfox, LoRaWAN, and NB-IoT. 2018 ieee international conference on pervasive computing and communications workshops (percom workshops), 2018. IEEE, 197-202.

MEKKI, K., BAJIC, E., CHAXEL, F. & MEYER, F. 2019. A comparative study of LPWAN technologies for large-scale IoT deployment. *ICT express,* 5**,** 1-7.

MOHAMMADYAN, M., ALIZADEH-LARIMI, A., ETEMADINEJAD, S., LATIF, M. T., HEIBATI, B., YETILMEZSOY, K., ABDUL-WAHAB, S. A. & DADVAND, P. 2017. Particulate air pollution at schools: Indoor-outdoor relationship and determinants of indoor concentrations. *Aerosol and Air Quality Research,* 17**,** 857-864.

MOUSAVI, A. & WU, J. 2021. Indoor-Generated PM2.5 During COVID-19 Shutdowns Across California: Application of the PurpleAir Indoor–Outdoor Low-Cost Sensor Network. *Environmental Science & Technology,* 55**,** 5648-5656.

MUKHERJEE, A. & AGRAWAL, M. 2017. World air particulate matter: sources, distribution and health effects. *Environmental Chemistry Letters,* 15**,** 283-309.

MUKHERJEE, A., STANTON, L. G., GRAHAM, A. R. & ROBERTS, P. T. 2017. Assessing the utility of low-cost particulate matter sensors over a 12-week period in the Cuyama valley of California. *Sensors,* 17**,** 1805.

NAGARAJ, S. & BIRADAR, R. V. Applications of wireless sensor networks in the real-time ambient air pollution monitoring and air quality in metropolitan cities—a survey. 2017 International Conference On Smart Technologies For Smart Nation (SmartTechCon), 2017. IEEE, 1393-1398.

NATIONAL ATMOSPHERIC EMISSIONS INVENTORY 2022. Pollutant Information: PM2.5.

NORTHCROSS, A. L., EDWARDS, R. J., JOHNSON, M. A., WANG, Z.-M., ZHU, K., ALLEN, T. & SMITH, K. R. 2013. A low-cost particle counter as a realtime fine-particle mass monitor. *Environmental Science: Processes & Impacts,* 15**,** 433-439.

OFFICE OF AIR AND RADIATION. 2003. *Particle Pollution and Your Health* [Online]. Online/USA: Environmental Protection Agency. Available: https://nepis.epa.gov/Exe/ZyPDF.cgi?Dockey=P1001EX6.txt [Accessed 14/03/2023].

OJO, K. D., SONEJA, S. I., SCRAFFORD, C. G., KHATRY, S. K., LECLERQ, S. C., CHECKLEY, W., KATZ, J., BREYSSE, P. N. & TIELSCH, J. M. 2015. Indoor particulate matter concentration, water boiling time, and fuel use of selected alternative cookstoves in a home-like setting in rural Nepal. *International journal of environmental research and public health,* 12**,** 7558-7581.

OUIMETTE, J. R., MALM, W. C., SCHICHTEL, B. A., SHERIDAN, P. J., ANDREWS, E., OGREN, J. A. & ARNOTT, W. P. 2022. Evaluating the PurpleAir monitor as an aerosol light scattering instrument. *Atmos. Meas. Tech.,* 15**,** 655-676.

OZGA, I., BONAZZA, A., BERNARDI, E., TITTARELLI, F., FAVONI, O., GHEDINI, N., MORSELLI, L. & SABBIONI, C. 2011. Diagnosis of surface damage induced by air pollution on 20th-century concrete buildings. *Atmospheric Environment,* 45**,** 4986-4995.

PANCHAL, R., PANAGI, M., MAY, H. R., OBSZYNSKA, J. A., EVANS, M. S., HANSELL, A. L., GULLIVER, J. & HEY, J. D. V. 2022. Personal air pollution exposure during morning commute car and active transport journeys. *Journal of Transport & Health***,** 101365.

PANT, P. & HARRISON, R. M. 2013. Estimation of the contribution of road traffic emissions to particulate matter concentrations from field measurements: A review. *Atmospheric Environment,* 77**,** 78-97.

PATEL, D. & WON, M. Experimental study on low power wide area networks (LPWAN) for mobile Internet of Things. 2017 IEEE 85th vehicular technology conference (VTC Spring), 2017. IEEE, 1-5.

PATEL, S., SANKHYAN, S., BOEDICKER, E. K., DECARLO, P. F., FARMER, D. K., GOLDSTEIN, A. H., KATZ, E. F., NAZAROFF, W. W., TIAN, Y., VANHANEN, J. & VANCE, M. E. 2020. Indoor Particulate Matter during HOMEChem: Concentrations, Size Distributions, and Exposures. *Environmental Science & Technology,* 54**,** 7107-7116.

PAVANI, M. & RAO, P. T. 2017. Urban air pollution monitoring using wireless sensor networks: a comprehensive review. *International Journal of Communication Networks and Information Security,* 9**,** 439-449.

PERRINO, C. 2010. Atmospheric particulate matter. *Biophysics and Bioengineering Letters,* 3.

PILLARISETTI, A., ALLEN, T., RUIZ-MERCADO, I., EDWARDS, R., CHOWDHURY, Z., GARLAND, C., HILL, L. D., JOHNSON, M., LITTON, C. D. & LAM, N. L. 2017. Small, smart, fast, and cheap: microchip-based sensors to estimate air pollution exposures in rural households. *Sensors,* 17**,** 1879.

PISCITELLO, A., BIANCO, C., CASASSO, A. & SETHI, R. 2021. Non-exhaust traffic emissions: Sources, characterization, and mitigation measures. *Science of The Total Environment,* 766**,** 144440.

PISONI, E., CHRISTIDIS, P., THUNIS, P. & TROMBETTI, M. 2019. Evaluating the impact of "Sustainable Urban Mobility Plans" on urban background air quality. *Journal of environmental management,* 231**,** 249-255.

POPE, F. D., GATARI, M., NG'ANG'A, D., POYNTER, A. & BLAKE, R. 2018. Airborne particulate matter monitoring in Kenya using calibrated low-cost sensors. *Atmospheric Chemistry and Physics,* 18**,** 15403-15418.

PÖSCHL, U. 2005. Atmospheric aerosols: composition, transformation, climate and health effects. *Angewandte Chemie International Edition,* 44**,** 7520-7540.

PRINGLE, K. J., TOST, H., POZZER, A., PÖSCHL, U. & LELIEVELD, J. 2010. Global distribution of the effective aerosol hygroscopicity parameter for CCN activation. *Atmos. Chem. Phys.,* 10**,** 5241-5255.
PURPLEAIR. 2023. *https://www2.purpleair.com/* [Online]. [Accessed 16.01.2023].
QUARMBY, S., SANTOS, G. & MATHIAS, M. 2019. Air quality strategies and technologies: A rapid review of the international evidence. *Sustainability,* 11**,** 2757.
QUEROL, X., MINGUILLÓN, M.-C. & VIANA, M. 2013. *Particulate Matter,* London, London: Future Science Ltd.
RAI, A. C., KUMAR, P., PILLA, F., SKOULOUDIS, A. N., DI SABATINO, S., RATTI, C., YASAR, A. & RICKERBY, D. 2017. End-user perspective of low-cost sensors for outdoor air pollution monitoring. *Science of The Total Environment,* 607**,** 691-705.
RAMSON, S. J. & MONI, D. J. Applications of wireless sensor networks—A survey. 2017 international conference on innovations in electrical, electronics, instrumentation and media technology (ICEEIMT), 2017. IEEE, 325-329.
RATASUK, R., VEJLGAARD, B., MANGALVEDHE, N. & GHOSH, A. NB-IoT system for M2M communication. 2016 IEEE wireless communications and networking conference, 2016. IEEE, 1-5.
ROGULSKI, M. & BADYDA, A. Current trends in network based air quality monitoring systems. IOP Conference Series: Earth and Environmental Science, 2019. IOP Publishing, 012085.
SAYAHI, T., BUTTERFIELD, A. & KELLY, K. 2019. Long-term field evaluation of the Plantower PMS low-cost particulate matter sensors. *Environmental Pollution,* 245**,** 932-940.
SCHIEBER, J. 2020. Air quality monitoring service Airly raises $2 million as fires, pollution force consumers to take note. *TechCrunch.* online.
SCHMITZ, S., CASEIRO, A., KERSCHBAUMER, A. & VON SCHNEIDEMESSER, E. 2021. Do new bike lanes impact air pollution exposure for cyclists?—a case study from Berlin. *Environmental Research Letters,* 16**,** 084031.
SEIGNEUR, C. 2019. Atmospheric Particles. *Air Pollution: Concepts, Theory, and Applications. Cambridge University Press***,** 190-238.
SEMMENS, E. O., NOONAN, C. W., ALLEN, R. W., WEILER, E. C. & WARD, T. J. 2015. Indoor particulate matter in rural, wood stove heated homes. *Environmental research,* 138**,** 93-100.
SHAH, J. & MISHRA, B. IoT enabled environmental monitoring system for smart cities. 2016 international conference on internet of things and applications (IOTA), 2016. IEEE, 383-388.
SHARMA, A., MISHRA, B., SUTARIA, R. & ZELE, R. Design and Development of Low-cost Wireless Sensor Device for Air Quality Networks. TENCON 2019-2019 IEEE Region 10 Conference (TENCON), 2019. IEEE, 2345-2350.
SHEHAB, M. A. & POPE, F. D. 2019. Effects of short-term exposure to particulate matter air pollution on cognitive performance. *Scientific Reports,* 9**,** 8237.
SHENG, Z., MAHAPATRA, C., ZHU, C. & LEUNG, V. C. 2015. Recent advances in industrial wireless sensor networks toward efficient management in IoT. *IEEE access,* 3**,** 622-637.
SHKURTI, L., BAJRAMI, X., CANHASI, E., LIMANI, B., KRRABAJ, S. & HULAJ, A. Development of ambient environmental monitoring system through wireless sensor network (WSN) using NodeMCU and "WSN monitoring". 2017 6th Mediterranean Conference on Embedded Computing (MECO), 2017. IEEE, 1-5.
SIGFOX. 2020. *What Is Sigfox? | Sigfox Build* [Online]. Available: https://build.sigfox.com/sigfox [Accessed 4 June 2020].
SINHA, R. S., WEI, Y. & HWANG, S.-H. 2017. A survey on LPWA technology: LoRa and NB-IoT. *Ict Express,* 3**,** 14-21.
SNYDER, E. G., WATKINS, T. H., SOLOMON, P. A., THOMA, E. D., WILLIAMS, R. W., HAGLER, G. S., SHELOW, D., HINDIN, D. A., KILARU, V. J. & PREUSS, P. W. 2013. The changing paradigm of air pollution monitoring. *Environmental science & technology,* 47**,** 11369-11377.

SONG, Y., LIN, J., TANG, M. & DONG, S. 2017. An Internet of energy things based on wireless LPWAN. *Engineering,* 3**,** 460-466.
SOROKA, E. G. 2020. Indoor and Outdoor Measurements of Particulate Matter with the Low-Cost Optical Sensor OPC-N3.
SOUSAN, S., GRAY, A., ZUIDEMA, C., STEBOUNOVA, L., THOMAS, G., KOEHLER, K. & PETERS, T. 2018. Sensor selection to improve estimates of particulate matter concentration from a low-cost network. *Sensors,* 18**,** 3008.
SOUSAN, S., REGMI, S. & PARK, Y. M. 2021. Laboratory evaluation of low-cost optical particle counters for environmental and occupational exposures. *Sensors,* 21**,** 4146.
TIMMERS, V. R. & ACHTEN, P. A. 2016. Non-exhaust PM emissions from electric vehicles. *Atmospheric Environment,* 134**,** 10-17.
TRYNER, J., L'ORANGE, C., MEHAFFY, J., MILLER-LIONBERG, D., HOFSTETTER, J. C., WILSON, A. & VOLCKENS, J. 2020a. Laboratory evaluation of low-cost PurpleAir PM monitors and in-field correction using co-located portable filter samplers. *Atmospheric Environment,* 220**,** 117067.
TRYNER, J., MEHAFFY, J., MILLER-LIONBERG, D. & VOLCKENS, J. 2020b. Effects of aerosol type and simulated aging on performance of low-cost PM sensors. *Journal of Aerosol Science,* 150**,** 105654.
UNITED STATES ENVIRONMENTAL PROTECTION AGENCY. 2023. *What is PM?* [Online]. online. Available: https://www3.epa.gov/region1/airquality/pm-what-is.html [Accessed 29.05.23].
VALLERO, D. A. 2008. 10 - Sources of Air Pollution. *In:* VALLERO, D. A. (ed.) *Fundamentals of Air Pollution (Fourth Edition).* Burlington: Academic Press.
VEJLGAARD, B., LAURIDSEN, M., NGUYEN, H., KOVÁCS, I. Z., MOGENSEN, P. & SORENSEN, M. Coverage and capacity analysis of sigfox, lora, gprs, and nb-iot. 2017 IEEE 85th vehicular technology conference (VTC Spring), 2017. IEEE, 1-5.
WALLACE, L. 2006. Indoor Sources of Ultrafine and Accumulation Mode Particles: Size Distributions, Size-Resolved Concentrations, and Source Strengths. *Aerosol Science and Technology,* 40**,** 348-360.
WANG, Y., LI, J., JING, H., ZHANG, Q., JIANG, J. & BISWAS, P. 2015. Laboratory evaluation and calibration of three low-cost particle sensors for particulate matter measurement. *Aerosol Science and Technology,* 49**,** 1063-1077.
WATERS, L. 2016. Summary results of the domestic wood use survery. Tech. rep., Renewable Energy Statistics, available at: https://www. gov. uk ….
WHO 2018. Ambient (outdoor) air pollution. online: World Health Organisation.
WHO. 2019. *Air Pollution* [Online]. Available: https://www.who.int/health-topics/air-pollution#tab=tab_1 [Accessed 24 March 2020].
WILLIAMS, R., KAUFMAN, A., HANLEY, T., RICE, J. & GARVEY, S. 2014a. Evaluation of field-deployed low cost PM sensors. *US Environmental Protection Agency*.
WILLIAMS, R., KILARU, V., SNYDER, E., KAUFMAN, A., DYE, T., RUTTER, A. & HAFNER, H. 2014b. Air Sensor Guidebook. *In:* AGENCY, U. S. E. P. (ed.). Washington DC.
WILSON, W. E., CHOW, J. C., CLAIBORN, C., FUSHENG, W., ENGELBRECHT, J. & WATSON, J. G. 2002. Monitoring of particulate matter outdoors. *Chemosphere,* 49**,** 1009-1043.
WON, W.-S., OH, R., LEE, W., KU, S., SU, P.-C. & YOON, Y.-J. 2021. Hygroscopic properties of particulate matter and effects of their interactions with weather on visibility. *Scientific Reports,* 11**,** 16401.
WOOD, M., WOOD, C., STYRING, P., JONES, C. R., SMITH, J., DAY, M., CHAKRABORTY, R. & MENSAH, G. 2022. Perceptions of Accountability and Trust in the Regulatory Governance of Wood Burning Stove Sustainability: Survey Evidence from the Post-Brexit UK. *Available at SSRN 4233888*.
WORLD HEALTH ORGANIZATION 2013. Health Effects of Particulate Matter: Policy implications for countries in eastern Europe, Caucasus and central Asia.

YOCOM, J. E. 1958. The deterioration of materials in polluted atmospheres. *Journal of the Air Pollution Control Association,* 8**,** 203-208.
YOUNG, D. T., CHAPMAN, L., MULLER, C. L., CAI, X.-M. & GRIMMOND, C. 2014. A low-cost wireless temperature sensor: Evaluation for use in environmental monitoring applications. *Journal of Atmospheric and Oceanic Technology,* 31**,** 938-944.
ZAMORA, M. L., RICE, J. & KOEHLER, K. 2020. One year evaluation of three low-cost PM2. 5 monitors. *Atmospheric Environment***,** 117615.
ZANELLA, A., BUI, N., CASTELLANI, A., VANGELISTA, L. & ZORZI, M. 2014. Internet of things for smart cities. *IEEE Internet of Things journal,* 1**,** 22-32.
ZARĘBA, M. & DANEK, T. 2022. Analysis of Air Pollution Migration during COVID-19 Lockdown in Krakow, Poland. *Aerosol and Air Quality Research,* 22**,** 210275.
ZHANG, Y. & LI, Z. 2015. Remote sensing of atmospheric fine particulate matter (PM2.5) mass concentration near the ground from satellite observation. *Remote Sensing of Environment,* 160**,** 252-262.
ZHANG, Y., LI, Z., BAI, K., WEI, Y., XIE, Y., ZHANG, Y., OU, Y., COHEN, J., ZHANG, Y., PENG, Z., ZHANG, X., CHEN, C., HONG, J., XU, H., GUANG, J., LV, Y., LI, K. & LI, D. 2021. Satellite remote sensing of atmospheric particulate matter mass concentration: Advances, challenges, and perspectives. *Fundamental Research,* 1**,** 240-258.
ZHENG, T., BERGIN, M. H., JOHNSON, K. K., TRIPATHI, S. N., SHIRODKAR, S., LANDIS, M. S., SUTARIA, R. & CARLSON, D. E. 2018. Field evaluation of low-cost particulate matter sensors in high-and low-concentration environments. *Atmospheric Measurement Techniques,* 11**,** 4823-4846.
ZHONG, J., HOOD, C., JOHNSON, K., STOCKER, J., HANDLEY, J., WOLSTENCROFT, M., MAZZEO, A., CAI, X. & BLOSS, W. J. 2021. Using Task Farming to Optimise a Street-Scale Resolution Air Quality Model of the West Midlands (UK). *Atmosphere,* 12**,** 983.
ZHU, Q., WANG, R., CHEN, Q., LIU, Y. & QIN, W. Iot gateway: Bridgingwireless sensor networks into internet of things. 2010 IEEE/IFIP International Conference on Embedded and Ubiquitous Computing, 2010. Ieee, 347-352.
ZIKOVA, N., MASIOL, M., CHALUPA, D. C., RICH, D. Q., FERRO, A. R. & HOPKE, P. K. 2017. Estimating hourly concentrations of PM2. 5 across a metropolitan area using low-cost particle monitors. *Sensors,* 17**,** 1922.
ZOU, Y., CLARK, J. D. & MAY, A. A. 2021. Laboratory evaluation of the effects of particle size and composition on the performance of integrated devices containing Plantower particle sensors. *Aerosol Science and Technology***,** 1-14.
ZUSMAN, M., SCHUMACHER, C. S., GASSETT, A. J., SPALT, E. W., AUSTIN, E., LARSON, T. V., CARVLIN, G., SETO, E., KAUFMAN, J. D. & SHEPPARD, L. 2020. Calibration of low-cost particulate matter sensors: Model development for a multi-city epidemiological study. *Environment International,* 134**,** 105329.

Chapter 3: Particulate matter in a lockdown home: evaluation, calibration, results and health risk from an IoT enabled low-cost sensor network for residential air quality monitoring

This chapter is published and can be found under the following citation:

COWELL, N., CHAPMAN, L., BLOSS, W., SRIVASTAVA, D., BARTINGTON, S. & SINGH, A. 2023. Particulate matter in a lockdown home: evaluation, calibration, results and health risk from an IoT enabled low-cost sensor network for residential air quality monitoring. Environmental Science: Atmospheres, 3, 65-84.

Or at the following doi:

https://doi.org/10.1039/D2EA00124A

Abstract

Exposure to atmospheric particulate matter is associated with a wide array of health impacts. Whilst ambient air pollution exposure is widely discussed both within the scientific literature and media, indoor exposure to pollutants has received less attention. However, humans spend a large amount of time in indoor environments, which increased significantly during the Covid-19 pandemic. This paper tests the application of a low-cost Internet of Things (IoT) enabled indoor sensor network to provide a relative assessment of variations in PM in a lockdown home. The paper tests the viability of the low-cost, IoT approach via sensor corrections and testing before assessing particulate concentrations for a ~7 week period within a typical suburban home in the UK. With the caveat that data from low-cost sensors are at best indicative, it was found that particulate matter concentrations in multiple rooms exceeded both 2021 and 2005 WHO Global Air Quality Guidelines, when extrapolated to annual exposure levels, despite relatively low ambient concentrations. Concentrations peaked at 488 µgm-3 (PM2.5) when cooking was occurring within the home. Whilst low-cost sensors have good inter-sensor correlations, agile corrections that account for activity and PM sources within a home will be needed to generate more accurate insights into PM concentrations, and higher sampling frequencies will be useful for gaining insight into short term activities such as cleaning sprays and aerosols. Sensors are suited to generating longer term averages in homes, but the sensors limited frequency of sampling (15 minutes) meant that shorter lived activities may be overlooked.

1 Introduction

Globally, 1 in 10 deaths are estimated to be associated with pollution-induced disease, contributing to 7 million premature deaths worldwide each year (González-Martín et al., 2021, World Health Organisation, 2022). Whilst ambient air pollution exposure is the predominant focus of research efforts, humans typically spend 60-90% of their time indoors. Time activity patterns have also changed in recent years due to the Covid-19 pandemic, which led to increased time spent in domestic indoor environments, with a subsequent modal shift to home and hybrid working schedules in specific

employment sectors (Guyot et al., 2018, Domínguez-Amarillo et al., 2020). Away from employment and working habits, typical residential activities such as cooking, sleeping and cleaning within the home are also associated with exposure to indoor pollutants. WHO suggest Air Quality Guidelines for key pollutants including $PM_{2.5}$ and PM_{10}. These guidelines are evidence based and are designed to suggest levels at which evidence for impacts on health have been reported (World Health Organisation, 2021). For this reason, this study uses these guidelines for comparing particulate concentrations.

Low-cost air quality sensors provide a novel opportunity for monitoring relative concentrations of particulate matter at previously unattainable spatial resolution, and the Internet of Things (IoT) allows for the development of indoor air quality (IAQ) networks (Hegde et al., 2020, Snyder et al., 2013). There are a number of existing studies that assess indoor particulate matter (PM) pollution, however a frequent limitation of these studies is monitoring is limited to only 1 or 2 locations within a property (often a kitchen or main living area) (Kaliszewski et al., 2020, Ezani et al., 2020, Susz et al., 2020, Domínguez-Amarillo et al., 2020, Zhao et al., 2020, Xu et al., 2020, Singer and Delp, 2018, Wang et al., 2016, Jeon et al., 2018, Ott and Siegmann, 2006, Wan et al., 2011, Chen et al., 2021, Jeong et al., 2019, Vilčeková et al., 2017, De Gennaro et al., 2016). Shen et al. (2021) reported a comprehensive multi-room study with multiple sensors, yet this was limited to $PM_{2.5}$. (particles with aerodynamic diameters <2.5µm) as the sensors were not calibrated for the PM_1 & PM_{10} (particles with diameters <1µm and <10µm respectively) fractions that they also monitored. Few previous studies have used IoT networks for monitoring, and those that did, tended to use IoT networks that are reliant on gateway or WiFi technology thus limiting deployment (Hegde et al., 2020, Jeon et al., 2018, Pitarma et al., 2016).

Whilst ambient corrections and calibrations for indicative monitoring devices are starting to become established within the scientific literature, there remains a need for this to be adapted to suit the nuances of indoor monitoring environments. Ambient correction methods are usually based on co-location with a reference grade instrument, taking into account the impact of humidity on hygroscopic particles, and often using 'buddy' matching or data validation from nearby ambient regulatory monitors. However, indoor air samples are problematic as indoor humidity levels are typically lower than ambient and indoor environments do not typically have regulatory monitors for comparison outside of a laboratory environment for buddy matching. Some studies have attempted to develop indoor calibrations methods to varying success, but tend to base corrections on a co-location with a reference instrument exposed to a specific particulate source which is not representative of the array of PM sources or activities that normally occur within a home (Mousavi and Wu, 2021, Kim et al., 2019, Li et al., 2018). The purpose of this study was to address these research gaps by deploying an IoT sensor network of 5 low-cost sensors (AltasensePM- compromised of an IoT enabled Plantower PMS5003) across a single residential property during a period of coronavirus restrictions, accounting for different rooms and the outside / ambient environment. Analysis is driven by the following foci:

1) Test the viability of IoT low-cost sensor networks for indoor air quality, including the development of a method for correcting and validating low-cost data within an indoor setting.
2) Evaluate the impact of human activity and different sources on relative real-time PM levels throughout a residential property.

2 Background

2.1 The problem of Indoor Particulate Matter

PM pollution is of public health concern due to the wide variety of health impacts its inhalation can cause. There are numerous sources of PM and with varying PM composition and health impacts of exposure are widespread, including cardio-vascular and respiratory morbidity and mortality (Kim et al., 2015, Anderson et al., 2012). The World Health Organisation (WHO) recommend air quality guidelines however historically these focused on ambient concentrations. IAQ advice was introduced in 2010, although they didn't specify guidelines for each PM size fraction within the home unlike the 2005 ambient guidelines which suggested guideline concentrations for different PM size fractions (World Health Organization, 2006, WHO, 2010). In the most recent WHO update in late 2021, the ambient guidelines for each size fraction were also recommended to be applicable to indoor environments too (World Health Organisation, 2021). This means that historically, despite the major health implications of PM, the domestic environment in which people spend the majority of their time is overlooked. This was highlighted further by the impact of coronavirus restrictions in 2020/21 which increased the amount of time people spent at home via work from home orders; the closure of social/entertainment environments such as restaurants and gyms and social contact restrictions. This provided both an opportunity to study indoor air quality in new detail, looking at the increased exposure and activity within the home but also challenges as access to infrastructure and instruments to support a study were limited by the pandemic restrictions.

There are many sources of PM within the home. Firstly, ambient (outdoor) PM pollution can infiltrate the home however these particles tend to have a limited size distribution as the more coarse and ultrafine particles (UFPs) are typically removed during transmission (Goldstein et al., 2021, Jeong et al., 2019). In older properties, infiltration occurs via leakage throughout the property, or by manual ventilation introduced by opening and closing windows and doors, however as building standards have evolved, properties have become increasingly air tight to increase energy efficiency (Derbez et al., 2014). These newer properties tend to rely on mechanical ventilation such as fans and extractors, yet these are not always as effective as promised and can even generate their own pollutants from running (i.e. mechanical wear) (Spiru and Simona, 2017, Steinemann et al., 2017). Secondly, everyday activities / interactions within the home can generate and influence PM concentrations, such as daily household activity from household chores and resuspension from movement. Prominent indoor sources include cooking and smoking however other sources such as candles, cleaning, vacuuming, humidifiers, combustion of solid fuels and resuspension have also been discussed within literature (Kaliszewski et al., 2020, Vicente et al., 2020, Goldstein et al., 2021, Shen et al., 2021, Lau et al., 2021, Qi et al., 2019). The prominence of the sources will vary both spatially and seasonally along with the Indoor:Outdoor ratio (I:O), and generally it is found that in winter PM from indoor sources contributes proportionately more and is higher in magnitude (Zhao et al., 2020, Jodeh et al., 2018).

People spend on average 1/3 of their life asleep- yet IAQ studies that assess bedroom and sleeping period particulates are limited to high income settings (Canha et al., 2019, Katsoyiannis and Cincinelli, 2019). Less than one quarter (23%) of studies reported in a review of field studies of IAQ during sleep (Canha et al., 2021)) captured both $PM_{2.5}$ and PM_{10} concentrations in bedrooms during the sleeping period. Bedroom PM concentrations will contribute significantly to individuals' total exposure due to the large periods of time spent in them. This is important as pollutant concentrations have been linked to sleep quality which is a major impactor on health. Accinelli et al. (2014) report lower particulate concentrations relate to better reported sleep quality in children. Poor sleep quality can have impacts on ability to concentrate and decrease cognitive performance, as well as long-term health implications such a links to depression, diabetes and cardiovascular disease (Strøm-Tejsen et al., 2016, Ahrberg et al., 2012, Nebes et al., 2009, Andruškienė et al., 2008, Sigurdson and Ayas, 2007), in addition to the

health risks normally associated with prolonged particulate exposure. Ventilation methods can also impact PM concentrations within a bedroom, with air conditioning appearing to reduce concentrations when compared to natural ventilation suggesting that ambient PM concentrations can also affect bedroom air quality (Wong and Huang, 2004, Kozielska et al., 2020). A review by Canha et al. (2021) reported daily $PM_{2.5}$ concentrations in naturally ventilated bedrooms at 35.1±32.4µgm^{-3} which exceeds than the WHO daily recommended guideline of 15µgm^{-3} (World Health Organisation, 2021) but also highlights great variation between concentrations reported in studies- although some of this variation is likely to be due to seasonal and local ambient PM concentrations between studies. Some of the variations are also likely due to 50% of reported studies capturing homes of smokers where particulates are reported higher than non-smokers. The review also suggests that optical particle counters are best practice for monitoring within bedrooms as compared to gravimetric methods they are much quieter and less disruptive to participants sleep patterns, and therefore arising behaviour changes. The above review highlights the importance of including the bedroom microenvironment in residential monitoring studies of particulate exposure. Not only is this an under-studied area but is also the room where likely most time is spent.

Kitchens are more widely researched when it comes to indoor air quality- there is a large focus on cooking and the effect on particulates within the scientific literature. This literature varies greatly due to the heterogenous nature of cooking globally- in economically developed nations cooking typically involves gas or electric ovens and hobs, in designated areas with mechanical ventilation. However, half of the global population rely on solid biomass fuel is for cooking using open stoves with reliance on natural ventilation, often inside (or if outside, near to entrances of) a multi-purpose or indeed the only room within the home (Nandasena et al., 2018, Shupler et al., 2022, Campbell et al., 2021). Here we focus on households reflective of the setting in which this study took place (cooking with gas/electric oven and stoves in a designated kitchen area in typical UK housing stock). Cooking has been reported to dramatically increase particle concentrations- Patel et al. (2020) report $PM_{2.5}$ concentrations exceeding 250 µgm^{-3} during cooking, with this activity being the single largest source of PM in their test house. O'Leary et al. (2018) reported that kitchens exceeded daily WHO $PM_{2.5}$ guideline concentrations for 10-14% of their study weeks. This peak in concentrations can last for some time after cooking, therefore post cooking periods contribute significantly to human particulate exposure as it takes time for particle concentrations to drop (Patel et al., 2020, Kim et al., 2018). Whilst unlike NO_x, it is reported that gas and electric appliances do not produce statistically different particle concentrations (Alves et al., 2020), the type of cooking activity (frying/baking/toasting etc) can influence particle emissions with frying and preparing large meals such as Thanksgiving dinners, being associated with higher concentrations (O'Leary et al., 2018, Patel et al., 2020). When studying the composition of PM Alves et al. (2020) reported that carbon represented 40% of total $PM_{2.5}$, mainly comprising soot with a low sulphur content. They also reported kitchen salt abundant in all indoor $PM_{2.5}$ samples.

Ventilation within kitchens can vary in approach- mechanical extraction methods that either externally vent or recirculate air such extractor hoods directly over a hob/oven or ceiling fans are common within homes. There is also the option for non-mechanical or natural ventilation via opening external windows and doors. Whilst ventilation aims reduce particulate exposure, optimal use of ventilation depends on human behaviour and can often be overlooked as residents are widely unaware of the particulate concentrations they are exposed too, nor the potential risk this poses. O'Leary et al. (2018) carried out a study which measured concentrations of PM in student kitchens for one week with "normal" behaviour, before showing residents the results and allowing them to adjust their activity as

they saw fit ahead of a second week of monitoring. Whilst this did increase ventilation efforts made by residents, the actual impact on concentration levels was reported as minimal. Kim et al. (2018) further reported that natural ventilation led to higher total concentrations due to ambient concentrations infiltrating indoors, but this may be due to the context (pollution level) of the ambient air in the study. Whilst the influence of cooking is more prominent than other indoor sources within the literature, there are still research gaps to address- particularly regarding the impact of cooking across multiple rooms, the length of impact and the effectiveness of ventilation efforts.

It is reported that in the UK £15 billion is lost due to reduced productivity and illness caused by indoor air quality and lack of fresh air (Mujan et al., 2019). According to (Office for National Statistics, 2021) in 2020 an average of 37% of the Uks population worked from home in comparison to 27% doing so in 2019 due to government guidance to work from home if possible. Whilst the number working from home has been declining since March 2021 with the restrictions easing (only 14% reported working from home exclusively during May 2022 (Office for National Statistics, 2022) , there is still a modal shift towards hybrid working with an increase in people reporting working from home in Spring 2022 compared to pre-pandemic levels (38% between 27.04.22-08.05.22 reported working from home at some point during the last week, compared to 12% before the Covid-19 pandemic)(Office for National Statistics, 2021, Office for National Statistics, 2022).This means more time spent at home for a section of the UK population of working age and increased time exposed to the typical particulate concentrations associated with home environments. Literature reports that poor IAQ impacts productivity when performing everyday tasks such as text typing, proof reading and mathematics (Mujan et al., 2019). Künn et al. (2019) reported that with a 10 μgm^{-3} increase of $PM_{2.5}$ the likelihood of chess players making an erroneous move increased by 26%, indicating cognitive performance impacts from PM concentrations. Shehab and Pope (2019) reported that candles, a common household source of particulates can reduce cognitive function and in 2022 the UK Health Security Agency recognised links between particulate exposure and dementia (Committee on the Medical Effects of Air Pollutants, 2022). This increases the need to understand the indoor particulate landscape as it will be playing a large part in human health, wellbeing and workplace productivity moving forward.

2.2 Low-cost sensors, IoT and indoor monitoring

Low-cost (here defined as ~£100-£2000) particulate matter sensors are increasingly popular and provide a novel opportunity for air quality monitoring - they are cheap, small, mobile and often have lower power needs than their traditional monitoring counterparts and can provide indicative insight into pollutant concentrations (Lewis et al., 2016, Snyder et al., 2013, Chong and Kumar, 2003, Bush et al., 2022). The limited noise pollution from these units also make them suitable for IAQ monitoring, as they are less intrusive (Shen et al., 2021). However, low cost sensors are often criticised- they can suffer biases, be limited in the size fractions they can effectively monitor and can be impacted by relative humidity. It is also not uncommon for literature to present contrasting results regarding sensor capability (Bulot et al., 2019, Sayahi et al., 2019, Levy Zamora et al., 2019, Crilley et al., 2018, Crilley et al., 2020). Hence, it is important that low-cost sensors are assessed and undertake data validation before any analysis or conclusions are drawn.

For relative comparisons between sensors across time and space, or for crude highlighting of high pollution events low-cost sensors measurement error from true value may be less important as long

as the inter-sensor correlation of a network during a colocation is strong and consistent. Previous work has shown that when corrected for the impact of humidity and calibrated against reference instrumentation, the PMS5003 was suitable for ambient monitoring for finite periods of time (see section 2.3 below for ambient correction details)(Cowell et al., 2022). However, adjusting sensor

Table 1- description of the correction calibration and data validation methods used by various studies that assessed indoor air particulate concentrations using low-cost sensors. Note that PurpleAir uses the same PMS5003 Plantower sensor that AltasensePM uses, however it has 2 sensors per unit allowing for dual reading and outlier corrections.

Study	Low-cost sensor	Data correction, calibration or validation methods
(Mousavi and Wu, 2021)	PurpleAir	Data were evaluated using systematic quality control- removing values above manufacturers stated sampling range, >75% data completeness, agreement of dual channel readings. Indoor data was then corrected using an average of correction factors developed by (Kim et al., 2019) when assessing IAQ from pan frying, second hand smoke and urban traffic hotspots.
(Kim et al., 2019)	ESCORTAIR & PurpleAir	Developed correction factors for each activity (second hand smoke, pan-frying, urban traffic hotspots) from step-wise linear regression.
(Krebs et al., 2021)	PurpleAir	No formal correction of data but uses data quality checks on particle number counts. This included removing negative/zero values, removing top percentile of each size bin, ensuring at least 30 days of data from a sensor, agreement between dual readings of $<10 \mu g^{-3}$.
(Patel et al., 2017)	Sharp GP2Y1010AU0F	Co-location with a SidePak and corrected with a linear correction factor.
(Hegde et al., 2020)	Dylos DC1100 pro Plantower PMS3003	Linear regression models for calibration from colocation against a mass-adjusted DustTrak timeseries followed by an aerosol specific correction factor (cooking, candle burning or general/unidentified PM events).

(Li et al., 2018)	Sharp GP2Y1010AU0F	Laboratory chamber calibration using an incense stick as a source of particulates and a SidePak for reference. A linear calibration equation was developed.

corrections and data validation for an indoor monitoring environment presents challenges. Unlike ambient sensors, reference grade base stations are unlikely to be available (and their use may be intrusive). The effect of humidity is likely to be smaller than for ambient sampling due to the more stable and lower humidity experienced indoors. Composition of particulates from different sources varies - for example varying cooking type (pan fry vs baking), cleaning methods, use of candles. Previous research suggests calibrating sensors in an environment similar to that they will sample in to capture the impact of PM composition and environment (i.e., RH) on the sensor performance within corrections (Sayahi et al., 2019). Whilst for ambient measurement this means corrections can be applied at a regional scale or adapted from a similar environment to the sampling site, indoor corrections may vary due to the type of activity that occurs in a home varying greatly by room, by property and by region with human behaviour. Previous research has attempted to calibrate and correct low-cost sensors for indoor air quality and a summary of some of these methods is presented in table 1. The table suggests that there are similarities between studies - sensors are often corrected using a correction factor derived from colocation with a reference instrument and multiple studies apply further data validation techniques post correction, such as removal of extreme values and checking data capture presence (% of potential data points successfully captured by sensor). Linear corrections have been proposed in multiple studies and sensor models (Kim et al., 2019, Hegde et al., 2020, Li et al., 2018, Patel et al., 2017). However, these studies also highlight the concern of changing activity and hence composition impacting correction, with both Kim et al. (2019) and Hegde et al. (2020) reporting correction factors which varied by activity. Whilst they didn't develop a correction factor Kaliszewski et al. (2020) and Singer and Delp (2018) also indicated that activity may impact low-cost sensor performance in their device comparison study.

Ultimately- a challenge here is to develop a correction factor for the IAQ measurements that is applicable across a household and is representative of not just one activity, but of the range of indoor PM sources that may be encountered. Whilst correction and validation of the data can enable low-cost sensors to provide insightful indicative data, these sensors are not providing absolute values such as regulation instruments and this need to be considered within any analysis.

3 Method & Materials

3.1 Study setting, sensor location and sampling design

This study deployed 5 Plantower PMS5003 PM sensors (4 indoors, 1 outdoors) across a property located at the edge of a suburban village in the East Midlands, UK for 7 weeks (31.03.21-18.05.21), with an additional week of colocation with a reference instrument ahead of monitoring (01.03.21-08.03.21).

The study location is located about 6km west of the town of Kettering, in a cul-de-sac. The village is surrounded by farmland, with farm buildings located <40 m away and the nearest A-road ~1.8km

lineally. The property is an end of terrace, 2 bed 'new build' (complete circa 2012) with 673 ft2 indoor space, which is representative of the average size of a small terrace home in the UK at 688 ft2 (Andrews., 2019).

Semi-detached and terraced houses are the 1st and 2nd most popular property type in the UK respectively, making this property somewhat typical of a UK residence (Andrews, 2019). The property has 2 residents who are both non-smokers. 1 resident was working hybrid between home and their usual workplace, and 1 resident was working entirely from their workplace away from the home. Figure 1 shows the floor plan of the property with approximate sensor locations, whilst table 2 describes sampling location details

Table 2- Description of the sensor location by room and description of potential sources and ventilation by room. NB. *Sensor E was earmarked to be deployed in the ensuite bathroom however it had an issue with the Arduino board in between colocation study and data collection so was unable to be deployed for this study.*

Room	*Sensor ID*	*Potential particulate sources of particulates*	*Ventilation*	*Sampling location details*
Master bedroom	A	Vacuuming, cleaning, ensuite shower/bathroom, aerosol cosmetics/toiletries	Windows, ensuite extractor,	On top of chest of drawers, near where aerosols are kept. Inlet and exhaust are facing into the room.
Living Room	B	Candles, oil burner, cleaning, vacuuming	Window	On top of small cabinet. Inlet and exhaust facing into room.
Kitchen/Diner	C	Cooking (frying/boiling/oven), cleaning, vacuuming,	Windows, double external door, extractor fan	On windowsill, opposite side of room from hob and extractor, above dining table. Inlet and exhaust facing into the room.
Outside	D	Traffic, nearby agricultural emissions, domestic burning, bbqs, ambient concentration	N/A	Attached to post on edge of property, near to double doors of kitchen. Farm facing side of property.
Bedroom 2/Home office	F	Drying laundry	Window	On shelf located against wall in middle of room. Inlet and exhaust are facing into the room.

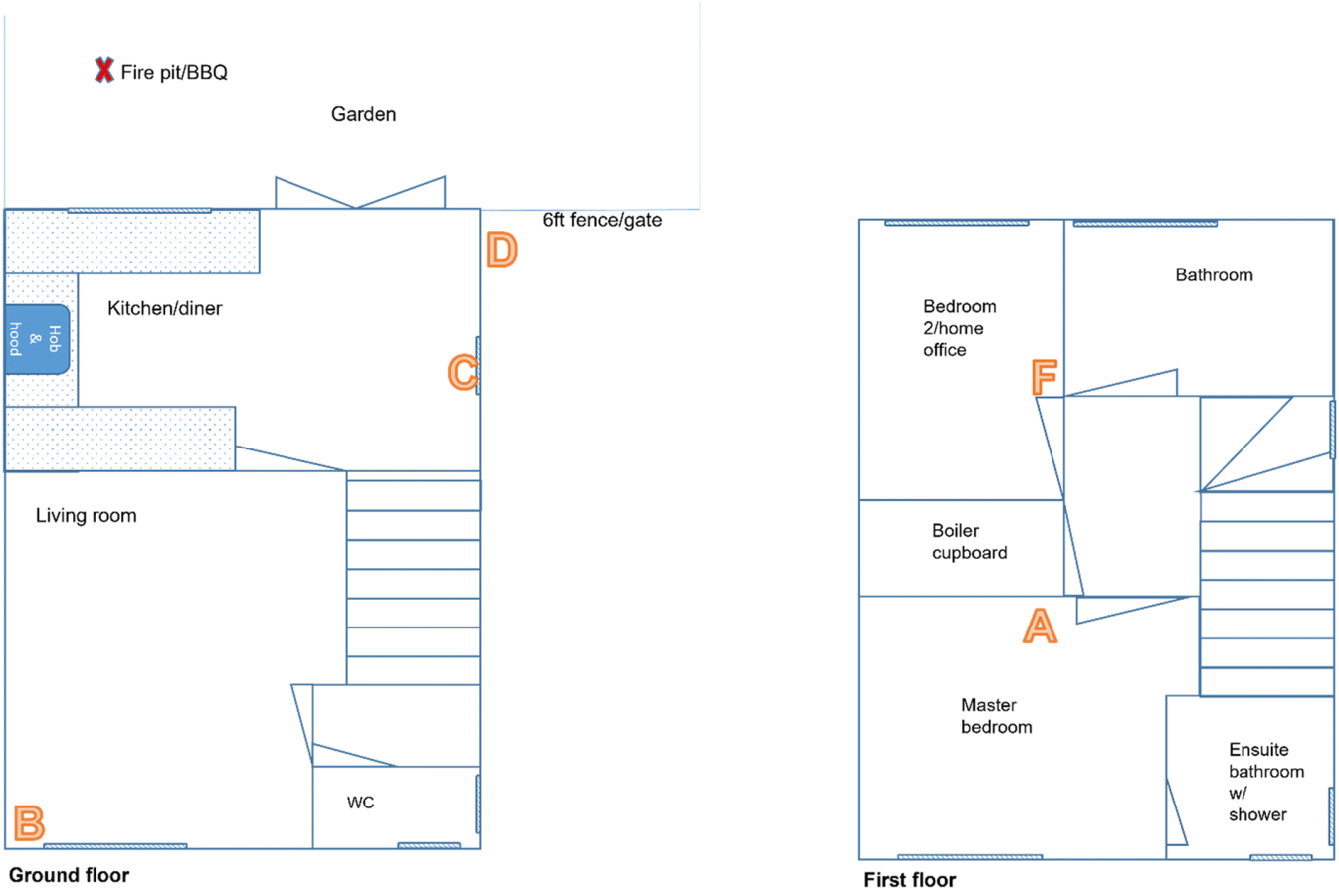


Figure 1 *Floor plan of house showing approximate sensor locations with sensor code associated with colocation period.*

All indoor sensors were kept between 1-1.5m height as furniture/fixings allow whilst the exterior sensor was mounted at ~2m. Table 2 outlines the key characteristic of each room the sensors were deployed in.

The sensors used are described in detail in Cowell et al. (2022) but are breifly covered here. The PMS5003 were connected to a custom PCB with an Arduino MKRFox1200 and SHT21 for Sigfox connectivity and temperature/humidity measurements respectively, creating a custom sensor platform called AltasensePM. The PMS5003 is a nephelometer which converts light from a laser scattered by particles into a voltage pulse and then a particle count using an undisclosed algorithm (Sayahi et al., 2019).

The PMS5003 is stated by manufacturer to detect particles of diameter >0.5 µm (98% counting efficiency), with a minimum distinguishable particle diameter of 0.3 µm (although at a lower counting efficiency of 50%) (Yong and Haoxin, 2016) however Ouimette et al. (2022) reported the PMS5003 detecting particles smaller than this diameter. It has an uncertainty of ± 10 μgm^{-3} and ±10 % for ranges 0-100 μgm^{-3} and 100-500 μgm^{-3} respectively.

For the indoor units, the PMS5003 was not placed in an enclosure- the electronic housing protected the PCB and batteries only with the PMS5003 unit resting on top to sample. The outdoor unit housed the PCB, batteries and PMS5003 for weather protection- the enclosure was suspended from a post with the PMS5003 inlet and exhaust located at the base of the enclosure.

The SHT21 has a small cap cover made of a protective mesh to stop the accumulation of condensation on the sensor. Altasense devices are identified and differentiated by letter- with 5 devices labelled A,B,C,D and F throughout the colocation analysis, before being assigned to a room (a 6th sensor, labelled E suffered microcontroller failure so was removed from the study). The Altasense devices record data every 15 minutes. The unit runs for 1 minute to stabilise before taking a reading, takes an instanteous measurement at the end of the minute and then powers down for the rest of the 15 minute period. This sampling method enables maximum power efficiency to extend battery life. Data capture is also limited to every 15 minutes by the allowance of message transmission on the Sigfox network. This compromise of frequency allows for deployment of 8-10 weeks+.

3.2 Activity log

A manual electronic log of activity that could potentially generate particulates or alter ventilation was created for indoor and outdoor environments at the study outset. For indoor rooms, key activities included but were not limited to cooking; cleaning; burning of candles; vacuuming; opening windows and oven extractors. As the dwelling main bedroom has an attached ensuite bathroom with shower, the shower usage, bathroom extractor and bathroom cleaning times were also noted. The outside activity noted was only activity from the garden of the study property- including fires and BBQs. Although there were other outdoor influences such as vehicular traffic in the village, emissions from the nearby farm and neighbours domestic burning, these could not be captured in a consistent way as start and end times were not known. Definitions/descriptions of the activity recorded are outlined in table 3.

Table 3- Definitions of the various activities recorded in the activity log.

Activity	*Description/definition*
Cooking-oven	The electric oven is in use on a standard oven/baking setting (not grilling).
Cooking-frying	Frying or using a pan to cook without water on the gas stove.
Cooking-boiling	Boiling/steaming food using a pan and water on the gas stove.
Cooking-other	Use of a grill/toaster or other method of cooking not described above.
Extractor	In the kitchen this refers to the stove top extractor which is manually controlled. In the bathroom/bedroom this refers to the room extractor which is manually controlled.
Cleaning	Cleaning of surfaces- including dusting, use of antibacterial products and wiping down work areas. Excludes dishwasher, washing machine or washing dishes.
Vacuuming	Use of a vacuum cleaner to clear floor. A SHARK bagless vacuum cleaner is used in this household.
Window/External ventilation	The opening of a window or in the case of the kitchen external window or door or both opened (external ventilation).
Candle	Lighting of a candle within the room.
Fire	Outdoors only- a small firepit burning wood is lit.
BBQ	Outdoors only- a coal powered BBQ is in use.
Oil burner	An oil burner which uses a tealight candle to melt scented wax melts into an oil is being used.
Shower	Ensuite bathroom shower is in use.

3.3 Colocation and correction of low-cost sensors

Literature suggests that low-cost particulate sensors should be calibrated in an environment similar to which they will be sampling in, due to particulate composition affecting performance (Zusman et al., 2020, Crilley et al., 2018). Whilst traditionally this is against a regulatory grade instrument such as a gravimetric method or gravimetric equivalent such as a FIDAS, the coronavirus restrictions and policies at the time of this work, we were unable to install an instrument of this type within the sampling home. To this end, the AltasensePM devices which sampled indoors were calibrated indoors in the same property by co-locating with a TSI DustTrak II 8532 handheld model, a laboratory grade instrument. Due to restrictions related to the pandemic, the Dusttrak was not co-located or calibrated against a reference instrument prior to this study- a limitation of conducting a study during a period of restrictions. This is a flaw in the study design, which means that PM concentrations within this paper are relative not absolute, and co-location between sensors and Dusttrak is a test of relative correlation, which will not correct the sensors to absolute values. Co-location (1 week) took place

within the kitchen of the property. Although this may not as rigorous colocation as against a regulation instrument, this method is well suited and scalable to in-home studies as it was less intrusive on occupants lives due to the small size/reduced noise of the instrument and required less staffing than a regulatory instrument. This also allows comparison of a low-cost sensor (<£100) against a mid-cost (£4000-7000) laboratory grade instrument and opportunity to test viability of this method for unintrusive in-home colocations (but it is important to note that any values from within this paper should be interpreted as indicative at best, not absolute concentrations).

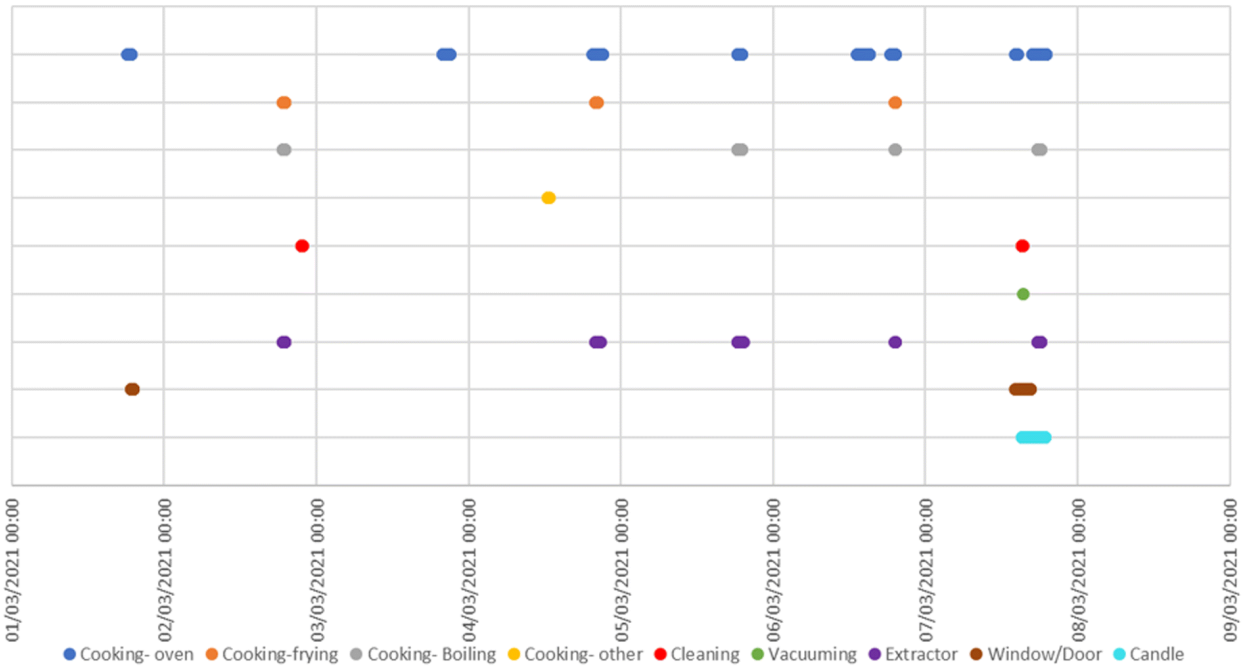


Figure 2 *Kitchen activity log for the colocation period. Dots show time when activity was occurring*.

As this study aims to create a correction factor that encapsulated all of the typical activity within a home, participants were encouraged to proceed with activity as normal - thus ensuring the correction factor captures the majority of typical particulate generating activity that normally occur within the home. Figure 2 shows activity over the colocation week and the hourly average time series in figure 3 shows how the Dusttrak and Altasense demonstrate similar patterns in concentrations over time (generated before any data manipulation of the Dusttrak data to match the AltasensePM sampling frequency).

The DustTrak is a light scattering laser photometer with an inbuilt pump designed for monitoring in a range of scenarios, including manufacturing and IAQ (TSI, 2014). Although designed for battery powered sampling, this study used mains power to enable continuous measurement for the colocation week as battery life was not able to support this. The DustTrak has a sampling ranging of $1\mu gm^{-3}$-$150mg^{-3}$ and a resolution of ±1% or $1\mu gm^{-3}$ whichever is largest (TSI, 2014). This study used a logging frequency of 1 minute. Whilst not a gravimetric or equivalent reference instrument, the Dusttrak has been successfully used to draw conclusions about IAQ; including comparing concentration to WHO guidelines and generating I:O ratios within past literature (Suvennie and Nordin, 2020, Shen et al., 2018). Wallace et al. (2011) report a Dusttrak vs gravimetric r^2 of 90%, although they also report issues with multiplicative bias. Overall, this suggests the Dusttrak should be suitable for calibrating the sensors to generate indicative and relative concentrations.

As the AltasensePM records an instantaneous measurement every 15 minutes, each AltasensePM reading was matched with its time matched counterpart from the Dustrak for data analysis and correction models with the remainder of the Dusttrak data discarded.

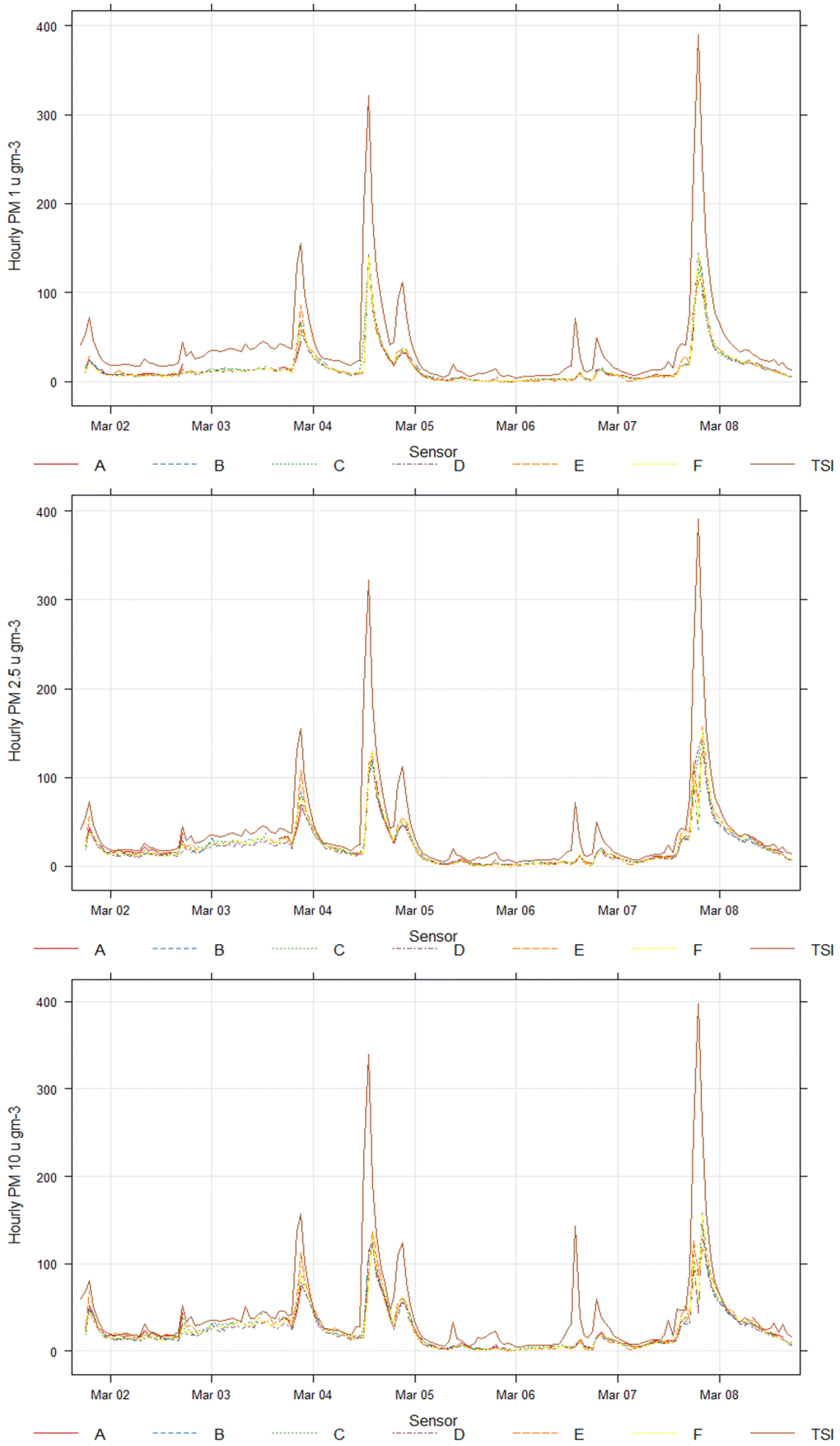


Figure 3 *Hourly average time series for AltasensePM devices and TSI for colocation week.*

Table 4 shows key statistics from the colocation period. Absolute values from the PMS5003 consistently under-read compared to the Dusttrak- The slope is low (0.28-0.52) between Altasense vs Dusttrak and the Dusttrak also recorded maximum values significantly higher than that of the AltasensePM for all species. 181,197 & 196µgm^{-3} are the maximum values recorded by the AltasensePM's for PM_1, $PM_{2.5}$ and PM_{10} respectively compared to 507, 508 & 541 µgm^{-3} for the Dusttrak. Initially, it may appear that the sampling range is likely to play some part here as the maximum values from the Dusttrak are all >500µgm^{-3} stated as max effective range for the PMS5003, however the AltasensePM do not record any maximums within 300µgm^{-3} of the stated limit suggesting the PlantowerPMS5003 are under-performing well below the stated limits. However, previous literature has shown the PMS5003 can report concentrations much greater than the suggested manufacturer limit (Tryner et al., 2020). Alternatively, the variations in maximum values could be an impact of the intermittent sampling method of the AltasensePM- whilst the Dusttrak measurements were compared at the same sampling frequency as the AltasensePM recorded, the Dusttrak was sampling continuously whilst the AltasensePM powered down between measurements. This could be an indication that the powering up/down of the sensor is limiting the capture of peaking concentrations.

Table 4- results of AltasensePM colocation with Dusttrak

Sensor ID	Species	Pearson's r	R^2	Max	Min	Mean	Slope
A	PM_1	93	0.87	98.0	0	11.3	0.37
	$PM_{2.5}$	92	0.85	127	0	18.16	0.52
B	PM_1	91	0.82	171	0	16.07	0.36
	$PM_{2.5}$	72	0.52	185	0	21.13	0.32
C	PM_1	93	0.87	174	0	15.22	0.34
	$PM_{2.5}$	79	0.62	185	0	22.3	0.34
D	PM_1	88	0.78	171	0	15.15	0.33
	$PM_{2.5}$	78	0.61	197	0	21.36	0.35
F	PM_1	90	0.81	168	0	15.56	0.35
	$PM_{2.5}$	72	0.52	189	0	23.04	0.32

Linear correlation between the reference and low-cost sensors was strong and Pearson's r values between Altasense and TSI Dusttrak are 0.84-0.93, 0.72-0.92 and 0.65-0.88 for PM_1, $PM_{2.5}$, and PM_{10} respectively (see table 4 for full details) for raw data. Figure 3 also highlights inter-sensor comparability between the AltasensePM devices, demonstrating good intersensory correlation (pearsons r= 84-99, 87-99, 86-98 and for PM_1, $PM_{2.5}$, and PM_{10} respectively). This suggests the sensors are comparable between themselves and therefore suitable for a network deployment which focuses on difference in concentrations by location.

3.3.1 Indoor sensor correction

Data used for the indoor correction was collected ahead of deploying, during 01.03.21-07.03.21 and the colocation data from 8th March was used to check the success of a correction method. It is clear from figure 3 that the correction for the AltasensePM needs to address the discrepancy experienced during peaks of particulate concentrations. Before correcting data, all corresponding AltasensePM values where Dusttrak concentrations exceeded 500 μgm^{-3} were removed as these values are beyond the manufacturer stated limits of measurement for the Plantower PMS5003. This is to follow manufacturer guidelines for use of the Plantower, but does suggest a threshold-step change, rather than a gradual trend, in performance of a sensor. Whilst this may be the case, the decrease in performance could be due to increasing undercounting at higher concentrations from coincident particles which would be more likely to present a gradual trend in performance decline. When plotting Dusttrak:AltasensePM by AltasensePM, it becomes clear that there is a logarithmic pattern (figure 4). Dustrak:AltasensePM ratio drops when the Altasense reports ~20 μgm^{-3} and thus under-reading occurs most as AltasensePM recorded concentrations increase. This is likely due to the PMS5003 atmospheric correction factor, an undisclosed algorithm Plantower recommend for ambient monitoring that reportedly reduces concentrations >30 μgm^{-3} (The World Air Quality Project, 2022). Whilst ideally an IAQ study would utilise the standard particle correction setting on the PMS5003, the AltasensePM was initially designed for use in an ambient monitoring network and this study was a result of lockdown delays to ambient sampling.

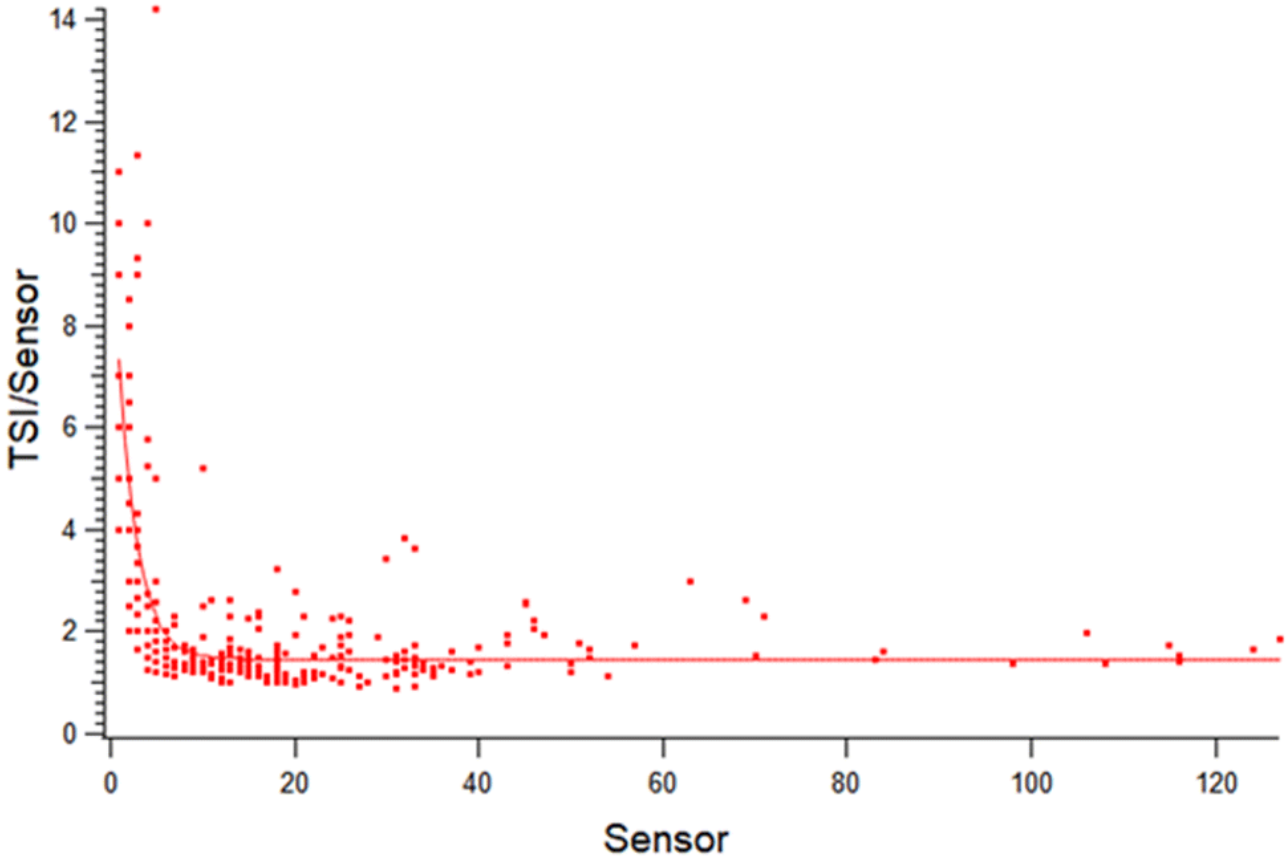


Figure 4 *TSI : Altasense ratio by sensor concentration demonstrations a logarithmic relationship between the 2 device types where the AltasensePM under-estimates concentrations.*

A range of correction models (scaling factors) were explored: Linear correction models failed to allow for the concentration-dependent variation in performance between reference and low-cost sensors didn't address the discrepancy in peaks. Polynomial models were plotted for reference: AltasensePM and a quadratic model proved good fit. Figure 5 shows results of a colocation after correction by an individual quadratic model for each sensor (note that there were not active sources during this period). It's important to note that different sources of particulate matter will be detected by varying levels of proficiency from the sensor, due to the role that particle size, shape and composition has on optical properties and interactions with the laser within the sensor (as discussed in chapter 1). This is evidenced by the varying performance of the sensor during peaks on the 3rd and 4th of March. On 3rd March peaks the sensors under-read compared to the Dusttrak a lot less than on the 4th March peaks (figure 3). On March 3rd, only cooking by the oven was used in the calibration room, but on March 4th cooking used oven, frying and other methods causing different sources of PM. A limitation of this study is that the day used for testing sensor calibrations had less activity than the days used to train the sensors (figure 5), thus impacting the source and types of PM the sensor is exposed to during the test period. This will affect sensor performance- ideally a validation period would be longer to allow for a wider range of activity to be captured. We recommend this for future indoor air quality assessments using low-cost sensors, when the limitations of research during a pandemic are lifted.

Table 5- r^2 values of AltasensePM and Dusttrak from colocation period after correction of sensors with a quadratic model. NB. ***Sensor A had significantly less data points (n=14, rather than n=71 for other units) throughout the post correction co-location than other sensors due to a power loss, it's poor performance may be linked to this.***

	PM_1		$PM_{2.5}$	
	slope	r^2	slope	r^2
A	2	0.73	2.4	0.79
B	0.93	0.82	1.4	0.88
C	0.9	0.81	1.3	0.89
D	0.8	0.78	1.3	0.92
F	0.79	0.7	1.5	0.85

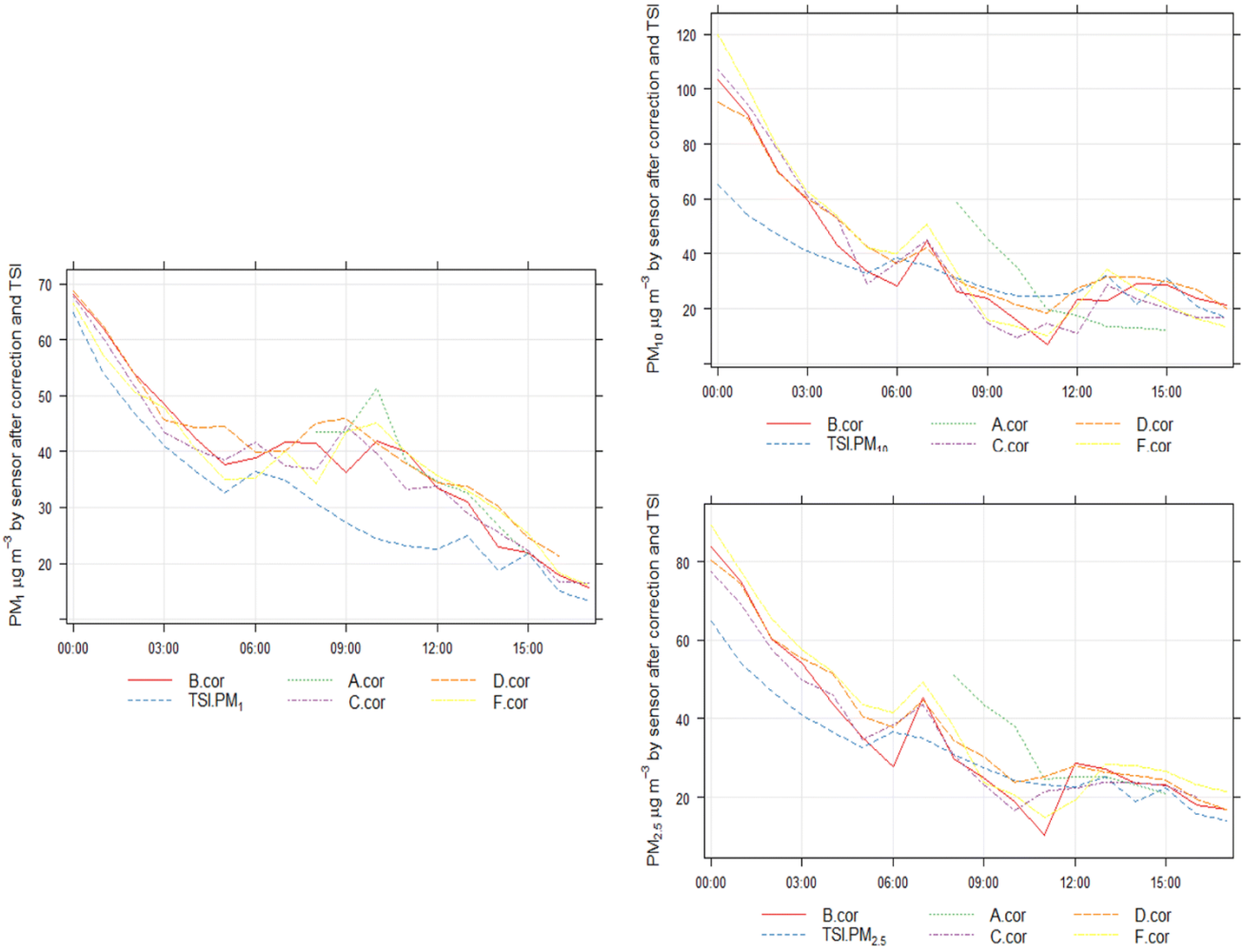


Figure 5 *Hourly average data from a colocation with TSI post sensor correction ("cor") by polynomial model. Note- there were no active sources during this period.*

3.3.2 Ambient sensor correction

Evidence suggests that for ambient monitoring, the effect of humidity on low cost sensors based on light scattering techniques calls for further correction past calibration (Crilley et al., 2018, Di Antonio et al., 2018) A previous study has demonstrated that the PMS5003 used in the AltasensePM requires a multi-linear model for correcting data when calibrating against a reference grade nephelometer (PALAS FIDAS) (Cowell et al., 2022). Whilst the indoor measurements are unlikely to reach >85% humidity the outdoor sensor likely will, thus in these instances the multi-linear correction developed in (Cowell et al., 2022) will be applied. To achieve this, sensor D (used outside) was back calibrated. After being deployed as part of this study, sensor D (used outside) was taken to Birmingham Air Quality Supersite (BAQS) and collocated with a PALAS FIDAS to generate data for a multi-linear correction based on humidity. Limitations of this method were expanded on in the previous chapter.

3.4 Data Validation

There is a need to validate low-cost sensor data- even after correction as sensors may malfunction and misreport data following deployment. This is particularly important when data cannot be checked against a nearby reference instrument. Lu et al. (2021) & Mousavi and Wu (2021) suggest a data validation method for quality control. The data validation steps outlined below are based upon those used for the commercial PurpleAir network, the devices of which utilise the same Plantower PMS5003 sensors as AltasensePM in both an indoor and outdoor setting (Lu et al., 2021, Mousavi and Wu, 2021). Data validations are adapted from these methods (minus steps which utilise the dual reading channels from having 2xPMS5003 within each PurpleAir unit as this is not applicable to the AltasensePM). Validation steps are outlined below:

1. Discard data of concentration >500 μgm^{-3} as this is outside of the manufacturers stated limitations of the sensor. Only 1 value fell beyond this threshold- a reading from the kitchen for PM_1.

2. A completeness criterion- only use sensors with >75% completeness of data. Results from presence are show in table 6.

Table 6- presence of sensors within study period. All are above the 75% completeness required as part of the data validation steps.

location	bedroom	living room	kitchen	outside	office
Presence (%)	98.4	86.5	93.6	83.3	98.5

3.5 Novel development in understanding of the Plantower PMS5003 for coarse size fractions

As explored in chapter 2, research has highlighted challenges surrounding the measurement of PM_{10} by low cost nephelometers. Hagan and Cross (2022) highlight multiple studies that indicate the inability of some such sensors to reliably report coarse PM fractions (>$PM_{2.5}$) (Kuula et al., 2020, Hagan and Kroll, 2020, Ouimette et al., 2022). They suggest that, in instances where PM_{10} seems to be reporting in agreement with a reference, that it is likely there are minimal larger particles present and the sensor is effectively reporting smaller size fraction concentrations that happen to correlate with PM_{10} concentrations. Ouimette et al. (2022) attribute the lower retrieval of PM_{10} to laser geometry and particle losses before reaching the laser (path of PM sample is too narrow/tight bends for PM10 to navigate without losses, through inertia) and the inability of the sensor to detect all of the light scattered by larger particles. This is reflected in the colocation week data in this study where PM_{10} performed worse than the smaller size fractions against a reference instrument (see table 4). Whilst our calibration efforts improved agreement (table 5), PM_{10} was still had the weaker relationship with the reference instrument than $PM_{2.5}$. PM_{10} is reported in figures throughout this study to avoid

censorship of data and to provide insight into sensor performance. However, authors are aware that reported PM_{10} are likely to be more reflective of smaller particle sizes than PM_{10} itself, and thus do not focus on PM_{10} during discussion and urge readers to be cautious in drawing conclusions from PM_{10} concentrations.

Another important feature to note from the literature is debate around the ability of low-cost sensors to report multiple size fractions. Ouimette et al. (2022), Kuula et al. (2020) report that the PMS5003 is most effective at recording PM_1 concentrations and Kuula et al. (2020) report that it may not accurately distinguish between size fractions well, particularly in unstable ambient air size distributions. Unlike ambient air, there are not large regional events that will drastically change the composition/size distribution of particulates from the from those experienced as part of the calibration and Kuula et al. (2020) also suggest that with stability, the PMS5003 can be calibrated to report $PM_{2.5}$ relatively well. Therefore, whilst PM_1 is reported in this study, authors also felt it was important to report $PM_{2.5}$ as this allows for comparison to global guidelines for PM.

3.6 Data analysis

Data analysis explores first the sensor presence presented in section 3.4 as this can provide key insight into the success and pitfalls of sensor performance.

Indoor:outdoor (i:o) ratios were calculated from hourly averaged data for each room to allow for data matching. An average indoor concentration hourly time series was also generated from the mean concentrations of all indoor measurements so an average indoor:outdoor ratio could also be analysed.

Activity log data was transformed into a time series so that activities could be plotted and analysed against concentration time series.

Data analysis made use of the OpenAir package in the R programming tool (Carslaw and Ropkins, 2012, Carslaw, 2019).

4 Results & Discussion

4.1 Particulate concentrations and activity

Figure 6 and table 7 present the corrected concentrations experienced within the property for the study period. Assuming the short duration measurements reported here were typical of those present over longer time periods (i.e., annually), of the 5 rooms, PM levels in all 4 rooms exceeded both the WHO 2021 and 2005 annual ambient particulate concentration guidelines of $10\mu gm^{-3}$ (2005) and $5\mu gm^{-3}$ (2021) for $PM_{2.5}$ (World Health Organisation, 2021), if extrapolated to annual levels. Ambient $PM_{2.5}$ was lower, not exceeding the 2005 guidelines and reporting just above the 2021 guideline concentration.

Table 7- Mean concentrations for the whole study period. Mean is colour coded to represent concentrations above and below WHO guidelines for $PM_{2.5}$ and PM_{10}. Green= mean concentration less than WHO 2021 Annual guideline. ***Orange= mean concentration falls inbetween WHO 2021 and WHO 2005 guidelines. Red= mean concentration greater than WHO 2005 annual guideline.***

	Bedroom		**Living room**		**Kitchen**		**Office**		**Outside**	
	PM_1	$PM_{2.5}$	PM_1	$PM_{2.5}$	PM_1	$PM_{2.5}$	PM_1	$PM_{2.5}$	PM_1	$PM_{2.5}$
Mean (μgm^{-3})	16.53	18.77	20.54	24.72	18.83	20.39	8.50	12.73	5.66	6.14
Max (μgm^{-3})	226.29	233.70	488.38	486.49	488.18	461.54	78.38	119.36	45.52	43.74

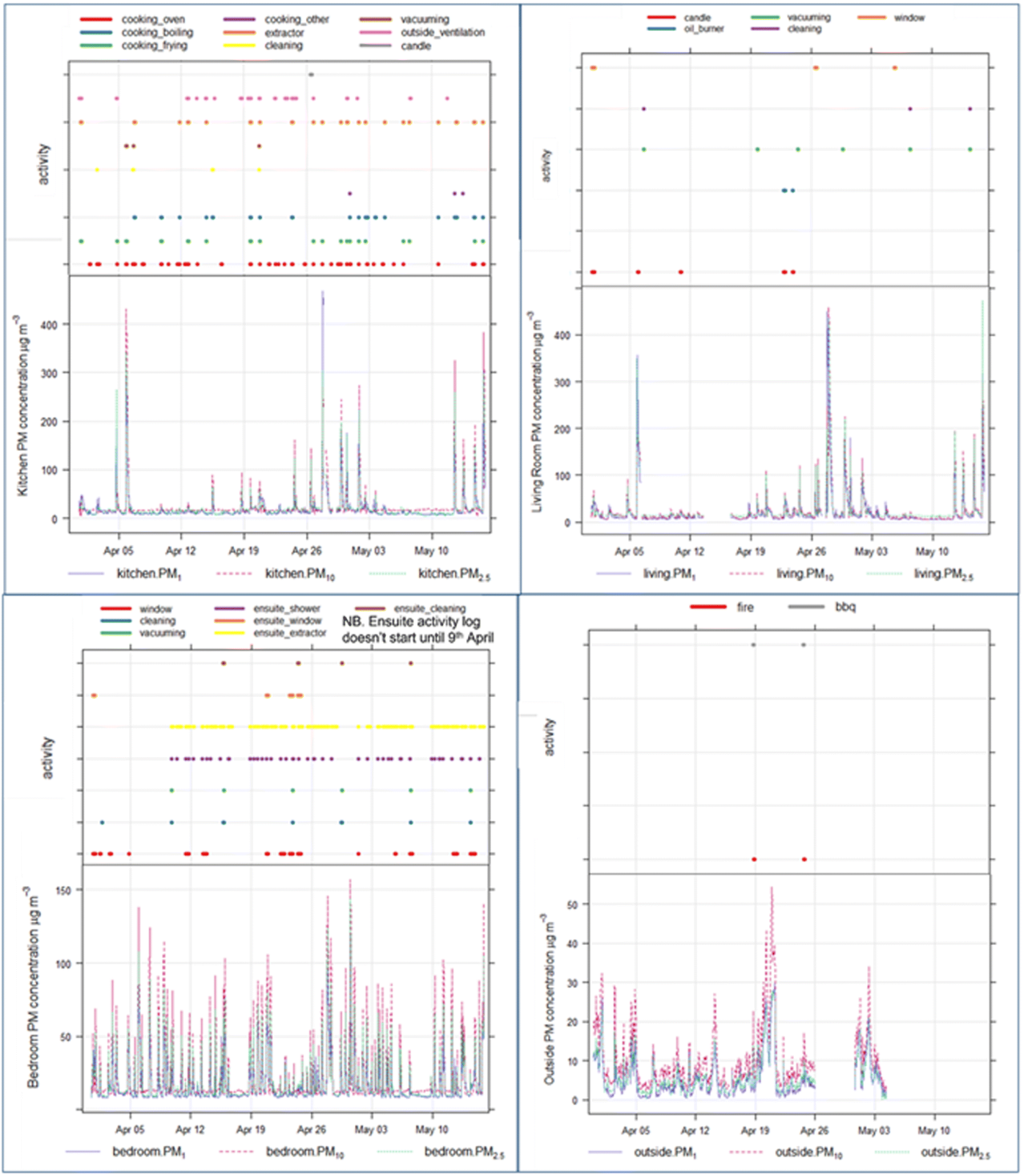


Figure 6 *Hourly average PM concentrations by room with activity log for each room above. Note kitchen and living room are located next to each other and share a doorway which was often open. Activities may also be affecting concentrations in other rooms.*

This suggests that if the 7 weeks of study were reflective of a typical year in the property, the bedroom, kitchen and living room could be considered as exposure that is harmful to health by WHO guideline levels. Maximum concentrations recorded significantly exceed WHO guidelines- the living room reported highest concentrations (488, 486 & 481µgm^{-3} for PM_1, $PM_{2.5}$, and PM_{10} respectively) followed closely by the kitchen (488. 462 & 478µgm^{-3} for PM_1, $PM_{2.5}$, and PM_{10} respectively) . Outside reported the lowest peak concentrations followed by the home office. The bedroom experienced some peaks in concentrations- this may be due to the proximity to the ensuite bathroom which would experience high humidity when the shower was used. Peaks could also be linked to use of aerosols such as deodorants, which were not recorded by the activity log due to their very short activity time (spraying a deodorant is usually a matter of seconds) being incompatible with the 15 minute sampling of the sensor.

Cooking and ventilation (both external via windows and mechanical via extractor fans) proved easier to analyse within this study as these activities all took place over periods time greater than the AltasensePM sampling resolution, whereas activity such as cleaning (spraying of cleaning sprays) and vacuuming occurred in short bursts which may not have been coincident with a sensor measurement. This highlights a notable disadvantage of the low power approach used by the AltasensePM to conserve battery power where readings are only taking for 1 minute of every 15- sensors can capture PM variability over the period of 15minutes-hours but cannot capture variability that occurs in short bursts.

The following analysis of activity vs concentrations focuses on cooking and ventilation due to this.

4.1.1 Cooking and downstairs concentrations

Cooking by oven was the most common type of cooking, with 75.5% of all cooking recorded being via oven. 'Other' (defined in table 3) was the least common type of cooking. The extractor was used 81% of the time when cooking was occurring and external ventilation via an open window or external door was used 44% of the time cooking occurred.

In the living room, maximum PM levels did not coincide with any recorded activity in that room but PM_1 and $PM_{2.5}$ did directly coincide with cooking with the oven in the kitchen. Whilst other max recordings in the kitchen and living room do not directly match with cooking being recorded at that time, the max PM_1 and $PM_{2.5}$ recording in the kitchen also occurred between 18:00 and 19:30 which is during the window that cooking regularly occurred on a daily basis (fig 7). Although the measurements didn't directly coincide, this is most likely due to the 15-minute sampling time of the sensor occurring just outside of the time cooking was occurring. This highlights a compromise of maintaining the battery power and IoT communications by reducing sampling frequency and thus not capturing cooking events at as high resolution as other studies. From the diurnal plot of $PM_{2.5}$ concentrations, PM levels in the kitchen and living room appear to be correlated particularly in the evening peaks around meal preparation time and this is reflected in the hourly average correlation with Pearson's r values of 93, 88 and 83 for PM_1, $PM_{2.5}$ and PM_{10} respectively. The higher correlation occurring with PM_1 between the 2 rooms suggests that the smaller particles are more effective at travelling between rooms- this is expected as larger particles are likely to settle sooner due to weight or be filtered out during transmission by walls/doors (Goldstein et al., 2021). Whilst PM levels in the rooms correlate around the peaks, they differ in their decline rate after cooking occurs with the kitchen returning to a lower concentration baseline much quicker than the living room does, with the

living room still experiencing elevated peaks in concentrations into the early morning hours. This could be attributed to a) lack of an extraction fan in the living room (unlike the kitchen) to reduce concentrations or b) other sources in the living room generating further PM in the evening (candle/oil burner although not as frequent a source as cooking, was used in the evening a few times). Figure 8 demonstrates the extreme values recorded during various activities with cooking by oven and frying

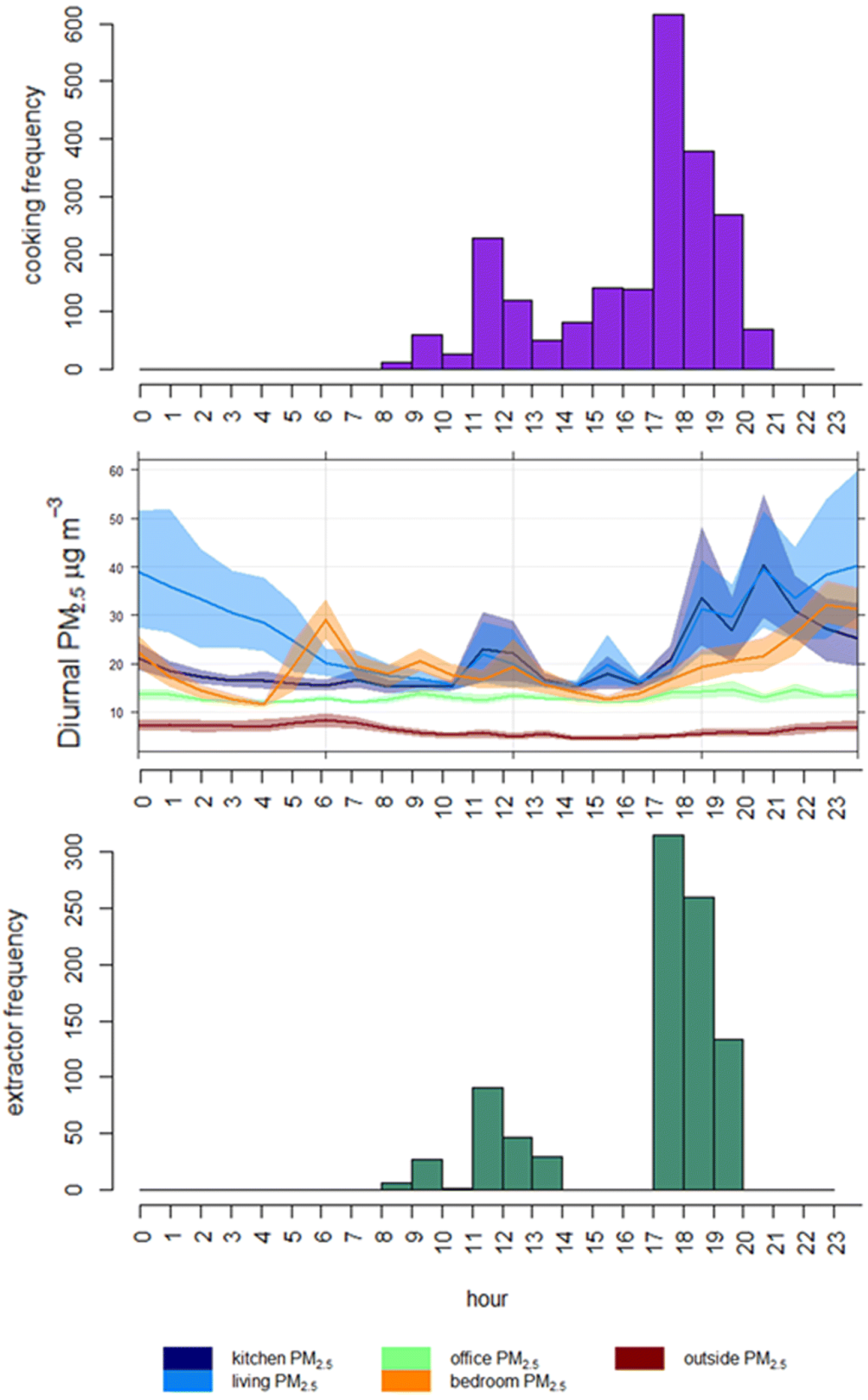


Figure 7 *Histograms demonstrating the frequent times of day for cooking activity (all cooking types combined) and kitchen extractor fan usage alongside diurnal patterns of $PM_{2.5}$ concentrations by room.* ***NB.*** *Frequency here describes the number of minutes the activity was marked as 'present' and is separated into bins by hour of day.*

coinciding with extreme high readings, however oil burning and candles do not produce peaks >200 μgm^{-3} and it appears the extreme peaks are associated with cooking in the adjacent kitchen. Extractor fans have been demonstrated by literature to reduce PM concentrations during and after cooking (Amouei Torkmahalleh et al., 2017). A similar phenomena was also recorded by Kim et al. (2018) where living room concentrations were greater than kitchen concentrations after a cooking event when extractor fans are in use in the kitchen alone. This highlights the importance of considering dispersion of particles from a cooking event, and ventilation in adjacent rooms, not just a kitchen.

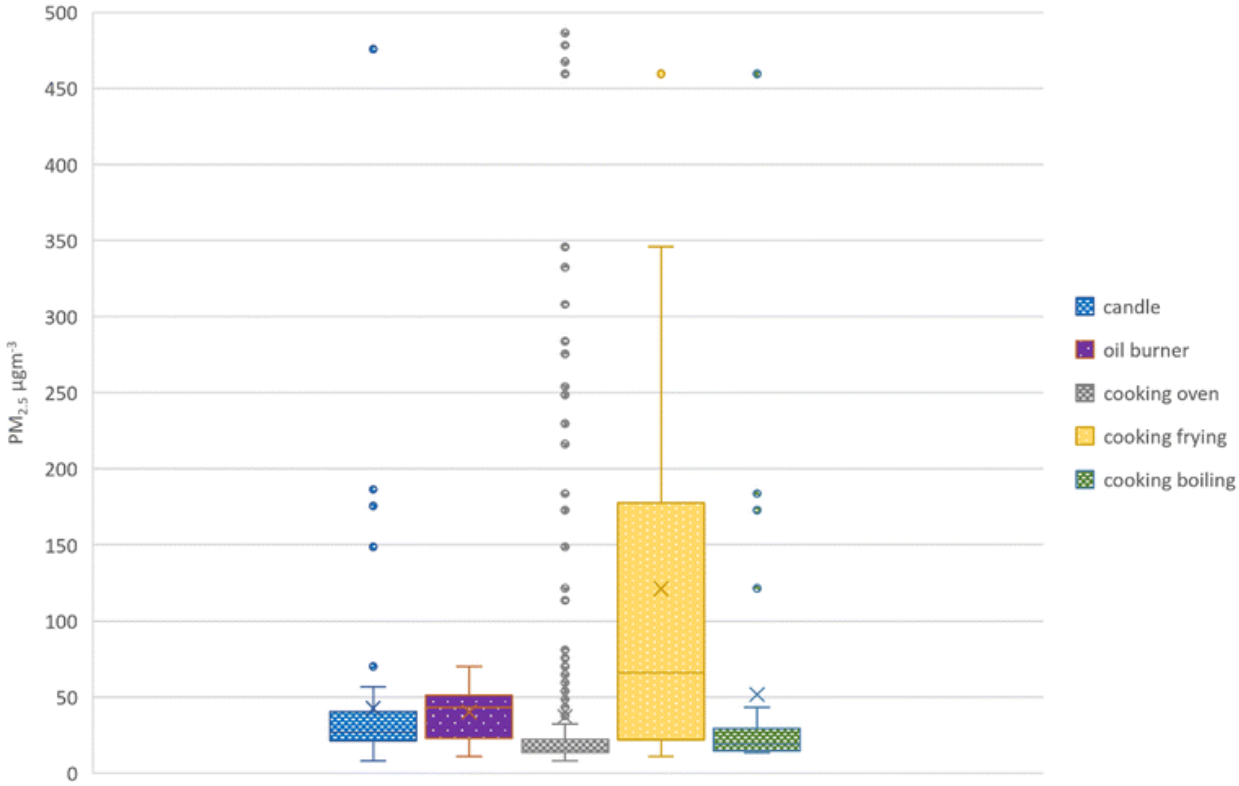


Figure 8 *Distribution of $PM_{2.5}$ concentrations in living room during various activities. Cooking occurred in the adjoining kitchen whilst oil burner and candle were located within the living room itself.*

4.1.2 External ventilation

Windows or external doors were open for 10805 minutes or 180.08 hours across the property for the 7 week period (bedroom window 5770 minutes, ensuite window 1652 minutes, living room 645 minutes, kitchen 2738 minutes). Sensors captured particulates data for 602 minutes where the window was open in the room they were directly measuring in (175 minutes in kitchen, 385 minutes in bedroom (bedroom window only), 42 minutes in living room). As this study occurred in spring, this amount is likely to increase in the summer months and reduce in the winter due to seasonal ambient temperature changes. Whilst the bedroom window opening occurred quite evenly spread across the day (with windows closed at night), the kitchen windows are most frequently opened between 4-6pm (median hour of window opening 5pm) coinciding with cooking activity frequency (figure 7). Figure 9 demonstrates the excess in extreme high values recorded when windows are closed vs when windows are open across all rooms for PM_1 and $PM_{2.5}$. It is difficult to draw conclusions regarding the influence

on external ventilation via windows/doors for the kitchen as PM levels were also being driven by other activity- notably cooking described above. The mean in the kitchen was higher with windows open, this may be due to the coinciding with cooking activity times, yet opening windows appears to reduce exposure to extreme values with less extreme high values recorded when windows or external door is open. A Mann-Whitney U test reported a statistically significant difference between kitchen PM concentrations when windows are closed vs open (for PM1 and PM2.5 , $p=2.2e^{-16}$) with a 95% confidence that median difference will be between 8.6-4.9μgm^{-3} and 7.7-5.4μgm^{-3} for PM_1 and $PM_{2.5}$ respectively.

As the bedroom has less activity recorded than the kitchen and has window openings more evenly spread across the day, there is less of a connected impact to another activity and thus differences may prove more insightful in terms of the impact of windows opening. Bedroom concentrations are statistically different when windows are shut vs open in the bedroom itself (p=0.0031 and p=0.0022 for PM_1 and $PM_{2.5}$ respectively), with a 95% confidence of a 2.7-7.3μgm^{-3} difference between having windows closed and open. Median and mean values for windows shut/open are close in value (18.9μgm^{-3}, 17.2μgm^{-3} means and 19.5μgm^{-3} , 18.6μgm^{-3} medians for $PM_{2.5}$) suggesting the major difference is in the reduction of high outlier values when windows are open.

In the context of this property (suburban, relatively low ambient PM concentrations) it is likely that the opening of windows is reducing the extreme highs generated from indoor sources, but an impact on mean concentrations is more uncertain. This may be due to the impact of other activity influencing concentrations at the same time as the windows being open (cooking), although literature suggests reductions in mean $PM_{2.5}$ from window ventilation alone may be possible (Yin et al., 2022, Manga and Allen, 2022). However, in other settings with poor ambient concentrations window ventilation is unlikely to be effective at reducing PM concentrations as it increases the infiltration of ambient air and hence potentially elevated PM concentrations into the home.

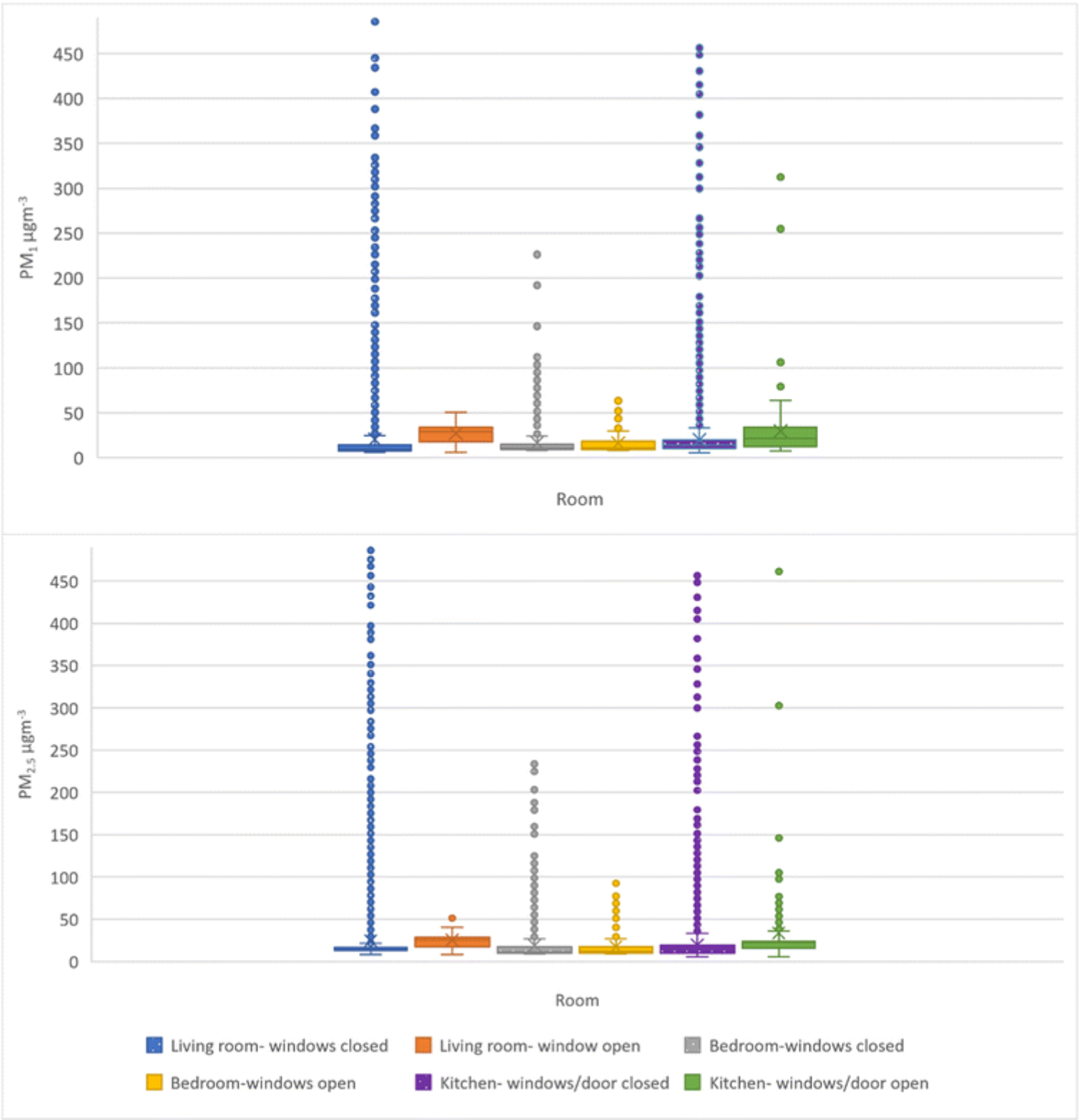


Figure 9 *Boxplot of PM_1 and $PM_{2.5}$ concentrations by room for when external windows/doors are open vs. when they are closed. NB. Bedroom only refers to bedroom window, not ensuite bathroom window.*

4.3 Limitations

Whilst this study presents meaningful insight into the application of low-cost, IoT sensing networks for measuring indicative particulate concentrations, there are some factors that limit the output of the study.

The pandemic and lockdown restrictions in place at the time of data collection may have limited residents' behaviour- generally spending more time inside, potentially eating out less and thus cooking more etc. Whilst this highlights the need for understanding of IAQ, it also means that this may not be reflective of 'normal' behaviour as we transition into a post-Covid context. This could also impact the generation of a generic correction factor for a home, as the particulate generating activities may have been influenced by the change in behaviour. Thus, the correction factor may not be reflective of pre or post-pandemic behaviour, although the method to develop a new correction factor should still be valid allowing for updates with behaviour change.

The correction factor is also activity specific- the sensors will perform differently in different PM compositions and this will vary over the sampling period. In future studies, an extended test period to test calibration during periods of more activity would be appropriate. The correction is also developed against a Dusttrak- which is not a reference grade device and was also serviced to standard setting which may not be most appropriate for indoor sampling as it will be based off of certain PM compositions and sources. This is also a study of only one home. The study property is fairly representative of a typical modern UK home, however the activity, appliances and maintenance of homes will vary and there is scope to expand future studies to gain more comprehensive insight into the wider picture of the UK housing stock.
This study is a short term data collection which may not be directly reflective of the data used to generate longer term guidelines (World Health Organisation, 2021). However, since this study's' data collection occurred, the platform which hosts the AltasensePM devices has been developed to apply correction models to data in near-real time which would reduce manual workload of correcting data and enhance sensors ability to generate easy-to-use long term timeseries. The reduced frequency sampling of the sensors (to align with the Sigfox message allowance) means that some peaks and short lived activity are missed and hard to assess, although the feasibility of deploying small forms sensors un-intrusively in a home suggests that with modifications to alternate communications methods to allow for increased sampling, these sensors could be deployed to measure short term peaks relatively easily. As explored in section 3.5 and the past chapter, sensors are limited in their ability to accurately report different size fractions. Figures in this report demonstrate again correlation between size fractions, and thus future technology would ideally overcome this limitation to allow for meaningful insight into size distributions.

A further challenge of IoT technology and developing a real time platform for low-cost sensors and in-home monitoring is security. By creating an online platform that can detect activity, there are methods to detect home occupancy by proxy. If creating a wider network of in-home sampling, security will need to be considered to ensure occupancy safety.

5. Conclusions

This study started with 2 key criteria:

1) Test the viability of IoT low-cost sensor networks for indoor air quality, including the development of a method for correcting and validating low-cost data within an indoor setting.

2) Evaluate the impact of human activity and different sources on PM levels throughout a residential property.

Sensor viability is described in the methods section, where with correction and data validation steps AltasensePM was able to detect with good accuracy ($r^2 > 0.7$ for PM_1 and >0.79 for $PM_{2.5}$) particulate concentrations. Importantly, sensors had really strong inter-sensor correlation (Pearsons r > 84 for all size fractions) meaning that as a network deployment they were suitable for comparing differences between locations. The IoT enabled sensors had good presence (83-99%) and were able to detect diurnal patterns within data. Their major drawback was time resolution, which was compromised by battery life to enable sensors to be mobile and unintrusive to deploy. Whilst peaks were captured, AltasensePM was unable to capture high resolution detail and some shorter activity periods were harder to assess as the sensor wasn't always recording as they occurred. Sensor's performance is subject to PM composition and agile correction methods that consider the activity and sources within a home will be needed for future indoor PM sampling. Overall, the low cost IoT network provided valuable insight into relative particulate concentrations and could be adjusted to be mains powered to increase measurement frequency considering that power access is rarely an issue in many households. The novelty of the IoT aspect is the unintrusive nature of sampling in a home environment, with the most labour intensive aspect of the study being the collection of activity log data which was manual. However, with the growth of IoT sensors and smart technology, as well as the ease of data collection demonstrated in this study, it is feasible to suggest IoT approaches to generating data logs for future studies. Smart appliances could create autonomous activity logs, or if smart appliances aren't available, low-cost temperature and motion sensors could be programmed to generate logs of activity by being integrated near cooking appliances etc (although there are challenges in consent and maintaining privacy and security around autonomous activity monitoring in a home).

Indicative indoor concentrations exceeded WHO guidelines for particulates. Cooking was clearly detected to influence particulate concentrations and often lead to extreme peaks in concentrations. Cooking by oven and frying increased particulate concentrations in both the kitchen and living room area despite the use of an extractor fan and windows over cooking periods. The living room experienced higher concentrations than the kitchen- this may be due to a lack of extractor fan in the living room and the lower use of windows for ventilation compared to the kitchen. The use of window opening for increased ventilation clearly reduces extreme peaks in concentrations and thus could be an affordable and effective suggestion to residents to reduce exposure to short term high concentrations, depending on location and ambient conditions.

Author Contributions

Conceptualization NC, LC and WB. Methodology NC, LC, WB, DS. Software NC, DS. Validation NC, LC, WB. Formal analysis NC. Investigation NC. Resources LC, WB, NC. Data curation NC. Writing- Original Draft NC, LC, WB. Writing- Review & Editing- SB, AS, DS. Visualization NC, DS. Supervision LC, WB. Project administration NC. Funding acquisition WJB, LC.

Conflicts of interest

There are no conflicts to declare.

Acknowledgements

The authors would like to thank the residents of the study property for their participation in the project. The assistance of Dr Siqi Hou and colleagues at the Birmingham Air Quality Supersite at the University of Birmingham in the colocation of sensors as part of this project is also acknowledged.

References

ACCINELLI, R. A., LLANOS, O., LÓPEZ, L. M., PINO, M. I., BRAVO, Y. A., SALINAS, V., LAZO, M., NODA, J. R., SÁNCHEZ-SIERRA, M. & ZÁRATE, L. 2014. Adherence to reduced-polluting biomass fuel stoves improves respiratory and sleep symptoms in children. BMC pediatrics, 14, 1-5.

AHRBERG, K., DRESLER, M., NIEDERMAIER, S., STEIGER, A. & GENZEL, L. 2012. The interaction between sleep quality and academic performance. Journal of Psychiatric Research, 46, 1618-1622.

ALVES, C., VICENTE, A., OLIVEIRA, A. R., CANDEIAS, C., VICENTE, E., NUNES, T., CERQUEIRA, M., EVTYUGINA, M., ROCHA, F. & ALMEIDA, S. M. 2020. Fine Particulate Matter and Gaseous Compounds in Kitchens and Outdoor Air of Different Dwellings. International Journal of Environmental Research and Public Health, 17, 5256.

AMOUEI TORKMAHALLEH, M., GORJINEZHAD, S., UNLUEVCEK, H. S. & HOPKE, P. K. 2017. Review of factors impacting emission/concentration of cooking generated particulate matter. Science of The Total Environment, 586, 1046-1056.

ANDERSON, J. O., THUNDIYIL, J. G. & STOLBACH, A. 2012. Clearing the Air: A Review of the Effects of Particulate Matter Air Pollution on Human Health. Journal of Medical Toxicology, 8, 166-175.

ANDREWS. 2019. What's the most popular type of a property in England and Wales? [Online]. Online: Andrews Property Group. Available: https://www.andrewspropertygroup.co.uk/market-insight/whats-the-most-popular-type-of-property/ [Accessed 19.03.21 2021].

ANDRUŠKIENĖ, J., VARONECKAS, G., MARTINKĖNAS, A. & GRABAUSKAS, V. 2008. Factors associated with poor sleep and health-related quality of life. Medicina, 44, 240.

BULOT, F. M., JOHNSTON, S. J., BASFORD, P. J., EASTON, N. H., APETROAIE-CRISTEA, M., FOSTER, G. L., MORRIS, A. K., COX, S. J. & LOXHAM, M. 2019. Long-term field comparison of multiple low-cost particulate matter sensors in an outdoor urban environment. Scientific reports, 9, 1-13.

BUSH, T., BARTINGTON, S. E., ANDERSON, R., ABREU, P., SINGH, A. & LEACH, F. 2022. Air quality sensing technology: opportunities and challenges for local application Oxford, UK.

CAMPBELL, C. A., BARTINGTON, S. E., WOOLLEY, K. E., POPE, F. D., THOMAS, G. N., SINGH, A., AVIS, W. R., TUMWIZERE, P. R., UWANYIRIGIRA, C., ABIMANA, P. & KABERA, T. 2021. Investigating Cooking Activity Patterns and Perceptions of Air Quality Interventions among Women in Urban Rwanda. International Journal of Environmental Research and Public Health, 18, 5984.

CANHA, N., LAGE, J., COUTINHO, J. T., ALVES, C. & ALMEIDA, S. M. 2019. Comparison of indoor air quality during sleep in smokers and non-smokers' bedrooms: A preliminary study. Environmental Pollution, 249, 248-256.

CANHA, N., TEIXEIRA, C., FIGUEIRA, M. & CORREIA, C. 2021. How Is Indoor Air Quality during Sleep? A Review of Field Studies. Atmosphere, 12, 110.

CARSLAW, D. 2019. The openair manual — open-source tools for analysing air pollution data. Manual for version 2.6-6. online: University of York.

CARSLAW, D. & ROPKINS, K. 2012. openair — An R package for air quality data analysis. Environmental Modelling & Software, 27–28(0), 52–61.

CHEN, H., DU, R., REN, W., ZHANG, S., DU, P. & ZHANG, Y. 2021. The Microbial Activity in PM2.5 in Indoor Air: As an Index of Air Quality Level. Aerosol and Air Quality Research, 21, 200101.

CHONG, C.-Y. & KUMAR, S. 2003. Sensor Networks: Evolution, opportunities, and challenges. Proceedings of the IEEE, 91, 1247-1256.

COMMITTEE ON THE MEDICAL EFFECTS OF AIR POLLUTANTS 2022. Air pollution: cognitive decline and dementia. In: AGENCY, U. H. S. (ed.). online: GOV.uk.

COWELL, N. H., CHAPMAN, L., BLOSS, W. & POPE, F. 2022. Field calibration and evaluation of an Internet of Things based particulate matter sensor. Frontiers in Environmental Science, 733.

CRILLEY, L. R., SHAW, M., POUND, R., KRAMER, L. J., PRICE, R., YOUNG, S., LEWIS, A. C. & POPE, F. D. 2018. Evaluation of a low-cost optical particle counter (Alphasense OPC-N2) for ambient air monitoring. Atmospheric Measurement Techniques, 709-720.

CRILLEY, L. R., SINGH, A., KRAMER, L. J., SHAW, M. D., ALAM, M. S., APTE, J. S., BLOSS, W. J., HILDEBRANDT RUIZ, L., FU, P., FU, W., GANI, S., GATARI, M., ILYINSKAYA, E., LEWIS, A. C., NG'ANG'A, D., SUN, Y., WHITTY, R. C. W., YUE, S., YOUNG, S. & POPE, F. D. 2020. Effect of aerosol composition on the performance of low-cost optical particle counter correction factors. Atmos. Meas. Tech., 13, 1181-1193.

DE GENNARO, G., DAMBRUOSO, P. R., DI GILIO, A., DI PALMA, V., MARZOCCA, A. & TUTINO, M. 2016. Discontinuous and Continuous Indoor Air Quality Monitoring in Homes with Fireplaces or Wood Stoves as Heating System. International Journal of Environmental Research and Public Health, 13, 78.

DERBEZ, M., BERTHINEAU, B., COCHET, V., PIGNON, C., RIBÉRON, J., WYART, G., MANDIN, C. & KIRCHNER, S. 2014. A 3-year follow-up of indoor air quality and comfort in two energy-efficient houses. Building and Environment, 82, 288-299.

DI ANTONIO, A., POPOOLA, O. A., OUYANG, B., SAFFELL, J. & JONES, R. L. 2018. Developing a relative humidity correction for low-cost sensors measuring ambient particulate matter. Sensors, 18, 2790.

DOMÍNGUEZ-AMARILLO, S., FERNÁNDEZ-AGÜERA, J., CESTEROS-GARCÍA, S. & GONZÁLEZ-LEZCANO, R. A. 2020. Bad Air Can Also Kill: Residential Indoor Air Quality and Pollutant Exposure Risk during the COVID-19 Crisis. International Journal of Environmental Research and Public Health, 17.

EZANI, E., BRIMBLECOMBE, P., HANAN ASHA'ARI, Z., FAZIL, A. A., SYED ISMAIL, S. N., AHMAD RAMLY, Z. T. & KHAN, M. F. 2020. Indoor and Outdoor Exposure to PM2.5 during COVID-19 Lockdown in Suburban Malaysia. Aerosol and Air Quality Research, 20.

GOLDSTEIN, A. H., NAZAROFF, W. W., WESCHLER, C. J. & WILLIAMS, J. 2021. How Do Indoor Environments Affect Air Pollution Exposure? Environmental Science & Technology, 55, 100-108.

GONZÁLEZ-MARTÍN, J., KRAAKMAN, N. J. R., PÉREZ, C., LEBRERO, R. & MUÑOZ, R. 2021. A state–of–the-art review on indoor air pollution and strategies for indoor air pollution control. Chemosphere, 262, 128376.

GUYOT, G., SHERMAN, M. H. & WALKER, I. S. 2018. Smart ventilation energy and indoor air quality performance in residential buildings: A review. Energy and Buildings, 165, 416-430.

HAGAN, D. & CROSS, E. 2022. Can your Plantower PMS5003-based Air Quality Sensor Measure PM10? Available from: https://blog.quant-aq.com/can-your-plantower-pms5003-based-air-quality-sensor-measure-pm10/?s=03 2022].

HAGAN, D. H. & KROLL, J. H. 2020. Assessing the accuracy of low-cost optical particle sensors using a physics-based approach. Atmos. Meas. Tech., 13, 6343-6355.

HEGDE, S., MIN, K. T., MOORE, J., LUNDRIGAN, P., PATWARI, N., COLLINGWOOD, S., BALCH, A. & KELLY, K. E. 2020. Indoor Household Particulate Matter Measurements Using a Network of Low-cost Sensors. Aerosol and Air Quality Research, 20, 381-394.

JEON, Y., CHO, C., SEO, J., KWON, K., PARK, H., OH, S. & CHUNG, I.-J. 2018. IoT-based occupancy detection system in indoor residential environments. Building and Environment, 132, 181-204.

JEONG, C.-H., SALEHI, S., WU, J., NORTH, M. L., KIM, J. S., CHOW, C.-W. & EVANS, G. J. 2019. Indoor measurements of air pollutants in residential houses in urban and suburban areas: Indoor versus ambient concentrations. Science of The Total Environment, 693, 133446.

JODEH, S., HASAN, A. R., AMARAH, J., JUDEH, F., SALGHI, R., LGAZ, H. & JODEH, W. 2018. Indoor and outdoor air quality analysis for the city of Nablus in Palestine: seasonal trends of PM10, PM5.0, PM2.5, and PM1.0 of residential homes. Air Quality, Atmosphere & Health, 11, 229-237.

KALISZEWSKI, M., WŁODARSKI, M., MŁYŃCZAK, J. & KOPCZYŃSKI, K. 2020. Comparison of Low-Cost Particulate Matter Sensors for Indoor Air Monitoring during COVID-19 Lockdown. Sensors, 20.

KANG, C. A. & CHOI, W. 2020. Indoor and Outdoor Levels of Particulate Matter with a Focus on I/O Ratio Observations: Based on Literature Review in Various Environments and Observations at Two Elementary Schools in Busan and Pyeongtaek, South Korea,. Korean Journal of Remote Sensing, 36, 1691-1710.

KATSOYIANNIS, A. & CINCINELLI, A. 2019. 'Cocktails and dreams': the indoor air quality that people are exposed to while sleeping. Current Opinion in Environmental Science & Health, 8, 6-9.

KIM, H., KANG, K. & KIM, T. 2018. Measurement of Particulate Matter (PM2.5) and Health Risk Assessment of Cooking-Generated Particles in the Kitchen and Living Rooms of Apartment Houses. Sustainability, 10, 843.

KIM, K.-H., KABIR, E. & KABIR, S. 2015. A review on the human health impact of airborne particulate matter. Environment International, 74, 136-143.

KIM, S., PARK, S. & LEE, J. 2019. Evaluation of Performance of Inexpensive Laser Based PM2.5 Sensor Monitors for Typical Indoor and Outdoor Hotspots of South Korea. Applied Sciences, 9, 1947.

KOZIELSKA, B., MAINKA, A., ŻAK, M., KALETA, D. & MUCHA, W. 2020. Indoor air quality in residential buildings in Upper Silesia, Poland. Building and Environment, 177, 106914.

KREBS, B., BURNEY, J., ZIVIN, J. G. & NEIDELL, M. 2021. Using Crowd-Sourced Data to Assess the Temporal and Spatial Relationship between Indoor and Outdoor Particulate Matter. Environmental Science & Technology, 55, 6107-6115.

KÜNN, S., PALACIOS, J. & PESTEL, N. 2019. Indoor air quality and cognitive performance.

KUULA, J., MÄKELÄ, T., AURELA, M., TEINILÄ, K., VARJONEN, S., GONZÁLEZ, Ó. & TIMONEN, H. 2020. Laboratory evaluation of particle-size selectivity of optical low-cost particulate matter sensors. Atmos. Meas. Tech., 13, 2413-2423.

LAU, C. J., LOEBEL ROSON, M., KLIMCHUK, K. M., GAUTAM, T., ZHAO, B. & ZHAO, R. 2021. Particulate matter emitted from ultrasonic humidifiers—Chemical composition and implication to indoor air. Indoor Air, 31, 769-782.

LEVY ZAMORA, M., XIONG, F., GENTNER, D., KERKEZ, B., KOHRMAN-GLASER, J. & KOEHLER, K. 2019. Field and Laboratory Evaluations of the Low-Cost Plantower Particulate Matter Sensor. Environmental Science & Technology, 53, 838-849.

LEWIS, A. C., LEE, J. D., EDWARDS, P. M., SHAW, M. D., EVANS, M. J., MOLLER, S. J., SMITH, K. R., BUCKLEY, J. W., ELLIS, M., GILLOT, S. R. & WHITE, A. 2016. Evaluating the performance of low cost chemical sensors for air pollution research. Faraday Discussions, 189, 85-103.

LI, J., LI, H., MA, Y., WANG, Y., ABOKIFA, A. A., LU, C. & BISWAS, P. 2018. Spatiotemporal distribution of indoor particulate matter concentration with a low-cost sensor network. Building and Environment, 127, 138-147.

LU, Y., GIULIANO, G. & HABRE, R. 2021. Estimating hourly PM2.5 concentrations at the neighborhood scale using a low-cost air sensor network: A Los Angeles case study. Environmental Research, 195, 110653.

MANGA, A. & ALLEN, C. Implications of a Natural Ventilation Retrofit of an Office Building. In: GORSE, C., SCOTT, L., BOOTH, C. & DASTBAZ, M., eds. Climate Emergency – Managing, Building , and Delivering the Sustainable Development Goals, 2022// 2022 Cham. Springer International Publishing, 137-148.

MOUSAVI, A. & WU, J. 2021. Indoor-Generated PM2.5 During COVID-19 Shutdowns Across California: Application of the PurpleAir Indoor–Outdoor Low-Cost Sensor Network. Environmental Science & Technology, 55, 5648-5656.

MUJAN, I., ANĐELKOVIĆ, A. S., MUNĆAN, V., KLJAJIĆ, M. & RUŽIĆ, D. 2019. Influence of indoor environmental quality on human health and productivity - A review. Journal of Cleaner Production, 217, 646-657.

NANDASENA, S., WICKREMASINGHE, R., KASTURIRATNE, A., WIMALASIRI, U., TIPRE, M., LARSON, R., LEVITAN, E. & SATHIAKUMAR, N. 2018. Particulate Matter fractions and kitchen characteristics in Sri Lankan households using solid fuel and LPG. bioRxiv, 461665.

NEBES, R. D., BUYSSE, D. J., HALLIGAN, E. M., HOUCK, P. R. & MONK, T. H. 2009. Self-reported sleep quality predicts poor cognitive performance in healthy older adults. The Journals of Gerontology: Series B, 64, 180-187.

O'LEARY, C., JONES, B. & HALL, I. An intervention study of PM2. 5 concentrations measured in domestic kitchens. 39th Air Infiltration and Ventilation Centre Conference, 2018. Antibes Juan-Les-Pins France, 1090-1099.

OFFICE FOR NATIONAL STATISTICS 2021. Business and individual attitudes towards the future of homeworking, UK: April to May 2021. In: EMPLOYMENT AND LABOUR MARKET (ed.). Online.

OFFICE FOR NATIONAL STATISTICS. 2022. Is hybrid working here to stay? [Online]. Online. Available: https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/employmentandemployeetypes/articles/ishybridworkingheretostay/2022-05-23#:~:text=The%20proportion%20of%20people%20hybrid,over%20the%20past%20seven%20days. [Accessed].

OTT, W. R. & SIEGMANN, H. C. 2006. Using multiple continuous fine particle monitors to characterize tobacco, incense, candle, cooking, wood burning, and vehicular sources in indoor, outdoor, and in-transit settings. Atmospheric Environment, 40, 821-843.

OUIMETTE, J. R., MALM, W. C., SCHICHTEL, B. A., SHERIDAN, P. J., ANDREWS, E., OGREN, J. A. & ARNOTT, W. P. 2022. Evaluating the PurpleAir monitor as an aerosol light scattering instrument. Atmos. Meas. Tech., 15, 655-676.

PATEL, S., LI, J., PANDEY, A., PERVEZ, S., CHAKRABARTY, R. K. & BISWAS, P. 2017. Spatio-temporal measurement of indoor particulate matter concentrations using a wireless network of low-cost sensors in households using solid fuels. Environmental Research, 152, 59-65.

PATEL, S., SANKHYAN, S., BOEDICKER, E. K., DECARLO, P. F., FARMER, D. K., GOLDSTEIN, A. H., KATZ, E. F., NAZAROFF, W. W., TIAN, Y., VANHANEN, J. & VANCE, M. E. 2020. Indoor Particulate Matter during HOMEChem: Concentrations, Size Distributions, and Exposures. Environmental Science & Technology, 54, 7107-7116.

PITARMA, R., MARQUES, G. & FERREIRA, B. R. 2016. Monitoring Indoor Air Quality for Enhanced Occupational Health. Journal of Medical Systems, 41, 23.

QI, M., DU, W., ZHU, X., WANG, W., LU, C., CHEN, Y., SHEN, G., CHENG, H., ZENG, E. Y. & TAO, S. 2019. Fluctuation in time-resolved PM2.5 from rural households with solid fuel-associated internal emission sources. Environmental Pollution, 244, 304-313.

SAYAHI, T., BUTTERFIELD, A. & KELLY, K. 2019. Long-term field evaluation of the Plantower PMS low-cost particulate matter sensors. Environmental Pollution, 245, 932-940.

SHEHAB, M. A. & POPE, F. D. 2019. Effects of short-term exposure to particulate matter air pollution on cognitive performance. Scientific Reports, 9, 8237.

SHEN, D., WU, S., DAI, P. Y., LI, Y. S. & LI, C. M. 2018. Distribution of particulate matter and ammonia and physicochemical properties of fine particulate matter in a layer house. Poultry Science, 97, 4137-4149.

SHEN, H., HOU, W., ZHU, Y., ZHENG, S., AINIWAER, S., SHEN, G., CHEN, Y., CHENG, H., HU, J., WAN, Y. & TAO, S. 2021. Temporal and spatial variation of PM2.5 in indoor air monitored by low-cost sensors. Science of The Total Environment, 770, 145304.

SHUPLER, M., HYSTAD, P., BIRCH, A., CHU, Y. L., JERONIMO, M., MILLER-LIONBERG, D., GUSTAFSON, P., RANGARAJAN, S., MUSTAHA, M., HEENAN, L., SERON, P., LANAS, F., CAZOR, F., JOSE OLIVEROS, M., LOPEZ-JARAMILLO, P., CAMACHO, P. A., OTERO, J., PEREZ, M., YEATES, K., WEST, N., NCUBE, T., NCUBE, B., CHIFAMBA, J., YUSUF, R., KHAN, A., LIU, Z., WU, S., WEI, L., TSE, L. A., MOHAN, D., KUMAR, P., GUPTA, R., MOHAN, I., JAYACHITRA, K. G., MONY, P. K., RAMMOHAN, K., NAIR, S., LAKSHMI, P. V. M., SAGAR, V., KHAWAJA, R., IQBAL, R., KAZMI, K., YUSUF, S. & BRAUER, M. 2022. Multinational prediction of household and personal exposure to fine particulate matter (PM2.5) in the PURE cohort study. Environment International, 159, 107021.

SIGURDSON, K. & AYAS, N. T. A. T. 2007. The public health and safety consequences of sleep disordersThis paper is one of a selection of papers published in this Special Issue, entitled Young Investigators' Forum. Canadian Journal of Physiology and Pharmacology, 85, 179-183.

SINGER, B. C. & DELP, W. W. 2018. Response of consumer and research grade indoor air quality monitors to residential sources of fine particles. Indoor Air, 28, 624-639.

SNYDER, E. G., WATKINS, T. H., SOLOMON, P. A., THOMA, E. D., WILLIAMS, R. W., HAGLER, G. S., SHELOW, D., HINDIN, D. A., KILARU, V. J. & PREUSS, P. W. 2013. The changing paradigm of air pollution monitoring. Environmental science & technology, 47, 11369-11377.

SPIRU, P. & SIMONA, P. L. 2017. A review on interactions between energy performance of the buildings, outdoor air pollution and the indoor air quality. Energy Procedia, 128, 179-186.

STEINEMANN, A., WARGOCKI, P. & RISMANCHI, B. 2017. Ten questions concerning green buildings and indoor air quality. Building and Environment, 112, 351-358.

STRØM-TEJSEN, P., ZUKOWSKA, D., WARGOCKI, P. & WYON, D. P. 2016. The effects of bedroom air quality on sleep and next-day performance. Indoor Air, 26, 679-686.

SUSZ, A., PRATTE, P. & GOUJON-GINGLINGER, C. 2020. Real-time Monitoring of Suspended Particulate Matter in Indoor Air: Validation and Application of a Light-scattering Sensor. Aerosol and Air Quality Research, 20, 2384-2395.

SUVENNIE, S. & NORDIN, S. 2020. Effect of indoor fine particulate matter (PM_{2.5}) associated in Petaling Jaya LRTs. IOP Conference Series: Earth and Environmental Science, 476, 012125.

THE WORLD AIR QUALITY PROJECT. 2022. The Plantower PMS5003 and PMS7003 Air Quality Sensor experiment [Online]. Available: https://aqicn.org/sensor/pms5003-7003/ [Accessed 11.10.22].

TRYNER, J., MEHAFFY, J., MILLER-LIONBERG, D. & VOLCKENS, J. 2020. Effects of aerosol type and simulated aging on performance of low-cost PM sensors. Journal of Aerosol Science, 150, 105654.

TSI 2014. DUSTTRAK™ II AEROSOL MONITORS MODELS 8530, 8530EP AND 8532. USA.

VICENTE, E. D., VICENTE, A. M., EVTYUGINA, M., CALVO, A. I., ODUBER, F., BLANCO ALEGRE, C., CASTRO, A., FRAILE, R., NUNES, T., LUCARELLI, F., CALZOLAI, G., NAVA, S. & ALVES, C. A. 2020. Impact of vacuum cleaning on indoor air quality. Building and Environment, 180, 107059.

VILČEKOVÁ, S., APOSTOLOSKI, I. Z., MEČIAROVÁ, Ľ., BURDOVÁ, E. K. & KISEĽÁK, J. 2017. Investigation of Indoor Air Quality in Houses of Macedonia. International Journal of Environmental Research and Public Health, 14, 37.

WALLACE, L. A., WHEELER, A. J., KEARNEY, J., VAN RYSWYK, K., YOU, H., KULKA, R. H., RASMUSSEN, P. E., BROOK, J. R. & XU, X. 2011. Validation of continuous particle monitors for personal, indoor, and outdoor exposures. Journal of Exposure Science & Environmental Epidemiology, 21, 49-64.

WAN, M.-P., WU, C.-L., SZE TO, G.-N., CHAN, T.-C. & CHAO, C. Y. H. 2011. Ultrafine particles, and PM2.5 generated from cooking in homes. Atmospheric Environment, 45, 6141-6148.

WANG, Z., CALDERÓN, L., PATTON, A. P., SORENSEN ALLACCI, M., SENICK, J., WENER, R., ANDREWS, C. J. & MAINELIS, G. 2016. Comparison of real-time instruments and gravimetric method when measuring particulate matter in a residential building. Journal of the Air & Waste Management Association, 66, 1109-1120.

WHO 2010. WHO guidelines for indoor air quality: selected pollutants.

WONG, N. H. & HUANG, B. 2004. Comparative study of the indoor air quality of naturally ventilated and air-conditioned bedrooms of residential buildings in Singapore. Building and Environment, 39, 1115-1123.

WORLD HEALTH ORGANISATION 2021. WHO global air quality guidelines. Particulate matter (PM2.5 and PM10), ozone, nitrogen dioxide,sulfur dioxide and carbon monoxide. Geneva.

WORLD HEALTH ORGANISATION. 2022. Air Pollution: Impacts [Online]. Online. Available: https://www.who.int/health-topics/air-pollution#tab=tab_2 [Accessed 12.08.2022 2022].

WORLD HEALTH ORGANIZATION 2006. Air quality guidelines: global update 2005: particulate matter, ozone, nitrogen dioxide, and sulfur dioxide, World Health Organization.

XU, R., QI, X., DAI, G., LIN, H., ZHAI, P., ZHU, C., WANG, L. & DING, A. 2020. A Comparison Study of Indoor and Outdoor Air Quality in Nanjing, China. Aerosol and Air Quality Research, 20, 2128-2141.

YIN, H., LI, Z., ZHAI, X., NING, Y., GAO, L., CUI, H., MA, Z. & LI, A. 2022. Field measurement of the impact of natural ventilation and portable air cleaners on indoor air quality in three occupant states. Energy and Built Environment.

YONG, Z. & HAOXIN, Z. 2016. Digital universal particle concentration sensor PMS5003 data manual. online PLANTOWER.

ZHAO, J., BIRMILI, W., WEHNER, B., DANIELS, A., WEINHOLD, K., WANG, L., MERKEL, M., KECORIUS, S., TUCH, T., FRANCK, U., HUSSEIN, T. & WIEDENSOHLER, A. 2020. Particle Mass Concentrations and Number Size Distributions in 40 Homes in Germany: Indoor-to-Outdoor Relationships, Diurnal and Seasonal Variation. Aerosol and Air Quality Research.

ZUSMAN, M., SCHUMACHER, C. S., GASSETT, A. J., SPALT, E. W., AUSTIN, E., LARSON, T. V., CARVLIN, G., SETO, E., KAUFMAN, J. D. & SHEPPARD, L. 2020. Calibration of low-cost particulate matter sensors: Model development for a multi-city epidemiological study. Environment International, 134, 105329.

Chapter 4: What can we learn from nested IoT low-cost sensor networks for air quality? A case study of $PM_{2.5}$

This chapter has been submitted for peer review to the journal *Meteorological Applications* as part of a special issue titled *Unconventional Observations for Meteorological Applications.*

It has been submitted as

Cowell, N., Baldo, C., Chapman, L., Bloss, W., Zhong, J. 2023. What can we learn from nested IoT low-cost sensor networks for air quality? A case study of $PM_{2.5}$

Abstract

Low-cost sensing, along with the Internet of Things (IoT), presents a new range of possibilities for non-standard (unconventional) monitoring of environmental parameters. This paper describes a series of intersecting networks of particulate matter sensors that were deployed across the Birmingham conurbation for a 12-month period and coincided with the introduction of the Birmingham Clean Air Zone (CAZ). The networks consisted of a combination of commercially available IoT sensors (Earthsense Zephyrs) and University developed PM IoT sensors (AltasensePM) both of which house the same PlantowerPMS5003 optical particle counter for PM measurement. Data from these networks were assimilated with data from a third-party Zephyr deployment, along with the DEFRA AURN network, where it was hosted on an open-source online platform to provide an air quality network totalling 28 locations across the city. This nesting of sensor networks allowed for new insights into sensor performance, including the accuracy of a large network to detect regional concentrations and the quantity of sensors needed for effective monitoring beyond indicative measurements. After comprehensive data validation steps, the sensors were shown to perform well during real-world co-location studies with reference instrumentation (exhibiting slopes of 0.74-1.3). The IoT sensors also demonstrated good capability of detecting temporal patterns of regional $PM_{2.5}$ with the mean of the entire sensor network recording an annual average $PM_{2.5}$ concentration within 0.2µgm^{-3} of the regulatory network annual average observation. Network derived statistics for estimating urban background concentrations increases in-line with the number of sensors available, however when assessing this for near-source concentrations the importance of sensor location is highlighted as an important factor. Overall, the network provided novel insights into local concentrations, detecting similar hotspots to those identified by a high-resolution model. The increased spatial coverage afforded by the sensor network has potential to support higher resolution evaluation of future models and provide air pollution monitoring coverage for reduced cost, meaning that larger segments of the population can live within areas of monitored air quality.

1. Introduction

1.1 Clean Air Zones and air quality management

Birmingham is a large city in the UK, with the wider conurbation being home to a population of approximately 1.14 million people (Birmingham City Council, 2021b). Like many cities, it faces the challenge of improving its air quality for public health benefit and in 2017 was highlighted as one of the first wave of cities in the UK to act to improve its roadside NO_2 concentrations by implementing air quality charging schemes (DEFRA, 2017).

Low emissions and Clean Air Zones (CAZ) are areas of action to improve air quality by targeting vehicular emissions, either by charging fees or by enhanced traffic management to reduce emissions (Williams et al., 2022). With the aim of reducing NO_2 exceedances, the CAZ is one of the most prominent measures recently introduced in Birmingham. Introduced on 1st June 2021, the CAZ applies to all roads inside of the inner ring road (excluding the ring road itself), 24 hours a day, 365 days a year (Figure 1). The ring road (A4540) forms a circle around the city centre zone, drivers are charged a daily fee dependent on their vehicle engine standard- vehicles with diesel engine of Euro 6 or better or petrol engines of Euro 4 or better are exempt from charges (Birmingham City Council, 2018). The daily fee is £8 per day for cars, taxis, vans (LGVs) and £50 a day for coaches, buses and HGVs (Birmingham City Council, 2021a).

The approach is not unique to Birmingham. Other UK cities such as Bath, Bradford and Portsmouth already have a CAZ and, at the time of writing, there are plans for CAZs in Bristol, Manchester, Sheffield and Tyneside. However not all CAZs are the same- Birmingham has a class D CAZ meaning charges apply to all vehicle types that do not meet engine standards (GOV.UK, 2022). Other CAZ types may opt to only target certain vehicle types such as buses and lorries rather than cars. London also has a very similar scheme. The Ultra-Low Emission Zone or ULEZ was introduced in 2019 and expanded in 2021 and charges vehicles for entering based on the same Euro emissions standards as the Birmingham CAZ (Transport for London, 2022).

Initial studies on CAZ and low emissions zones demonstrate mixed results for improving air quality. Whilst generally successful at reducing their target pollutant of NO_2, their impact on PM has been found to be limited (Williams et al., 2022). For example, Ma et al. (2021) study on the London ULEZ reported $PM_{2.5}$ responses from -6% to 4% change across roadside and background monitoring sites, with aggregated concentration change to PM2.5 within the ULEZ deemed insignificant. This is important as $PM_{2.5}$ is a pollutant of increasing concern. As vehicle fleets shift towards lower emission combustion engines, hybrid engines and electric vehicles the contribution gaseous emissions from exhausts will reduce, but the impact of this transition on non-exhaust emissions of particulates will be limited (Harrison et al., 2021). Exposure to particulates has been linked to a number of health excess risks with links to; cardiovascular disease, respiratory disease, lung cancer, diabetes and adverse birth outcomes (Lu et al., 2015, Feng et al., 2016) In line with other studies, an initial analysis at the 6 month anniversary of the Birmingham CAZ reported a 13% reduction in average NO_2 but no evidence of a reduction in $PM_{2.5}$ (Birmingham City Council, 2022). This report recognised that further data analysis was needed, which would now be possible by consulting a range of low-cost sensor networks now operational in the city. These provide a novel opportunity to evaluate concentrations at higher resolutions than traditional monitoring networks, providing understanding into the exposure of particulates on the population alongside the impacts of management techniques.

1.2 IoT low-cost PM sensors

IoT sensors can take many forms-ranging from commercial sensing units that come with a range of functionality, customer support and online data hosting to basic sampling units that require more manual support from the consumer. Prices can vary reflective of this range in product, from <£50 per unit for the most basic of samplers, to £1000-5000 for the more complex devices. Many units come with additional costs that will also need to be considered including but not limited too; communication subscriptions such as cellular connection, servicing and replacement parts, online data storage and hosting and staffing needs. Low-cost sensors are growing in popularity, within both the research, government and local authority air quality community. The small stature, real-time measurement, portability and reduced cost of these units compared to traditional regulatory monitoring efforts make air quality sampling more accessible and are leading to an increase in the spatial resolution of air quality measurements (Zhang et al., 2018).

For particulate matter, many low-cost sensing units use an Optical Particle Counter or OPC to measure particulates. OPCs use light scattering technology to detect particles being pulled through the unit and are commonly featured within low-cost sensor literature (Zhang et al., 2018). However, there is some uncertainty associated with measuring particulates via OPC; these devices are known to be influenced by humidity although via calibration with regulatory instrumentation and correction factors literature has shown them able to generate indicative particulate concentrations (Crilley et al., 2018, Cowell et al., 2022, Magi et al., 2020).

The PlantowerPMS5003 is a commonly used OPC within low-cost sensor units. It can be found in various instruments, including PurpleAir units and Earthsense Zephyrs. Previous work has demonstrated successful calibration and correction for humidity of this sensor for indicative measurement (Cowell et al., 2022, Cowell et al., 2023). These studies use a multi-linear model developed against a FIDAS reference instrument to apply a correction dependent on sensor detected humidity. This method reported Pearsons R against a reference instrument of 0.81–0.91 and strong intersensory correlations- which is important when wanting to deploy sensors as a network for spatial analysis (Cowell et al., 2022). However, literature also reports challenges with this sensor being unable to effectively measure PM_{10} due to laser geometry and particle loss within the sampling chamber (Ouimette et al., 2022, Kuula et al., 2020, Hagan and Kroll, 2020). The Zephyr unit which utilises the PMS5003 has received MCERTS status for the indicative monitoring of $PM_{2.5}$ and PM_{10} (Earthsense, 2022a). In line with this certification, in February 2023 they updated their undisclosed calibration method, data used in this study was downloaded before these updates. It's important to note that term indicative is used in several ways throughout the literature and definitions can vary. For MCERTS indicative monitors, instruments data must be within ±50% uncertainty. The AltasensePM have not be compared to the MCERTS standards, and for these and the rest of the paper a more colloquial definition of indicative is used, where indicative refers to sensors which are able to detect trends and patterns, including step changes in concentrations but not expected to provide absolute values for concentrations.

1.3 Sensor Networks

Despite the growing popularity with both local authorities and researchers alike, low-cost sensor networks for air quality tend to be isolated deployments, generated and maintained by their own interested party with the focus of their own monitoring goal. Examples of such networks include the SAMHE project in UK schools (SAMHE Project, 2022), Coventrys' Earthsense Zephyr deployment

(Earthsense, 2019) and the Aeroqual AQY network in California (South Coast AQMD, 2023). This can lead to multiple overlapping deployments which, if used together, could enhance hyperlocal understanding of air quality as well as providing an excellent opportunity to explore both the integrity and utility of data from such networks.

However, there remains some novel issues developing from the ad-hoc approaches to deployment inevitable in nested deployments of sensors. Data sharing can be an issue with data being hosted and collected by different bodies using different protocols and metadata standards (Topping et al., 2021). A further challenge is how to integrate and manage this data. Whilst there is an abundance of air quality data available, this is often of contrasting quality and standards ranging from regulatory networks to citizen science. Added to this, low-cost measurements and data can be presented in a confusing way making it hard for non-specialist users to understand (Kosmidis et al., 2018). Here, online platforms and big data storage offer potential solution to this problem by allowing data from various sources to be automatically pulled onto an online platform for viewing and analysis (Chang et al., 2018).

This paper uses a cloud-based approach to collate the data from new deployments of IoT sensors across Birmingham nested within pre-existing IoT deployments and standard deployed instrumentation. The aim is to bring together a much wider selection of the available data to not only assess the particulate concentrations across the city, but also to assess the wider applications of low-cost sensor data to increase understanding of variability in particulate concentrations across an urban environment.

2 Methods

2.1 Data and Instrumentation

This paper utilises the Birmingham Urban Observatory, an online cloud-based platform which, amongst a range of other data, hosted an integrated array of AQ sensors. This included data from two university-based deployments of air quality sensors (AltasensePM – an in-house designed PM sensor and Earthsense Zephyrs), as well as Zephyr data from a network maintained by BCC and standard observations from the DEFRA AURN. For this paper, 15-minute average data from the Urban Observatory online platform was used.

2.1.1 AltasensePM

AltasensePM are an IoT enabled particulate matter sensor. The AltasensePM connects a PlantowerPMS5003 and SHT21 temperature/humidity sensor with an Arduino MKRFox1200 microcontroller via a custom PCB to connect the sensor to the Sigfox network. As previously stated, the PMS5003 is an optical particle counter which converts scattered light into a voltage and then particle count via an undisclosed algorithm (Sayahi et al., 2019). The PMS5003 is manufacturer stated to report particles with a minimum particle diameter of 0.3µm although a recent study has reported detecting particles smaller than this with the PMS5003 (Yong and Haoxin, 2016, Ouimette et al., 2022). The manufacturer reports uncertainty of ±10µgm^{-3} for concentrations 0-100µgm^{-3} and ±10% for concentrations 100-500µgm^{-3} (Yong and Haoxin, 2016). AltasensePM make an instantaneous measurement every 15 minutes after running for 1 minute to stabilise the fan and sensor.

AltasensePM are collocated for ~8 weeks against a FIDAS at the Birmingham Air Quality Supersite (BAQS) urban background site for calibration and are corrected for the impact of humidity in real-time online via the Urban Observatory platform. Full details of the calibration can be found in (Cowell et al., 2022).

2.1.2 Zephyr

Zephyrs, by Earthsense, are a commercial sensing unit that can measure both gaseous and particulate pollutants and which can be mains or solar powered. The sample rate of the Zephyr is 10 seconds with an upload rate of 15 minutes in normal operation, reducing to 1 minute sample rate with 60 minutes upload rate in winter mode which is utilised when there is low solar insolation during winter to extend the battery power within the unit (Earthsense, 2022b). Like AltasensePM, Zephyrs utilise a PlantowerPMS5003 but with an undisclosed algorithm to measure particulates and report estimate accuracy of 5μgm^{-3} for PM_1, $PM_{2.5}$ and PM_{10} and limits of detection of 0.2μgm^{-3},1.3μgm^{-3} and 1.4μgm^{-3} respectively (Earthsense, 2022b). Ideally, the solar panel powering the Zephyr will face due south with no obstructions or shadow as recommended by the supplier however in a city centre this was sometimes challenging due to building/tree shadow and existing infrastructure limitations combined with limited access to alternative locations to install the units on. Therefore, some of the Zephyrs in the observatory experienced power outages / data loss in the winter. Zephyrs undergo manufacturer calibration via colocation against a GRIMM EDM180 in an urban background environment in Derby, UK. A limitation of this is that the GRIMM is also an optical based instrument, which means it is subject to potential error introduced by hygroscopicity of particles affecting light interactions (much like the low-cost OPCs themselves). Derby is a small city in the Midlands of the UK approximately ~35 miles from Birmingham, and for this study we have are presuming that PM sources between the two cities are similar, as literature suggests calibrating sensors in an environment similar to that which they'll be deployed in, to allow calibrations to capture the impact of particulate composition on performance (Crilley et al., 2018, Zusman et al., 2020). This again is a limitation as there may be differences between the two cities or site specific sources that could be altering the performance of a zephyr. The lack of transparency around the calibration process leads to some uncertainty in the data, as we can not be sure of the role that sources and meteorology play in calibration if the methods haven't been disclosed.

2.1.3 DEFRA AURN

Data from the DEFRA AURN network was also hosted as third-party data on the Birmingham Urban Observatory. The Automatic Urban and Rural Network (AURN) is the largest network of regulatory grade instruments in the UK, with current active sites and data spanning back to 1972. The goal of the network is to check for statutory air quality standards are being met and data is used for compliance reporting as set out under the Air Quality Standards Regulations 2010. Two sites were hosted on the platform, namely Ladywood and the A4540 (DEFRA, 2023a). These sites provide hourly average particulate data- with the $PM_{2.5}$ data being used for this study. Ladywood is classified as an urban background site, situated in the east of the city centre region on a local residential street behind a small school (DEFRA, 2023b). Importantly, the Ladywood location is within the CAZ. The A4540 roadside site is classified as an urban traffic site and is located on the westerly stretch of the city's ring-road, a major traffic route around the city centre (DEFRA, 2023b). The A4540 site is outside of the CAZ.

The DEFRA AURN locations provide hourly average data which was used in this study. Data from both low-cost sensor types are analysed using hourly averages generated from the 15-minute reported values, after validation explained in the next step. Due to the challenges around measuring PM_{10} outlined in section 2.4, this analysis focuses on $PM_{2.5}$ from all sensors in the network (Zephyrs & AltasensePM). A further reference site on the University campus, BAQS, is also used within the study. This is an urban background site located outside of the CAZ on the University Campus to the south of the city centre. The instrument at BAQS used for comparing PM measurements is the PALAS FIDAS. R studio was used to analyse data via the OpenAir package (Carslaw, 2019, Carslaw and Ropkins, 2012).

2.2 Sampling locations

Across Birmingham, a total of 28 locations were included in the network at various stages across the year (01.06.21-31.05.22) of sampling used in this project. A map of the sensor locations is presented in figure 1. 24 of the locations were monitored by Zephyrs (8 BCC Zephyrs, 16 UoB Zephyrs) with 4 monitored by AltasensePM. 13 locations were located inside the CAZ and 15 were outside of the CAZ. For analysis, sensors were grouped into site types using the (Department of Environmental Food and Rural Affairs, 2023) definitions of site type for the Automatic Urban Rural Network (AURN) as guidance for defining the sites. The majority of sites (19) were classified as urban traffic types and urban background was the second most prominent site type (6). There were also limited examples of urban industrial (1) and suburban background (2) sites from locations driven by work with partners outside of the city centre region. Most units were installed at heights of 2.5-3m above ground level, so far as the infrastructure would allow. This height prevents tampering whilst sampling at a height similar to human exposure. Sensors were considered semi-mobile; this means units are able to be redeployed with relative ease to suit sampling needs. This is reflective in the sampling of this project- where some units were moved throughout the year to capture specific sites of interest.

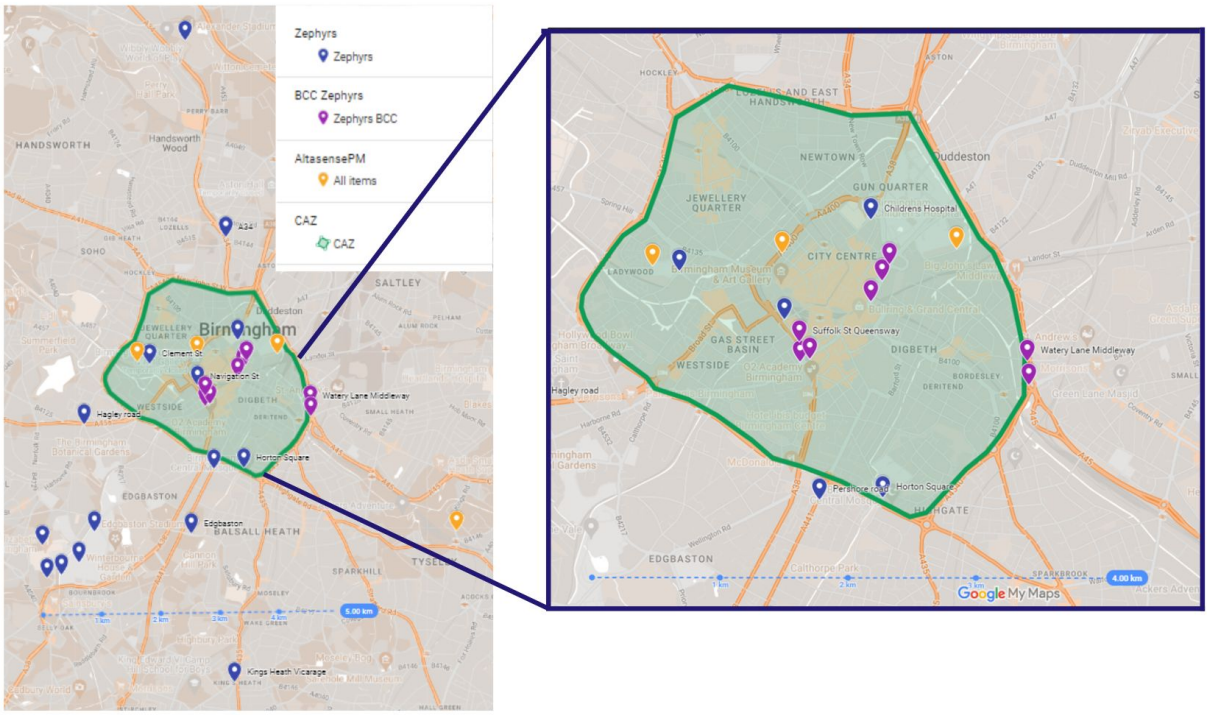


Figure 1- *map showing Birmingham Clean Air Zone and the location of the various sensors across Birmingham. Figure 1 shows the CAZ area in green- which captures the majority of the city centre attractions, shopping and the CBD. The A38 is a key road that runs through the city joining onto the M6 motorway- a major access route to the region.*

As this paper takes advantage of a range of coinciding and separate sensors deployments, each with their own foci and goals, the rationale underpinning the choice of sampling locations is varied. For sensors deployed by the University team, these were part of the WM-Air and Birmingham Urban Observatory projects. These projects had varied sampling agendas, including working with local stakeholders to support targeted monitoring at events and areas of interventions and more generic ambient sampling to assess PM concentrations across the city. However, the choice of locations were limited somewhat by restricted permissions to access to street furniture for installing sensors, particularly at roadside environments (including around the CAZ). Table S1 outlines the rationale behind sensor locations of units deployed by the University of Birmingham managed sensors within the study. Birmingham City Council had their own rationale for their monitoring sites, which mostly targeted roadside environments on major transport routes. Therefore, these coinciding networks don't represent a planned spatial distribution across the city, however they do represent a situation which is reflective of the sampling occurring in many urban centres. It is not uncommon for local authorities, citizen scientists, researchers and other interested parties to have overlapping air quality sampling where each user is deploying with their own goals. By combining the wealth of air quality data from different sources like this, there is room for opportunistic analysis of air quality in a city and this is a methodology which could be easily replicated in many cities to enhance air quality understanding by simply collaborating or data sharing. Whilst there are limitations, with sampling locations not being evenly distributed across the city, there are benefits in that these sampling

networks are capturing some of the concerns of local stakeholders and therefore data analysis from these sites has room to support impactful change if interpreted carefully.

2.3 Data validation

Best practice to ensure trust in low-cost sensor networks data is via thorough evaluation and data validation in real-world scenarios (Mahajan et al., 2021). Unlike regulatory instruments which have extensive certification and procedures to ensure that data quality standards are met, there is not set practice for validating low-cost sensor networks (Fishbain et al., 2017). (Mousavi and Wu, 2021, Lu et al., 2021) both propose quality control methods for PurpleAir PM sensors (that also utilise the PMS5003) that captures low frequency of change, values greater than the sensors effective measurement range and data loss/completeness. They also propose removing outliers that deviate far from a time averaged median, as these are likely not reflective of the true concentrations at the sensor site. (Bush et al., 2022) recommend a series of meteorological filters based on evidence of contexts in which sensors performance may be affected, including extreme temperatures and low humidity (which is not frequently experienced in this study location). From these suggestions, there are some clear traits of low-cost sensor data that need to be addressed through a validation method; sensor completeness, low frequency of change, extreme outlier values and impact of external factors. Therefore, this study utilised a 4-step data validation (drawn from the above literature) outlined below.

Step 1- 75% completeness criteria *3 or more measurements an hour (sensors measure every 15 minutes), 18hours or more coverage a day, 23 days or more coverage a month cumulative. Hours/days/months that fell outside of these criteria were discarded.*

Step 2- Meteorology filter *Keep data that falls within the confines of manufacturer specifications - 10°C<t<35°C and RH>35% using temperature and humidity data from the Birmingham Air Quality Supersite (BAQS) located on the University of Birmingham campus.*

Step 3- Static data *Remove data with 5 hour moving standard deviation=0.*

Step 4-Exclude outliers *Exclude data based on a threshold defined from 3x the Median Absolute Deviation as shown below in equation 1 & 2 drawn from (Lu et al., 2021), where X_i is the PM2.5 reading of the sensor, $\tilde{X}$is the median of X_i in a month and b=1.4826 (a set constant).*

$$MAD = b * median(X_i - \tilde{X})$$

(eq 1)

$$X_i < \tilde{X} - 3 * MAD \; or \; X_i < \tilde{X} + 3 * MAD$$

(eq 2)

After these steps 121,037 of valid hours of data were available for analysis (79.1% of data hours were kept as hourly averages). The range of % data hours kept after validation ranged from 36-96% by location, with the average location retaining 76% of data after validation.

It is important to note that there are presumptions made about the sensors and data during the validation state- namely that extreme peaks are false. There is room for future work to refine this process, and validations should consider the sampling context before processing. For example, indoor environments (such as those explored in the last chapter) are more likely to experience sudden extreme peaks in PM for nearby sources and therefore this validation process may not be entirely appropriate for that context.

2.4 High-resolution air quality model

The final part of the evaluation process was to overlay sensor data with a high-resolution air quality map of $PM_{2.5}$ (at 10 m × 10 m resolution) using ArcMap. The air quality map was derived from a local scale ADMS-Urban dispersion model, which takes into account explicit point and road sources, and grid sources (e.g. energy, industry, residential, waste, agriculture, natural and other sectors) at a 1 km2 resolution from UK National Atmospheric Emissions Inventory (NAEI, 2019) for the baseline year of 2019. The model also accounts for the effect of advanced canyon and urban canopy on the dispersion with building data from (Digimap, 2019). The model adopts Generic Reaction Set (GRS) chemistry scheme to capture NOx-O3-VOC chemistry and sulphate chemistry to represent the formation of secondary particulate matter (Cambridge Environmental Research Consultants Ltd, 2020). When compared to reference grade station observations, the model performs well and full details of West Midlands case study can be found in (Zhong et al., 2021). Only the Birmingham segment of the model was used in this study. The data for each site was averaged to overlay with the modelled air quality map. As discussed below, the model predictions are for a specific year – 2019 – which did not correspond to the sensor deployment dates. Therefore, absolute levels are expected to vary and only insight into spatial distribution of PM levels is considered here. This is discussed further in section 3.3 below.

3 Results and discussion

3.1 Sensor performance

3.1.1 Data capture

After quality control, the proportion of the year captured at each location varied considerably from 6.8%-94.4%, with the average % cover of 51.2%. Hagley Road was the lowest performing location in terms of % of year captured and this was due to the unit needing repair. Other low performing sensors in this test are Perry Park and BAQS and this is due to the sensors only being deployed for a segment of the year. Many of the Zephyr units struggled for power during the winter months. Although the solar panel is designed to power the unit in winter mode with clear solar insolation this is not always possible in urban locations due to building/infrastructure shadows. This limits some of the Zephyr's presence in the winter. In contrast, AltasensePM were limited by their calibration/deployment cycles and battery life, as some units required refurbishment after an initial deployment round after suffering some environmental damage. This meant there wasn't always a unit available to switch out when the sensors came in for recalibration/new batteries. As the AltasensePM can only be reset in person due

to the 1-way comms, this also led to some downtime. The issue of sensor capture completeness is not unique to this study, (Connolly et al., 2022) reported sensor presence within a low-cost sensor network being a major reliability issue with only 54% data capture with the outdoor segment of their network. It is evident that power and communications resilience needs investigation to ensure future reliability of these types of sensors. However, the power of multiple nested networks ensures that whilst all the network may not be functioning concurrently, sufficiently large sections should be operational to ensure data coverage. No individual locations were excluded completely after data filtering as this allowed for sites to be looked at individually, even if only present for short time, comparative to other sites for the equivalent reduced time periods. However, for some of the below analysis, sites were chosen that had >75% when looking at annual averages compared to a model or by location and data captured periods when making spatial conclusions. The complete details are outlined alongside the analysis. The representativeness of the overall network compared to regional concentrations from regulatory instruments is discussed in 4.1.2.

3.1.2 Co-location of sensors

Using both urban background and urban traffic site sensor:reference instrument colocations within the deployment network, it was generally shown that the lower cost IoT sensors perform well and could provide indicative values (Figure 2). The urban backgrounds sites used were Ladywood AltasensePM vs Ladywood AURN, Clement St Zephyr vs Ladywood AURN (~200m away) and BAQS Zephyr vs BAQS FIDAS. Slopes for daily averages from these co-locations were 1.3 (R^2 0.62), 1.1 (R^2 0.91) and 0.98 (R^2 0.94) respectively. Notably, the Zephyr performed better than the AltasensePM in an Urban Background setting- this may be due to the additional external fan on the Zephyr unit which helps maintain airflow through the sensor. The Urban Traffic site was located at Watery Lane, ~160m from the A4540 AURN site on the opposite side of the carriageway. This colocation has a sensor:reference slope of 0.74 (R^2 0.62). These slopes are reflective of previous values reported in the literature where the PlantowerPMS5003 and other similar low-cost OPCs tend to overread compared to reference instruments (Bulot et al., 2019) but still demonstrate reasonable closeness to the reference instrument concentrations. Some discrepancy in the roadside slope was to be expected given the location on opposite sides of the carriageway. Here, the A4540 AURN site is on an approach to a junction where there is occasional queuing traffic whereas the Watery Lane site is on the exiting carriageway which is less likely to queue. This highlights the importance of ensuring representative sampling, especially at near-source locations. Ideally, co-locations for checking device consistency against a reference instrument would occur in close proximity (i.e. on the same side of a carriageway) so that sampling is reflective of the same near-source environment and comparison can be made between units rather than between environments. However, deployment restrictions often lead to compromises.

It is also important to consider similar challenges when assessing co-location between sensors themselves at near-source sites. Co-location of sensors can allow for checks to ensure device consistency. Previous research has shown that the AltasensePM demonstrates a good inter-sensor

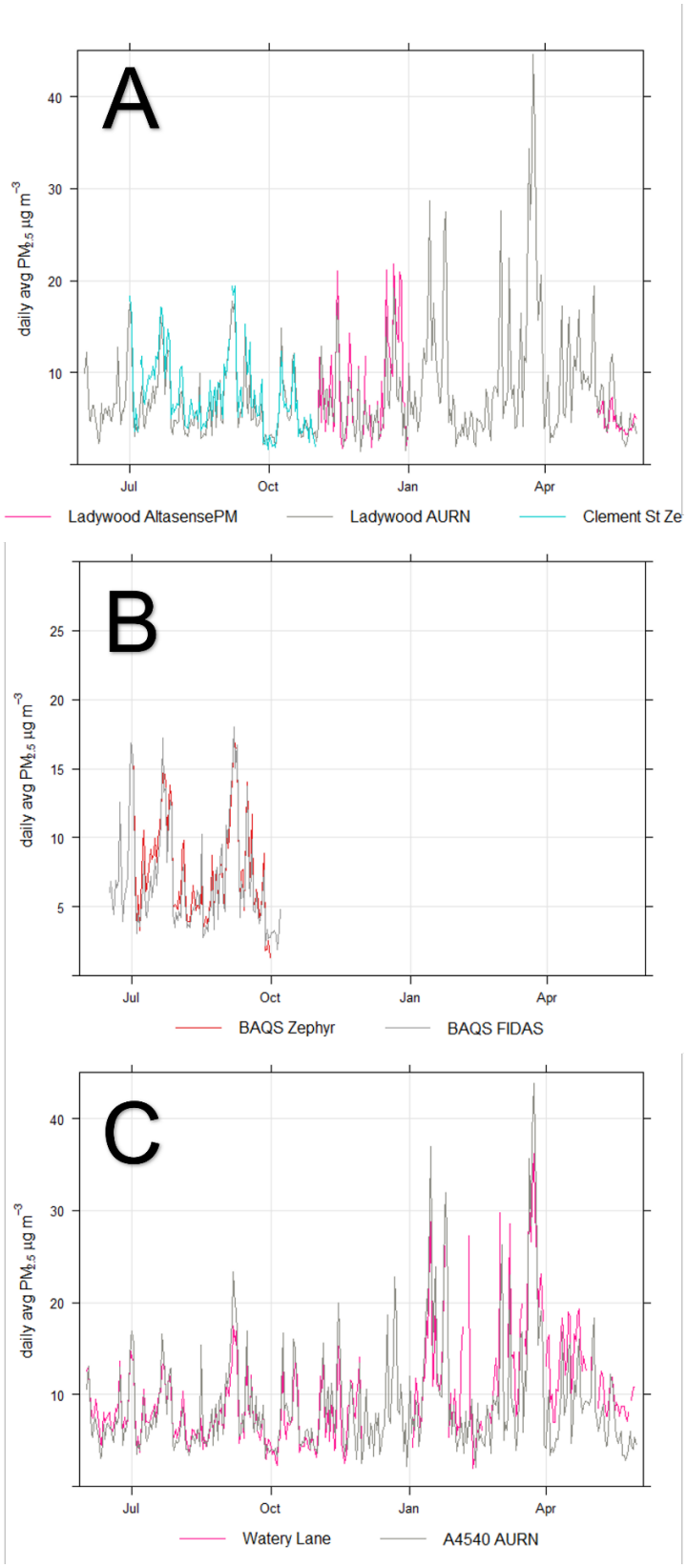


***Figure 2**- colocation daily average time plots of A) urban background Ladywood site, B) urban background BAQS site and C) roadside A4540 site*

linearity between devices as showcased in (Cowell et al., 2022) where Pearsons R between sensors ranged from 0.93-0.99 for $PM_{2.5}$. However, when using nested networks from different sources, field colocations can be insightful into understanding the co-linearity between the devices that may be managed externally. If sampling near-source (such as roadside environments as explored in the Watery Lane and reference site colocation above) it is essential that sensors are located in very close proximity (i.e. ideally on the same piece of street furniture), otherwise it is hard to decipher whether any differences or similarities between sensors are reflective of source emissions or sensor performance. An example of this from the nested network is a near-colocation of Zephyrs located across major junction in the city centre.

The local authority network also provided an opportunity to explore small scale spatial variability. Here, three Zephyrs were clustered, with one sensor in the middle of the junction and two located on different approaches immediately before Holloway Circus junction. Holloway Circus and Holloway Head Zephyrs were located ~90m apart with a third zephyr unit (Suffolk St Queensway) located ~160m

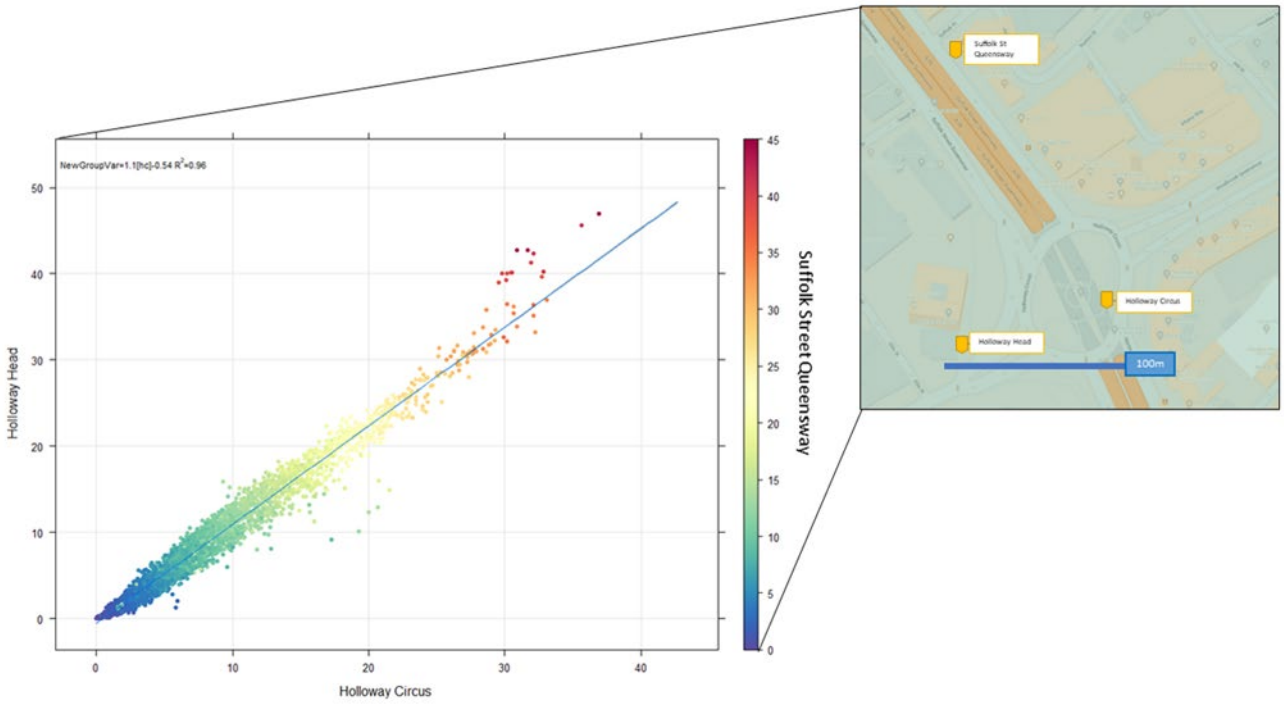


Figure 3- *hourly average data points of Zephyrs in near-colocation inside the CAZ and city centre of Birmingham. All 3 roadside sites located within ~90-160m of each other across a busy junction on a major road. Holloway Head and Holloway Circus are the closest located at ~90m apart, and the colour of the plot is by Suffolk St Queensway location which is ~160m away.*

from the other two. Figure 3 shows the inter-sensor correlation between Holloway Circus and Holloway Head with a slope of 1.1 and r^2 of 0.96, with shading/colouring relating to correlation with the Suffolk Street Queensway unit. All sensors experience higher concentrations at lower windspeeds, suggesting the roads they are situated on are a source of PM, however they all have a pattern of higher concentrations with easterly winds. The junction is expected to be a source of PM, however these results indicate that the junction is not as significant a source as other sources to the east. A suggestion

for future networks would to be considering a period of co-location of all sensor types at one near-source site, if possible, to test if sensors are sensitive enough to detect a point source before deployment as a wider network. Small scale clusters, such as described, can represent best practice when deploying networks. Over time, the insights collected identify redundancies within the network. This then allows for redundant sensors to be deployed elsewhere.

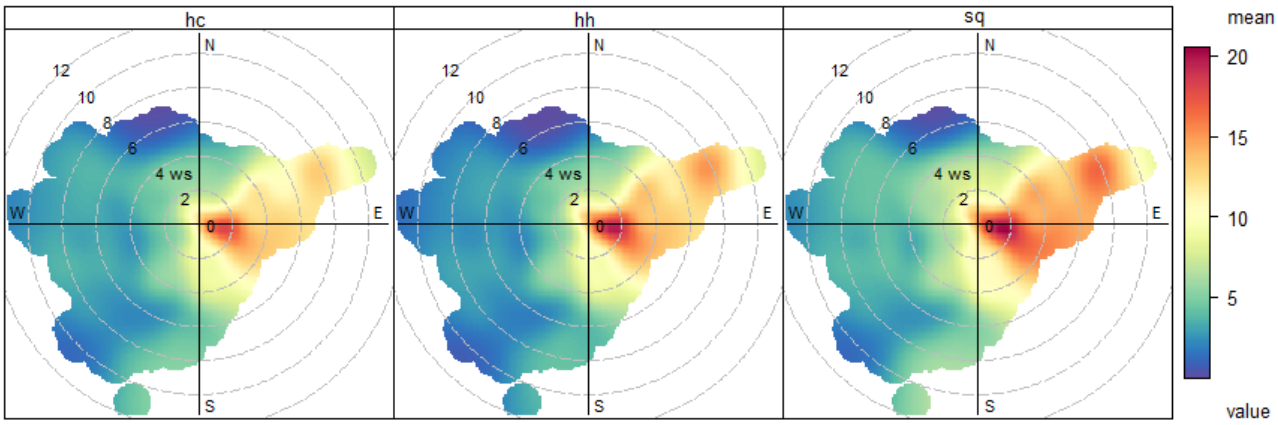


Figure 4- *polar plot of Holloway Head (hh), Holloway Circus (hc) and Suffolk Street Queensway (SQ) sensor $PM_{2.5}$ concentrations in µgm^{-3} by colour, plotted by wind speed and wind direction. Wind speed and wind direction data is from the nearby Elms Cottage weather station on the University of Birmingham campus.*

3.1.3 Insights into regional concentrations

The sensor network was able to detect trends and patterns in regional particulate concentrations throughout the year. The annual average $PM_{2.5}$ mass concentration for the study period from the entire low-cost sensor network is 8.56µgm^{-3} which is comparable to the average from the 3 DEFRA AURN sites of 8.37µgm^{-3}, further demonstrating the ability of the sensor network to accurately detect regional air quality. Despite the sampling locations of the network only representing a small area of the city, the sensor network average also estimated concentrations within <2µgm^{-3} of the 2019 high resolution model, which estimates citywide annual average concentrations at 10.3 µgm^{-3}. 80.6% of monthly averages across all sites were >WHO annual guidelines (5µgm^{-3}) and monthly averages ranged from 2.2-22.9µgm^{-3} As shown in figure 5a, sensors detected monthly patterns and the overall variability tracks across the city. Units also detected a dust storm that hit the UK in March 2022 and this is clearly shown in Figure 5. This insight is not novel to low-cost sensors, the AURN sites already provide regional coverage of the city. However, to see the low-cost network replicating events, values and patterns detected by the regulatory instruments adds to the confidence in network performance. Figure 6 demonstrates that the greater number of individual sensor readings available during an observation (one hour average), the more representative of regional urban background concentrations the sensor network averages are. As sensor numbers increase, the network urban background/urban traffic average falls closer to a 1:1 ratio with the relevant DEFRA site, particularly during urban background sampling. This is showing that although sensors are sampling in a wide variety of locations and detecting local trends, when averaged together in large numbers they can be used as proxy for regional concentrations. For urban background locations, with just 5 sensors

available in a network regional concentration estimates from the network average fall within ~10% of the DEFRA regulatory urban background measurement with strong correlation (sensor network average: regulatory station slope =0.899 and R^2 =0.807). This is a vast improvement on when only 2 sensors are present where although slope remains within a ~10% difference range (sensor network average: regulatory station slope =1.12), the correlation between sensors and regulatory instrument is weak with R^2 of 0.52. This pattern is less clear for Urban Traffic sites despite the fact the network had greater quantities of roadside sensors than urban background sensors. The linear fit between sensor:regulatory measurement fluctuates with sensor numbers, performing similarly well at 2 and 10 sensor presence (slope= 0.776, 0.776, R^2 = 0.802, 0.782 for 2 and 10 sensors respectively), but less so at 5 and 14 (max number) of sensors (slope= 0.618, 0.436 and R^2=0.725, 0.476 for 5 and 14 sensors respectively). This may be reflective of the sampling location of the roadside sensors vs the DEFRA roadside location rather than the number of sensors or that we are comparing to the one roadside DEFRA location within the network area. The DEFRA location is a busy section of a major traffic route which often experiences congestion whilst the majority of the sensor locations were less busy roads due to lack of available street furniture for installation on the busiest traffic routes. Therefore, the generally poor linear fit between the sensor network and reference is to be expected. This highlights the risk around relying on a small number of locations as indications of city wide levels and the potential of low-cost sensors to increase sampling resolution. However, it is clearly important to ensure low-cost sensors are deployed in larger quantities across a range of site locations if the goal is to achieve accurate insight into regional air quality. For roadside or near point source sites, the accuracy of regional concentrations estimates may fluctuate in line with the number of sensors, especially where units are directly capturing variations associated with near source sampling.

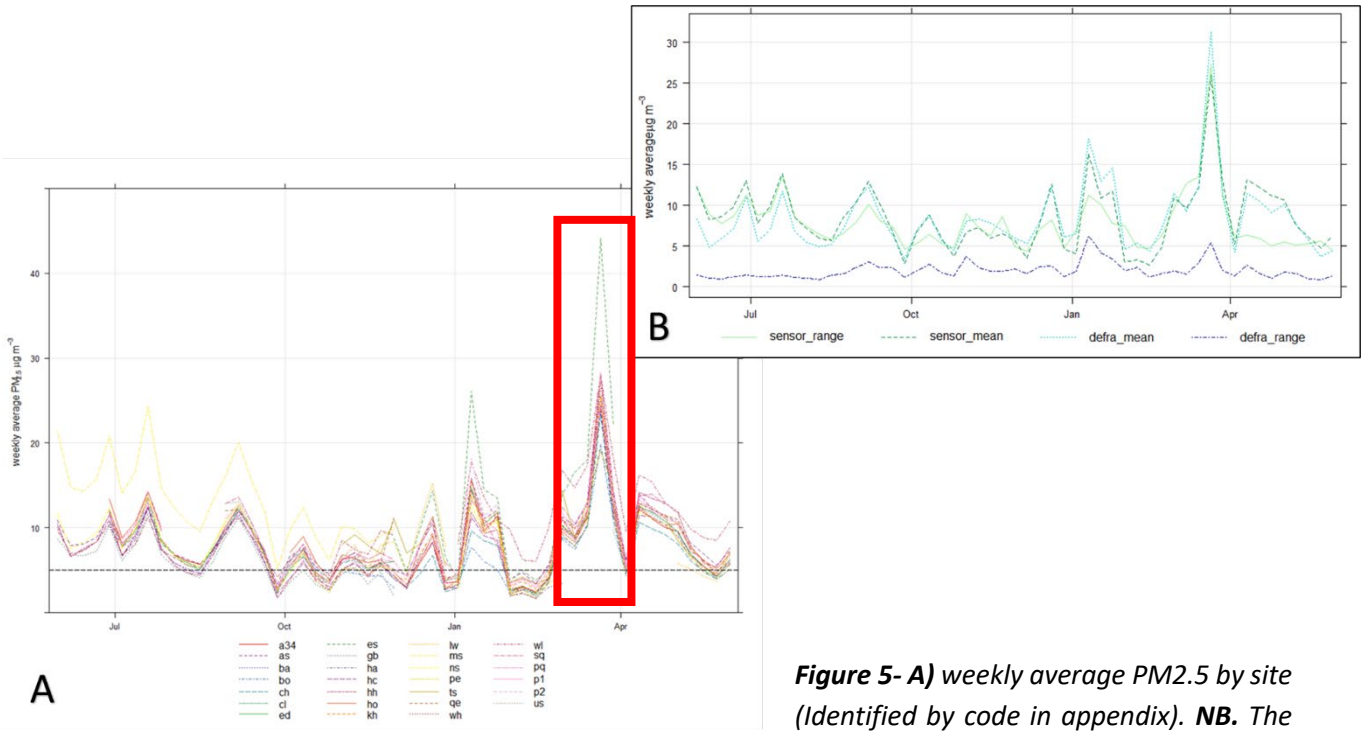


Figure 5- A) *weekly average PM2.5 by site (Identified by code in appendix).* ***NB.*** *The horizontal black dashed line demonstrates the WHO annual average guideline concentration of* $5\mu gm^{-3}$ *and the red box highlights the peak associated with a regional dust storm* **B)** *weekly averages of the mean and the variation between sampling sites (range) of the sensor network and DEFRA AURN network measurements (DEFRA AURN sites Ladywood urban background site and A4540 Ring road urban traffic site, sensor network takes into account all sensor sites present at any given time stamp).*

It is also important to note that although sensors perform better as a network at detecting urban background concentrations with more sensors present, this is due to the averaging of sensors across space. Urban background concentrations are not homogenous and there will be variation between sites. There are large numbers of people living within urban background regions with no monitoring and future deployments should consider not only the environment type being captured, but population density and coverage of monitoring across populations (including populations characteristics such as health risks, income and vulnerable populations). Low-cost sensors present an opportunity here to ensure that the concentrations within these populations are also represented within wider city averages.

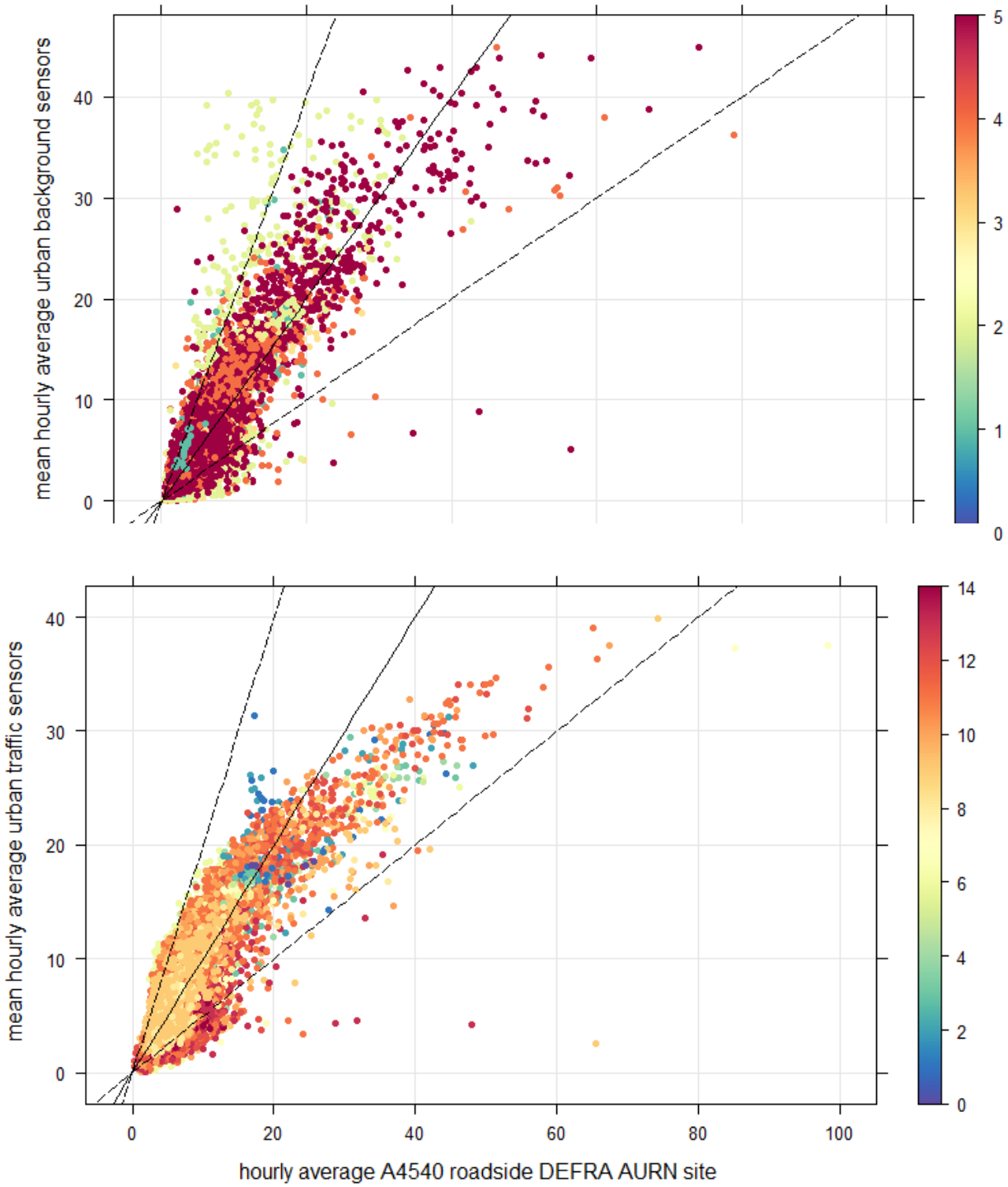


***Figure 6**- DEFRA AURN location vs sensor network mean separated for Urban Background and Urban Traffic sites with coloured by number of sensor observations at each mean point. **NB**. solid line denotes the 1:1 relationship*

3.1.4 Insights in local spatial variability in concentrations

The novelty of low-cost sensor insight into air quality is clearly highlighted when the local variability in particulate matter is assessed. Unlike their regulatory counterparts, the high spatial resolution the network allows for evaluation of hotspots and spatial variability across the city. The two regulatory AURN sites across the city centre demonstrated average concentration ranging from 7.8-9.06µgm^{-3} for the study period, however sensors reported averages of 6.18-13.16µgm^{-3} across all sites. This is also shown in figure 4b which compares variation (range) between sites over time. The average range (defined as the difference in concentration recorded between sites at the same timestamp, maximum concentration recorded minus minimum concentration recorded) of DEFRA measurements across the two city centre sites is 1.99µgm^{-3} whereas the average range of the sensor network was 7.92µgm^{-3}. This highlights how the lack of spatial coverage from the DEFRA sites leads to an underestimate in variability. The sensor network shows range of the similar magnitude to mean concentrations, demonstrating hyperlocal site variation. Table 1 shows how the range in peaking concentrations (95th percentile measurements for sensors that captured >75% of the study year) is 6.11 µgm^{-3} whereas the regulatory instruments only show a range of 2.42 µgm^{-3}. This demonstrates how the current coverage of the regulatory network doesn't capture the areas of high PM which could be in exceedance of future target levels. As a result, there is a clear need for increased coverage of monitoring in urban areas to capture these exceedances with low-cost sensors being well placed to help resolve. This is further emphasized by the high-resolution model, which experiences $PM_{2.5}$ concentration ranging from 8.57-20.23µgm^{-3} showing further how regulatory instrument networks are not capturing the wide distribution of concentrations.

Table 1- $PM_{2.5}$ concentration range and mean for sensor sites with >75% capture over the entire sample period and DEFRA AURN regulatory instruments for the sample period. ***NB. The 2 regulatory DEFRA AURN sites were chosen because they fall into the ~39km² area covered by the sensor network. 1 other regulatory station in Birmingham area (Acocks Green) was not used as this is >2km away from the nearest sensor and is not considered a city centre location.***

Location	Sensor or regulatory instrument	$PM_{2.5}$ concentration 5^{th}-95^{th} percentile range (µgm^{-3})	Mean $PM_{2.5}$ concentration (µgm^{-3})
Watery Lane	Sensor	2.48-24.02	9.88
Navigation St	Sensor	1.65-20.88	8.31
Holloway Head	Sensor	0.89-20.53	7.74
Holloway Circus	Sensor	1.25-18.1	7.2
Geog Building	Sensor	1.27-19.09	7.16
Children's Hospital	Sensor	1.32-17.91	7.1
Albert St	Sensor	1.85-20.49	8.51
A34	Sensor	1.12-20.19	7.68
A4540	Regulatory	2.55-23.76	9.06
Ladywood	Regulatory	1.78-21.34	7.8

Moor St (MS on Figure 2) is an example of a detected pollution hotspot with continuously higher concentrations than other locations, likely due to the proximity of the train station, bus stops and traffic. This echoes the results of (Johnston et al., 2019a) who reported their small AQ network of 6

low-cost sensors (including the Plantower PMS5003) was suitable for detecting local PM trends and (Morawska et al., 2018) who reported low-cost sensor networks can detect pollution hotspots.

Clearly, there is a need for an increase in spatial resolution of particulate monitoring to further understand the variability eluded at from this network. Whilst expansive networks are not needed to detect regional patterns such as dust storms, the increased granularity of $PM_{2.5}$ data from the sensor network can capture important insight into local particulate exposures that are missed by the low spatial coverage of regulatory instruments. In the UK, the Environmental Targets (fine particulate matter) (England) 2023 set out national targets for particulate matter, including suggestions for monitoring efforts (Secretary of State, 2023). These regulations propose that the West Midlands Urban Area (which covers most of Birmingham and some surrounding neighbourhoods) will require a minimum of 15 monitoring sites (10 at urban or suburban background, five near source such as roadside locations) by 2028 (Secretary of State, 2023). This network demonstrates the relatively easy scalability of low-cost sensing networks to meet and exceed these targets at a significantly lower cost than regulatory monitoring site expansion. Whilst the majority of the 28 locations featured in this paper were near source sites, the mobility of the units would make it easy for this to be adjusted to reflect the requirements. As previously shown, five sensors can give good insight into regional urban background concentrations and performance is expected to increase with sensor numbers, especially if locations chosen are well representative of a region as a whole. Low-cost sensors are likely to be the most feasible option for meeting these requirements in most places due to their affordability. However, it will be important to ensure that if meeting these guidelines using low-cost technology, that sampling strategy is carefully considered to ensure representative coverage of the urban area. This is especially true, as demonstrated in this paper, for near source monitoring (such as roadside). Fundamentally, the location of a sensor is more important than sensor quantities in these instances. Although, as highlighted in Section 3.1.2, to achieve this may need an acceptance of some short-term redundancy in the network. Overall, sampling guidelines will need to evolve beyond just quantity of sensors, to consider which sources are important and the area range that these sources will be likely to affect as part of sampling design.

3.2 Comparison with a high-resolution model

Figure 6 shows the overlay of sensor averages for the entire study year with the high-resolution air quality map of $PM_{2.5}$ based on a 2019 baseline. The sensors record concentrations lower than maximum concentrations reported by the model; model maximum concentration is about 10μgm^{-3} higher than the sensors average concentrations when assessing the entire map, however when drawing out individual site comparisons between map cells and sensor locations, the average difference between model and sensor is 4.02μgm^{-3} and the median difference is 3.61μgm^{-3}. The difference between individual sensor location ranges from 2.5-7.3μgm^{-3}. One limitation of this methodology is that sensors are being compared to 2019 data- simulating a different calendar year to the observations, with different meteorology, emissions, traffic fleet and commuter behaviours. As a result, analysis between the model and sensors is only indicative, exploring relative location to location variability. There is a need to further consider how this may be impacted by changing annual weather/emissions. For example, this may reflect why the sensors are reading low to the model, as the model is based on pre-Coronavirus pandemic conditions, since which there has been a shift in

working patterns. Alternatively, the model may just be reading high compared to real world observations. A benefit of the sensor observations would be the ability to look at year-to-year patterns with an extended deployment, this could inform future models on temporal changes in concentrations capturing modal shifts such as the uptake of home working and the impact on emissions from commuters. Despite the baseline year difference there are some similarities in location to location variability between sensor observations and model. Roadside locations report high concentrations with hotspots around key urban features such as Moor St station and the A38/A4540 ring road major traffic routes and urban background sites to the south of the city centre report lower concentrations. Figure 7 shows locations with >75% annual capture and outliers removed. Whilst this insight is limited in the amount of spatial coverage at high temporal capture, there are more sites available for observation: model evaluation than in the original model evaluation by Zhong et al. (2021) as spatial coverage of $PM_{2.5}$ for the city was enhanced by the sensor network. This past evaluation compared 2016 baseline model against 3 sites for $PM_{2.5}$ concentrations that were available across the region, and found the model performed generally well although slightly underestimated concentrations. The deployment of a nested network of sensors (such as our sensor dataset presented here) provide opportunity to reassess model evaluations for future baseline years against a spatially enhanced set of observations.

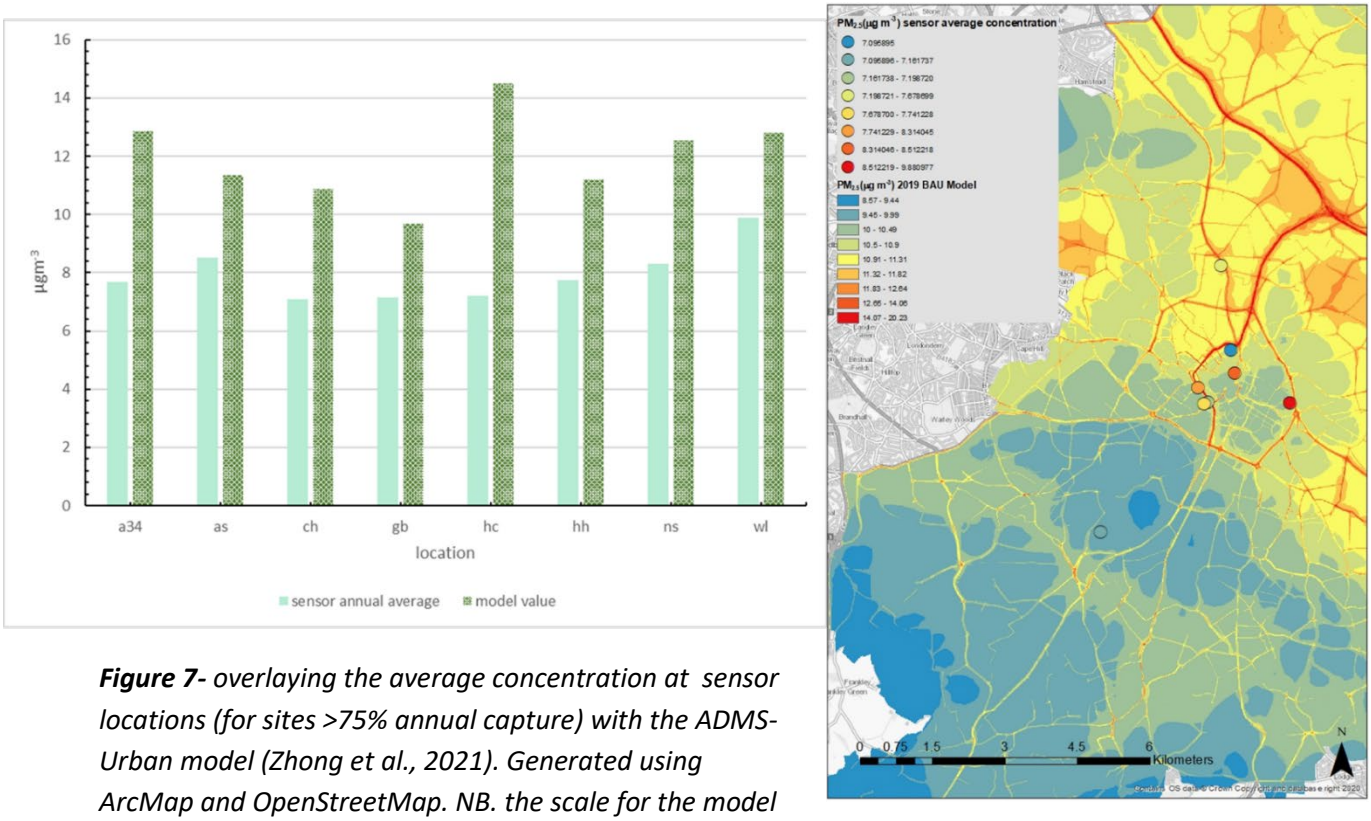


Figure 7- *overlaying the average concentration at sensor locations (for sites >75% annual capture) with the ADMS-Urban model (Zhong et al., 2021). Generated using ArcMap and OpenStreetMap. NB. the scale for the model and the sensors is different but scaled to show relative highs and lows of each in the same colour scheme. Bar chart shows the annual average value at the overlayed sensor sites vs the comparative model value for that cell.*

One location that stands out from figure 6 is Holloway Circus (HC) which is a roadside site that underreads considerably compared to the model. This may be due to the model being evaluated against different locations and only 3 city centre sites, causing disparity. However, it is more likely that the sensors are under-reading, as Holloway Circus is a busy junction where we'd expect elevated concentrations. As mentioned previously, more near source colocations with reference instruments should be explored to test the low-cost sensors sensitivity to nearby sources.

3.3 Lessons learned from a low-cost sensing network for particulate matter

This nested network can be viewed as a test bed for IoT low-cost sensor networks. Such networks are an emerging approach and as such it is important to evaluate them to enable future best practice. The large amounts of data available brings great potential for how we understand and manage air quality, but often this data is collected by many different groups and is rarely bought together as a single network (Topping et al., 2021). This data was also provided as open access via the Birmingham Urban Observatory. This meant that anyone could access and use this data as needed, increasing data accessibility to those who many do not have as much funding for monitoring such as community groups and educational projects. Whilst open access data sharing is an opportunity, it also comes with challenges. Non-specialist audiences may not be aware of the caveats and data validation needed alongside low-cost sensor data and this may lead to misinformation, especially as quantifying the scientific value of such sensors is challenging (Luo et al., 2018, Topping et al., 2021). This project added a caveat to the online description of low-cost sensor units, suggesting that they are providing indicative measurements and had calibrations for the AltasensePM (all data pulled from the Zephyrs also had undergone manufacturer calibration) built into the online platform so data was provided 'calibrated' to the end user. Future work could also try to embed some form of data validation into an online platform to flag data that may be potentially erroneous. All data handling, meta data and validation processes should be as transparent as possible (respecting manufacturers need to protect intellectual property aka sensor algorithms) as this allows users to fully understand the data.

Reliability of sensor networks will need to be improved if they are to become more broadly accepted - this study experienced power and comms issues symptomatic of deployments elsewhere. Jiao et al. (2016) report comms signal issues, Connolly et al. (2022) report loss of wireless connection and sensor breakages and malfunctions, Johnston et al. (2019b) report hardware bugs and reliability issues with comms technology. Environmental degradation is to be expected when deploying any sensor into a field environment, but best practice should ensure that hardware is rugged and reliable for outdoor monitoring. Comms often presents issues as they can be a significant power drain on the device, which is a challenge with field deployments of sensors where mains power isn't always accessible. Low Power Wide Area Networks (LPWANs) provide novel opportunity here, as they are often power and economically efficient and can transmit small quantities of data over long-range distances (Mekki et al., 2019, Song et al., 2017, Patel and Won, 2017). With data coverage checks, this technology could be a solution to increasing reliability of sensor networks.

Another challenge this project faced was accessing infrastructure to install sensors upon. Whilst in practice, installing self-contained sensors such as those in this study is simple, gaining permission for the University owned sensors to be placed in locations of interest was challenging and required navigating bureaucracy. This slowed down initial deployment, created as a barrier for co-location

studies, but also any maintenance efforts and limited the locations available to us. This also limited the ability of the network to be wholly representative of the entire city, or even the specific interventions such as the CAZ that we initially planned to focus on. Best practice moving forward would involve strong collaborations between researchers, communities and the local agencies in control of infrastructure to reduce these limitations on installation.

4. Conclusions

This study has shown some benefits of IoT low-cost sensor networks; the networks were successful at monitoring at a regional level comparable to reference instrument concentrations and provided insight into concentrations in locations which were not covered by a reference network. The low-cost sensing network proved successful at generating long term average concentrations for the city compared to the reference network- estimating concentrations within 0.2µgm^{-3} of the regulatory network for the annual citywide concentration. This echoes the results of chapter 2, where sensors are found to be suitable for longer term averaging. However, when looking at more site specific concentrations, the sensor performance becomes more challenging, partially due to down time but also due to how sensors will perform differently when experiencing different sources (such as at a roadside vs an urban background site). The benefit of a low-cost sensor network is that it provides opportunities for users to understand exposures in places that wouldn't normally have monitoring coverage for a fraction of the cost of a traditional monitoring campaign. Low-cost sensors provide opportunity to ensure vulnerable populations that are not currently covered by regulatory monitoring networks can have their concentrations included into air quality analysis. Due to the greater number of monitors available from the low-cost network, even with data gaps from sensor downtime, regional episodes such as dust storms were able to be detected and sensors could be suitable for indicating periods of regional increased concentrations in areas where traditional monitoring is lacking.

This paper has shown that whilst with a relatively small network size (≥5 low-cost sensors), estimates into regional urban background $PM_{2.5}$ concentrations were within ~10% of the regulatory measurements (which demonstrates low-cost sensors suitability for supporting novel monitoring guidelines in the UK) (Secretary of State, 2023), location is a very important factor in determining sensors performance against a specific research question. Sampling locations will need to consider representation of the area or source that is the aim of the research, and sampling strategies need to consider the sensitivity of sensors and impact of sources on their performance. Sensors will require calibrating for the types of PM compositions that they are going to be monitoring. The lack of transparency around the calibration models used for commercial sensors makes it challenging to know if this is being applied, and calibrating near sources can provide challenges itself, not only in logistics but also if trying to calibrate a sensor for a location where potential sources are unknown. Data gaps and bureaucracy of deploying and maintaining the low-cost sensors make more detailed analysis between sites challenging as downtimes limit data available for comparison. Spatial analysis was able to draw limited conclusions about roadside concentrations- future deployments should test sensor colocations at near point sources are needed to test if they are sensitive enough to detect a source.

To conclude, whilst the limitations of low-cost sensors are still prevalent, and there is still work to be done before they are widely accepted as a tool for regulatory monitoring, this work has highlighted both the potential of the approach and started to identify best practice for use. Fundamentally, it is evident that the densification of observations can now be achieved without excessively increasing

spend on instrumentation, and various sensor types can be integrated into a network, but that further collaboration and transparency around data calibrations would make it easier to fully assess and trust data insights.

Author Contributions

Conceptualization NC, LC and WB. Methodology NC, LC, WB, CB, JZ. Software NC, CB. Validation NC, CB, LC, WB. Formal analysis NC. Investigation NC. Resources LC, WB, NC. Data curation NC. Writing – Original draft NC, LC, WB. Writing – review & editing – CB, JZ. Visualization NC, JZ. Supervision LC, WB. Project administration NC. Funding acquisition WJB, LC.

Acknowledgements

Authors would like to thank Dr Siqi Hou for assisting in the colocation of sensors at Birmingham Air Quality Supersite at the University of Birmingham. We would like to thank colleagues at Birmingham City Council for collaborating in this project, sharing access to their Zephyr network and their support in the installation of our sensors on their infrastructure. We'd also like to thank University Hospitals Birmingham, Birmingham Women's' and Children's Hospital, the Commonwealth Games, Birmingham City Council Redfern Depot and the University of Birmingham Estates team for hosting units.

Funding

This work was funded as part of the NERC RISE WM-Air project (NE/S003487/1), EPSRC UKCRIC Urban Observatories project (EP/P016782/1), and EPSRC IAA funding which helped support the translation. BAQS is supported through the NERC project OSCA (NE/T001976/1).

References

BIRMINGHAM CITY COUNCIL 2018. Consultation: A Clean Air Zone for Birmingham. In: BRUMBREATHES (ed.). online.

BIRMINGHAM CITY COUNCIL. 2021a. #brumbreathes Charges and operation [Online]. Available: https://www.brumbreathes.co.uk/info/25/welcome-2/45/charges-operation-1 [Accessed 04.11.22].

BIRMINGHAM CITY COUNCIL. 2021b. Population and census: Overview [Online]. online. Available: https://www.birmingham.gov.uk/info/20057/about_birmingham/1294/population_and_census [Accessed 04.11.2022].

BIRMINGHAM CITY COUNCIL 2022. Clean Air Zone Six Month Report. online.

BUSH, T., PAPAIOANNOU, N., LEACH, F., POPE, F. D., SINGH, A., THOMAS, G. N., STACEY, B. & BARTINGTON, S. 2022. Machine learning techniques to improve the field performance of low-cost air quality sensors. Atmospheric Measurement Techniques, 15, 3261-3278.

CAMBRIDGE ENVIRONMENTAL RESEARCH CONSULTANTS LTD 2020. ADMS-Urban Urban Air Quality Management System User Guide. 5 ed.

CARSLAW, D. 2019. The openair manual — open-source tools for analysing air pollution data. Manual for version 2.6-6. online: University of York.

CARSLAW, D. & ROPKINS, K. 2012. openair — An R package for air quality data analysis. Environmental Modelling & Software, 27–28(0), 52–61.

CHANG, Y. S., LIN, K. M., TSAI, Y. T., ZENG, Y. R. & HUNG, C. X. Big data platform for air quality analysis and prediction. 2018 27th Wireless and Optical Communication Conference (WOCC), 30 April-1 May 2018 2018. 1-3.

CONNOLLY, R. E., YU, Q., WANG, Z., CHEN, Y.-H., LIU, J. Z., COLLIER-OXANDALE, A., PAPAPOSTOLOU, V., POLIDORI, A. & ZHU, Y. 2022. Long-term evaluation of a low-cost air sensor network for monitoring indoor and outdoor air quality at the community scale. Science of The Total Environment, 807, 150797.

COWELL, N., CHAPMAN, L., BLOSS, W., SRIVASTAVA, D., BARTINGTON, S. & SINGH, A. 2023. Particulate matter in a lockdown home: evaluation, calibration, results and health risk from an IoT enabled low-cost sensor network for residential air quality monitoring. Environmental Science: Atmospheres, 3, 65-84.

COWELL, N. H., CHAPMAN, L., BLOSS, W. & POPE, F. 2022. Field calibration and evaluation of an Internet of Things based particulate matter sensor. Frontiers in Environmental Science, 733.

CRILLEY, L. R., SHAW, M., POUND, R., KRAMER, L. J., PRICE, R., YOUNG, S., LEWIS, A. C. & POPE, F. D. 2018. Evaluation of a low-cost optical particle counter (Alphasense OPC-N2) for ambient air monitoring. Atmospheric Measurement Techniques, 709-720.

DEFRA 2017. UK plan for tackling roadside nitrogen dioxide concentrations detailed plan. In: AFFAIRS, D. O. E. F. A. R. (ed.). online.

DEFRA. 2023a. Automatic Urban and Rurual Network (AURN) [Online]. Available: https://uk-air.defra.gov.uk/networks/network-info?view=aurn [Accessed 17.03.2023].

DEFRA. 2023b. Site Information for Birmingham Ladywood(UKA00655) [Online]. Available: https://uk-air.defra.gov.uk/networks/site-info?site_id=BMLD [Accessed 17.03.2023].

DEPARTMENT OF ENVIRONMENTAL FOOD AND RURAL AFFAIRS. 2023. Site Environment Types [Online]. Available: https://uk-air.defra.gov.uk/networks/site-types [Accessed 11/01/2023].

DIGIMAP. 2019. Digimap [Online]. Available: https://digimap.edina.ac.uk/ [Accessed 28th May 2019].

EARTHSENSE. 2019. Zephyr® Sensors Send Alerts to Divert Traffic From Pollution Hotspots in Coventry [Online]. Online. Available: https://www.earthsense.co.uk/post/zephyr-sensors-send-alerts-to-divert-traffic-from-pollution-hotspots-in-coventry [Accessed 17.03.2023].

EARTHSENSE. 2022a. EarthSense's Zephyr® Air Quality Monitor Meets MCERTS Performance Standards [Online]. Available: https://www.earthsense.co.uk/post/zephyr-meets-indicative-mcerts [Accessed 25th November 2022 2022].

EARTHSENSE 2022b. Zephyr Air Quality Monitor Specification Sheet. online.

FENG, S., GAO, D., LIAO, F., ZHOU, F. & WANG, X. 2016. The health effects of ambient PM2.5 and potential mechanisms. Ecotoxicology and Environmental Safety, 128, 67-74.

FISHBAIN, B., LERNER, U., CASTELL, N., COLE-HUNTER, T., POPOOLA, O., BRODAY, D. M., IÑIGUEZ, T. M., NIEUWENHUIJSEN, M., JOVASEVIC-STOJANOVIC, M. & TOPALOVIC, D. 2017. An evaluation tool kit of air quality micro-sensing units. Science of the total environment, 575, 639-648.

GOV.UK. 2022. Guidance: Clean Air Zones [Online]. Available: https://www.gov.uk/guidance/driving-in-a-clean-air-zone#cities-with-clean-air-zones [Accessed 10.11.22].

HAGAN, D. H. & KROLL, J. H. 2020. Assessing the accuracy of low-cost optical particle sensors using a physics-based approach. Atmos. Meas. Tech., 13, 6343-6355.

HARRISON, R. M., ALLAN, J., CARRUTHERS, D., HEAL, M. R., LEWIS, A. C., MARNER, B., MURRELLS, T. & WILLIAMS, A. 2021. Non-exhaust vehicle emissions of particulate matter and VOC from road traffic: A review. Atmospheric Environment, 262, 118592.

JIAO, W., HAGLER, G., WILLIAMS, R., SHARPE, R., BROWN, R., GARVER, D., JUDGE, R., CAUDILL, M., RICKARD, J. & DAVIS, M. 2016. Community Air Sensor Network (CAIRSENSE) project: evaluation of low-cost sensor performance in a suburban environment in the southeastern United States. Atmospheric Measurement Techniques, 9, 5281-5292.

JOHNSTON, S. J., BASFORD, P. J., BULOT, F. M., APETROAIE-CRISTEA, M., EASTON, N. H., DAVENPORT, C., FOSTER, G. L., LOXHAM, M., MORRIS, A. K. & COX, S. J. 2019a. City scale particulate matter monitoring using LoRaWAN based air quality IoT devices. Sensors, 19, 209.

JOHNSTON, S. J., BASFORD, P. J., BULOT, F. M. J., APETROAIE-CRISTEA, M., EASTON, N. H. C., DAVENPORT, C., FOSTER, G. L., LOXHAM, M., MORRIS, A. K. R. & COX, S. J. 2019b. City Scale Particulate Matter Monitoring Using LoRaWAN Based Air Quality IoT Devices. Sensors, 19, 209.

KOSMIDIS, E., SYROPOULOU, P., TEKES, S., SCHNEIDER, P., SPYROMITROS-XIOUFIS, E., RIGA, M., CHARITIDIS, P., MOUMTZIDOU, A., PAPADOPOULOS, S. & VROCHIDIS, S. 2018. hackAIR: Towards raising awareness about air quality in Europe by developing a collective online platform. ISPRS International Journal of Geo-Information, 7, 187.

KUULA, J., MÄKELÄ, T., AURELA, M., TEINILÄ, K., VARJONEN, S., GONZÁLEZ, Ó. & TIMONEN, H. 2020. Laboratory evaluation of particle-size selectivity of optical low-cost particulate matter sensors. Atmos. Meas. Tech., 13, 2413-2423.

LU, F., XU, D., CHENG, Y., DONG, S., GUO, C., JIANG, X. & ZHENG, X. 2015. Systematic review and meta-analysis of the adverse health effects of ambient PM2. 5 and PM10 pollution in the Chinese population. Environmental research, 136, 196-204.

LU, Y., GIULIANO, G. & HABRE, R. 2021. Estimating hourly PM2.5 concentrations at the neighborhood scale using a low-cost air sensor network: A Los Angeles case study. Environmental Research, 195, 110653.

LUO, L., ZHANG, Y., PEARSON, B., LING, Z., YU, H. & FU, X. 2018. On the Security and Data Integrity of Low-Cost Sensor Networks for Air Quality Monitoring. Sensors, 18, 4451.

MA, L., GRAHAM, D. J. & STETTLER, M. E. 2021. Has the ultra low emission zone in London improved air quality? Environmental Research Letters, 16, 124001.

MAGI, B. I., CUPINI, C., FRANCIS, J., GREEN, M. & HAUSER, C. 2020. Evaluation of PM2.5 measured in an urban setting using a low-cost optical particle counter and a Federal Equivalent Method Beta Attenuation Monitor. Aerosol Science and Technology, 54, 147-159.

MAHAJAN, S., GABRYS, J. & ARMITAGE, J. 2021. AirKit: a citizen-sensing toolkit for monitoring air quality. Sensors, 21, 4044.

MEKKI, K., BAJIC, E., CHAXEL, F. & MEYER, F. 2019. A comparative study of LPWAN technologies for large-scale IoT deployment. ICT express, 5, 1-7.

MORAWSKA, L., THAI, P. K., LIU, X., ASUMADU-SAKYI, A., AYOKO, G., BARTONOVA, A., BEDINI, A., CHAI, F., CHRISTENSEN, B., DUNBABIN, M., GAO, J., HAGLER, G. S. W., JAYARATNE, R., KUMAR, P., LAU, A. K. H., LOUIE, P. K. K., MAZAHERI, M., NING, Z., MOTTA, N., MULLINS, B., RAHMAN, M. M., RISTOVSKI, Z., SHAFIEI, M., TJONDRONEGORO, D., WESTERDAHL, D. & WILLIAMS, R. 2018. Applications of low-cost

sensing technologies for air quality monitoring and exposure assessment: How far have they gone? Environment International, 116, 286-299.

MOUSAVI, A. & WU, J. 2021. Indoor-Generated PM2.5 During COVID-19 Shutdowns Across California: Application of the PurpleAir Indoor–Outdoor Low-Cost Sensor Network. Environmental Science & Technology, 55, 5648-5656.

NAEI. 2019. Data [Online]. Available: http://naei.beis.gov.uk/data [Accessed 18th July 2019].

OUIMETTE, J. R., MALM, W. C., SCHICHTEL, B. A., SHERIDAN, P. J., ANDREWS, E., OGREN, J. A. & ARNOTT, W. P. 2022. Evaluating the PurpleAir monitor as an aerosol light scattering instrument. Atmos. Meas. Tech., 15, 655-676.

PATEL, D. & WON, M. Experimental study on low power wide area networks (LPWAN) for mobile Internet of Things. 2017 IEEE 85th vehicular technology conference (VTC Spring), 2017. IEEE, 1-5.

SAMHE PROJECT. 2022. SAMHE [Online]. Online. Available: https://samhe.org.uk/ [Accessed 17.03.2023].

SAYAHI, T., BUTTERFIELD, A. & KELLY, K. 2019. Long-term field evaluation of the Plantower PMS low-cost particulate matter sensors. Environmental Pollution, 245, 932-940.

SECRETARY OF STATE 2023. The Environmental Targets (Fine Particulate Matter) (England)Regulations 2023 In: ENGLAND, E. P. (ed.). online.

SONG, Y., LIN, J., TANG, M. & DONG, S. 2017. An Internet of energy things based on wireless LPWAN. Engineering, 3, 460-466.

SOUTH COAST AQMD. 2023. Aeroqual AQY Sensor Network [Online]. Available: http://www.aqmd.gov/aq-spec/special-projects/aeroqual-aqy-deployments [Accessed 17.03.2023].

TOPPING, D., BANNAN, T., COE, H., EVANS, J., JAY, C. E., MURABITO, E. & ROBINSON, N. 2021. Digital twins of urban air quality: opportunities and challenges. Frontiers in Sustainable Cities, 141.

TRANSPORT FOR LONDON. 2022. ULEZ:Where and when [Online]. Available: https://tfl.gov.uk/modes/driving/ultra-low-emission-zone/ulez-where-and-when [Accessed 10.11.2022].

WILLIAMS, H., BARTINGTON, S., POPE, F. & LANDEG-COX, C. 2022. Low Emission (Clean Air) Zones-Policy Briefing Note produced by the TRANSITION Clean Air Network. TRANSITION Clean Air Network Policy Briefing Notes.

YONG, Z. & HAOXIN, Z. 2016. Digital universal particle concentration sensor PMS5003 data manual. online PLANTOWER.

ZHANG, J., MARTO, J. P. & SCHWAB, J. J. 2018. Exploring the applicability and limitations of selected optical scattering instruments for PM mass measurement. Atmospheric Measurement Techniques, 11, 2995-3005.

ZHONG, J., HOOD, C., JOHNSON, K., STOCKER, J., HANDLEY, J., WOLSTENCROFT, M., MAZZEO, A., CAI, X. & BLOSS, W. J. 2021. Using Task Farming to Optimise a Street-Scale Resolution Air Quality Model of the West Midlands (UK). Atmosphere, 12, 983.

ZUSMAN, M., SCHUMACHER, C. S., GASSETT, A. J., SPALT, E. W., AUSTIN, E., LARSON, T. V., CARVLIN, G., SETO, E., KAUFMAN, J. D. & SHEPPARD, L. 2020. Calibration of low-cost particulate matter sensors: Model development for a multi-city epidemiological study. Environment International, 134, 105329.

Supplementary information:

Table S1- rationale of sensor locations for University deployed units. NB. Site type definitions used (Department of Environmental Food and Rural Affairs, 2023) site classification as guidance.

Sensor	**Rationale**	**Site type**
Kings Heath Vicarage	This location is on the edge of a LTN on a major through-route for traffic. Deployed to support WM-Air work with local authority/community interest.	Urban traffic
Edgbaston	Located outside Edgbaston Stadium on the Edgbaston road near the A441. A major traffic route which is also influenced by traffic control measures for events at the stadium. Deployed to support WM-Air work with the Commonwealth Games.	Urban traffic
Geography Building	On the University campus. This was the initial Zephyr deployed for testing. Urban background location.	Urban background
University Station	Located outside University station, this unit was deployed in collaboration with WM-Air and University Hospitals Birmingham (UHB) as this station and walkway in a key access route to the QE hospital for pedestrians.	Urban background
QE Main Entrance	Deployed in collaboration with WM-Air and UHB, this entrance area to the hospital has a drop off point for vehicles and is prone to idling.	Urban background
Womens Hospital	Deployed in collaboration with WM-Air and UHB, this entrance area to the hospital has a drop off point and carpark for vehicles and is prone to idling.	Urban background
BAQS	Birmingham Air Quality Supersite (BAQS) is run by the University of Birmingham and was used as a colocation site with regulatory instruments.	Urban background
Pershore Road	Pershore road is a busy traffic route into the city centre from the south. This roadside monitor is also close the A4540 ring road and CAZ boundary.	Urban traffic
Horton Square	Located just inside the CAZ, close to the boundary and A4540.	Urban traffic
Tyseley	Deployed in collaboration with WM-Air and Tyseley Energy Park as background measurements ahead of development within the area. Kings Road is a key traffic route through the industrial park.	Urban industry
Hagley Road	Roadside monitor located at junction known for traffic congestion on major city access route to the SW of the city and CAZ.	Urban traffic

Navigation St	Roadside monitor, near the A38 traffic route and busy junction within the CAZ.	Urban traffic
Clement St	Provides near-colocation with DEFRA AURN site for Zephyr (no suitable install location within AURN site itself).	Urban background
Ladywood	Within DEFRA AURN enclosure to allow for colocation of AltasensePM.	Urban background
Great Charles/Newhall St	Roadside location near junction to exit A38 traffic route.	Urban traffic
Childrens Hospital	Deployed in collaboration with WM-Air and UHB, this entrance area to the hospital with drop off points in close proximity to A38 traffic route. On a public road.	Urban traffic
Eastside City Park	Urban background location within CAZ giving coverage of the east of the city centre.	Urban background
A34	Roadside location on key traffic route into the city from the north. Outside of the CAZ.	Urban traffic
Perry Park 1	Deployed in collaboration with WM-Air and Commonwealth Games. Background monitoring of Perry Park stadium site during development, ahead of the games.	Suburban background
Perry Park 2	Deployed in collaboration with WM-Air and Commonwealth Games. Background monitoring of Perry Park stadium site during development, ahead of the games.	Suburban background

Chapter 5: Moving from monitoring to real-time interventions for air quality: the future role of low-cost sensors, IoT and digital twins

This chapter draws information from reports, presentations and other informal outputs from the Economic Data Innovation Fund (EDIF) project which are currently unpublished but are available upon request. The author of this chapter (Nicole Cowell) contributed to these outputs alongside Lee Chapman*, Philip James†, Daniel Bell†, Jenine Jonczyk†, David Topping‡, Thomas Bannan‡, Ettore Murabito‡, Dustin Carlino¥, Alex Gluhakˇ, Sarah Gallacherˇ and DfT colleagues. Reports from this project will eventually be published at:*https://www.gov.uk/search/research-and-statistics?content_store_document_type=research&keywords=&organisations%5B%5D=department-for-transport

*University of Birmingham †Newcastle University ‡University of Manchester ¥Alan Turing Institute ˇUrban Data Exchange

1. Introduction

Numerous studies have demonstrated how the internet of things (IoT) can potentially transform the way in which air quality measurements (both indoor and outdoor) are made (Hegde et al., 2020, Cowell et al., 2023b, Cowell et al., 2022, Candia et al., 2018, Ali et al., 2021). In many cases, this is underpinned by the IoT facilitating the densification of observations, but there is also host of other advantages (Cowell et al., 2023a). For example, IoT also supports the convergence of information, between devices themselves and with further infrastructure (Vermesan, 2013). For example, Cowell et al (2023a), used low-cost PM sensors underpinned by LPWAN technology to communicate data to an online platform alongside other AQ sensors, the DEFRA AURN network and a wide array of meteorology sensors. Whilst this autonomous fusion of data is one application, this is only the start of what IoT can be used for. The convergence of IoT technology goes beyond sensors. With increasing devices moving online such as key infrastructure, mobile phones, vehicles and more, bidirectional communication between sensors and other device types, combined with increasingly ubiquitous artificial intelligence (AI) techniques, can lead to autonomous real-time decision making and asset management (Vermesan and Bacquet, 2022, Mosco, 2017). This paper makes a start at assessing the potential applications of this in the context of low-cost air quality sensors and digital twins. It aims to outline the next steps for this technology in supporting real-time decision making for cleaner air.

1.1 The smart city

Smart cities integrate data and digital technology to increase sustainability, development and quality of life in urban environments, often via the deployment of IoT enabled infrastructure and sensors that can feed data onto online platforms (Mishra and Chakraborty, 2020, Ivanov et al., 2020). Smart cities cover a range of components, integrating smart infrastructure, health, homes, services, energy, industry, transportation and agriculture to create sustainable societal benefits for citizens (Syed et al., 2021). The boom in low-cost sensors, specifically environmental monitors, means that cities are being monitored at a much higher resolution than ever before. These sensor networks allow for monitoring of environmental phenomena such as the urban heat island, public health (e.g. air pollution episodes)

as well as the performance of infrastructure (Chapman et al., 2015, Schrotter and Hürzeler, 2020, Ullo and Sinha, 2020). The architecture of a smart city system embeds such sensors into a chain of communications and applications (Table 1). The IoT removes the limitations of traditionally required human data-input to our computer systems and empowers the computer to "hear and sense the world" for themselves- assessing their own needs and environment and communicating it to the relevant bodies (Ashton, 2009). These devices are increasingly vital to modern technical infrastructure as IoT systems can process the state of a 'thing' and feedback to users, creating unprecedented management and decision-making opportunities (Chapman et al., 2016, Zhu et al., 2010). It is now easy to know when a 'thing' needs replacing, repairing or adjusting without assessing the thing in person. Whilst traditional statistical sampling can provide insight to this data, samples can be outdated by the time results are ready and can lead to delays in decision making until after an event occurs (Ivanov et al., 2020).

Smart cities have many potential advantages. They are designed with innovation and sustainability in mind, which means they often aim to integrate technology with environmental and social challenges associated with urban growth (Law and Lynch, 2019). They enhance the quality of life for citizens, by supporting the meeting of climate, energy and transport targets often aiming to reduce carbon footprint of city systems (Syed et al., 2021). They also create large economic incentives- both from the development of the technology itself and its contribution to society where the smart city can both generate new industries and innovation opportunities and save money by streamlining city wide processes. It is estimated that by 2025 the smart city market value will be between US$1-3.5 trillion (Syed et al., 2021, Mehmood et al., 2017, Law and Lynch, 2019).

However, despite the benefits of smart cities, there are challenges associated with their development. Defining a smart city itself is difficult. Many cities and projects use different criteria to describe themselves as smart city infrastructure such as; e-governance schemes, sustainability schemes and embedded communication technology (Syed et al., 2021). An example of this is the Living Labs movement, which whilst originally established in 2006 as programmes of innovative ecosystems based in real-life environments, have in practice had varied definitions and use cases (Følstad, 2008, Schuurman et al., 2015). Whilst many smart city elements exist and are documented within literature, examples of wholly integrated infrastructure are rare. Most deployments focus on single applications (e.g. air quality) and don't reach full integration potential by converging with wider applications. Furthermore, many applications don't even surpass a demonstration stage with projects being decommissioned due to the closure of funding periods (Chapman et al., 2023). For those that do extend beyond the demonstrator phase, there still exists many interoperability challenges as various scales- from devices to network and applications. Technology in a smart city can vary in protocols and standards at these different levels making barriers to integration success (Mehmood et al., 2017). Linked to this is the lack of open standards for operation and robustness when moving away from centralised deployments and integrating data from different sources (Syed et al., 2021). Security poses an additional challenge with 70% of IoT devices at risk of cyber-attack due to poor security protocols which leaves key infrastructure vulnerable (Mehmood et al., 2017). Finally, management of data presents security challenges in terms of anonymising data that may be linked to people such as traffic and CCTV footage.

Table 1- IoT Architecture, information drawn from (Syed et al., 2021, Silva et al., 2018).

Layer	Elements	Description
Sensing layer	Sensors, actuators, mobile elements (aka car sensors, mobile phones data)	Generates information about physical phenomena via sensors. Actuators can act upon physical phenomena to generate/change data.
Network layer	Network technology and topologies	The layer that communicates data between hardware and software using wireless technology like WiFi, Sigfox, Bluetooth.
Middleware layer	APIs, Databases, Security	The interface between data and application, including database management and security services
Applications layer	Services provided by using data	This layer provides end users with services by using forms of data analysis to inform and change the smart city
Business layer	Optimisation, AI, deep learning	Attached to the applications layer, this uses complex data analysis to optimise performance and support the development of strategy and policies which manage the smart city system

1.2 Urban Observatories

The Urban Observatory (UO) approach was conceptualised to overcome some of the shortfalls of smart city projects. The fundamental ethos is that more can be learned by combining data from various sources, providing insights far beyond the means of which the data was originally intended. UO's act as a virtual platform bringing together urban data from an array of sources to enable a holistic view to the urban environment.

UO's collect data from the urban environment and use their networks to facilitate data sharing and data-driven research and policy making. The first clear example of a defined UO concept was in the 1960s, when the term was used to describe a model in which science-based decision making and data collection was encouraged by partnerships between universities and governments (Dickey et al., 2021). This concept has continued to evolve with the 4th industrial revolution and in the UK a number of UO's now exist, deploying and hosting an array of sensing and monitoring technology and working with various governmental and policy making agencies. Whilst some UO's directly refer to themselves as such, there are other institutions generating UO functions without the explicit title (Dickey et al., 2021). The UN-Habitat programme has guidance for UO's and sets out 5 generic aims that all observatories should try to cover, outlined below (UN Habitat, 2022);

1. *"Develop, collect and analyze data on a set of localized indicators to monitor a range of local or national priority issues – e.g. social development, economic performance, service delivery, etc."*

2. *"Establish long-term mechanisms for monitoring SDGs (sustainable development goals) and Urban indicators"*

3. *"Promote the use of urban data in planning and policymaking at local and national level"*

4. *"Disseminate information to strengthen accountability and transparency*"

5. *"Promote local ownership of urban indicators systems and a culture of monitoring and assessment."*

Six UK universities recently participated in a project to develop a national UO network. One of those was the Birmingham UO, UK, which provided an online platform used to host data from an array of meteorology and air quality sensors. Alongside other university-based observatories (notably the Manchester UO and Newcastle UO), the project developed strategy for data management and access as well as establishing potential applications of networks for improving their city's financial, social and environmental wellbeing. Deployed sensors were mostly chosen to be self-contained- powered by battery or solar and provide data in real or near real time, monitoring continuously. This means they provide large and continuous data sets across a variety of urban phenomena. In addition to this, an important consideration of the UO approach, is that in addition to deployed sensors themselves, they also host a range of 3rd party data that is applicable to urban management. Examples include ANPR devices and air quality sensors that are operated and managed by public and private bodies but that share their data with their local UO. Bringing the data together in a single place has the potential to drive entirely new innovation ecosystems.

Overall, the UO approach unlocks the potential for the application of the vast streams of real-time data collated by the observatories to be used beyond what has been possible with traditional monitoring efforts. The 'live' nature of the data and common platform improve the temporal rate at which decisions can be made from data. Combined with increasing technological advances such as modelling systems and AI, this has led to interest in simulation and decision making from this data as part of a bigger digital twin agenda.

1.3 The growth of air quality data sources

Air quality sensors are a key common component of UO's in the UK. The growth of the low-cost sensor market means that sensor networks are being deployed at unprecedented spatial scales (Snyder et al., 2013, Karagulian et al., 2019), with sensors for air quality now featuring high on the priority list for smart cities across the globe. Low-cost sensors for air quality range in price from <£100 per unit for a basic sensor component with no additional communications or data storage, to £1000's per unit for multi-pollutant sensors with built-in communications, data management and corrections and online data storage. Whilst low-cost monitors for gas pollutants are available on the market, gas sensors generally perform worse than PM sensors in colocation with a reference instrument and experience cross-sensitivity issues from interferences from non-target gasses on measurements (Kang et al., 2022). Low-cost PM sensors are vulnerable to interference from humidity and particulate composition, calibration efforts are generally successful in enabling low-cost sensors to generate accurate data (Karagulian et al., 2019, Cowell et al., 2022).

Three UOs (Birmingham, Manchester, Newcastle) hosted a total of 8 different types of AQ monitors outlined in table 2. These included commercially manufactured low-cost monitors as well as an in-house low-cost sensing unit developed and deployed by University of Birmingham (AltasensePM) and government regulatory sites whose open data was integrated where possible. Effectively arranged in a nested array, these sensors collected data with various sampling strategies; 1 minute average, 15 minutes average, 15 minute instantaneous and 1 hour average measurements.

Table 2- outlining the types of AQ monitors used by the UOs.

AQ monitor	Featured on UOs	Commercial/regulatory/ in-house design	Pollutants measured
Arisense	Manchester	Commercial	CO, CO_2, NO, NO_2, O_3, PM_1, PM_{10}, $PM_{2.5}$,
Airsensa	Manchester	Commercial	O_3, NO_2, PM_{10}, $PM_{2.5}$,
Plume	Manchester	Commercial	PM_1, $PM_{2.5}$, PM_{10}, NO_2, VOC
Emote	Newcastle	Commercial	CO, NO, NO_2
DEFRA AURN	Birmingham, Newcastle, Manchester	Regulatory	NO_2, NO, NOx, PM_{10}, O_3, SO_2, BC
AQ mesh	Newcastle	Commercial	
Zephyr	Birmingham	Commercial	NO, NO_2, O_3, PM_1, PM_{10}, $PM_{2.5}$,
AltasensePM	Birmingham	In-house design	PM_1, $PM_{2.5}$, PM_{10}

The government regulatory stations (DEFRA AURN) are reflective of traditional monitoring efforts- however commercial and low-cost sensors are growing in popularity with local authorities to compliment regulatory methods by providing air quality data at greater spatial resolutions (Morawska et al., 2018). An example of this is the Zephyr data array from Birmingham, which consists of a mixture of university and third party owned units. Another example of widescale low-cost sensor deployment is the PurpleAir network of PM monitors, which is the largest network of monitors in the USA (over 20,000 units deployed since 2017) and includes units deployed by individuals, community groups and local authorities (Wallace et al., 2022).

1.4 Digital twins

IBM define a digital twin as '*a virtual representation of an object or system that spans its life cycle, is updated from real-time data and uses simulation, machine learning and reasoning to help decision making'* (IBM, 2022). Initially developed to improve manufacturing, digital twins create an ever evolving model of the real world which is fed by the growing wealth of data from the IoT boom which can support monitoring and understanding of the physical world to improve human wellbeing (Saddik, 2018, Fuller et al., 2020).

Precursors to digital twins, were digital models and shadows. A model is usually a term used to describe a simplified mirror image of a process, often focussing on features that are under scrutiny by the user and discarding other features considered not relevant to a project (Batty, 2018). Digital shadows are models which represent a physical phenomenon and have one way communication, with the physical entity feeding into the digital model only, creating a so called shadow of the real world (Sepasgozar, 2021). Importantly, the digital shadow doesn't feedback into the physical, meaning that any decision making isn't reflective of the changing real-world scenarios.

One of the current issues in this research area is that the terms digital model and digital shadow are incorrectly referred to collectively as digital twins. A true digital twin is not static. Whereas models are built off baseline data to create estimates of scenarios, digital twins experience automatic data exchange between the digital image and inputs from the physical object being mirrored (Fuller et al., 2020, Batty, 2018). Fundamentally, this communication with the real or 'physical' twin occurs in real, or near real time, is two-way and is often facilitated via IoT enabled sensors detecting important phenomena within the physical twin. AI (such as machine learning) is then often utilised by the digital twin to make decisions based on the information from the physical twin (Saddik, 2018). Through this

bidirectional feedback, digital twins allow for online testing of decisions and detection of failures ahead of occurrence in the physical world, saving costs, time and resources (Sharma et al., 2022).

This approach provides novel opportunities for decision making- by utilising real time IoT data to manage key infrastructure within the city. For example- the impact of extreme weather events can be detected via sensors, fed into the digital twin alongside citywide infrastructure data to assess the impact on transport infrastructure, allowing interventions to be tested for efficacy ahead of time and then translated into the real world to limit disruption (Schrotter and Hürzeler, 2020). The data from the physical twin during the management is then fed back into the digital twin to help the AI learn and improve. Examples are available from a range of sectors, underlining the wide array of applications of Digital twins. NASA use digital twins to monitor spacecraft during flight, Chevron use digital twins to monitor wind turbine operations and are even being used in cardio-vascular medicine to help test recovery pathways of patient treatment (Tao and Qi, 2019, Corral-Acero et al., 2020). The increasing use of IoT technology and rapid computational developments mean that the possible applications of digital twin technology are vast.

However, while digital twins have been around for some time in other sectors, environmental examples at scale in the real world has been limited. A rare example is the Climate Resilience Demonstrator (CReDo) project a digital twin (shadow) project aimed at improving resilience of energy, water and communication networks from climate change driven flood and weather risk. The initial phase of CReDo integrated data from a major water supplier, power company, communications company and the Met Office onto a digital twin, allowing users to view embedded failure changes that could occur in changing climatic events such as heavy rains and droughts (Digital Twin Hub, 2023). A further example of an urban digital twin is the Zurich Digital Twin, which uses automatically updated 3D spatial data of the city to assist in town planning and monitoring of ongoing construction projects (Shahat et al., 2021). However, the digital shadow nature of such projects underlines the challenges in producing digital twins for environmental applications. In many cases, this is a result of jumping straight to the familiar territory of modelling and simulation rather than taking a step back to ensure the fundamentals of real-time data curation, i.e. metadata and interoperability are adequately addressed. This paper calls for the need to focus on this area before presenting potential use cases of digital twins for air quality.

2. Challenges of achieving large scale digital twins

2.1 National Digital Twin Programme

The UK has an ambitious vision to integrate a national digital twin and in 2018, the National Digital Twin Programme (NDTP) was launched to support this aim. The NDTP focusses on generating a collection of interconnected digital twins rather than one individual large twin. These twins will be developed by a range of organisations but will be interoperable, using federated and standardised systems to support decision making across a range of fields (Government Office for Science, 2023). The programme is a collaborative effort between industry, government and researchers (Digital Twin Hub, 2022). This is an ongoing effort, however, there have been some key outputs from the programme already that will shape the formation of the digital twin to ensure that the NDTP meets its promise of delivering benefits to society, economy, business and environment (Centre for Digital Built Britain, 2022).

There are significant challenges facing the NDTP; fundamentally around the utilisation of large datasets. When integrating data from multiple sources, the metadata becomes as important as the data itself. It is important to consider factors such as who owns the data at each stage, how the data is protected, what computational power is required to process and store such data and are datasets interoperable. Away from technical questions, there are also ethical challenges around big data usage, ensuring that data doesn't further inequality and isn't bias towards certain populations is one

challenge. Another comes in the form of the collection and security of sensitive data that is integral to multi-sector digital twins (Government Office for Science, 2023). One key output is the Gemini Principles which set out the key principles needed to build a national digital twin that meets the above promises and considers the challenges highlighted (Centre for Digital Built Britain, 2022). Outlined in figure 1 below, the Gemini Principles are a tool to ensure that a digital twin framework is purposeful, trustworthy and functional to enable better operability, management and delivery of digital twin assets (Bolton et al., 2018). Yet, the Gemini Principles are not yet fully achieved by air quality data sets- sensor networks are not yet able to adapt autonomously to different environments and require user adaptation via calibrations to ensure performance. The data sets are also not yet long term- both due to the life span of sensors frequently being suggested as 1-2 years by manufacturers, but also due to the project based mindset in which environmental data is often procured. A further limitation to progress towards the Gemini Principles is the data skills shortage currently experienced in the UK. In 2021, the Department for Education stated that 52% of the workforce for not have the essential digital skills required of modern work (Department for Education, 2021). Without these skills, it is unlikely that data will be suitable to progress towards a digital twin, nor will the workforce be able to develop and integrate digital twin technology readily into decision making processes. Given the scale of the research required, a national digital twin remains a long-term ambition. Progress will comprise of building blocks of much smaller digital twins – perhaps for a particular sector, location or use-case, which can later be integrated as bigger connected twin.



Figure 1 *An overview of the Gemini Principles taken from (Bolton et al., 2018) under CC BY 3.0 licence*

There is a clear need for collaborative effort of harnessing data for digital twin use in the UK, particularly real-time data that could support autonomous decision making. It is this data which will fundamentally underpin any digital twin in this space, regardless of size. An example of such data could be the real-time data from a low-cost air quality sensor. Combining data from low-cost sensor networks alongside regulatory and commercial instruments has already been demonstrated in Cowell et al (2023a) to expand spatial understanding of air quality, and thus this is a clear candidate of data

that could be utilised to create more sustainable decision making. There is also opportunity to expand the coagulation of data further, via the UO concept, onboarding other relevant datasets such as traffic data to enhance decision making efforts further. The problem is this area of research is seen as mundane, and is far less glamorous than that involved for modelling and simulation. However, without the fundamental principles being firmly established in this area, a large-scale digital twin is simply not possible.

2.2 Interoperability & metadata of live streams

An important first step in bringing together the wealth of air quality data from low-cost sensors alongside regulatory measurements and wider air quality related indicators (such as traffic data and meteorology) is a standardisation of data protocols. Data catalogues can be used to collate and store metadata around live streams and if managed correctly can provide insight into a stream's health and applications. Whilst metadata is often collected by individual projects deploying low-cost sensors, there is not one clear method of data standardisation to making collating data easier. Metadata is vital for enabling the use of smart city data- metadata enables decision makers to understand the data being provided by the IoT networks (Schrotter and Hürzeler, 2020). It is an imperative feature of data streams that will be used for digital twins, as it describes characteristics of the digital twin it will form, such as data refresh rate, digital twin spatial coverage and data quality and uncertainties. The best suited datasets for digital twin use will capture as much metadata as possible to support end users. Without metadata it is challenging to assess a streams health and applicability to a use case. Furthermore, low-cost sensors present new challenges that need to be captured by metadata. They can experience mechanical and electrical issues due to exposure and damage from the natural environment, as well as power outages, lack of maintenance, drift, changing calibrations and data processing procedures (Shakeri et al., 2020, Chan et al., 2021). Therefore, metadata will also require regular updates to ensure these changes and any outages are reflected to the user.

One of the key challenges across generating metadata is ensuring terminology and understanding of terminology is uniform across datasets (Saddik, 2018). Ontologies provide a solution to ensure that the various components of metadata for live streams are standardised and universal. Ontologies allow for streamlined management of complex data by organising data semantically and intuitively and making it easier to integrate data into different interfaces (Erkoyuncu et al., 2020, Kharlamov et al., 2018). To further enhance and future proof the standardisation of metadata efforts, data models are an excellent way of enabling compatible representation of entities for interoperable smart solutions whilst allowing for growth with changing technology. Open-source information models for data (aka Smart Data Models) offer great opportunity here. These are dynamic formats and semantics that can be used to share data in a standardised way, which are adaptable and informed by feedback from users to ensure they are fully capturing the wealth of information required by applications (Abellagarcia, 2022, Smart Data Models, 2023). For example, in the context of low-cost sensors models can be adapted to contextualise challenges such as those around ownership of sensors and data, and 3rd party sensor providers. This allows the models to evolve with technology- ensuring they continue to support data interoperability within rapidly developing fields (Smart Data Models, 2023).

Air quality sensors provide an ideal target to test these underlying principles. The abundance of sensors from different manufacturers, measuring different parameters in different settings poses a vast, but manageable, challenge in itself (e.g. Table 2) (Topping et al., 2021). Cowell et al, (2023) have demonstrated the power of fusing these data from different sources, but we are still some way off achieving this data fusion in real time as demanded by digital twins. Digital twins will require the merging of real-time data streams and real-time metadata updates to support the filtering of data used for decision making based off of the health of a data stream. The advantage of using air quality

as a target is that there is also low-hanging fruit in terms of use cases where real-time, autonomous, decision making could make a significant improvement.

3 Air Quality Use Cases

Air quality management and traffic management can have a symbiotic relationship. Often the best practice for traffic management that reduces congestion and smooths traffic flow can also have positive impacts for air quality. Current examples of traffic management for targeted AQ benefit include static signage and 'don't drive' campaigns. For example, static signage warning people of the impact of their driving behaviour has been reported to reduce $PM_{2.5}$ concentrations in Canterbury, UK, where road signs were displayed at a rail crossing encouraging drivers to turn off their engine whilst waiting resulted in behaviour change and reduced concentrations (Abrams et al., 2021).

In Stuttgart, Germany, multimedia messaging via signs and local broadcasting encouraged 'Don't Drive Appeals' during forecasted periods of high PM concentrations (based off seasonal meteorologically driven decision tree). This city wide (i.e. blanket message) method caused minor reductions in city centre traffic during weekdays but also had potential to increase traffic on city periphery (Dangel and Goeschl, 2022). Further examples can be seen in Birmingham, UK, where traffic management has been at the core of recent air quality management with table 3 outlining some of the recent implemented methods. These methods are mostly static, creating standardised in-flexible change to traffic management, however, the IoT is starting to be introduced by the use of online camera technology creating potential for data driven decision making via traffic/cycle counts. It demonstrates a hint of how IoT enabled solution are becoming mainstream making real-time and dynamic decision making a possibility (Carter and Rushton, 2020), which will ultimately see the emergence of digital twins in this area.

3.1 Dynamic Messaging

In Coventry, UK, IoT data is already being integrated into traffic management to underpin a more dynamic system. Here, Variable Messaging Signs (VMS) which provide guidance to road users are being used to provide updates when air quality crosses a threshold concentration, triggering signage to advise traffic to alter their routes to avoid identified hotspots (Chaplin and Taylor, 2020). Signs can potentially also display travel times by public transport and real time air quality information to encourage the public to utilise public and active travel over private vehicle (Coventry City Council, 2007). Currently, this traffic management is currently driven by one directional real-time data, i.e the air quality concentrations from the sensors trigger a reaction response in changing traffic advisories when concentrations cross a threshold level. However, AI could readily be used to develop this further allowing for AQ predictions to be generated from the sensor data to allow for preventative decision making. Real-time data could also be used to generate predictions a short distance into the future (hours-days), allowing the council to visualise potential hotspots and use traffic advisories to prevent them before the threshold concentrations are crossed. The digital twin approach could take this even further integrating other data sources, traffic counts and vehicle speeds from cameras integrated into a UO platform to monitor and adapt to the reaction of traffic to VMS driven from AQ predictions and update route guidance and traffic flow via traffic lights accordingly for maximum efficiency and lowest environmental impact.

3.2 Traffic Routing

A more ubiquitous example of real-time traffic management with air quality benefits is the use of modern navigation applications by drivers. Apps such as GoogleMaps that update routes based on real-time traffic data to provide users with the most time-efficient routing option have also been found to reduce PM2.5 and NO2 emission by proxy (Huang and Hu, 2018). Whilst these quality benefits are unintentional, this demonstrates the potential of real-time data streams such as those provided by

IoT networks. Researchers are now taking this a step forward. For example, the GeoSTMUM tool collects telematics data from apps such as GoogleMaps and Waze to generate information about traffic flow and travel times to infer speed-time-acceleration profiles of vehicles and links this to emission factors and fleet composition data to infer real world CO2 and NOx emissions (Ghaffarpasand and Pope, 2023). There is scope to expand this beyond exhaust emissions, which will become increasingly important as decarbonisation efforts intensify. Ultimately, this means that a new set of air quality interventions will be required to deal with increased PM emissions from EVs (see Cowell et al., 2023a) which in itself presents an ideal digital twin use case. Ultimately, low-cost sensor data could feed back directly into traffic routing apps supporting the routing choices by combining telematics and real time pollution data into the routing algorithm for minimal emissions.

Table 3- air quality management techniques in Birmingham which target traffic emissions specifically

Air quality management technique	Description	Birmingham characteristics	Key findings from literature
School streets	Closing the streets outside of a school to motor vehicles at the beginning and end of the school day. Enforced by cameras or volunteers. (Thomas et al., 2022)	Introduced in 2019 outside of 17 schools. Schools were selected if they didn't disrupt major arterial roads, bus routes and if nearby streets could accommodate extra parking/traffic. Local infrastructure had to be in place to support alternative travel, including active travel. (Birmingham City Council, 2022a)	• School streets in London are not reaching schools where children are likely to be most exposed to poor AQ- only 13% of schools in that experience the worst AQ have school streets (Thomas et al., 2022) • Non-school street schools have higher mean NO2 concentrations than school streets (Thomas et al., 2022). • School streets in Camden reduced traffic by 7-8% across the entire area, not just outside of the school (Hopkinson et al., 2021) • 5% improvement in NO_2 concentrations at school streets (Thomas, 2022).
Low traffic neighbourhood (LTN)	LTNs prevent motor traffic passing through an area of residential and side streets by placing low-cost barriers such as planters, bollards and cameras to prevent throughfare (Yang et al.).	From 2020, BCC established 2 LTN zones: Kings Heath and Lozells. They also identified 2 other areas of potential LTN management in Bournville and Castle Vale which are undergoing trial and consultation in 2022 (Birmingham City Council, 2022b).	• Can be controversial and in some cases have been removed as local stakeholders are concerned about displacement of air pollution to surrounding areas (Yang et al.). • NO_x and PM_{10} concentration decrease around LTNs in London (Gustafsson, 2022). • People in deprived areas 2.5x more likely to live in an LTN compared to less deprived areas (Aldred et al., 2021) • 7% decrease in car ownership after 3 years reported (Laverty et al., 2021)
Cycle routes	Segregated cycle ways that keep cyclists mostly separate from motor traffic. Designed to offer an alternative to travelling by motor vehicle and to encourage active transport.	Two blue cycle routes were recently introduced in Birmingham along major roads (A38/A34). These routes are mostly segregated from traffic and on central reservations and side roads, cyclists have priority over cars (Birmingham City Council, 2022c).	• Introduction of a segregated cycle way saw a decrease in cyclists NO_2 exposure (Schmitz et al., 2021). • Cyclists have reduced exposure to ultrafine particles and CO at 7m and 19m away from road compared to on road cyclist (Pattinson et al., 2017). • 22-25% reduction in NO_2 exposure on segregated cycleways (Dajnak et al., 2018).

The approach could also be integrated into active travel routing technology. For example, cycleways are often segregated pathways that run alongside busy roads, whereas others are routes which utilise canal towpaths and side streets. As highlighted in Table 3, the more cyclists are segregated from traffic, exposure to air pollutants decreases (Schmitz et al., 2021, Pattinson et al., 2017, Dajnak et al., 2018). CycleStreets is an online tool and application that provides cyclists with routing options, using static map data to suggest various routes between locations by busy-ness and speed to support cyclists varying confidence levels (CycleStreets, 2023). Due to the open-access nature of Urban Observatory data, it could easily be readily called via API onto this platform, giving cyclists insight into real-time exposure to particulates on their routes and supporting decision making by the algorithm in suggesting the lowest exposure route when suggesting a "quiet" route.

3.3 Controlling Traffic flow

Further opportunity arises from the low-cost sensors to optimise traffic flow via the Green Wave theory of traffic management. Green Wave is a method of traffic management in which the signal sequence is optimised to limit congestions by creating a flow where traffic can pass through junctions without meeting a red light (Xu et al., 2014). The goal of a Green Wave is to reduce congestion and by proxy, emissions by optimising flow. Often literature has focused on reduced journey time as a way of measuring success however it has been suggested that this doesn't necessarily reflect best practice for emissions and that Green Waves should target reducing non-essential stop-starts and idling at high exposure zones such as pedestrian crossings (Xu et al., 2014, Kelly, 2012). An approach that reduces travel time doesn't necessarily always directly equate to reduce pollutant emissions and vice versa (De Coensel et al., 2012). Sensors could be utilised here alongside other traffic data to optimise the Green Wave process, highlighting particulate hotspots where traffic stop/starts should be limited. Smart traffic lights can already integrate infra-red detectors and wireless communication regarding congestion to streamline performance- pollution concentrations are an obvious next step in enhancing this further (Oliveira et al., 2021).

3.4 Testing interventions

There is opportunity to utilise digital twins for agent-based modelling of air quality interventions. The growth of live stream data can allow for more complex modelling of interventions, integrating data at higher resolutions, from a range of sources and of a greater range of variables (Topping et al., 2021). Using an example from table 3, a good candidate for this is low-traffic neighbourhoods as there is an abundance of air quality and traffic data available in most urban centres in the Global North to capture any changes. Thomas et al., (2022b) combined data from travel activity alongside model and measurement data of air pollutions to simulate exposures of populations to PM2.5. With the integration of more live stream data, digital twins of LTNs can be created to generate estimated routes for traffic before and after LTN introduction (which restricts some vehicle routes alongside roads), to calculate potential new traffic volumes and particulate exposures ahead of implementation. This allows for dynamic testing of LTNs ahead of and during implementation, supporting public consultation efforts and helping predict where LTNs might cause the need for further supportive infrastructure such as bike lanes on major alternate traffic routes. The increased hyper local PM data from low-cost networks supports this analysis by providing unprecedented insight into concentrations and exposures in LTN regions, enhancing planning and development for lower exposures. This methodology could be applied to an array of interventions and could be used to evaluate and adapt interventions dynamically depending on live data from the city. Clean Air Zones, School Streets, Congestion Charges, Zones of interventions could be adjusted to reflect the real-time traffic patterns, meteorology and pollution concentrations after a digital twin has anticipated the potential best outcomes of various scenarios interpreted from live data.

3.5 Feasibility

As explored in chapter 4, air quality sensors are still not uniformly or widely spread covering the entirety of the UK so the opportunity for a national digital twin for air quality, or national use cases of digital twins is not yet likely. Moreover, the low-cost sensors are not yet sensitive enough to reliably detect concentrations of minor concentrations near sources such as roadside sites and therefore creating decision making targeting specific junctions currently is unlikely (although may be possible soon with the boom of the low-cost sensor industry driving competition). Digital twins from low-cost sensors at this stage do not and cannot exist due to the availability of sensors data and metadata and sensors currently inconsistent performance between places and pollution sources. However, regional decision making is feasible as sensor networks have shown that they can provide good insight into regional patterns and concentrations- examples of this include resource management such as informing healthcare systems of potential risk for increased regional concentrations and providing real time citizen advice around outdoor concentrations during regional peaks, such as reducing outdoor activity by real-time messaging. The best placed networks for supporting digital twins currently are those that integrate data types, such as reference data, model data and low-cost sensing data to give a holistic picture of air quality. Networks and platforms that integrate this data with other real-time data such as resource availability, traffic and activity and meteorology and likely to be best placed to be integrated into potential digital twin technology.

4 Challenges of sensor data

Whilst air quality monitoring is not novel practice, the development of more agile, connective, low-cost sensing is enabling a new paradigm of urban decision making. Air quality is one of the largest challenges facing modern urban societies and is an obvious candidate for smart city and digital twin infrastructure. However, there are challenges in making this a reality.

Firstly, it is clear that embedding unstandardised low-cost sensor data into integrated UO platforms presents a significant, and arguably overlooked, challenge, but the infrastructure to support interoperability is now becoming established, with ontologies and data models developed specifically with the aim of ensuring interoperability and longevity of metadata methods.

Secondly, low-cost sensors, particularly for air quality monitoring, often raise concern within the scientific community due to both their data quality and lack of a uniform method in solving calibration and data quality issues (Kang et al., 2022, Morawska et al., 2018, Rai et al., 2017). Whilst good practice in data processing, sensor deployment (Cowell et al, 2023a) and management can overcome the limitations associated with low-cost AQ sensors (impact of humidity, pollutant source, drift), there is not a uniform approach to this with researchers presenting different methods with varying degrees of success (Popoola et al., 2018, Rai et al., 2017). An example of this was highlighted in the previous chapter, when sensors were bought together in an integrated network to enhance the spatial density of measurements allowed for data analysis of PM concentrations, despite the challenges of low-cost sensors (Cowell et al., 2023c). Whilst sensors such as AltasensePM, the sensor developed in-house at University of Birmingham, has peer-reviewed calibration and validation methods which are scalable, this is not always the case with such sensor deployments, especially when integrating data from non-specialists such as citizen scientists. Challenges arise in communicating this need for potential error without destroying trust in the data. Low-cost AQ data can be useful when properly managed but needs to be understood well before applying to decision making.

Thirdly, the 3rd party management of sensor networks also creates challenges beyond the owner- many AQ sensor providers offer data management as part of their data collection service. Whilst the hardware of many commercial AQ sensors is often the same components, the software is the way sensor companies can market a unique product. Whilst some offer raw data direct from the sensors, other advertise packages that include data calibration and management where the company will use

proprietary software to calibrate and correct the sensors to make data collection easier for the non-scientific target market. As these methods of correction and calibration are a unique selling point to the business, the methods are often kept private and only shared in very basic detail with the consumer meaning end users are unlikely to know exactly how data has been manipulated and if these manipulations fully address data quality issues outlined in the literature. Furthermore, some sensor companies then present data at a cost by making it available via locked software only and charging for access. This limits the availability and usability of this data.

Furthermore, in nation such as the UK, where emissions from traffic sources are decreasing, the importance of near source monitoring at roadsides is being thrown into contention. Regional and transboundary PM sources from further afield is going to become increasingly important to monitor and understand and this will require wide scale monitoring at an international scale in a standardised way if this is going to be fully reflected into any future potential digital twins.

Finally, as low-cost sensor networks are accessible to communities that are not directly from a scientific research background, there is no guarantee that data interpretation methods used will be appropriate for generating reliable data for decision making applications (Morawska et al., 2018). Even if sensors are undergoing proper data management, this may not be captured fully and shared which makes capturing and understanding data from external stakeholder networks challenging. This is particularly challenging in the UK as there government recognised digital skills shortage, meaning that many workers are ill prepared for managing and interpreting the technology needed to support sensor networks, let alone digital twins (Department for Education, 2021).

5 Conclusions

Overall, as shown by the use cases in this viewpoint, there is clear potential of low-cost AQ networks for digital twins, but barriers need to be tackled. Moving forward, works needs to be done to ensure that there is a common practice for generating and managing big data sets so that it is open and useable for digital twin technology. There is huge value, if interpreted correctly, in the outputs of low-cost sensors. Their accessibility is leading to data densification, via citizen science, enhanced research outputs and government monitoring using these sensor types. The change live stream data can support in decision making is not to be under-estimated; live air quality data has potential to decrease health risks from pollution exposure by supporting decision making throughout various time scales. Planning will be enhanced by the dynamic nature of digital twin technology, which allows for complex testing of potential air pollution mitigation efforts with the integration of real-world data feedback. At shorter-term, rapid-fire decision making by technology will be able to optimise real-time air quality management within the changing conditions of a city environment to reduce inhabitants' exposure. Traffic will be able to be managed with not just journey time in consideration, but also current and predicted pollution concentrations, meteorology and surrounding traffic flow.

Not withstanding the barriers presented, if AQ digital twins become mainstream, consideration also needs to be given to the underpinning durability of such networks. Whilst there is a plethora of open-access sensor networks available to gather environmental data from, many of these were deployed with a single purpose or aim by the end user. This often means that when this aim is met, or a project comes to a close, the sensors are retired due to lack of ongoing funds or platforms to host data. Data streams need to be reliable and the collapse of streams like this will limit capability of digital twins. To ensure digital twins for air quality meet their full potential, there will need to be a shift from demonstrator and project-based sensor deployment to legacy and collaborative deployments which ensure data stream longevity. This is increasingly challenging as we move apace to consumable driven, 'transient' sensing (Chapman et al, 2023) which effectively underpins the IoT and digital twin paradigm.

References

ABELLAGARCIA, A. 2022. smart-data-models/SmartCities. github.

ABRAMS, D., LALOT, F., HOPTHROW, T., TEMPLETON, A., STEEDEN, B., ÖZKEÇECI, H., IMADA, H., WARBIS, S., SANDIFORD, D., MELEADY, R., FELL, E., ABRAMS, Z., ABRAMS, A., NGAN, X. Q., CELINA, S., TANYERI, A., GAMMON, M., ABRAMS, B., FISCHER, L., DRYSDALE, S., DEWI, R., LEITE, A., MILLS, A. & PECKHAM, S. 2021. Cleaning up our acts: Psychological interventions to reduce engine idling and improve air quality. Journal of Environmental Psychology, 74, 101587.

ALDRED, R., VERLINGHIERI, E., SHARKEY, M., ITOVA, I. & GOODMAN, A. 2021. Equity in new active travel infrastructure: A spatial analysis of London's new Low Traffic Neighbourhoods. Journal of Transport Geography, 96, 103194.

ALI, S., GLASS, T., PARR, B., POTGIETER, J. & ALAM, F. 2021. Low Cost Sensor With IoT LoRaWAN Connectivity and Machine Learning-Based Calibration for Air Pollution Monitoring. IEEE Transactions on Instrumentation and Measurement, 70, 1-11.

ASHTON, K. 2009. That 'internet of things' thing. RFID journal, 22, 97-114.

BATTY, M. 2018. Digital twins. Environment and Planning B: Urban Analytics and City Science, 45, 817-820.

BIRMINGHAM CITY COUNCIL. 2022a. Car free school streets [Online]. Available: https://www.birmingham.gov.uk/info/20163/safer_greener_healthier_travel/1891/car_free_school_streets [Accessed 04.11.2022].

BIRMINGHAM CITY COUNCIL. 2022b. Places for people [Online]. Available: https://www.birmingham.gov.uk/info/50250/active_travel_fund/2203/places_for_people [Accessed 04.11.2022].

BIRMINGHAM CITY COUNCIL. 2022c. Where can I cycle? [Online]. Available: https://www.birmingham.gov.uk/info/50122/cycling_in_birmingham/1322/where_can_i_cycle/2#:~:text=In%20the%20north%20of%20Birmingham,an%20A38%20cycle%20route%20map. [Accessed 04.11.2022].

BOLTON, A., ENZER, M. & SCHOOLING, J. 2018. The Gemini Principles: Guiding values for the national digital twin and information management framework. In: CENTRE FOR DIGITAL BUILT BRITAIN (ed.). online.

CANDIA, A., REPRESA, S. N., GIULIANI, D., LUENGO, M. Á., PORTA, A. A. & MARRONE, L. A. Solutions for SmartCities: proposal of a monitoring system of air quality based on a LoRaWAN network with low-cost sensors. 2018 Congreso Argentino de Ciencias de la Informática y Desarrollos de Investigación (CACIDI), 28-30 Nov. 2018 2018. 1-6.

CARTER, C. & RUSHTON, C. 2020. Road Transport and Air Quality. The Internet of Things: From Data to Insight, 189-206.

CENTRE FOR DIGITAL BUILT BRITAIN. 2022. National Digital Twin Programme [Online]. online: The University of Cambridge. Available: https://www.cdbb.cam.ac.uk/what-we-did/national-digital-twin-programme [Accessed 23.04.23].

CHAN, K., SCHILLEREFF, D. N., BAAS, A. C., CHADWICK, M. A., MAIN, B., MULLIGAN, M., O'SHEA, F. T., PEARCE, R., SMITH, T. E. & VAN SOESBERGEN, A. 2021. Low-cost electronic sensors for environmental research: Pitfalls and opportunities. Progress in Physical Geography: Earth and Environment, 45, 305-338.

CHAPLIN, N. & TAYLOR, F. 2020. 2020 Air Quality Annual Status Report. In: PROTECTION, E. (ed.). online: Coventry City Council.

CHAPMAN, L., BELL, S. & RANDALL, S. 2023. Can crowdsourcing increase the durability of an urban meteorological network? Urban Climate, 49, 101542.

CHAPMAN, L., MULLER, C. L., YOUNG, D. T., WARREN, E. L., GRIMMOND, C. S. B., CAI, X.-M. & FERRANTI, E. J. 2015. The Birmingham urban climate laboratory: An open meteorological test bed and challenges of the smart city. Bulletin of the American Meteorological Society, 96, 1545-1560.

CHAPMAN, L., WARREN, E. & CHAPMAN, V. Using the internet of things to monitor low adhesion on railways. Proceedings of the Institution of Civil Engineers-Transport, 2016. Thomas Telford Ltd, 321-329.

CORRAL-ACERO, J., MARGARA, F., MARCINIAK, M., RODERO, C., LONCARIC, F., FENG, Y., GILBERT, A., FERNANDES, J. F., BUKHARI, H. A., WAJDAN, A., MARTINEZ, M. V., SANTOS, M. S., SHAMOHAMMDI, M., LUO, H., WESTPHAL, P., LEESON, P., DIACHILLE, P., GUREV, V., MAYR, M., GERIS, L., PATHMANATHAN, P., MORRISON, T., CORNELUSSEN, R., PRINZEN, F., DELHAAS, T., DOLTRA, A., SITGES, M., VIGMOND, E. J., ZACUR, E., GRAU, V., RODRIGUEZ, B., REMME, E. W., NIEDERER, S., MORTIER, P., MCLEOD, K., POTSE, M., PUEYO, E., BUENO-OROVIO, A. & LAMATA, P. 2020. The 'Digital Twin' to enable the vision of precision cardiology. European Heart Journal, 41, 4556-4564.

COVENTRY CITY COUNCIL 2007. Air Quality Action Plan for Coventry.

COWELL, N., BALDO, C., BLOSS, W. & CHAPMAN, L. 2023a. What can we learn from nested IoT low-cost sensor networks for air quality? A case study of PM2. 5 in Birmingham UK. Copernicus Meetings.

COWELL, N., BALDO, C., CHAPMAN, L., BLOSS, W., ZHONG, J. 2023c. What can we learn from nested IoT low-cost sensor networks for air quality? A case study of PM2. 5. *Submitted for review to Meteorological Applications special issue, Unconventional Observations for Meteorological Applications.*

COWELL, N., CHAPMAN, L., BLOSS, W., SRIVASTAVA, D., BARTINGTON, S. & SINGH, A. 2023b. Particulate matter in a lockdown home: evaluation, calibration, results and health risk from an IoT enabled low-cost sensor network for residential air quality monitoring. Environmental Science: Atmospheres, 3, 65-84.

COWELL, N. H., CHAPMAN, L., BLOSS, W. & POPE, F. 2022. Field calibration and evaluation of an Internet of Things based particulate matter sensor. Frontiers in Environmental Science, 733.

CYCLESTREETS. 2023. CycleStreets Cycling intelligence for Birmingham [Online]. Available: https://birmingham.cyclestreets.net/ [Accessed 02.05.23].

DAJNAK, D., WALTON, H., GREGOR, S., SMITH, J. D. & BEEVERS, S. 2018. Air quality: Concentrations, exposure and attitudes in Waltham Forest. Environmental Research Group, School of Analytical, Environmental and Forensic Sciences, King's College London. Retrieved from https://walthamforest. gov. uk/sites/default/files/WalthamForest_ Kings% 20Report_310718. pdf.

DANGEL, A. & GOESCHL, T. 2022. Air Quality Alerts and Don't Drive Appeals: Cautionary Evidence from Germany.

DE COENSEL, B., CAN, A., DEGRAEUWE, B., DE VLIEGER, I. & BOTTELDOOREN, D. 2012. Effects of traffic signal coordination on noise and air pollutant emissions. Environmental Modelling & Software, 35, 74-83.

DEPARTMENT FOR EDUCATION 2021. Skills for Jobs: Lifelong Learning for Opportunity and Growth.

DICKEY, A., ACUTO, M. & WASHBOURNE, C.-L. 2021. URBAN OBSERVATORIES:

A COMPARATIVE REVIEW. Available: https://unhabitat.org/sites/default/files/2021/01/urban_observatories_report_v2.pdf.

DIGITAL TWIN HUB. 2022. National Digital Twin Programme [Online]. online. Available: https://digitaltwinhub.co.uk/ndtp/ [Accessed 29.04.23].

DIGITAL TWIN HUB. 2023. What is CReDo? [Online]. Available: https://digitaltwinhub.co.uk/credo/credo/ [Accessed 21.04.2023].

ERKOYUNCU, J. A., DEL AMO, I. F., ARIANSYAH, D., BULKA, D., VRABIČ, R. & ROY, R. 2020. A design framework for adaptive digital twins. CIRP Annals, 69, 145-148.

FØLSTAD, A. 2008. Living labs for innovation and development of information and communication technology: a literature review.

FULLER, A., FAN, Z., DAY, C. & BARLOW, C. 2020. Digital Twin: Enabling Technologies, Challenges and Open Research. IEEE Access, 8, 108952-108971.

GHAFFARPASAND, O. & POPE, F. Using vehicle telematics data within a digital twin of urban transport systems; a case study in the West Midlands, UK. European Geoscience Union General Assembly 2023, 2023 Vienna. EGU.

GOVERNMENT OFFICE FOR SCIENCE 2023. RTA: Digital twins. online.

GUSTAFSSON, G. 2022. Urban Planning for Better Air Quality: A case study of the Low-Traffic Neighbourhoods in London.

HEGDE, S., MIN, K. T., MOORE, J., LUNDRIGAN, P., PATWARI, N., COLLINGWOOD, S., BALCH, A. & KELLY, K. E. 2020. Indoor Household Particulate Matter Measurements Using a Network of Low-cost Sensors. Aerosol and Air Quality Research, 20, 381-394.

HOPKINSON, L., GOODMAN, A., SLOMAN, L., ALDRED, R. & THOMAS, A. 2021. School Streets Reducing children's exposure to toxic air pollution and road danger.

HUANG, W. & HU, M. 2018. Estimation of the Impact of Traveler Information Apps on Urban Air Quality Improvement. Engineering, 4, 224-229.

IBM. 2022. What is a digital twin? [Online]. online. Available: https://www.ibm.com/uk-en/topics/what-is-a-digital-twin [Accessed 17.08.2022].

IVANOV, S., NIKOLSKAYA, K., RADCHENKO, G., SOKOLINSKY, L. & ZYMBLER, M. Digital Twin of City: Concept Overview. 2020 Global Smart Industry Conference (GloSIC), 17-19 Nov. 2020 2020. 178-186.

KANG, Y., AYE, L., NGO, T. D. & ZHOU, J. 2022. Performance evaluation of low-cost air quality sensors: A review. Science of The Total Environment, 818, 151769.

KARAGULIAN, F., BARBIERE, M., KOTSEV, A., SPINELLE, L., GERBOLES, M., LAGLER, F., REDON, N., CRUNAIRE, S. & BOROWIAK, A. 2019. Review of the Performance of Low-Cost Sensors for Air Quality Monitoring. Atmosphere, 10, 506.

KELLY, B. 2012. A 'Green Wave'Reprieve. Traffic Engineering & Control, 53.

KHARLAMOV, E., MARTIN-RECUERDA, F., PERRY, B., CAMERON, D., FJELLHEIM, R. & WAALER, A. Towards Semantically Enhanced Digital Twins. 2018 IEEE International Conference on Big Data (Big Data), 10-13 Dec. 2018 2018. 4189-4193.

LAVERTY, A. A., GOODMAN, A. & ALDRED, R. 2021. Low traffic neighbourhoods and population health. British Medical Journal Publishing Group.

LAW, K. H. & LYNCH, J. P. 2019. Smart City: Technologies and Challenges. IT Professional, 21, 46-51.

MEHMOOD, Y., AHMAD, F., YAQOOB, I., ADNANE, A., IMRAN, M. & GUIZANI, S. 2017. Internet-of-Things-Based Smart Cities: Recent Advances and Challenges. IEEE Communications Magazine, 55, 16-24.

MISHRA, K. N. & CHAKRABORTY, C. 2020. A Novel Approach Toward Enhancing the Quality of Life in Smart Cities Using Clouds and IoT-Based Technologies. In: FARSI, M., DANESHKHAH, A., HOSSEINIAN-FAR, A. & JAHANKHANI, H. (eds.) Digital Twin Technologies and Smart Cities. Cham: Springer International Publishing.

MORAWSKA, L., THAI, P. K., LIU, X., ASUMADU-SAKYI, A., AYOKO, G., BARTONOVA, A., BEDINI, A., CHAI, F., CHRISTENSEN, B., DUNBABIN, M., GAO, J., HAGLER, G. S. W., JAYARATNE, R., KUMAR, P., LAU, A. K. H., LOUIE, P. K. K., MAZAHERI, M., NING, Z., MOTTA, N., MULLINS, B., RAHMAN, M. M., RISTOVSKI, Z., SHAFIEI, M., TJONDRONEGORO, D., WESTERDAHL, D. & WILLIAMS, R. 2018. Applications of low-cost sensing technologies for air quality monitoring and exposure assessment: How far have they gone? Environment International, 116, 286-299.

MOSCO, V. 2017. Becoming Digital : Toward a Post-Internet Society, Bingley, UNITED KINGDOM, Emerald Publishing Limited.

OLIVEIRA, L. F. P. D., MANERA, L. T. & LUZ, P. D. G. D. 2021. Development of a Smart Traffic Light Control System With Real-Time Monitoring. IEEE Internet of Things Journal, 8, 3384-3393.

PATTINSON, W., KINGHAM, S., LONGLEY, I. & SALMOND, J. 2017. Potential pollution exposure reductions from small-distance bicycle lane separations. Journal of Transport & Health, 4, 40-52.

POPOOLA, O. A. M., CARRUTHERS, D., LAD, C., BRIGHT, V. B., MEAD, M. I., STETTLER, M. E. J., SAFFELL, J. R. & JONES, R. L. 2018. Use of networks of low cost air quality sensors to quantify air quality in urban settings. Atmospheric Environment, 194, 58-70.

RAI, A. C., KUMAR, P., PILLA, F., SKOULOUDIS, A. N., DI SABATINO, S., RATTI, C., YASAR, A. & RICKERBY, D. 2017. End-user perspective of low-cost sensors for outdoor air pollution monitoring. Science of The Total Environment, 607-608, 691-705.

SADDIK, A. E. 2018. Digital Twins: The Convergence of Multimedia Technologies. IEEE MultiMedia, 25, 87-92.

SCHMITZ, S., CASEIRO, A., KERSCHBAUMER, A. & VON SCHNEIDEMESSER, E. 2021. Do new bike lanes impact air pollution exposure for cyclists?—a case study from Berlin. Environmental Research Letters, 16, 084031.

SCHROTTER, G. & HÜRZELER, C. 2020. The Digital Twin of the City of Zurich for Urban Planning. PFG – Journal of Photogrammetry, Remote Sensing and Geoinformation Science, 88, 99-112.

SCHUURMAN, D., DE MAREZ, L. & BALLON, P. 2015. Living Labs: a systematic literature review. Open Living Lab Days 2015.

SEPASGOZAR, S. M. 2021. Differentiating digital twin from digital shadow: Elucidating a paradigm shift to expedite a smart, sustainable built environment. Buildings, 11, 151.

SHAHAT, E., HYUN, C. T. & YEOM, C. 2021. City Digital Twin Potentials: A Review and Research Agenda. Sustainability [Online], 13.

SHAKERI, M., SADEGHI-NIARAKI, A., CHOI, S.-M. & ISLAM, S. R. 2020. Performance analysis of IoT-based health and environment WSN deployment. Sensors, 20, 5923.

SHARMA, A., KOSASIH, E., ZHANG, J., BRINTRUP, A. & CALINESCU, A. 2022. Digital Twins: State of the art theory and practice, challenges, and open research questions. Journal of Industrial Information Integration, 100383.

SILVA, B. N., KHAN, M. & HAN, K. 2018. Towards sustainable smart cities: A review of trends, architectures, components, and open challenges in smart cities. Sustainable Cities and Society, 38, 697-713.

SMART DATA MODELS. 2023. Smart Data Models About [Online]. online. Available: https://smartdatamodels.org/index.php/mision-and-vision/ [Accessed 08.05.23].

SNYDER, E. G., WATKINS, T. H., SOLOMON, P. A., THOMA, E. D., WILLIAMS, R. W., HAGLER, G. S., SHELOW, D., HINDIN, D. A., KILARU, V. J. & PREUSS, P. W. 2013. The changing paradigm of air pollution monitoring. Environmental science & technology, 47, 11369-11377.

SYED, A. S., SIERRA-SOSA, D., KUMAR, A. & ELMAGHRABY, A. 2021. IoT in Smart Cities: A Survey of Technologies, Practices and Challenges. Smart Cities, 4, 429-475.

TAO, F. & QI, Q. 2019. Make more digital twins. Nature, 573, 490-491.

THOMAS, A. 2022. Making School Streets Healthier: Learning from temporary and emergency closures.

THOMAS, A., FURLONG, J. & ALDRED, R. 2022. Equity in temporary street closures: The case of London's Covid-19 'School Streets' schemes. Transportation Research Part D: Transport and Environment, 110, 103402.

TOPPING, D., BANNAN, T., COE, H., EVANS, J., JAY, C. E., MURABITO, E. & ROBINSON, N. 2021. Digital twins of urban air quality: opportunities and challenges. Frontiers in Sustainable Cities, 141.

ULLO, S. L. & SINHA, G. R. 2020. Advances in smart environment monitoring systems using IoT and sensors. Sensors, 20, 3113.

UN HABITAT 2022. A guide to setting up an Urban Observatory popular version. Kenya: United Nations HABITAT.

VERMESAN, O. 2013. Internet of Things: Converging Technologies for Smart Environments and Integrated Ecosystems, Aalborg, DENMARK, River Publishers.

VERMESAN, O. & BACQUET, J. 2022. Internet of Things–The Call of the Edge: Everything Intelligent Everywhere, CRC Press.

WALLACE, L., ZHAO, T. & KLEPEIS, N. E. 2022. Calibration of PurpleAir PA-I and PA-II Monitors Using Daily Mean PM2.5 Concentrations Measured in California, Washington, and Oregon from 2017 to 2021. Sensors, 22, 4741.

XU, J., SUN, W., SHIBATA, N. & ITO, M. GreenSwirl: Combining traffic signal control and route guidance for reducing traffic congestion. 2014 IEEE Vehicular Networking Conference (VNC), 3-5 Dec. 2014 2014. 175-182.

YANG, X., MCCOY, E., HOUGH, K. & DE NAZELLE, A. Evaluation of Low Traffic Neighbourhood (Ltn) Impacts on No2 and Traffic. Available at SSRN 4132059.

ZHU, Q., WANG, R., CHEN, Q., LIU, Y. & QIN, W. Iot gateway: Bridgingwireless sensor networks into internet of things. 2010 IEEE/IFIP International Conference on Embedded and Ubiquitous Computing, 2010. Ieee, 347-352.

Chapter 6: Conclusions

This thesis has investigated the role of novel IoT-enabled sensing technology in supporting enhanced particulate matter monitoring.

This has been achieved by investigating the following research goals, initially highlighted in Chapter 1:

1. Design, build and deploy a low-cost IoT enabled PM sensing device (Ch2)

2. Evaluating the performance of low-cost sensors and IoT adaptability (Ch2)

3. Developing scalable calibration methods for low-cost sensors (Ch2, Ch4)

4. Applying the use of low-cost sensors for meaningful insights into both indoor and ambient PM exposures (Ch3, Ch4)

5. Evaluating and presenting learnings and best practice for using and future proofing automated sensor data (Ch5)

In **Chapter 2**, a low-cost PM sensor (AltasensePM) was designed and deployed in a field calibration and evaluation (Cowell et al., 2022). The sensor was designed to be self-contained (battery powered and wireless communication using LPWAN IoT technology) to overcome some of the challenges of environmental sampling, such as power access and sensor mobility. In agreement with the literature around low-cost OPCs, the evaluation highlighted the impact of RH and PM composition on sensor performance (Crilley et al., 2018, Sayahi et al., 2019, Levy Zamora et al., 2019). The impact of meteorology and PM composition on the performance of AltasensePM was evaluated, and a multi-linear regression model was developed to correct the sensors using their internal humidity measurements. This calibration is site and seasonally specific- applying to the sources and meteorology experienced at the sensor during the study period. Applications of the sensors will need to consider the impact that differing sources of PM and changing meteorology will have on sensor performance, and the sensors are well suited to stable environments with known sources of PM and stable meteorology such as indoor environments. AltasensePM data live streams were hosted on the Birmingham Urban Observatory online platform. Here the calibrations could become automated procedures in real-time, allowing for live stream calibrated data to be available open access online for users. The data should some variation in performance over time- the study was not long enough to fully assess if this was drift, but when data was average out over a longer period the sensors performed well against averaged reference instruments. As there was uncertainty around drift, it was concluded that recalibration should occur regularly. The battery life of the AltasensePM device was limited to just over 8 weeks so a sampling routine of recalibration upon battery change was established. AltasensePM was designed to be semi-mobile, which meant that relocating units in and out of the field for calibration was practically straightforward, with the biggest challenge to this being the bureaucracy of permissions required to access the infrastructure upon which sensors were deployed.

The next two chapters applied the AltasensePM network to various air quality monitoring settings to assess concentrations and exposures. As a result of material delays and restrictions due to the Coronavirus pandemic, the AltasensePM network was first applied to an accessible indoor environment, a lockdown home., before being deployed (as per the original thesis plan) in the city environment.

Chapter 3 evaluated the sensor performance indoors, developing a scalable indoor calibration that overcame the limitations of a pandemic and practicalities of sampling in a home, and assessed residents' exposures to particulate matter associated to activity. Recognising that 1) humidity is much less likely to reach the high thresholds that trigger the multi-linear regression of an outdoor calibration

and 2) that sources and composition inside a home are different to those in an ambient setting, a different calibration method was needed to the one proposed in chapter 2 (Mousavi and Wu, 2021, Kim et al., 2019, Li et al., 2018). As installing a reference grade instrument such as FIDAS or gravimetric sampler was both limited by the pandemic and difficult in terms of practicality (size, noisiness to residents, staff requirements), the colocation used for calibration was instead against a portable laboratory grade instrument (TSI DustTrak). The sensor showed some indication of performance varying with activity and source type during the colocation. A polynomial model was used to calibrate sensors and the calibration method was unintrusive and suited to sampling in a real home environment. Residents continued typical activity throughout the study which was within a "typical" suburban home, with sensors in multiple rooms and outside of the property. This allowed for meaningful insights into indoor exposure at a typical UK home to particulates. It was recognised that when extrapolated to annual exposure levels 2021 WHO Global Air Quality guidelines (World Health Organisation, 2021) were exceeded in multiple rooms, with concentrations peaking at >400μgm^{-3} when cooking was occurring in the home. High temporal resolution of AltasensePM measurements allowed for insights into activity, including cooking and ventilation efforts. In agreement with the literature (Yin et al., 2022, Manga and Allen, 2022), external ventilation via opening windows or doors was found likely to reduce exposure to extreme high indoor $PM_{2.5}$ concentrations generated from activity such as cooking- although had uncertain impact on the overall mean concentrations. This presented an affordable method to reduce short term exposures to concentrations, which is particularly valuable during a period of increasing financial strain and high energy prices which may limit use of electrically powered extractor fans. Cooking activity also elevated concentrations in rooms other than the kitchen, and these rooms experienced longer periods before concentrations returned to baseline than the kitchen, likely due to ventilation efforts when cooking being focused on the kitchen rather than the alternate rooms. Overall, it was discovered that the AltasensePM could give indicative insight into exposures within a home with limited interruption to residents and could provide novel hyperlocal concentration estimates. The high temporal resolution of the sampler made it effective for detecting activity within a home, a limitation of gravimetric methods which tend to have sampling frequencies of hours-days. The semi-mobile and wireless design of the AltasensePM demonstrated the adaptability of the unit to monitor concentrations in an array of environments with minimal disruption. The future of IoT and smart home technology could lead to automated activity logging making studies even less work for residents, but there are concerns around the security and safety with online home monitoring.

Chapter 4 builds on the test deployment of chapter 2 and integrated the AltasensePM sensors within a wider network of commercial low-cost sensors and regulatory instruments across the city of Birmingham. Due to indications from both chapter 2, and the latest literature that the Plantower cannot distinguish PM_{10} accurately, analysis focused on $PM_{2.5}$. A data validation process was adapted from the literature (Mousavi and Wu, 2021, Lu et al., 2021, Bush et al., 2022) and after validation, low-cost sensors performed well against reference instruments and had good inter-sensor correlations during in-field colocations. The sensors performed particularly well in regional long-term averaging (as suggested from chapter 2), where the low-cost network estimated annual concentrations within 0.2μgm^{-3} of the regulatory network. There were some limitations to the low-cost sensor network, namely outage time due to power issues and bureaucracy restricting sensors data capture, which are reported as common issues with these types of environmental sensor networks (Jiao et al., 2016, Connolly et al., 2022, Johnston et al., 2019). There is uncertainty as to whether the sensors are sensitive enough to detect point sources which need further exploring. Whilst sensors could support UK efforts to increase the amount of monitoring in urban areas, this chapter highlighted the importance of representative sampling and site selection along side the need for increased numbers of sensors. More agile methods for calibration could assist in ensuring that low-cost sensors perform well against the array of sources they will experience in field deployments.

Chapter 5 evaluated the present state of low-cost sensors and their applications, considering the potential that high spatio-temporal resolution data streams could provide. Here, a wider view was taken to explore the utility of low-cost IoT monitoring in the context of smart cities and digital twins, assessing the potential (and challenges) of applying air quality data streams to real-time interventions and decision making. This chapter evaluated the best practice of metadata and data stream management. With a growing wealth of real-time air quality, meteorology and traffic data, the importance of standardised and complete metadata is vital to ensuring data can be used to its full potential (Syed et al., 2021, Schrotter and Hürzeler, 2020, Saddik, 2018). Whilst clear use cases were highlighted of how, if correctly interpreted, low-cost sensors could enhance decision making and support dynamic air quality interventions, there is not suitable data or practice to create a true digital twin of UK air quality at this stage. Low-cost sensing technology is not yet sensitive enough to create hyper-local management of traffic, but could support regional insights and resource management. Best practice moving forward will need to ensure legacy of low-cost sensing networks, including transparency of QA/QC methodologies and effective communication describing uncertainties in the data.

Table 1- summary of key findings and recommendations from within the thesis chapters

Chapter	Key findings	Recommendations
2	• AltasensePM device performs well against reference instrument following multi-linear calibration model and inter-sensor correlations are strong, over the limited period of data available. • The AltasensePM experiences fluctuation in performance against over time, likely due to the different PM compositions and meteorology experienced. • The Plantower is limited in its ability to measure PM_1 as a number of smaller particles fall outside of the sampler threshold of detection. • There is suggestion that the sensor is not independently measuring PM_{10} and is estimating concentrations from $PM_{2.5}$ fraction. • IoT technology performs well at allowing OPCs to communicate data in real-time. • This study gives insight into the raw data from low-cost sensors, including their fluctuating performance. The raw data from low-cost sensors isn't always provided when using commercial sensors, and insight into sensor performance can be lost behind undisclosed corrections and calibrations by commercial manufacturers. • The sensor limitations highlighted within this chapter propagate throughout the rest of the thesis and create limitations around potential applications of sensors.	• Despite short term fluctuations in sensor performance, they perform well when averaged out over longer time periods and thus are suited to generating longer term average concentrations. • Sensors are well suited to stable environments with regular sources and less meteorological fluctuation, such as indoor environments. • Future studies should assess drift in field deployments of the sensors for longer time periods (scale of months-years rather than weeks) as well as the impact of seasonal variation. • It is important to recognise that sensors performance will be affected by meteorology and particle composition and as such, site specific calibrations such as the one in this paper are going to be limited in their application in other environments and meteorological conditions. • Future studies should consider the best methods to test high frequency sampling from low-cost sensors against gravimetric methods as further tests of performance.

3	• Without reference grade instruments for calibration, sensors can give insight into home concentrations, detecting activity such as cooking and ventilation, although experienced similar limitations as outlined in chapter 2. • This chapter was subject to limitations due to the covid-19 pandemic which restricted access to equipment and limited sampling strategy. • Performance of the sensors against a reference instrument varied when different cooking types occurred, demonstrating how different PM sources and compositions affect performance. Sensor performance is driven by sources and inhabitant behaviour (rather than by sources and meteorology as in chapter 2). Sensor calibrations that capture all activities will perform differently against individual activities and sources, but will perform well over longer time periods of averaging. • External and mechanical ventilation was associated with reduction in extreme concentration peaks associated with cooking, in both the kitchen and adjacent rooms. • IoT technology is unintrusive and there is scope that smart home technology could automate the activity logging process for future studies.	• Ventilation efforts should be made throughout the house, not just in the room where an activity occurs. • Sensor calibration and validation periods should include an all activities that may occur during a study period to create the most effective training data for sensor performance. • Security and privacy needs to be considered in IoT monitoring, particularly within homes. • A limitation of current Sigfox communications is the limitation around how many messages can be sent in a day. Future indoor studies should consider options with higher message frequencies to allow for capturing the short lived activities that occur within homes. • This study doesn't evaluate the sensor locations within a room and how this may affect performance. As sensors performance changes by source, future studies should consider their objectives when designing sampling strategy and sensor locations within a room. Multiple sensors within a room, or investigation into changes in performance depending on sensor placement within a room could be a focus of future work.
4	• The term indicative is subjective- used to describe both set standards and colloquially, and it isn't always clear what is meant by the term. • Sensor network performed well at long term insights into PM- network-wide annual average $PM_{2.5}$ concentrations within 0.2μgm^{-3} of city regulatory stations annual average. • There are challenges around the deployment of low-cost sensors in real-world environments, with data outages, a need for more agile calibrations to combat the impact of varying sources on performance and challenging bureaucracy around deploying and maintaining a city wide network. • If these challenges are overcome, Low-cost sensors provide opportunity to support greater equity in air quality data, by offering a low-cost option for monitoring in previously overlooked	• Further colocation studies are needed at near source environments to test if sensors are sensitive enough to detect point sources. • Data validation processes should be tailored to the network context- users consider what would be expected from a data set before filtering data. • Low-cost sensors could support the UK guidance on increasing sampling sites, but focusing guidance on number of sites rather than location overlooks the importance of site selection for representative sampling. • The importance of location of sensors and designing networks with monitoring objectives in mind was highlighted in this chapter. This could also be explored in future studies by expanding to consider the optimal placement of reference and regulatory networks based off lessons

	neighbourhoods and regions with vulnerable populations.	learnt from sensor networks at spatial variation of pollution.
5	• Currently, the necessary metadata standards and Gemini Principles are not being met by air quality and other environmental live stream data. • Interoperability of live streams from various sources, including non air quality data is vital to ensure the success of future digital twins. • There are a number of applications in which live stream AQ data, including AltasensePM data has potential to support real-time air quality interventions but the sensing technology is not yet sensitive enough to realise these applications. • Currently a national digital twin for air quality is not feasible.	• Open-access and transparency around meta data needs to be fostered as standard for the full potential of digital twins to be realised. • Methods (such as online live stream repositories) for low-cost sensing networks needs to be established to ensure longevity of live-stream data, transitioning away from project based mindsets. • Integration of national and international datasets will be essential for any future digital twins, as the decrease in local sources such as road emissions will shift importance towards regional and boundary PM sources.

Looking forward, there is a considerable potential for low-cost sensors to be used to create a shift in how we interpret and respond to air quality concentrations. As the technology grows in popularity, particularly as part of a larger digital twin ecosystem, there is potential to assess air quality in previously unattainable ways. It is clear from this thesis and current literature that these sensors can be calibrated to perform well in various settings (if PM composition and meteorology are accounted for), and that IoT connectively can reliably communicate data. Whilst this thesis has focussed upon local ambient monitoring and in-home monitoring as use cases, there are many further applications which these sensors could be utilised due to their small footprint, un-intrusiveness and wireless design (including but not limited too; industry, mobile monitoring and other indoor applications such as healthcare settings and schools). The affordability and small stature of these sensors could provide unprecedented insight into these settings, helping support change for better public health. The potential for the livestream nature of these sensors has been demonstrated in chapter 5, however a major challenge to overcome is the longevity / durability of sensing networks (Chapman et al., 2023). For full potential to be reached, there needs to be a movement from demonstrator or project-based sampling to long-term reliable networks with secure funding for open-access data hosting and maintenance. Future development of this technology could also address the challenges around measuring coarser particles- new designs of samplers such as the PlantowerPMS5003 which are physically able to measure PM_{10} would enhance sampling further, especially in environments where natural dusts (aka from deserts/quarries) dominate particulate concentrations.

Finally, particulate matter is a growing problem and is arguably the pollutant of the future. As transport fleets transition towards non-combustion engines, the emissions of NO_x and CO_2, which have been the target of many historic air quality interventions, will be less significant. As such, particulate matter will continue to pose a challenge to policy makers. From non-exhaust transport emissions, to industrial, agricultural and domestic burning emissions, there will be a need to greater spatial understanding of PM concentrations for public health protection. This thesis has proposed technology that is able to support this monitoring need- and with further development the data will be ready for the digitised applications and interventions, considering the increasing role that big data, live streams and digital twins will play in future public health management.

References

BUSH, T., PAPAIOANNOU, N., LEACH, F., POPE, F. D., SINGH, A., THOMAS, G. N., STACEY, B. & BARTINGTON, S. 2022. Machine learning techniques to improve the field performance of low-cost air quality sensors. Atmospheric Measurement Techniques, 15, 3261-3278.

CHAPMAN, L., BELL, S. & RANDALL, S. 2023. Can crowdsourcing increase the durability of an urban meteorological network? Urban Climate, 49, 101542.

CONNOLLY, R. E., YU, Q., WANG, Z., CHEN, Y.-H., LIU, J. Z., COLLIER-OXANDALE, A., PAPAPOSTOLOU, V., POLIDORI, A. & ZHU, Y. 2022. Long-term evaluation of a low-cost air sensor network for monitoring indoor and outdoor air quality at the community scale. Science of The Total Environment, 807, 150797.

COWELL, N. H., CHAPMAN, L., BLOSS, W. & POPE, F. 2022. Field calibration and evaluation of an Internet of Things based particulate matter sensor. Frontiers in Environmental Science, 733.

CRILLEY, L. R., SHAW, M., POUND, R., KRAMER, L. J., PRICE, R., YOUNG, S., LEWIS, A. C. & POPE, F. D. 2018. Evaluation of a low-cost optical particle counter (Alphasense OPC-N2) for ambient air monitoring. Atmospheric Measurement Techniques, 709-720.

JIAO, W., HAGLER, G., WILLIAMS, R., SHARPE, R., BROWN, R., GARVER, D., JUDGE, R., CAUDILL, M., RICKARD, J. & DAVIS, M. 2016. Community Air Sensor Network (CAIRSENSE) project: evaluation of low-cost sensor performance in a suburban environment in the southeastern United States. Atmospheric Measurement Techniques, 9, 5281-5292.

JOHNSTON, S. J., BASFORD, P. J., BULOT, F. M., APETROAIE-CRISTEA, M., EASTON, N. H., DAVENPORT, C., FOSTER, G. L., LOXHAM, M., MORRIS, A. K. & COX, S. J. 2019. City scale particulate matter monitoring using LoRaWAN based air quality IoT devices. Sensors, 19, 209.

KIM, S., PARK, S. & LEE, J. 2019. Evaluation of Performance of Inexpensive Laser Based PM2.5 Sensor Monitors for Typical Indoor and Outdoor Hotspots of South Korea. Applied Sciences, 9, 1947.

LEVY ZAMORA, M., XIONG, F., GENTNER, D., KERKEZ, B., KOHRMAN-GLASER, J. & KOEHLER, K. 2019. Field and Laboratory Evaluations of the Low-Cost Plantower Particulate Matter Sensor. Environmental Science & Technology, 53, 838-849.

LI, J., LI, H., MA, Y., WANG, Y., ABOKIFA, A. A., LU, C. & BISWAS, P. 2018. Spatiotemporal distribution of indoor particulate matter concentration with a low-cost sensor network. Building and Environment, 127, 138-147.

LU, Y., GIULIANO, G. & HABRE, R. 2021. Estimating hourly PM2.5 concentrations at the neighborhood scale using a low-cost air sensor network: A Los Angeles case study. Environmental Research, 195, 110653.

MANGA, A. & ALLEN, C. Implications of a Natural Ventilation Retrofit of an Office Building. In: GORSE, C., SCOTT, L., BOOTH, C. & DASTBAZ, M., eds. Climate Emergency – Managing, Building , and Delivering the Sustainable Development Goals, 2022// 2022 Cham. Springer International Publishing, 137-148.

MOUSAVI, A. & WU, J. 2021. Indoor-Generated PM2.5 During COVID-19 Shutdowns Across California: Application of the PurpleAir Indoor–Outdoor Low-Cost Sensor Network. Environmental Science & Technology, 55, 5648-5656.

SADDIK, A. E. 2018. Digital Twins: The Convergence of Multimedia Technologies. IEEE MultiMedia, 25, 87-92.

SAYAHI, T., BUTTERFIELD, A. & KELLY, K. 2019. Long-term field evaluation of the Plantower PMS low-cost particulate matter sensors. Environmental Pollution, 245, 932-940.

SCHROTTER, G. & HÜRZELER, C. 2020. The Digital Twin of the City of Zurich for Urban Planning. PFG – Journal of Photogrammetry, Remote Sensing and Geoinformation Science, 88, 99-112.

SYED, A. S., SIERRA-SOSA, D., KUMAR, A. & ELMAGHRABY, A. 2021. IoT in Smart Cities: A Survey of Technologies, Practices and Challenges. Smart Cities, 4, 429-475.

TRYNER, J., MEHAFFY, J., MILLER-LIONBERG, D. & VOLCKENS, J. 2020. Effects of aerosol type and simulated aging on performance of low-cost PM sensors. Journal of Aerosol Science, 150, 105654.

WORLD HEALTH ORGANISATION 2021. WHO global air quality guidelines. Particulate matter (PM2.5 and PM10), ozone, nitrogen dioxide,

sulfur dioxide and carbon monoxide. Geneva.

YIN, H., LI, Z., ZHAI, X., NING, Y., GAO, L., CUI, H., MA, Z. & LI, A. 2022. Field measurement of the impact of natural ventilation and portable air cleaners on indoor air quality in three occupant states. Energy and Built Environment.

ZHONG, J., HOOD, C., JOHNSON, K., STOCKER, J., HANDLEY, J., WOLSTENCROFT, M., MAZZEO, A., CAI, X. & BLOSS, W. J. 2021. Using Task Farming to Optimise a Street-Scale Resolution Air Quality Model of the West Midlands (UK). Atmosphere, 12, 983.