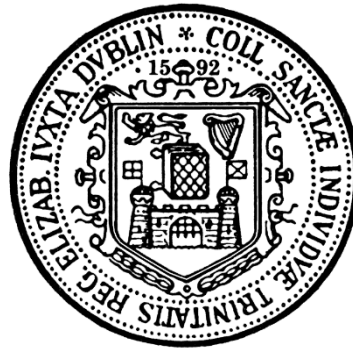




Trinity College Dublin
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**ASSESSING AIR QUALITY AND RELATED HEALTH IMPACTS IN URBAN SEMI-ENCLOSED
RAILWAY STATIONS: SOURCE ATTRIBUTION, MACHINE LEARNING APPROACH, AND
EXPOSURE ASSESSMENT**

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A thesis submitted in partial fulfilment of the requirements for the degree of

Doctor Of Philosophy

in

the Department of Civil, Structural and Environmental Engineering Trinity College Dublin,
the University of Dublin, Ireland

January 2026

Declaration

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Executive Summary

Air pollution in transport hubs presents a growing public health challenge due to concentrated emission sources and high commuter exposure. While airports and seaports have been extensively studied, urban railway stations, particularly those operating diesel-powered trains have received comparatively limited attention. This thesis aims to identify and attribute train-related pollutant sources within and near railway terminals and to examine how environmental factors and train operations influence pollutant levels within the terminal. Furthermore, the study estimates the associated health impacts on commuters and staff, as well as the potential economic savings associated with efficient train operations.

An initial study employed low-cost monitoring (LCM) devices for fixed-site monitoring near a railway station in Dublin, Ireland, to quantify ambient $\text{PM}_{2.5}$ and NO_2 concentrations and disaggregate contributions from railway operations and adjacent road traffic. Sensor data were calibrated using machine learning models, including Extreme Gradient Boosting (XGBoost) and Random Forest (RF) regression. XGBoost demonstrated superior performance (NO_2 : $R^2 = 0.80$, $\text{RMSE} = 9.1 \mu\text{g}/\text{m}^3$; $\text{PM}_{2.5}$: $R^2 = 0.92$, $\text{RMSE} = 2.2 \mu\text{g}/\text{m}^3$), highlighting its suitability for LCM calibration. Model interpretation showed that local wind conditions, atmospheric pressure, $\text{PM}_{2.5}$ concentrations, and road traffic intensity were the primary drivers of NO_2 variability, while raw sensor signals dominated $\text{PM}_{2.5}$ predictions. A one-month monitoring campaign revealed exceedances of the annual World Health Organization (WHO) guideline values by 1.6–1.8 times for $\text{PM}_{2.5}$ and 3.2–5.2 times for NO_2 . Wind-direction-based source apportionment identified the railway station as the main $\text{PM}_{2.5}$ source and road traffic as the dominant NO_2 contributor.

Following this, an examination of air quality at the same fixed monitoring site was undertaken over a longer monitoring period (June 2024–January 2025) using a statistical modelling approach. Generalised Additive Model (GAM) results demonstrated good model performance for $\text{PM}_{2.5}$ ($R^2 = 0.81$) and moderate performance for NO_2 ($R^2 = 0.73$). For NO_2 , background concentrations, wind direction, and wind speed emerged as the strongest drivers of variability. For $\text{PM}_{2.5}$, background $\text{PM}_{2.5}$ was the most influential variable, followed by meteorological factors such as temperature, humidity, and wind conditions, highlighting the important role of regional background pollution in influencing local concentrations.

To examine the sources of pollution within a semi-enclosed railway station environment, an investigation of continuous fixed monitoring was undertaken, to correlate to operational train

data. Fixed monitoring showed 24-hour average PM_{2.5} concentrations of 3.18–32.56 µg/m³ and 5.6–42.4 µg/m³, respectively, with Diesel multiple unit (DMU) trains dominated platforms exceeding WHO PM_{2.5} guideline values during approximately 90% of the monitoring period. NO₂ 24-hour averages ranged from 135.6 to 169.8 µg/m³, with 11–15% of hourly values exceeding the EU hourly guideline value. An XGBoost model was used to explain NO₂ variability achieved a moderate predictive performance ($R^2 = 0.61$; RMSE = 15.12 µg/m³) and identified ambient temperature and average train idling time as the most influential predictors. Partial dependence analysis indicated that reducing average idling time by two minutes could lower NO₂ concentrations by approximately 2.5 µg/m³ per train. Operational assessments suggested that shutting down engines when dwell times exceed 30 minutes, restarting 15 minutes prior to departure, and maintaining idle speeds below 600 RPM could reduce fuel consumption by 40–45%, save over 7,000 litres of diesel per month and approximately €12,140 per month in fuel costs, and decrease NO_x and PM emissions by approximately 54%.

A complementary characterisation study of exhaust and non-exhaust sources of PM_{2.5} in the semi-enclosed railway station environment was also embarked upon, using chemical speciation and receptor modelling techniques. The 24-hour PM_{2.5} concentrations at the station ranged from 15.1 to 19.6 µg/m³, exceeding the WHO guideline value of 15 µg/m³ but remaining below the proposed EU guideline value of 25 µg/m³. Chemical analysis showed that PM_{2.5} was dominated by carbonaceous matter (83–90%), followed by elemental species (8–12%) and ionic species (4–5%). Positive Matrix Factorisation (PMF) analysis identified four stable sources, with good agreement between modelled and measured PM_{2.5} concentrations ($R^2 = 0.87$). Train exhaust was the dominant contributor (80–85%), followed by secondary organic and inorganic aerosols (10–15%), sea salt aerosols (3–7%), and non-exhaust sources (2–3%).

Finally, health impacts were quantified using disability-adjusted life years (DALYs) and translated into economic losses for staff and commuters. The DALY analysis estimated that staff could lose up to 0.04 years (15 days) of healthy life annually, corresponding to an average monetary loss of €9,731 per staff member from combined exposure to PM_{2.5} and NO₂. Commuters experienced a DALY loss of 0.004 years (1 day) per year, corresponding to a total economic impact of approximately €6.25 million per year across all daily users. These findings highlight the importance of implementing practical, cost-effective measures, such as reducing train idling times, to improve air quality and minimize health risks.

This study outlines the importance and value of LCM devices and complementary monitoring and modelling techniques to improve our understanding of spatio-temporal conditions, pollutant sources and health risk in and around semi-enclosed train station, emphasizing the potential for evidence-based strategies to improve air quality and sustainability in semi-enclosed railway stations.

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Abbreviations

ADD	Average daily exposure dose	NH ₄ NO ₃	Ammonium Nitrate
AQ	Air quality	Ni	Nickel
Al	Aluminium	NO _x	Oxides of nitrogen
As	Arsenic	NO ₂	Nitrogen dioxide
Ba	Barium	NO	Nitrogen oxide
BC	Black carbon	NH ₄ ⁺	Ammonium ion
Ca	Calcium	NO ₃ ⁻	Nitrate ion
Cd	Cadmium	OC	Organic carbon
CR	Cancer risk	Pb	Lead
Cr	Chromium	PM	Particulate matter
CO	Carbon oxide	PEMS	Portable Emissions Measurement System
Co	Cobalt	PAHs	Polycyclic Aromatic Hydrocarbons
CO ₂	Carbon dioxide	PCA	Principal component analysis
Cl ⁻	Chloride ion	PNC	Particle number concentration
Cu	Copper	PMF	Positive matrix factorisation
DALY	Disability-adjusted life years	RF	Random Forest
DMU	Diesel multiple unit	SHAP	SHapley Additive Explanations
EC	Element carbon	SO ₂	Sulphur dioxide
EF	Emission factor	SO ₄ ²⁻	Sulphate ion
EU	European Union	Sb	Antimony
Fe	Iron	TEF	Toxic Equivalency Factor
FMS	Fixed Monitoring Station	TH	Transport Hubs
FTIR	Fourier-Transform Infrared	UFP	Ultrafine Particles
HC	Hydrocarbon	V	Vanadium
HI	Hazardous Index	VOCs	Volatile Organic Compounds
K	Potassium	WHO	World Health Organization
LTO	Landing and Take-Off	XGBoost	eXtreme Gradient Boosting
MDL	Minimum Detection Limit	Zn	Zinc
Mn	Manganese		
Na	Sodium		
NH ₃	Ammonia		
(NH ₄) ₂ SO ₄	Ammonium Sulphate		

1. INTRODUCTION

Air pollution problem is faced globally and has resulted in great economic and health loss (Manisalidis et al., 2020; Sivarethinamohan et al., 2021). Approximately 99% of the global population lives in areas where air quality (AQ) levels exceed the guideline values set by the World Health Organization (WHO, 2022). It is estimated that 4.2 million premature deaths were linked to exposure to outdoor air pollution worldwide in 2019 (WHO, 2022). There is a considerable amount of evidence on wide range of health effects associated with air pollution, which include premature mortality, impaired fertility outcomes, lower birth weight, cardiovascular and respiratory diseases, lung cancer and stroke (Chawala et al., 2023; Priyan et al., 2023).

The critical pollutants contributing to poor AQ in urban areas include particulate matter (PM), nitrogen dioxide (NO₂), sulphur dioxide (SO₂), volatile organic compounds (VOCs), and carbon monoxide (CO) (Perillo et al., 2022). Combustion processes directly emit one or more of these primary pollutants, whereas secondary pollutants such as ozone (O₃), peroxyacetyl nitrates (PANs), sulphuric acid (H₂SO₄), nitric acid (HNO₃), and secondary PM are formed through photochemical reactions involving precursor species, primarily nitrogen oxides (NO_x) and VOCs (Priyan et al., 2022). In addition to emissions from combustion sources, natural contributors such as soil dust, sea salt, and resuspended particles also play a role in urban air pollution (Karri et al., 2024).

Understanding urban form and the contribution of pollution between different sources is important to inform decision making for recommending pollution mitigation measures that protect human health (Deshmukh et al., 2020). Pollutant concentrations are not uniformly distributed across urban environments, often resulting in localized hotspots near traffic intersections, major roadways, industrial zones, transport hubs (THs), and central business districts. Furthermore, variations in meteorological and topographical conditions also influence the spatial distribution of pollutant concentrations within urban areas (Gulia et al., 2015).

One of the major combustion-related sources of urban air pollution is the transport sector, in addition to industrial and commercial emissions (Gulia et al., 2015). Although considerable attention has been directed toward reducing vehicular emissions at the urban scale, THs such as airports, ports, bus terminals, and train stations often serve as localized hotspots of air pollution. While THs facilitate the mass movement of people and goods, they can also

generate substantial quantities of emissions (Priyan et al., 2024). In particular, train stations are of significant concern, as they act as point sources within cities and expose large numbers of people to elevated pollutant levels on a daily basis (Priyan et al., 2025).

While AQ in Ireland is generally good compared to other European countries, its capital city Dublin has still promoted a recent 2021 city level AQ Plan to address pollution as an exceedance in NO₂ was observed in 2019 (Dublin City Council, 2021). Recent research has reported increased short-term admission for respiratory and cardiovascular diseases due to poor ambient AQ (Quintyne & Kelly, 2023). In comparison to other transport modes, the rail sector contributes a relatively small share to national transport emissions in Ireland (approximately 1%) (Energy Ireland, 2023). However, it is a major contributor to air pollution hotspots, particularly in the railway stations, due to the use of diesel-powered trains. Railway stations in Ireland present a unique case study within the European context because of their roofed design with semi-enclosed platforms that host a large proportion of diesel-powered trains. Although the public typically spends only a limited amount of time at train stations, exposure to high levels of pollution over short periods can still have a significant impact on their health. In contrast, rail staff are likely to face a much higher health risk due to their prolonged occupational exposure, when spending a significant amount of time within the station environment. Therefore, impacts of diesel train emissions on local ambient and indoor station air in Ireland require further research.

1.1 Problem Definition

In 2019, EPA continuous monitoring stations located in the local environment of the three major train station terminals (e.g., Connolly, Heuston, and Pearse Street) in Dublin have recorded exceedances of NO₂ (UTRAP, 2021). All three locations are major railway hubs, where heavy rail, public transport services such as buses and taxis, and private cars intersect. In addition, concentrations inside Connolly Station were reported to be more than EU NO₂ guideline values (Government of Ireland, 2021). The train terminals in the city host diesel trains that emit significant amounts of pollutants while operating at the platforms. Also, the terminals are enclosed which further accumulates the pollutant levels.

1.2 Aim & Objectives

This research study aims to identify and attribute train-related pollutant sources both near and within the terminal, and to examine how environmental conditions and train operations influence pollutant levels inside the terminal. In addition, the study seeks to estimate the associated health impacts on commuters and rail staff, as well as the economic losses resulting from inefficient train operations. To achieve this aim, the following objectives have been outlined:

- Calibration of the low-cost AQ devices using machine learning techniques such as random forest modelling and extreme gradient boosting.
- Detection and quantifying train and road traffic emission contribution to $\text{PM}_{2.5}$ and NO_2 in the vicinity of train terminal using generalised additive model and data filtration method.
- Characterizing the impact of influencing factors such as train traffic, idling time, engine power and ambient conditions on AQ within the station using extreme gradient boosting.
- Chemical characterisation of PM and quantification of exhaust and non-exhaust sources of PM within the station using receptor modelling.
- Estimation of potential health impacts and associated economic losses for commuters and rail staff using the DALY approach.

1.3 Outline of the Thesis

Chapter 1: Problem definition, aim, and objectives of the study.

Chapter 2 Provides a brief introduction to air pollution, including the different criteria air pollutants, their sources, and associated health effects. It further discusses the research gaps related to the types of pollutants studied and their sources and evaluates the effectiveness of existing source apportionment approaches in transport hub (TH) settings such as ports, airports, and train and bus terminals. The third section of the chapter reviews health impact studies conducted in these settings. The fourth section discusses the different calibration techniques used to calibrate low-cost air quality monitoring devices.

Chapter 3: The study area considered in this research, followed by a description of the EPA air quality station used in the analysis.

- Chapter 4:** Air quality and meteorological instruments used in this study
- Chapter 5:** Evaluation of low-cost air quality monitoring devices, including the derivation of correction factors and calibration models.
- Chapter 6:** Levels of $\text{PM}_{2.5}$ and NO_2 inside the Heuston terminal. It also focuses on detecting and quantifying the contributions of train and road traffic emissions to PM and NO_2 in the vicinity of the terminal.
- Chapter 7:** Estimating emissions from train and road traffic and on characterising $\text{PM}_{2.5}$ and NO_2 sources in the vicinity of the terminal based on long-term measurements.
- Chapter 8:** Levels of $\text{PM}_{2.5}$ and NO_2 inside the Dublin Connolly. It also focuses on characterising the impact of train idling, along with other contributing factors such as train traffic, engine power and ambient conditions, on NO_2 levels within the station.
- Chapter 9:** Estimate fuel consumption and emissions resulting from excessive train idling, as well as the potential economic savings associated with more efficient train operations.
- Chapter 10:** Chemical characterisation of $\text{PM}_{2.5}$ and quantification of exhaust and non-exhaust sources of $\text{PM}_{2.5}$ within the station using Positive Matrix Factorisation (PMF).
- Chapter 11:** Short-term commuter and occupational $\text{PM}_{2.5}$ concentrations, along with the associated potential health impacts assessed using the DALY approach and the corresponding economic losses.

2. LITERATURE REVIEW

Part of this chapter has been published in Atmospheric Pollution Research ([DOI: 10.1016/j.apr.2025.102709](https://doi.org/10.1016/j.apr.2025.102709)). The candidate is a co-first author, and the content related to air pollution characteristics in THs, and the source apportionment methods applied in THs was conceived, analysed, and written by the candidate.

2.1 Air Pollution, Sources and Health Effects

2.1.1 Air pollutants

Air pollutants consist of both gaseous and particulate contaminants present in the atmosphere. Gaseous pollutants include sulphur dioxide (SO₂), nitrogen oxides (NO_x), nitrogen dioxide (NO₂), nitrogen oxide (NO), ozone (O₃), carbon monoxide (CO), volatile organic compounds (VOCs), and gaseous forms of metals (Holman, 1999). Particulate pollution, commonly categorized as PM_{2.5} (particle size less 2.5µm) and PM₁₀ (particle size less than 10µm), is composed primarily of elemental (black) carbon, organic carbon, inorganic ions (such as sulphates and nitrates), heavy metals, elements and crustal materials (Karri et al., 2024). Air pollutants enter the atmosphere in two main forms, primary and secondary pollutants.

Primary pollutants are emitted directly from anthropogenic sources such as transport sources, industrial process, residential combustion, agricultural activities, waste management, construction activities and as well as from natural sources, including wind-blown dust, sea salt aerosols, volcanic activities, forest fires and, biogenic emissions from vegetation (Kuebler et al., 2001).

Secondary pollutants are not emitted directly, rather, they are formed in the atmosphere through chemical transformations of primary pollutants. For instance, ground-level ozone is produced when nitrogen oxides (NO_x) and volatile organic compounds (VOCs) undergo photochemical reactions in the presence of sunlight (Kuebler et al., 2001; Priyan et al., 2022). While secondary particles are formed through atmospheric reactions involving gaseous precursors such as nitrogen oxides (NO_x), ammonia (NH₃), sulphur dioxide (SO₂), and non-methane volatile organic compounds (NMVOCs) (Pye et al., 2022). The NMVOCs should also be recognised as short-lived climate forcers, as they contribute significantly to near-term climate warming through strong radiative forcing (Fry et al., 2014). Their mitigation is therefore

particularly important because reductions can deliver simultaneous benefits for both public health and climate protection.

The WHO identified and regulated five major pollutants known as the criteria air pollutants. These include carbon monoxide (CO), nitrogen dioxide (NO₂), ozone (O₃), particulate matter (PM₁₀ and PM_{2.5}), and sulphur dioxide (SO₂). These pollutants were the first to be regulated due to their prevalence in the environment and their established impacts on human health and the ecosystem (WHO, 2021).

2.1.2 Sources and health effects of criteria air pollutants

2.1.2.1 PM₁₀ and PM_{2.5}

PM₁₀ and PM_{2.5} are defined as dispersed solid or liquid particles in the atmosphere with aerodynamic diameters smaller than 10 µm and 2.5 µm, respectively (Monn et al., 1997). Unlike gaseous pollutants, PM₁₀ and PM_{2.5} are not single chemical entities but complex and dynamic mixtures (Li et al., 2023). Their composition varies spatially and temporally, depending on emission sources, pathways of formation, and prevailing meteorological conditions. For instance, PM concentrations are not uniformly distributed within urban areas, leading to hotspots at traffic intersections, major roads, and central business districts (Gulia et al., 2015). Variations in meteorological and topographical factors further influence the spatial and temporal distribution of PM (Chawala et al., 2023).

The emission sources also reflect its chemical composition. Particles emitted from industrial combustion of high-sulphur fuels contain elevated levels of vanadium (V) and nickel (Ni) (Corbin et al., 2018). PM from wildfires and agricultural burning is typically enriched in OC and potassium (K) ions, whereas emissions from trains and ships at idling conditions exhibit high OC/EC ratios (Bessagnet et al., 2022). Desert storms and soil dust contribute particles rich in silica and aluminium (Liu et al., 2022).

PM can also form through secondary pathways in the atmosphere and is classified into inorganic and organic secondary particles. Secondary inorganic aerosols are produced via homogeneous and heterogeneous reactions of NO_x and SO₂ in the gas or aqueous phase (Ting et al., 2024). These particles are commonly observed as ammonium sulphate (NH₄SO₄) and ammonium nitrate (NH₄NO₃) (Wang et al., 2020). Due to their relatively long atmospheric residence time, typically 3 to 9 days, secondary inorganic aerosols can be transported over long distances (Manavi et al., 2025).

Secondary organic aerosols are generated through complex oxidation reactions of non-methane volatile organic compounds (NMVOCs), often in combination with primary organic compounds emitted from the combustion of fossil fuels, coal, and biomass (Růžicková et al., 2022). NMVOCs also play a crucial role in the formation of ground-level ozone via photochemical reactions with NO_x (Kuebler et al., 2001).

PM is associated with a wide spectrum of acute and chronic health effects, including cardiopulmonary diseases and lung cancer (Xing et al., 2016). Globally, PM exposure is estimated to contribute to approximately 1% of respiratory infections, 5% of cardiopulmonary deaths, and 9% of lung cancer deaths. Fine particles, particularly those carrying chemically bound compounds, are considered the primary drivers of these health impacts (Chen & Hoek, 2020; Passi et al., 2021). Polycyclic aromatic hydrocarbons (PAHs), which are often adsorbed onto PM, are of particular concern due to their highly toxic, mutagenic, and carcinogenic properties (Bessagnet et al., 2022). Consequently, PAHs are commonly used as indicators in health risk assessments related to particulate air pollution (Bodor et al., 2022).

2.1.2.2 NO_2

Nitrogen dioxide (NO_2) is a reddish-brown gas with a sharp odour and is a significant air pollutant due to its role in the formation of photochemical smog and tropospheric ozone (WHO, 2024a). These secondary pollutants have considerable impacts on human health, including exacerbation of respiratory diseases (Chen et al., 2024). The primary source of NO_2 is transport emissions in urban areas, beside industrial processes, residential heating and power generation (Casquero-Vera et al., 2019). Elevated concentrations of NO_2 can reduce visibility and increase the risk of both acute and chronic respiratory illnesses (Xiaoshi et al., 2024).

2.1.2.3 CO

Carbon monoxide (CO) is an odourless and colourless gas primarily produced by the incomplete combustion of carbon-containing fuels (WHO, 2024a). Vehicular emission is the largest contributor in urban areas, followed by industrial combustion, residential heating, and emissions from aircraft and ships (Aminzadegan et al., 2022). Inhalation of CO reduces the blood's oxygen-carrying capacity, and exposure to high concentrations can result in headaches, dizziness, unconsciousness, or even death (Afzal et al., 2025).

2.1.2.4 O₃

Tropospheric, or ground-level, ozone (O₃) is a secondary pollutant formed through photochemical reactions between NO_x and VOCs in the presence of sunlight (WHO, 2024a). Major sources of these ozone precursors include automobile exhaust, industrial emissions, power plants, household products such as paints and solvents, and natural VOC emissions from vegetation (Wang et al., 2024). Ozone concentrations typically peak during the afternoon, when sunlight is most intense and temperatures are higher, which enhances the rate of photochemical reactions (Priyan et al., 2023). Elevated ozone levels can cause eye irritation, aggravate respiratory conditions, and damage vegetation and other ecosystems (Zhang et al., 2019).

2.1.3 Global air pollution

Outdoor air pollution remains a serious concern in cities throughout the world. According to the WHO, 99% of the world's population lives in places where air quality levels exceed WHO guideline values, exposing them to unhealthy air pollution that increases disease risk (WHO, 2024b). Among the air pollution, the fine particulate matter has the greatest effect on human health. The PM_{2.5} and PM₁₀ concentrations in many of the megacities across the globe are exceeding the safety standards specified by the WHO by a factor of three or more. In 2021, ambient (outdoor) air pollution was estimated to cause around 8.1 million premature deaths worldwide, with over 90% of these deaths linked to PM_{2.5} exposure (UNICEF, 2024). Figure 2.1 shows the worldwide distribution of death rate due to exposure to PM.

2.1.4 Air pollution in Ireland

Outdoor air pollution remains a significant public health issue in Ireland, particularly in urban centres. AQ in Ireland is generally good compared to other European countries, it's capital city Dublin has still promoted a recent 2021 city level AQ Plan to address pollution as an exceedance in NO₂ was observed in 2019 (Dublin City Council, 2021). It is estimated that approximately 1,700 premature deaths annually in the Republic of Ireland are attributable to exposure to air pollution, including around 680 deaths from cardiovascular disease (Irish Heart Foundation, 2023). The mortality burden of air pollution is highest in Dublin, although attributable deaths occur across all counties in Ireland (Irish Heart Foundation, 2023). The air pollutants of most concern in Ireland are NO₂ and PM_{2.5} (EPA Ireland, 2023). In Ireland, the

annual guideline value for NO₂ is 40 µg/m³, in accordance with EU AQ standards. Monitoring data published in September 2020 indicated that Dublin exceeded this guideline value, with an annual average NO₂ concentration of 43 µg/m³ recorded for 2019 (UTRAP, 2021). The main source of NO₂ in urban areas is road transport, particularly due to the dominant fleet of diesel vehicles, which emit substantially higher levels of NO₂ compared to petrol engines (Mahesh et al., 2023). Elevated NO₂ concentrations are also observed near train stations in urban centres, where diesel-powered trains are commonly operated. In both urban and rural areas, residential heating, especially the use of solid fuels such as wood, coal, and peat, represents a significant source of both NO₂ and PM_{2.5}, particularly during the winter months (Gallagher, 2021).

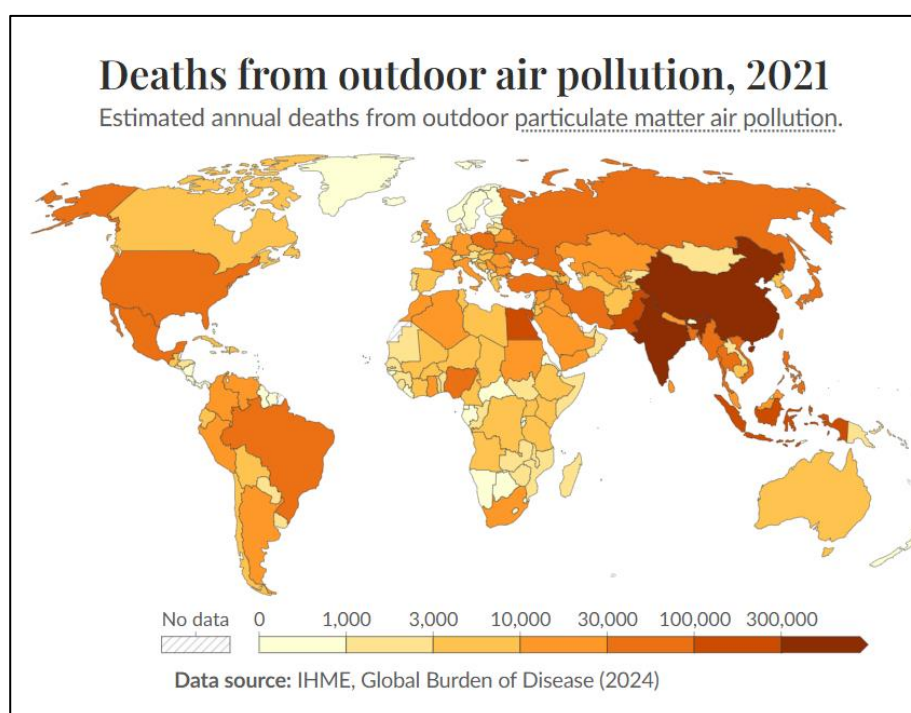


Figure 2.1. Worldwide distribution of deaths attributable to exposure to particulate matter (PM), shown as the absolute number of deaths by country (IHME, Global Burden of Disease, 2024).

2.1.5 Air pollution from Rail

Rail is considered as a greener mode of transport when compared with air and road as it has a lower rate of emissions per passenger and thus a lesser relative impact on climate change and the environment (Font et al., 2020). The entire transportation industry is responsible for around 22% of worldwide emissions (Railway Technology, 2016), with railway transport only

accounting for 0.8% of the sector. However, railway services, specifically powered by diesel emit significant amount of air pollutants along their routes and while stationed. In the European union (EU-27), diesel trains contribution to the mobile sources of PM_{2.5}, black carbon, and nitrogen oxides emissions were estimated to be 2.8%, 2.5% and 2%, respectively (Borken-kleefeld & Ntziachristos, 2012).

The concentration of air pollutants in the vicinity and within railway terminals is influenced by the emissions from the trains; these includes NO₂ and PM from the diesel-powered train exhaust at idling and notch 1 condition (accelerating and deaccelerating in station) (Ozigis et al., 2021), and particles generated by wheel and brake wear of the train (Font et al., 2020; Hickman et al., 2018). The emissions from diesel trains are lower during idling than during the notching operation (Vojtisek-Lom et al., 2020). However, still the idling emissions are significant. The PM₁₀, NO_x, CO, and Hydrocarbon (HC) emissions from diesel locomotives during idling were estimated to be 43.4 mg/m³, 147 ppm, 94 ppm, 4.3 ppm, respectively whilst during notch 1 condition were found to be 60 mg/m³, 243 ppm, 53 ppm, 4 ppm, respectively (Kim et al., 2020). In addition, train emissions, eateries, and the resuspension of dust from commuters and train movement are also sources of emissions (Priyan et al., 2024).

About 60% of the European rail network is already electrified with 80% of the train traffic running on these lines (European Commission, 2023). However, in Ireland, only 2% of railway lines are equipped with electrification ranking it lowest in Europe (European Commission, 2023). The impacts of diesel trains on AQ within railway terminals and in the surrounding environment also require further research. Irish Rail has articulated a strategic pathway to achieve a 51% reduction in emissions by 2030 (Iarnród Éireann, 2023). This target is to be met through a progressive reduction in reliance on diesel propulsion, facilitated by the deployment of alternative fuels and the phased transition to electric and hybrid-powered train fleets (Iarnród Éireann, 2023).

Many studies have reported AQ in subway systems (e.g. Grana et al., 2017; Kim et al., 2008; Martins et al., 2016; Passi et al., 2021; Vilcassim et al., 2014). Their focus has been on assessing the PM₁₀, PM_{2.5} and ultrafine particles (UFP) concentrations and their sources in the subway network, where there is a sole presence of non-exhaust emission in the absence of diesel-powered trains. Only four studies have been performed in ground level railway station environments, all of which were conducted in the UK: in Birmingham New Street (Hickman et al., 2018); in London Paddington (Chong et al., 2015); and in Edinburgh Waverley and London King's Cross stations (Font et al., 2020).

2.1.6 Summary

This chapter outlined the major air pollutants, their sources, and associated health impacts, with a particular focus on fine PM_{2.5} and NO₂. Globally, PM_{2.5} is responsible for major air-pollution-related mortality, contributing to over 90% of the estimated 8.1 million premature deaths attributed to ambient air pollution in 2021.

In Ireland, air quality is generally good compared to other European countries; however, air pollution remains a significant public health concern. Approximately 1,700 premature deaths annually are attributed to air pollution, with NO₂ and PM_{2.5} identified as the pollutants of greatest concern. In Dublin, annual mean NO₂ concentrations exceeded the EU guideline value of 40 µg/m³ in 2019, reaching 43 µg/m³, largely due to emissions from diesel-powered road transport.

The impacts of diesel train operations on air quality within railway terminals and in the surrounding environment in Ireland require further investigation, particularly given that only 2% of the national rail network is electrified. However, only a limited number of air pollution studies have been conducted at ground-level train stations. Therefore, studies conducted at other transport hubs are reviewed in the next chapter to identify methodologies that may be transferable to Ireland's uniquely enclosed train station environments.

2.2 Identifying air pollution characteristics, source apportionment methods in the settings

In-depth knowledge of AQ levels and source characteristics is crucial for developing effective AQ management strategies to ensure a healthy environment within and around train stations. Due to lack of AQ studies on ground level train stations, a systematic literature review of studies conducted in THs such as ports, airports and bus terminals, since 2005, aiming to identify research gaps related to the types of pollutants studied, and their sources, as well as to evaluate the effectiveness of existing source apportionment approaches in these settings. The primary objective of this review is to identify methodologies applied in THs that could be transferable to Ireland's unique enclosed train station environments. However, abovementioned four studies performed at ground train station were also included in the review.

The review summarizes current knowledge on various air pollutants and their typical concentrations and assesses different methods for quantifying and identifying source

contributions, considering their cost-effectiveness, efficiency, feasibility, and practicality in THs.

2.2.1 Search strategy

A substantial number of research articles related to AQ assessment using monitoring and/or source apportionment assessments performed in, and around different THs were examined in this review. Articles published between 2005 and 2024 were considered. Database searches for each TH were performed separately. Keyword combinations for each TH setting e.g. “airport” was paired with the following words/terms “particulate”, “monitoring”, “dispersion modelling”, “air pollution”, “assessment”, “effect”, “prediction”, “source apportionment”, “measurement”, “vicinity”, “neighbourhood”, “terminal”, “platform”, “nitrogen dioxide”, “sulphur dioxide”, and “carbon monoxide” were used in different combinations and coupled with Boolean operators (“AND”, “OR”, and “NOT”) to optimise the search strategy. A total of 4,103 research articles were accessed through Google Scholar, Web of Science, and Scopus. All duplicates were removed after the search completion. The literature search was completed in December 2024.

Studies focusing on underground train stations were omitted from this review as the monitoring methodologies applied were different due to the indoor setting that is reflective of undergrounds, whilst airport, port, train and bus terminals are governed more by outdoor physical and environmental characteristics. In addition, studies that adopted secondary emission factors for emission inventories and did not directly monitor or model TH conditions were excluded from this study.

2.2.2 Data inclusion, extraction, and analysis

Table 2.1 presents the inclusion and exclusion criteria of the systematic literature review. A total of 111 articles were considered. For each article, details relating to the pollutants measured, pollutant concentrations, location of the study, modelling and source apportionment techniques, and the measurement period were extracted for all four TH types. Detail on the inclusion and exclusion criteria is shown in Figure 2.2. For ports and airports, the review focuses on outdoor environment and the surrounding vicinity. For bus and train terminals, the review considers semi-enclosed indoor environment and the surrounding vicinity. The pollutant concentrations reported in different THs were analysed and compared.

Furthermore, source apportionment techniques used in studies to quantify the contribution of TH emissions, as well as the modelling approaches employed to examine the distribution of pollutant concentrations around TH, were discussed.

2.2.3 Air pollution characterisation in different TH

The geographical distribution of the AQ studies performed at THs are presented in Figure 2.3. Most of these were performed in Europe followed by Northern America and China. A large number of studies has been performed assessing the AQ impacts in the vicinity of large-scale THs such as ports and airports, yet only a limited number of studies have focused on AQ in and around smaller semi-enclosed THs, such as bus and train terminals. Also, there is a significant research gap in assessing the building indoor AQ in ports and airports. Figure 2.4 and Figure 2.5 presents the concentrations (averaged over their study period) of major pollutants reported in the vicinity of and within the TH environments, respectively. PM₁₀, PM_{2.5}, and NO₂ are commonly reported criteria pollutants across all THs, while UFP and TVOCs are measured at airports and SO₂ is measured at ports. The averaging periods of pollutants vary between studies; therefore, their concentrations were not compared to regulatory standards.

The comparison of PM concentrations at different THs show that average PM₁₀ concentrations were found higher at bus terminals (36.8±11.2 to 210±75.2 µg/m³) whereas average PM_{2.5} were dominant in port open areas (12.4±5.4 to 147.8±55.5 µg/m³) (Cheng et al., 2012; Hagler et al., 2021; Hickman et al., 2018; Ledoux et al., 2018; Nogueira et al., 2020). High PM₁₀ concentrations were observed at bus terminals in Asian and South American cities, whereas higher PM_{2.5} concentrations in port studies were primarily observed in China. The high concentrations of PM₁₀ in bus stations in Asian and south Asian cities were mainly attributed to resuspension of road dust due to continuous movement of buses, rather than direct exhaust and non-exhaust emissions sources (Loyola et al., 2009; Qiu et al., 2016). High PM_{2.5} concentrations in port open areas was linked to road traffic emissions from inside the port in Chinese cities (Ducruet et al., 2024; Kotowska & Kubowicz, 2019).

Table 2.1. Inclusion/exclusion criteria for studies considered within the scope of the systematic literature review.

Metric	Inclusion criteria	Exclusion criteria
1.Species	Contains gaseous pollutants and PM	Contains noise & thermal comfort.
2.Data type	Contains below listed data type • Ambient air concentration in the vicinity of TH • Ambient AQ within the TH • Semi-enclosed indoor AQ in the TH • Sources associated with TH. • Emissions based on measurements • Dispersion AQ modelling • Numerical modelling • CFD modelling • Emission modelling • Regional modelling	Does not contain listed data of interest. Exclusions include e.g., • Global modelling • Estimating emission inventory (based on secondary literature emission factors)
3.Transport hub	• Commercial and general aviation • Commercial & cargo ports • Bus Terminal • Train Terminal	• Airports such as military base • Inland ports, fishing ports and docks • Roadside bus station • Intermediate train station & UG subway station
4.Distance from transport hub	Radius of 20 km from the TH – monitoring Square domain up to 50 km with TH as centre – modelling	> 20 km radius from the TH – monitoring > 50 km square domain with TH as centre - modelling

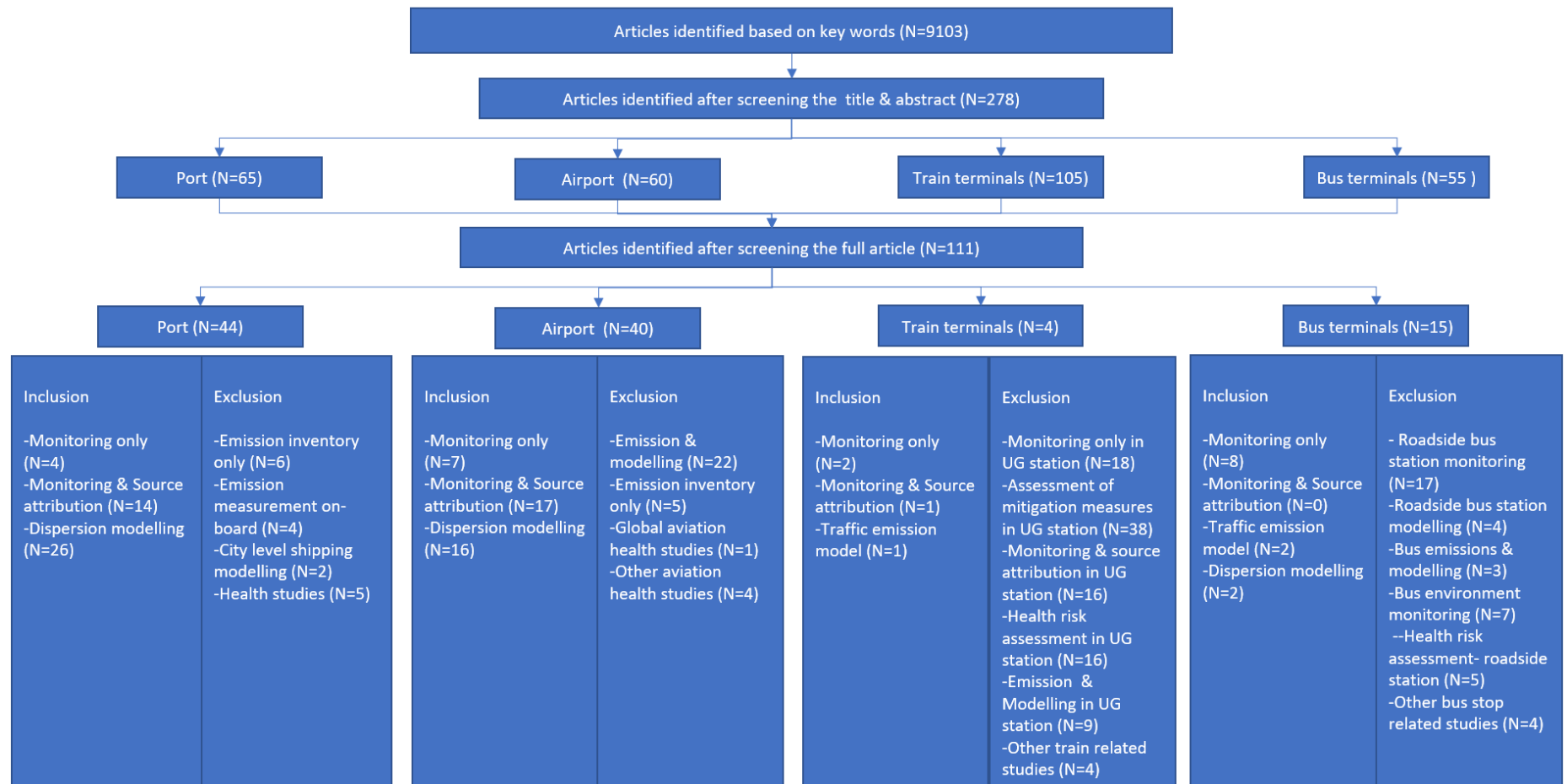


Figure 2.2. Overview of inclusion and exclusion process undertake to identify appropriate publications for each transport hub within the systematic literature review.

The average NO₂ concentrations were predominantly high in train terminal investigations (52.2±4.6 to 472.5±50.2 µg/m³), specifically from findings of studies performed in the United Kingdom (London, Paddington, Edinburgh & Birmingham) (Chong et al., 2015; Font et al., 2020; Hickman et al., 2018). The terminals in these cities host diesel trains which emit significant NO₂ during idling conditions (Chong et al., 2015; Font et al., 2020). Also, the terminals are semi-enclosed which further exacerbates NO₂ concentrations. NO₂ levels were found to be higher on the train station platform, followed by the concourse.

Almost all studies performed at ports reported SO₂ concentrations due to the use of high sulphur content in marine fuel used by ships. Average SO₂ levels in the studies ranged between 2.62±1.0 to 78.2±7.5 µg/m³. High SO₂ levels (54.1±7.7 to 78.3±17.2 µg/m³) were predominantly observed at ports in China. Low concentrations (2.62±1.0 to 14±3.1 µg/m³) were observed in the studies performed in European ports after 2016. This may reflect the implementation of the EU directive allowing low-sulphur content (0.10%) in marine fuel at berth.

A maximum sulphur content of 0.10% in marine fuels has been enforced since 2015 in Emission Control Areas (ECAs), including the Baltic Sea, North Sea, and coastal regions of North America and the Caribbean. Outside ECAs, the sulphur limit is restricted at 0.5%. Since 2020, the International Maritime Organization (IMO) has mandated a global sulphur limit of 0.5%, reduced from the previous limit of 3.5% (IMO, 2020).

Limited studies have reported on VOCs in THs, and their concentrations were considerably higher in airports (123±41.1 to 973±113.3 ppb). VOCs at airports are mainly released from aircraft exhaust, fuel handling and ground support vehicles (Chen et al., 2024). The highest concentrations of VOCs were observed during aircraft idling, ignition, and taxiing conditions (Masiol & Harrison, 2014). The most abundant VOC species detected at the airport are toluene, m,p-xylene, styrene, o-xylene, and i-pentane. Toluene (14±1.7 to 94±21 ppb) shows the highest concentration, suggesting emissions mainly from light-duty gasoline engines. Moreover, toluene has a relatively lower photochemical reactivity compared to other VOC compounds (Fukusaki et al., 2021; Zhu et al., 2023). The presence of m,p-xylene, styrene, o-xylene, and i-pentane indicates typical fuel-related constituents. Similarly, the port area is dominated by VOC species such as toluene, acetone, m,p-xylene, n-butane, and o-xylene, primarily emitted from vehicle and ship activities (Ahmed et al., 2021).

In terms of PAH levels, only a few studies have reported their concentrations. Total PAH concentrations in the vicinity of Los Angeles Airport ranged from 37±10 to 124±40 ng/m³,

whereas a study conducted at Fiumicino Airport reported levels ranging from 1.0 ± 0.6 to 4.3 ± 1.8 ng/m³ within the airport area (Vichi et al., 2016; Westerdahl et al., 2008). Benzo(b)fluoranthene, Benzo[a]pyrene, Benzo[e]pyrene, and Benzo[ghi]pyrene have been identified as the dominant PAH species in airport, primarily bound to ultrafine particles and emitted from combustion exhaust (Rodríguez-Maroto et al., 2024). At a bus terminal in Singapore, total PAH concentrations ranged from 1.6 ± 1.1 to 2.6 ± 1.4 ng/m³, with benz[a]anthracene identified as the dominant species (Lee et al., 2022).

BC has been more extensively studied at airports compared to other THs. Reported BC concentrations at airports range from 0.34 ± 0.3 to 3.5 ± 1.4 µg/m³, with higher levels observed near runways and terminals (Stacey et al., 2021; Targino et al., 2017). The primary sources of BC in airports are aircraft exhaust and ground support equipment. In port areas, BC concentrations range from 0.4 ± 0.3 to 2.6 ± 1.4 µg/m³. BC, along with SO₂ and vanadium (V), can serve as tracers for apportioning ship emissions in and around ports (Hagler et al., 2021; Wang et al., 2019). More studies should focus on characterising the levels of VOCs, BC and PAHs, as well as to develop strategies for mitigating these pollutants in the THs, given their significant impacts on climate change and human health.

UFP is another pollutant consistently reported in the airport's vicinity. Elevated levels of UFP ($5.0 \pm 1.2 \times 10^3$ to $4.8 \pm 1.3 \times 10^6$) are consistency found in the vicinity of airports compared to within airport itself, owing to landing and take-off (LTO) operation (Stacey et al., 2021; Riley et al., 2016). Traces of UFP during LTO activities were found up to 7.3km downwind of the airport (Hudda et al., 2016). In bus terminals, UFP concentrations range from $2.4 \pm 1.5 \times 10^4$ to $19.6 \pm 7.6 \times 10^4$ particles/cm³, with significantly higher levels in terminal areas compared to indoor environments (Cheng et al., 2012). All pollutant concentrations reported in the vicinity of a TH were considerably lower than concentrations measured within TH itself.

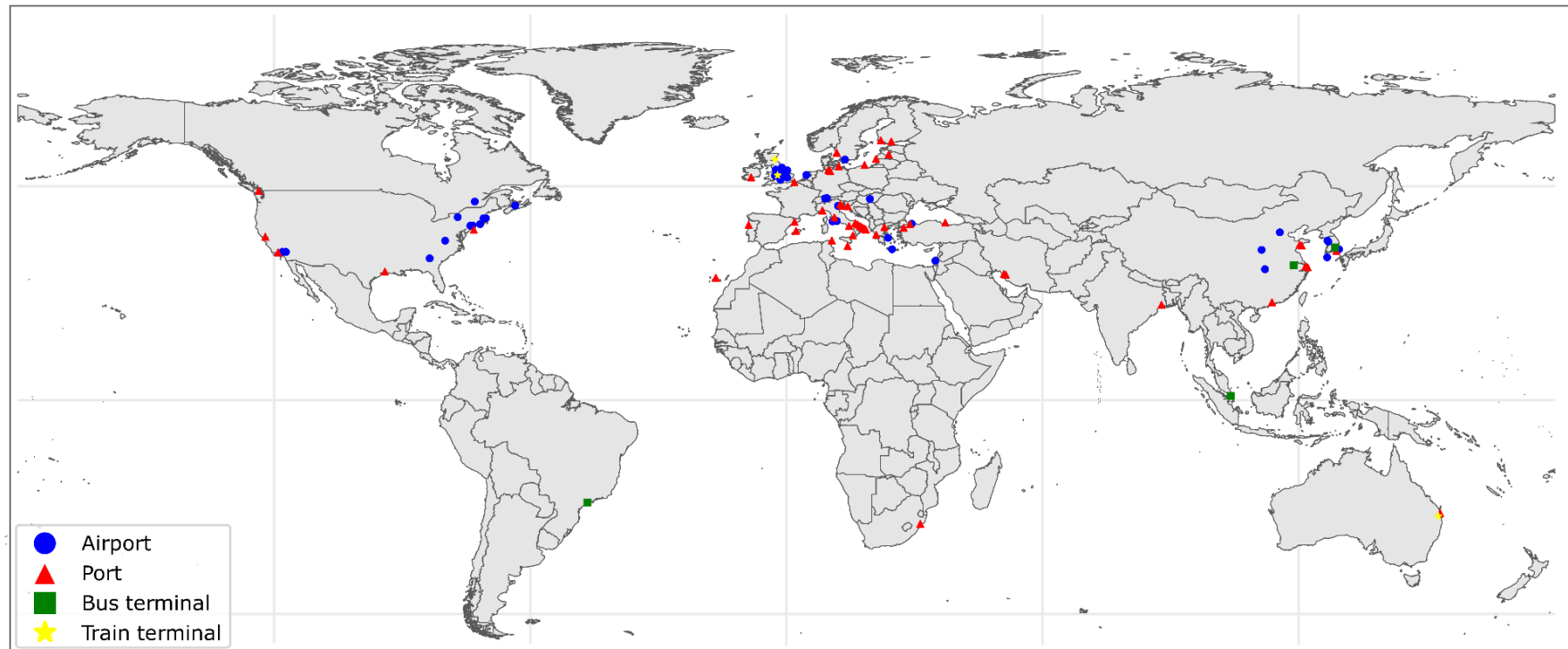


Figure 2.3. Geographical distribution of AQ studies performed at THs (Priyan et al., 2025).

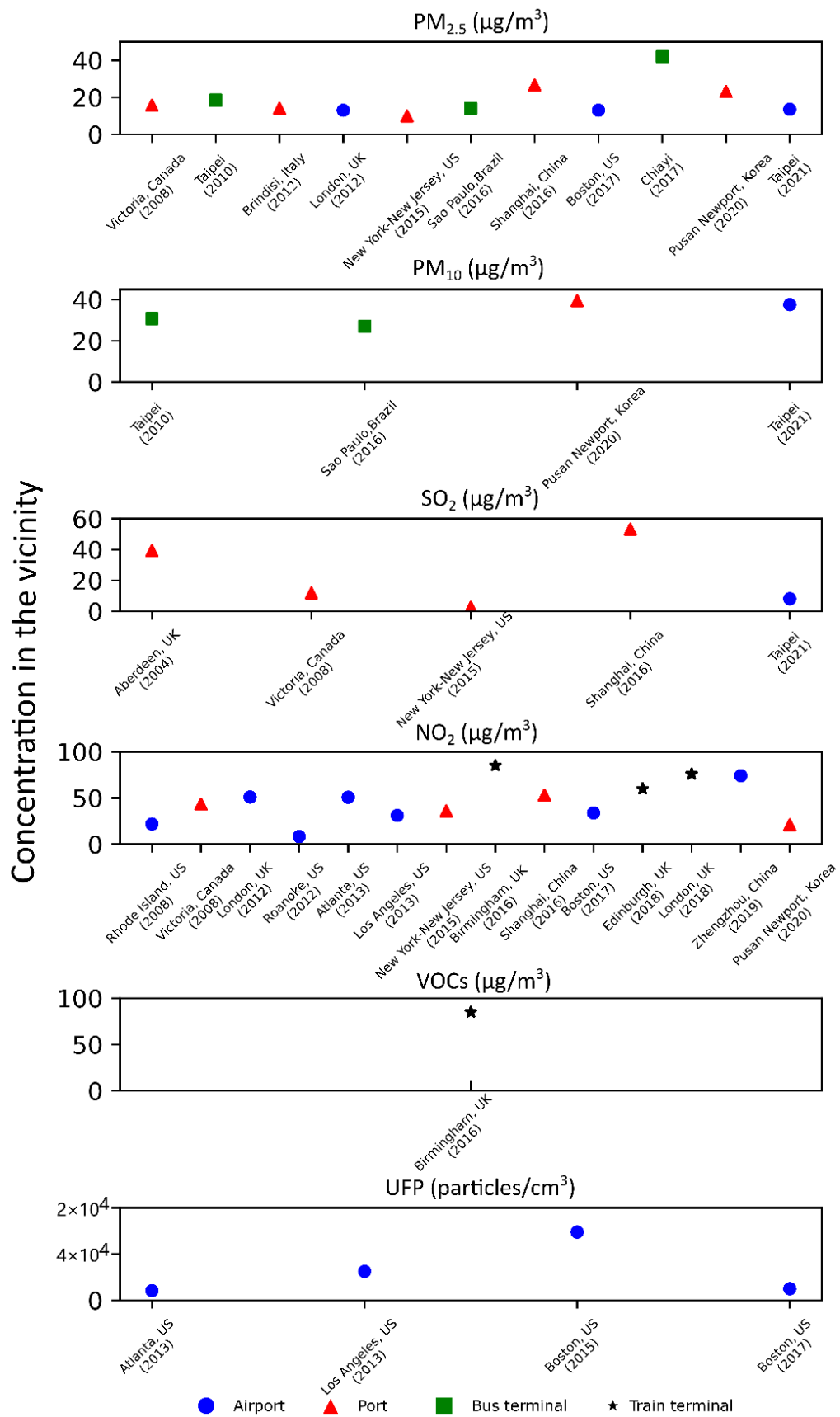


Figure 2.4. Concentration of major pollutants (PM_{10} , $PM_{2.5}$, SO_2 , NO_2 , UFP) reported in the vicinity of TH environments (Priyan et al., 2025).

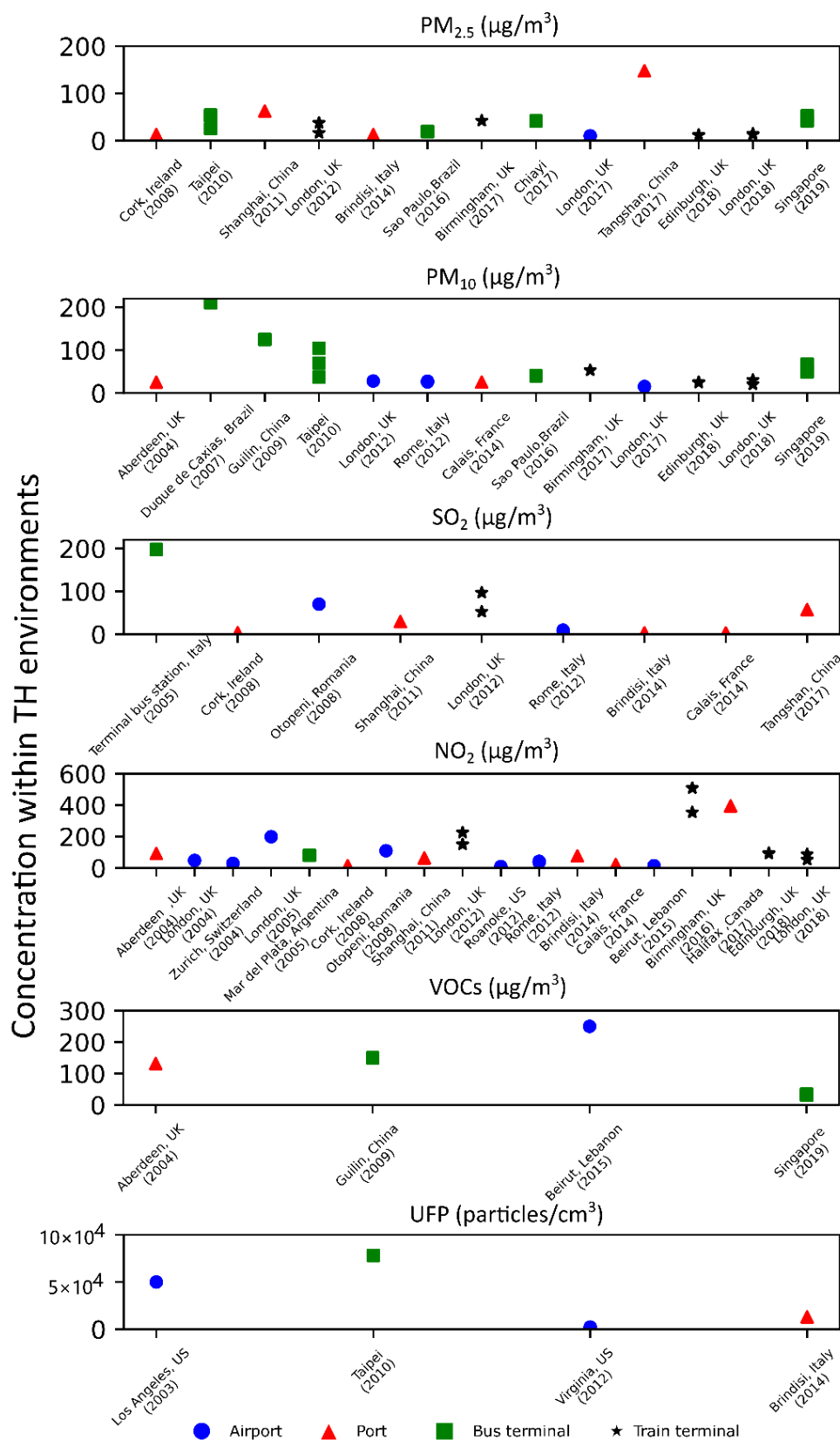


Figure 2.5. Concentration of major pollutants (PM_{10} , $PM_{2.5}$, SO_2 , NO_2 , UFP) reported within TH environments (Priyan et al., 2025).

2.2.3.1 Bivariate polar plots & data filtration technique

Bivariate polar plots are employed to discriminate between ground level sources of pollutants (emitted with little or no buoyancy (e.g., local traffic)) and sources of pollutants emitted with significant level of buoyancy (e.g., industrial, ships and aircraft plumes) (Carslaw et al., 2006). Bivariate polar plots are the extended idea of a pollution rose by incorporating the wind speed as the third variable which provides more information regarding the nature of the sources rather than the direction only (Uria-Tellaetxe & Carslaw, 2014). Bivariate polar plots are effectual in highlighting the potential sources of pollutants only when sufficient data exists from other monitoring sites to subtract background concentrations. By accounting pollutant concentration of several wind sectors affected by the similar nature of source (e.g., direction of aircraft jet plumes) and subtracting background concentration for those sectors, clear contribution of that source can be gained (Masiol & Harrison, 2015; Popoola et al., 2018).

Another quantitative method to detect pollution sources is by filtering data for a specific time period of interest such as choosing hours of the day when traffic is high, filtering data when wind direction is upwind of the measurement sites, or based on unique activity such as selecting data based on transport movements (e.g., LTO of aircraft, hostelling and manoeuvring of ships, arrival and departure of buses and trains) and filtering data based on characteristics of the transport (e.g., type of engine, fuel type etc) (González et al., 2011; Hudda et al., 2016; Lelièvre et al., 2006). The average pollutant concentration corresponding to these conditions after removing the background concentration, can demonstrate the contribution of the specific source or activity (Wang et al., 2019). However, filtering on these conditions does not result in explicit quantification of sources if the influence of non-local sources is significant, which is especially challenging to disaggregate between different PM sources (Hudda et al., 2020). Wind direction becomes highly inconsistent during calm wind conditions (<1 m/s). Under such conditions, filtering data to discriminate sources becomes difficult. Some studies have restricted on the use of wind direction data under calm wind conditions (Carslaw et al., 2006; Hudda et al., 2016).

The bivariate polar plot and data filtration techniques are simple statistical methods widely used to differentiate between airport emissions and road traffic emissions in the vicinity of airports. Similarly, in port neighbourhood, these methods have been employed to distinguish port emissions from other anthropogenic activities. These techniques consistently use multiple monitoring sites measuring multiple pollutants to capture and discriminate between pollutant sources. The use of multiple sites aids in triangulating and resolving sources in

greater detail around the TH. These methods assume that all activities occurring within the port or airport are treated as a single emission source during the analysis. For instance, Carslaw et al. (2006) used network of seven monitoring sites to quantify the contribution of airports to three years hourly mean concentrations of NO_2 and NO_x around the neighbourhood of Heathrow Airport, using bivariate polar plots. The study identified that airport emissions were estimated to be $27 \pm 14\%$ of the annual mean NO_2 and NO_x concentrations in the vicinity of the airport. A study conducted in Los Angeles International Airport used LTO activity data to filter the pollutant concentrations measured at seven sites around the airport. The study reported that the aircraft emitted about $4.8 \pm 1.2 \times 10^6$ particles/ cm^3 (UFP) along with high NO_x (~ 1000 ppb) and BC ($16.5 \mu\text{g}/\text{m}^3$) concentration during take-off (Westerdahl et al., 2008).

Bivariate polar plot studies have typically employed longer monitoring periods, with data collected over more than one year, to capture a wide range of dominant sources at different times at a receptor site. In contrast, data filtration techniques have been applied over shorter monitoring durations to focus on specific sources during defined time periods (e.g., emissions from LTO operations at airports). These studies consistently highlight sources of NO_2 and UFPs in airport neighbourhood environments, whereas in port areas, NO_2 and SO_2 are often emphasised.

However, these methods are not effective at quantifying the dominant source of pollutants when the receptor site is influenced by a large number of sources, especially when trying to discriminate multiple emission sources within airport or port premises. Additionally, these methods are more suited for specific size range of particles (UFP range) and gaseous pollutants which arise from specific emissions. While analysing pollutants at multiple sites with high-end equipment can be expensive, the advent of low-cost monitors and effective calibration techniques has made this type of analysis more affordable in recent studies. The 17 electrochemical sensors were deployed at London Heathrow Airport over a period of five week to discriminate airport and non-local source contribution to NO_2 in the proximity of airport. The bivariate polar plots indicated that majority of the observed NO_2 concentration (75%) (after ignoring the background concentration) arises from the emissions which are not associated with the airport sources (Popoola et al., 2018). Low-cost sensors were employed around Heuston train terminal in Dublin to discriminate and quantify the contributions of the railway station and road traffic to $\text{PM}_{2.5}$ and NO_2 levels. Data filtering based on wind orientation revealed that train station emissions were the major source of $\text{PM}_{2.5}$ (67%), while road traffic was the major source of NO_2 (52%) when winds were coming from the train station (Priyan et

al., 2024). However, studies have not clearly specified the statistical evaluation of concentration estimated at the receptor sites compared to background sites after applying data filtration or bivariate polar plot methods. However, AQ studies have employed one-way analysis of variance (ANOVA), followed by Duncan's multiple range test, to determine whether the pollution level at one location is significantly different from that at another (Miao et al., 2024; Ipeaiyeda et al., 2017). This approach allows for the evaluation of source contribution quantified between sites.

2.2.3.2 Regression models

Regression models are another simplified method for identifying major sources in the TH. Unlike dispersion models, regression models lack an analytical expression, but they allow for the exploration of detailed relationships between pollutants and variables such as traffic and emission rates, which significantly impact pollutant concentrations. These models are used to assess potential reductions in pollutant levels when the magnitudes of these variables are decreased. However, they cannot quantitatively estimate the individual contributions of sources (e.g., airport and road traffic) to the pollutant levels. Studies using regression models have consistently highlighted sources of NO₂ at TH. Like bivariate polar plots and data filtration techniques, regression models are also more effective at discriminating gaseous pollutant sources. Han et al. (2022) adopted a generalised additive model to analyse the impact of airport related emissions on hourly measured NO_x concentrations in Xinzheng International Airport, China. This study used hourly airport emission data (take-off, landing, ground taxi, ground support equipment) together with meteorological and environmental data and found that 13% of the NO_x concentrations were explained by the airport activity emissions. Adamkiewicz et al. (2010) applied a land use regression (linear model) to identify the impact of airport and local traffic on NO₂ concentrations (7- and 14-day measurements using diffusion tubes) in proximity to the airport for three months (644 measurements). NO₂ concentrations were modelled against land use variables (such as traffic density, road length, and distance to road, terminal, and runway) and the model demonstrated that local traffic has a strong influence on the NO₂ concentrations. Studies related to generalised additive models have modelled pollutants with an R² of 0.41–0.60, while studies using linear models have shown lower performance, with an R² of 0.30–0.32. Using linear models poses difficulties as many variables are unexplained and confidence in these models is fairly modest.

Linear regression models and generalised additive models have frequently been used in studies, but recent studies have increasingly adopted machine learning models such as random forests, stochastic gradient boosting, and boosted regression trees due to their superior predictive power (Font et al., 2020; Pan et al., 2023). These models can handle a mix of variables, including both categorical and continuous types, efficiently manage missing data, and are resistant to outliers in the variables.

A study conducted in Edinburgh Waverly and London King's Cross railway stations modelled hourly PM_{2.5} and NO₂ concentration (4-week measurements) and activity data of trains (such as train fuel type, train schedule, platform distance). Model enabled the prediction of individual contributions from different train types using a random forest model, with an R² between 0.50 and 0.80. The model identified a strong association between pollutants and diesel trains. Furthermore, it predicted that reducing the number of diesel trains would decrease PM_{2.5} concentrations by an average of 0.18–0.48 µg/m³ per train and NO₂ concentrations by 8.6–23.7 µg/m³ per train. (Font et al., 2020). Both generalised additive model and machine learnings models are better in explaining the variables than linear models. Additionally, the studies have used longer monitoring period for outside environment (3-12 months) and shorter monitoring period for semi-enclosed indoor environment (7-30 days).

2.2.3.3 Speciated receptor modelling

The above methods are less effective in quantifying PM and VOCs sources when a receptor site is influenced by a large number of sources, especially within TH premises. However, PM and VOCs sources can be effectively quantified even at extremely complex sites with a wide range of differing sources using the speciated receptor modelling approach. Besides emissions from aircraft, ships and trains, this method can be used to quantify emissions from ground service equipment, domestic heating, heavy-duty trucks, and non-combustion sources such as soil and road dust, brake wear, and tire wear within as well as in the vicinity of the TH.

Speciated receptor modelling aims at analysing the physical (size distribution) or chemical characteristics of particles. This helps in identifying potential chemical or size markers and statistically matching them to sources signature, and finding their contribution (Hopke, 2016; Priyan et al., 2021). Over the decades, receptor models have become effective tools in managing AQ. The receptor models reported in AQ studies include Principal Component

Analysis (PCA), Positive Matrix Factorisation (PMF), Chemical Mass Balance (CMB), Unmix, and Multi-linear Engine 2 (ME-2), with more than 1,000 studies applying these methods (Hopke, 2016). However, source apportionment studies conducted in and around THs have not employed Unmix and ME-2.

The study conducted in Brindisi port, Italy characterised $PM_{2.5}$ based on its chemical composition (elements, ions, and organic content) and used PCA to identify the sources of $PM_{2.5}$ sampled for 93 days. The study identified ship emissions, sea salts, crustal dust, vehicular emissions, and secondary aerosols as the main source of $PM_{2.5}$ (Cesari et al., 2021). Hellebust et al. (2010) utilised a PMF model to quantify the sources of $PM_{2.5}$ using gaseous pollutants, $PM_{2.5}$ organic fraction and sulphate particles as factor variables sampled for four months in the harbour of Cork, Ireland. The study identified fuel oil combustion (31%) as the major contributor followed by vehicular emissions (19%) and domestic solid fuel burning (14%). A study conducted in Shenzhen, China, collected VOCs samples at 110 sites using steel canisters, quantifying 22 VOCs species at each site. PMF model identified airport emissions as the major VOCs source in and around Shenzhen Airport (Zhu et al., 2023).

This approach relies solely on PM and VOCs chemical composition collected at the receptor site, without the need for emission rates, traffic flow data, background levels, or meteorological information. Studies using the receptor modelling approach have employed both shorter and longer monitoring periods (1-5 months) to effectively discriminate between sources. However, this approach is expensive, requiring sophisticated sampling and laboratory instruments. Hence, single site is mostly preferred in the studies.

PMF and ME-2 model has been the preferred model in recent years as they resolves factor contribution without significant negative values (Comero et al., 2009) and are more accurate than CMB and UNMIX for sources quantification. In contrast, PCA is limited to identifying important sources at a receptor site (qualitative). The advantage of using a PMF and ME-2 model are improved accuracy and effectiveness in identifying and quantifying the individual contributions of different sources and hence is more suitable for complex environments.

In these models, source profiles are used either as input data (e.g., in CMB) or as reference profiles for comparison with model outputs (e.g., in PMF, UNMIX, ME-2, and PCA). Many countries have developed their own country-specific source profiles; however, these profiles are often limited in their applicability to THs. In such cases, the USEPA speciate database can be utilised. The speciate database provides an extensive range of source profiles specifically for airport-related activities including aircraft exhaust, ground idling and thrust operations,

LTO cycles, and nonroad ground support equipment as well as for port-related sources such as propulsion engines, auxiliary engines, marine vessel boilers, and ground support equipment. For instance, Jeong et al. (2017) used USEPA speciate 4.3 marine vessel database and CMB model to quantify the contribution of ship emissions powered by heavy fuel oil at the port of Busan, South Korea. Furthermore, receptor modelling studies were mainly focused on quantifying the sources of PM in ports and airports vicinity, with no studies have been found for train and bus terminals.

2.2.3.4 Plume Capture Method

The plume capture method is another approach used to evaluate the effectiveness of policy implementations and technological emission control measures, as well as to estimate emission factors for modelling purposes. Pollutant emission rates from sources such as aircraft, trains, and ships are measured while they are moving by capturing their plume. These emission rates are directly measured from the plume with ground-based stations or indirectly estimated by measuring CO_2 concentrations from the plume using the emission ratio method.

Differential Optical Absorption Spectroscopy (DOAS) and Fourier-transform infrared (FTIR) absorption spectroscopy are the common ground-based instruments used to measure the emissions rates of gaseous pollutants from moving sources (Premuda et al., 2011). DOAS measures different trace gases along an optical path in a narrow band absorption structure in the visible and UV spectral region, while FTIR measures the trace gases in the infrared region (Schürmann et al., 2007)

Emission rates by emission ratio method were computed using Eqn.1 & 2.

$$ER_X = \frac{X - X_{bg}}{CO_2 - CO_{2,bg}} = \frac{\Delta X}{\Delta CO_2} \quad (\text{Eqn.2.1})$$

$$EF_X = ER_X \cdot \frac{M_X}{M_{CO_2}} \cdot EF_{CO_2} \quad (\text{Eqn.2.2})$$

where

ER_X is the emission ratio for pollutant X ;

X_{bg} and $CO_{2,bg}$ are the background concentrations for pollutant X and CO_2 , respectively.

EF_X is the emission factor for the pollutant X ;

M_X and M_{CO_2} are the molecular mass of the pollutant X and CO_2 , respectively

EF_{CO_2} is the emission factor of the CO_2 .

These methods do not require long monitoring periods (typically between 7 days - 60 days is reported), and the emission estimates reflect real-world conditions. Premuda et al. (2011) carried out two months of measurements using DOAS to estimate NO₂ and SO₂ emissions from large and medium-sized ships passing through the channels in two ports (Stazione Marittima and Porto Marghera, Italy). The study found that NO₂ and SO₂ emissions ranged between 4.64-5.49 g/s and 1.47-2.63 g/s respectively, with the larger ship emitting less than the medium ships. A study performed at Brisbane, Australia adopted an emission ratio method to quantify pollutant emissions (PM_{2.5}, PNC, SO₂, NO_x) from diesel trains entering and leaving the local port. The sampling was carried out for 7 days with the continuous measurement of pollutants and CO₂. EF values of PM_{2.5}, PNC, SO₂ and NO_x were found to be (1.1±0.5) g/kg fuel, (17.1±1) × 10¹⁶/kg fuel, (14±0.4) g/kg fuel, (28±14) g/kg fuel, respectively (Johnson et al., 2013).

In the emission ratio method, measurements are taken close to the source to capture the plume, typically 100–125 m from the runway at airports, 15–100 m from the channels in ports, and 9-10 m from trains. The measurements are conducted at a specific height, ensuring no obstructions exist between the source and the instrument. Additionally, measurements are taken upwind to account for background concentrations.

Emission rates measured using DOAS and FTIR can be conducted from much greater distances (1–6 km). These methods often yield more accurate estimates than the emission ratio method. However, DOAS and FTIR instruments are expensive and require an elevated, fixed station without any obstructions between the instruments and the source plume. These instruments are applicable only to gaseous pollutants (SO₂ and NO₂).

2.2.4 Summary

In this review, information relating to air quality assessment, through monitoring and modelling, has been collated and synthesised to evaluate conditions in and around different THs. First and foremost, the concentrations of major pollutants (PM₁₀, PM_{2.5}, NO₂) were found to exceed regulatory standards in most of the studies evaluated.

The bivariate polar plot is a commonly employed statistical method in the studies to detect and quantify the contributions of THs to the local ambient environment followed by additive models and data filtration techniques. The statistical methods utilised in these studies deem the meteorology and background concentration as a crucial variable beside historical

air pollution data. All source apportionment methods mentioned in the review are transferable between THs, their applicability depends on the type of pollutant and source characteristics.

Data filtration, regression models, and bivariate polar plot techniques are more appropriate for gaseous pollutants such as NO₂ and SO₂, particularly when these originate from specific, localised sources. In contrast, speciated receptor modelling is more suitable for PM and VOCs, which typically originate from multiple sources. This method is not transferable to sites focused on assessing NO₂ and SO₂ sources. The plume capture method is specifically suited for assessing pollutants emitted from moving transportation sources.

Based on the literature reviewed, knowledge gaps were identified at local-scale THs i.e., bus and train terminals. Therefore, it is recommended that future research should focus on: (i) characterising PM and gaseous pollutant sources in the vicinity of bus and train terminals to understand their contribution to ambient conditions; ii) investigating the relationship between pollutants and controlling variables (such as transport activity, meteorology, and emission control tools) using statistical models in bus and train terminals; (iii) characterization of UFP from terminal related activities (idling, arrival, and departure) in bus and train terminals; (iv) characterization of VOCs and PM-bound PAHs in the vicinity and within the TH; and (v) integrating measurement and AQ modelling approaches to evaluate the impacts of non-exhaust emissions in TH.

2.3 Health impact studies at the settings

The same search strategy used in the previous chapter to identify air pollution characteristics and source apportionment methods was applied to identify health impact studies conducted in THs. Since, only limited health impacts were performed in the THs, we also included the health impacts studies performed in subway environments.

Various approaches have been employed to assess the health effects of air pollution on individuals commuting through, working within, or living near THs. These methods evaluate the relationship between exposure to air pollutants and both mortality and morbidity, considering differences in methodological design and application. The choice of method in the reviewed studies depends largely on whether short-term or long-term health outcomes are being examined. Commonly used approaches include the case-crossover design, Cox

regression models, cross-sectional analyses, carcinogenic and non-carcinogenic risk characterisation, and disability-adjusted life years (DALYs) approach.

Table 2.2. Methods reported in the literature to characterise the sources in the vicinity of the THs.

Methodology	Pollutant/Variables	Resolution of the data	Statistical Techniques	Inference	Reference
Bivariate polar plot (8)	Gaseous pollutants, PM, wind speed & direction	15 min to 1 hr	Conditional bivariate probability function	Sufficient monitoring sites to subtract the background concentrations Both high end equipment & low-cost sensors are employed	(Carslaw et al., 2006; Hagler et al., 2021; Hudda et al., 2020; Ledoux et al., 2018; Masiol & Harrison, 2015; Merico et al., 2016; Popoola et al., 2018; Xu et al., 2023)
Data filtration technique (7)	Gaseous pollutants, PM, period of take-off and landing of aircraft, period of hostelling and manoeuvring of ships, arrival and departure time of trains and buses, type of engine, fuel type, wind speed and direction	1 sec to 2 min	Filtration of data on a specific period of interest (based on transport movement period, based on transport characteristics, when wind direction is upwind of measurement sites)	Sufficient monitoring sites to subtract the background levels High end equipment is required	(Carslaw et al., 2006; González et al., 2011; Hudda et al., 2016, 2020; Ledoux et al., 2018; Wang et al., 2019; Westerdahl et al., 2008)
Regression models (6)	Gaseous pollutants, PM, meteorological variables, emissions, vehicles and train count, road density, distance of road and rail from monitoring site	1 hr (additive and black box model) 7-14 days (land use regression)	Additive model, land-use model, and black box models	High end equipment, diffusion tubes & low-cost sensors are employed	(Adamkiewicz et al., 2010; Carslaw et al., 2012; de Foy et al., 2021; Font et al., 2020; Han et al., 2022; Valotto & Varin, 2016)
Speciated receptor modelling (5)	PM, VOCs, PAHs	24 hr	PCA/PMF/CMB/ME-2/UNMIX	Involves laboratory and require low or high-volume samplers	(Cesari et al., 2021; Hellebust et al., 2010; Masiol et al., 2016; Pirhadi et al., 2020; Vichi et al., 2016)
Plume Capture method (7)	NO _x , CO, HC, SO ₂ and PM	1 sec	Pollutants emissions are estimated through direct measurement or relative to CO ₂ emission factor	Direct measurement requires DOAS and FTIR. Emission ratio method requires high end equipment's	(G. R. Johnson et al., 2013; Juwono et al., 2013; Klapmeyer & Marr, 2012; Merico et al., 2016; Pirjola et al., 2014; Premuda et al., 2011; Seyler et al., 2017)

2.3.1 Case-Crossover Approach

Short-term exposure to air pollution has been linked to respiratory and cardiovascular mortality, hospital admissions, and acute exacerbations of chronic diseases (Huang et al., 2023). Studies performed at THs have employed the case-crossover approach to estimate the acute mortality and morbidity associated with air pollution (Huang et al., 2023; Taracido et al., 2010). In this approach, pollutant exposure on the index day (the day of the health event) is compared with exposure on selected control days. In most applications, each case is matched with several control days (typically six or seven) chosen from the same day of the week and the same month to control for time-related confounders (Wang et al., 2020). The association between case-specific mortality or morbidity and pollutant concentrations is then examined using a conditional logistic regression model, adjusted for factors such as temperature, noise, precipitation, holidays, and firework days (Wang et al., 2020). This method provides robust spatiotemporal estimates, particularly when high-resolution exposure data are available.

A study conducted near Zurich Airport in Switzerland applied a case-crossover design to assess acute cardiovascular mortality associated with daily mean $PM_{2.5}$ and NO_2 concentrations at residential locations surrounding the airport. Using time-stratified mortality data, the study evaluated short-term effects of these pollutants and found NO_2 to be the primary pollutant associated with acute cardiovascular mortality, with delayed effects observed for heart failure 3-5 days after exposure (Saucy et al., 2021).

Another case-crossover study investigated the short-term health impacts of UFPs emitted from aircraft LTO at Los Angeles International Airport. The study recruited 22 non-smoking adults with mild to moderate asthma and measured their circulating inflammatory cytokines and lung-deposited particle surface area before and after exposure (Habre et al., 2018). Results indicated that airport-related UFP concentrations were associated with increased circulatory inflammation, whereas traffic-related UFPs were more strongly linked to reductions in forced expiratory volume.

2.3.2 COx regression model

The Cox regression model is one of the most widely used statistical techniques for survival analysis. It is commonly applied in epidemiological and clinical research to examine the influence of multiple variables on the time until a specific health outcome occurs (Schwartz

et al., 2021). The model estimates the hazard ratio (HR), which represents the relative risk of a defined health outcome associated with a particular variable or risk factor (Xu et al., 2013).

Risk factors included in Cox models can be categorical such as sex, ethnicity, occupation, region of birth, or socio-economic status or continuous, such as age or the distance between an exposed population and a pollution source (Schwartz et al., 2021). A key assumption of the model is that the effect of these risk factors on survival is constant over time and additive on the chosen scale. The Cox model estimates the HR (also referred to as relative risk) per unit increase in the independent variable, providing insight into how a specific exposure or demographic factor influences the likelihood of a health event (Wolf et al., 2023). However, the method relies heavily on accurate temporal information. Without incorporating detailed time-varying covariates, the model may produce unrealistic or biased estimates (Wolf et al., 2023).

A study conducted in Civitavecchia, Italy, applied the Cox regression model to evaluate associations between exposure to PM₁₀ and NO_x and mortality from non-accidental and cardiac causes among residents living within and beyond 500 m of the harbour. The study also examined the influence of demographic and socio-economic variables such as age, occupation, socio-economic status, and gender on mortality risk (Bauleo et al., 2018). The study highlighted that populations living in close proximity to harbour activities face elevated risks of lung cancer and neurological diseases.

2.3.3 Cross-sectional studies

A cross-sectional study is an observational study design that assesses health outcomes and air quality data in a representative population over a defined period of long-term exposure (Ronaldson et al., 2022). In THs, cross-sectional studies have applied various statistical methods to assess the association between pollutant concentrations and health endpoints. The choice of statistical method depends on the distribution of dependent and independent variables, the number of confounders and covariates, and the performance characteristics of the method. For example, a study conducted at Copenhagen Airport, Denmark, investigated the association between long-term exposure to ultrafine particles (UFP) and cerebrovascular and ischemic heart diseases among airport workers. Medical histories of 6,515 men employed at the airport and 61,617 men employed in other firms were analysed to estimate relative risk, using Poisson regression with log-transformation of the population at risk. The study found no significant association between occupational UFP exposure and

heart disease (Lauenborg et al., 2019). Similarly, Hwang and Gentile (2008) used unconditional logistic regression to examine the association between respiratory hospital admissions and residential proximity to airports. Their findings indicated that residents living within 5 miles of an airport had the highest relative risks of hospital admission for respiratory illnesses.

2.3.4 Cancer and Non-Cancer Risk

Exposure to the metal constituents of particulate matter (PM) can lead to both cancerous and non-cancerous health effects. Heavy metals are persistent, bio accumulative, and often carcinogenic, posing serious risks to human health and the environment (Priyan et al., 2022). Emissions of heavy metals such as Cd, Pb, Ni, Mn, Zn, and Cu arise from the combustion of gasoline and diesel fuels in transport hubs (THs), while wear and tear of vehicle components contribute additional metals, including Cr, Fe, Cu, Ba, Zn, and Sb (Charron et al., 2019; Fan et al., 2021; Singh et al., 2020).

According to the human health risk assessment guidance (USEPA, 2011), carcinogenic and non-carcinogenic risks are evaluated based on three exposure pathways: inhalation, ingestion, and dermal absorption. Intake via these pathways is calculated using variables such as inhalation rate, ingestion rate, body weight, age, skin surface area, exposure time, adherence factor, dermal absorption factor, and the concentration of the metals (Priyan et al., 2022). Carcinogenic and non-carcinogenic risks can also be assessed for volatile organic compounds (VOCs) and polycyclic aromatic hydrocarbons (PAHs) (Hyun et al., 2022). Exposure time assumptions vary depending on the cohort studied: commuters typically have shorter exposures (1–15 hours/week), workers have moderate exposures (30–40 hours/week), and residents have continuous exposure (24 hours/day) (Li et al., 2019; Priyan et al., 2022). Non-carcinogenic risk is expressed as a Hazard Index (HI), which is calculated as the sum of the ratios of the daily intake of each heavy metal (through all three exposure pathways) to its reference dose. A Hazardous Index (HI) value greater than 1 indicates potential non-carcinogenic effects, with higher values corresponding to greater risk (Nie et al., 2018). Carcinogenic risk is expressed as Cancer Risk (CR), calculated from daily intake and the slope factor or inhalation unit risk for each metal. A CR value exceeding 1×10^{-4} is considered significant (Fan et al., 2021).

For example, a study in the harbour area of Qingdao, China, characterized PM_{2.5} chemical composition (Cr(VI), Mn, Co, Ni, Cu, Zn, As, Cd, Pb, and V) between March and May 2016.

Cancer and non-cancer risks were estimated for workers through inhalation and dermal exposure, assuming an exposure frequency of 350 days/year over 30 years. The study concluded that both risks were below USEPA guideline values. Similarly, Hyun et al. (2022) assessed non-cancer risks associated with VOCs and PAHs at integrated transport hubs in Singapore (January–March 2019). Inhalation was the dominant exposure route for VOCs, whereas dermal absorption dominated for PAHs. Naphthalene (HI = 49.81) and Benzo(a)pyrene (HI = 1.89) exceeded safe guideline values, while other compounds were within acceptable levels.

In a study conducted at bus terminals in São Paulo, Brazil, PM-associated toxic metals (V, Cr, Mn, Ni, Pb) were measured over 59 days in 2016. Results indicated that inhalation of PM posed a high carcinogenic risk to daily commuters, with Cr contributing the highest risk among all metals (Nogueira et al., 2020).

2.3.5 Toxic Equivalency Factor (TEF)

PM-bound PAHs are highly toxic, exhibiting mutagenic and carcinogenic potential. These compounds are commonly used as indicators for health risk assessment (Mueller et al., 2019). Cancer risk from chronic exposure to PM-bound PAH mixtures is often estimated using the Toxic Equivalency Factor (TEF) approach (Liu et al., 2017).

The TEF approach does not assess the carcinogenicity of individual PAHs but provides an overall cancer risk estimate for PAH mixtures by scaling the doses of individual PAHs relative to the potency of an index PAH, typically benzo[a]pyrene (BaP) (Aquilina & Harrison, 2023). The BaP-equivalent dose of the mixture is calculated, and the corresponding cancer risk is estimated using the dose-response relationship for BaP. Inhalation cancer risk is then determined by multiplying the BaP-equivalent concentration by the unit risk factor for BaP (Liu et al., 2017).

This method assumes that interactions among PAH compounds within the mixture are negligible at the low exposure concentrations typically found in the environment and that all PAHs exhibit similar toxicological effects (Mueller et al., 2019). For example, a study conducted in Bushehr, Iran, assessed the inhalation cancer risk associated with PM_{2.5}-bound PAHs in the vicinity of the Bushehr port. Sixteen PAHs were analysed, and the TEF approach was used to estimate the cancer risk. The study found that the inhalation cancer risk (4.5×10^{-5}) was potentially higher during winter compared to other seasons. However, the

calculated risk remained below the acceptable guideline values set by USEPA (1 case per million individuals) and WHO (10 cases per million individuals).

2.3.6 Disability-adjusted life years (DALYs) approach

The Disability-Adjusted Life Year (DALYs) is a metric used to quantify the burden of disease by combining the years of life lost due to premature mortality with the years lived with disability. It reflects the difference between the current health status of a population and an ideal scenario in which individuals live their full life expectancy free from illness and disability. The DALY framework was introduced by the Global Burden of Disease (GBD) study to facilitate regional and global assessments of mortality and disease burden across more than 100 health conditions. DALYs play a critical role in disease control by supporting evidence-based health interventions, informing cost-benefit analyses, and guiding policymakers and health institutions in the effective allocation of resources.

A study conducted at the Nanjing metro system applied the DALYs metric to assess the health impacts of PM₁₀ exposure among staff and commuters in three areas: the metro cabin, concourse, and platform. The findings indicated that staff experienced greater health damage (0.07 years lost per year) compared to commuters (0.02 years lost per year). Among the monitored locations, DALYs values were highest on the platforms, followed by the concourse and train cabins. Another study examining commuting trips across four travel modes, cycling, metro, bus, and car in Xi'an, China estimated the public health effects associated with PM_{2.5} exposure. The results showed that cycling commuters experienced the greatest reduction in life expectancy, with an estimated loss of 5.51–6.43 months per capita for the studied cohort.

2.3.7 Summary

Studies have evaluated both short and long-term health effects among populations living near THs and have consistently reported significant exposure-related risks. However, no health impact assessments have yet been conducted within or in the immediate vicinity of train terminals. Conducting such studies around THs is challenging because they require high-resolution health, demographic, and socio-economic data for surrounding populations, which are often difficult to obtain. Among the approaches reviewed, cancer and non-cancer risk assessment, TEF method, and DALY metric are comparatively simpler, as they do not require direct health data from exposed individuals. Cancer and non-cancer risk

assessments and the TEF approach rely on modelled exposure doses and reference doses or toxicity factors for the chemical species involved. In contrast, DALYs are derived from pollutant exposure levels and their associated health damage, expressed as years of healthy life lost, using relative risk functions for the pollutants of interest, and can subsequently be translated into economic loss.

2.4 Calibration of low-cost sensors using different statistical methods

Calibration of AQ sensors is highly studied area, 490 research articles related with low-cost calibration methods and performance have been identified and 9 literature review studies associated with performance of the sensors and different calibration methods (linear as well as non-linear methods) have been identified between 2013 to 2023 (Alfano et al., 2020; Dong et al., 2025; Le et al., 2025; Li et al., 2020; Liang, 2021; Mai et al., 2025). Since several comprehensive review studies already exist, detailed critical analyses of individual research articles were not conducted. Instead, this chapter summarises the various evaluation methods used to assess low-cost sensor performance, as well as the calibration approaches and their reported performance in the review articles.

2.4.1 Evaluation Methods for Low-Cost Sensor Performance

Statistical indicators such as root mean square error (RMSE), bias, standard deviation (SD), and the coefficient of determination (R^2) are commonly reported in the literature, with RMSE often regarded as the most informative metric for evaluating overall sensor performance (Le et al., 2025). Target and Taylor diagrams have been identified as effective tools for visualizing these metrics. However, RMSE values are not frequently reported in published LCS studies, which limits the ability to make consistent comparisons across studies (Li et al., 2020; Liang, 2021; Mai et al., 2025).

2.4.2 Availability of statistical metrics in the literature

The most consistently reported indicators were R^2 , along with the slope and intercept of the linear regression between sensor measurements and reference measurements. Table 2.3 shows that the number of studies reporting metrics such as MAE, bias, and RMSE is limited, and measurement uncertainty is almost entirely absent (Alfano et al., 2020; Karagulian et al.,

2019; Li et al., 2020; Ródenas García et al., 2022). Consequently, the evaluation of the sensors had to rely primarily on R^2 and regression parameters.

R^2 indicates how well sensor readings vary in relation to the reference measurements, but it does not account for relative errors. A sensor can exhibit a high R^2 while still showing significant relative bias (slope $\neq 1$) or absolute bias (intercept $\neq 0$). Therefore, R^2 reflects agreement in the pattern of variation but does not necessarily indicate agreement in magnitude (Ródenas García et al., 2022). Metrics such as MNB, MNE, and RMSE are equally important for assessing accuracy and the magnitude of bias, but they are reported only in a limited number of studies (Karagulian et al., 2019).

Table 2.3. Number of studies categorized by reported metrics in the literature (Karagulian et al., 2019).

Metrics	No. of studies
No of study	1290
R^2 , calibrations	218
R^2 , comparisons	1160
slope of regression line	1063
intercept	1027
RMSE	285
Measurement uncertainty (U)	153
MAE	40
Bias	19

2.4.3 Calibration of Low-Cost Sensors (LCS)

Calibration is a critical procedure to ensure the reliability of LCS, establishing a mathematical relationship between sensor measurements and reference instruments to improve accuracy (Dong et al., 2025). Most studies reported in the literature focus on field-based calibrations, with fewer conducted under controlled laboratory conditions (Feenstra et al., 2019; Wang et al., 2023). Calibration methods range from simple statistical approaches, such as linear or multiple linear regression and k-means clustering, to advanced machine-learning techniques, including artificial neural networks (ANN), random forest (RF), extreme gradient boosting (XGBoost), and support vector regression (SVR) (Srishti et al., 2023).

2.4.4 Types of Calibration Models

Common calibration methods for LCS include linear and multiple linear regression, often incorporating covariates such as temperature, relative humidity, traffic flow, wind speed and direction, hours of the day, days of the month and cross-sensitivities to other gases (NO, NO₂, O₃) to enhance accuracy (Liang, 2021; Mai et al., 2025). Additional approaches include logarithmic, exponential, and quadratic regression models, as well as supervised machine-learning techniques such as ANN, RF, SVM, XGBoost, and SVR. Time-dependent sensor drift is rarely considered as a variable in these calibrations (Mai et al., 2025).

Electrochemical and metal-oxide LCS are highly sensitive to environmental conditions, particularly relative humidity (Raheja et al., 2023). For instance, PM sensors can be affected by high relative humidity (>70–80%), which promotes particle growth and may result in overestimation of particle counts (Ródenas García et al., 2022). Corrective approaches, such as the Köhler growth model or exponential adjustments, are commonly applied to account for these effects and provide more accurate particle mass concentrations (Le et al., 2025).

2.4.5 Performance of the calibration model

The performance of calibration models varies substantially by pollutant type. For gaseous pollutants such as CO, NO, NO₂, and O₃, linear calibration models generally show poor performance, with median R² values often below 0.30 for NO₂ and highly inconsistent results for CO and NO. This indicates that linear relationships fail to capture the effects of environmental variables, sensor drift, and cross-sensitivities that strongly influence electrochemical gas sensors. In contrast, multivariate models such as MLR, RF, SVM/SVR, XGBoost and ANN consistently yield higher R² values, typically in the range of 0.80–0.95, demonstrating their ability to correct for complex interferences. NO and CO show particularly strong improvements under MLR and RF approaches (R² ≈ 0.9), while NO₂ benefits significantly from ANN, RF, and SVM models (R² ≈ 0.85–0.94).

For PM sensors, the best-performing calibrations differ. PM_{2.5} and PM₁₀ respond well to exponential, quadratic, and modified Köhler-based corrections, with many studies reporting comparison R² values above 0.90, especially for exponential and quadratic fits (Le et al., 2025; Mai et al., 2025). Linear models provide moderate performance for PM (R² ≈ 0.60–0.80), reflecting the more predictable optical response of PM sensors compared to gas sensors (Mai et al., 2025). Overall, gaseous pollutants require more complex and nonlinear calibration

approaches, whereas PM pollutants often calibrate effectively using physical humidity-correction models or empirical nonlinear equations (Qin et al., 2020). Table 2.4 provides the performance of the calibration models found in the literature. The R^2 values reported across studies show a wide range (0.40–1.00), reflecting differences in calibration approaches, field conditions, and seasonal influences. Variations in averaging times and other experimental parameters further contribute to inconsistencies in sensor performance, highlighting the need for standardized calibration protocols (Qin et al., 2020; Wang et al., 2023).

Table 2.4. Performance of the calibration models (Mai et al., 2025; Nan et al., 2026; Wang et al., 2023).

Pollutant	Calibration Model	No. of studies	Median R^2 Calibration	Median R^2 Comparison
CO	ANN	2	-	0.58
CO	Linear	11	0.85	0.15
CO	MLR	20	0.89	0.83
CO	Quadratic	11	0.63	-
CO	RF	2	0.91	-
NO	ANN	3	-	0.57
NO	Linear	7	0.96	0.032
NO	MLR	19	0.92	0.91
NO	RF	3	-	0.9
NO	XGBoost	3	-	0.90
NO ₂	ANN	6	0.87	0.94
NO ₂	Linear	23	0.25	0.17
NO ₂	Logarithmic	2	0.89	-
NO ₂	MLR	47	0.81	0.81
NO ₂	Quadratic	5	0.61	-
NO ₂	RF	8	0.86	0.91
NO ₂	XGBoost	5	0.85	0.94
NO ₂	SVR	3	-	0.78
O ₃	ANN	3	-	0.89
O ₃	Linear	14	0.84	0.53
O ₃	Logarithmic	2	0.88	-
O ₃	MLR	21	0.91	0.88
O ₃	Quadratic	10	0.72	-
PM ₁	Kohler	3	-	0.74
PM ₁	Logarithmic	5	-	0.76
PM ₁₀	Exponential	5	-	0.59
PM ₁₀	Linear	4	0.77	0.73
PM ₁₀	Logarithmic	8	-	0.58
PM ₁₀	Quadratic	2	0.65	-
PM _{10-2.5}	Linear	5	0.63	0.98
PM _{2.5}	Exponential	4	0.91	0.97

Pollutant	Calibration Model	No. of studies	Median R ² Calibration	Median R ² Comparison
PM _{2.5}	Kohler	1	-	0.78
PM _{2.5}	Linear	35	0.84	0.64
PM _{2.5}	Logarithmic	6	0.73	-
PM _{2.5}	MLR	18	0.81	0.65
PM _{2.5}	Quadratic	7	0.87	0.88
PM _{2.5}	RF	4	-	0.79
PM _{2.5-0.5}	Linear	9	0.84	0.98
PM _{2.5-0.5}	MLR	1	0.6	0.45
PM _{2.5-0.5}	Quadratic	6	0.82	-

2.4.6 Summary

Calibration of low-cost sensors has been widely investigated, yet persistent limitations remain in both evaluation and calibration practices. Although numerous statistical indicators are available, most studies continue to rely primarily on R² and regression parameters, while important metrics such as RMSE, MAE, MNB, and MNE are not frequently reported. Calibration approaches also differ considerably across studies. Linear and multiple linear regression are the most applied methods, but they often perform poorly for gaseous pollutants, particularly NO₂, due to strong cross-sensitivities and environmental influences that limits linear model reliability. In contrast, multivariate and machine learning-based techniques, including ANN, RF, SVM, SVR, and XGBoost, consistently yield good calibration accuracy for gaseous sensors. For PM sensors, linear models provide moderate performance; however, effective calibration must also incorporate humidity-related effects, especially hygroscopic particle growth under high relative humidity, which requires specialized correction approaches such as Köhler theory or exponential adjustment models.

3. CASE STUDY AREAS

Two case study area were identified for this project and focused on the two major train stations in Dublin, Dublin Heuston and Dublin Connolly.

3.1 Dublin Heuston

Heuston Station, located on St. John's Road Street in the west of Dublin city, is the Ireland's busiest intercity railway hubs in the country's capital (Figure 3.1). It serves as the main hub for intercity rail services connecting Dublin with major cities and regions in the south, southwest, and west of Ireland, including Cork, Limerick, Galway, and Waterford. Established in 1846, the station houses the head office of Irish Rail, and the St John's Road West site is also home to the Irish Railway Record Society. The station is well integrated into Dublin's public transport network, with access to Luas tram services, Dublin Bus routes, and nearby road connections, making it a key transport gateway for commuters. Adjacent to the train station is the St John's Road West which is one of the major roads in Dublin connecting the city the with the arterial M50 motorway via the N4 corridor. Figure 3.2 shows the terminal platforms at Heuston Station and the south entrance of Heuston Station on St. John's Road.

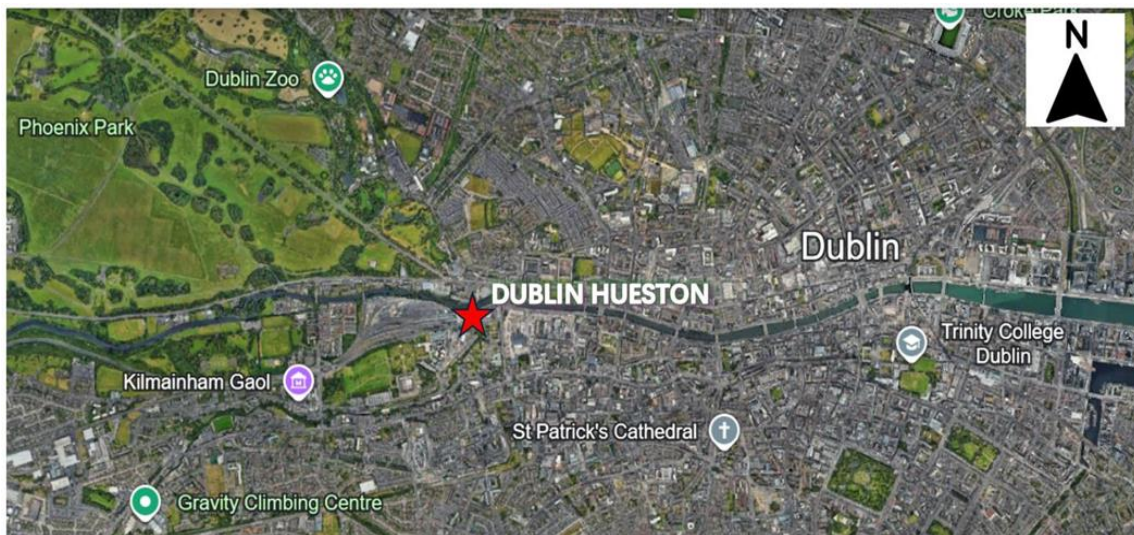


Figure 3.1. Location of Heuston station in Dublin city.

The railway station is a terminal station with tracks aligned in an East-West direction. The station is partially enclosed, with four platforms housed under a glazed roof (with longitudinal vent on its roof, approximately 30 cm height), while three platforms are not enclosed (Figure 3.3). The longitudinal vent in the roof is the major outlet through which pollutants from the

train exhaust exit the railway station. The primary external opening for the enclosed platforms is at the western end where trains exit and enter the station. There are two additional openings, a pedestrian and vehicles access point located south and north of the station, respectively.



Figure 3.2. (a) Terminal platforms at Heuston. (b) Heuston south entrance at St. Johns Road.

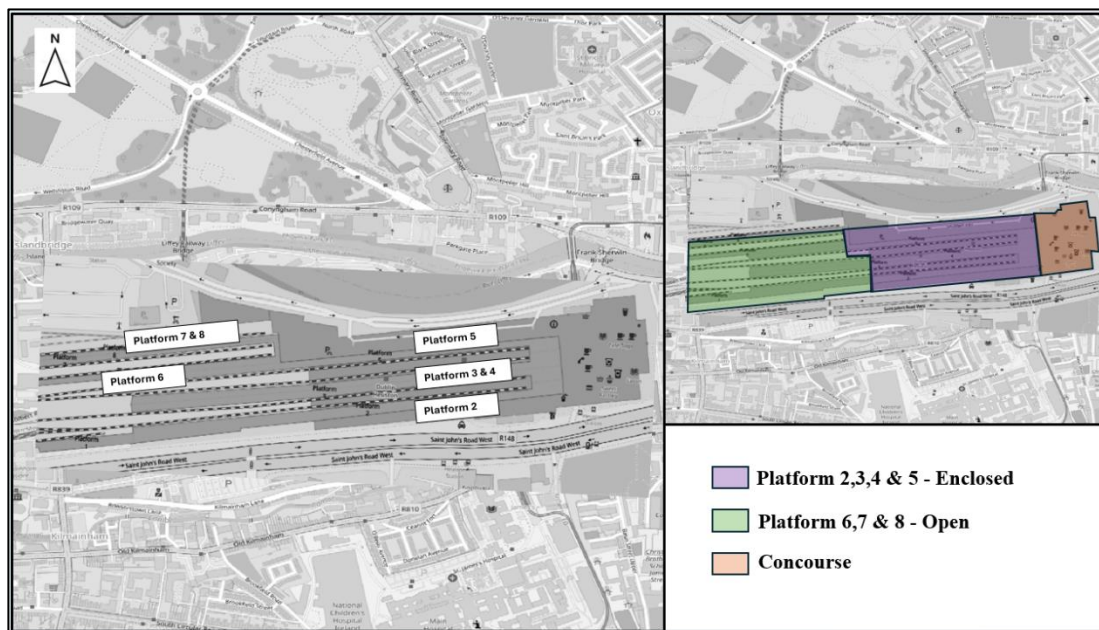


Figure 3.3. Layout of Heuston train station located in the Dublin, Ireland.

3.2 Dublin Connolly

Connolly Station, located on Amiens Street in Dublin city centre, is Ireland's busiest suburban railway hub and the second-busiest intercity train terminal in the capital (Figure 3.4). Opened

in 1844, the station housing the offices and headquarters of Irish Rail. The station serves as the primary hub for rail services to the north, northwest, and southeast of Ireland, including the Belfast Enterprise service, as well as DART suburban services along the Dublin coast. Connolly Station is well connected to the city's public transport network, with direct access to the Luas Red Line and numerous Dublin Bus routes, making it a key interchange for both local commuters and intercity passengers.

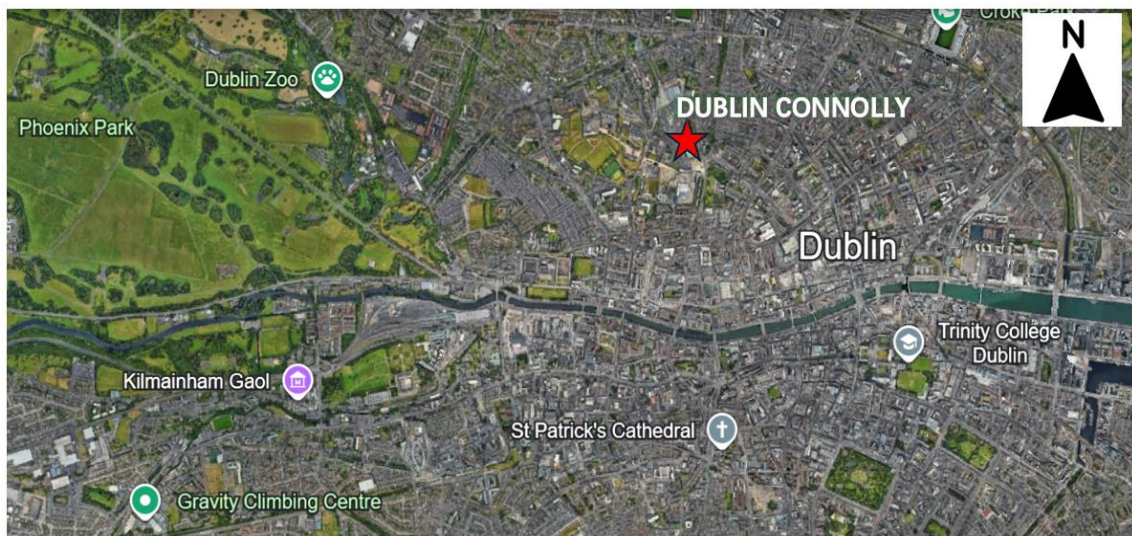


Figure 3.4. Location of Connolly station in Dublin city.

The station is semi-enclosed and comprises six platforms, accommodating both terminus and through tracks aligned in a north-east & south-west direction (Figure 3.5). Platforms 2 to 4 are partially enclosed, with major portions of the platforms are placed under a triangular glazed roof, which is ventilated passively at the roof peaks, with no supporting form of mechanical ventilation. These platforms serve as terminus tracks. In contrast, Platforms 5 to 7 are open and serve as through tracks. The primary external opening for enclosed Platforms 2 to 4 is located where trains enter and exit the station. Additional openings include pedestrian access points at Platform 2 to the east connecting to the parking area, and at Platform 4, providing access to Platform 5. Trains stationed at enclosed Platforms 2 to 4 are powered by diesel engines. Platforms 5 to 7 accommodate both electric and diesel trains, though they predominantly serve electric trains that connect to suburban areas of Dublin. Figure 3.6 shows the terminal and through platform of Connolly.

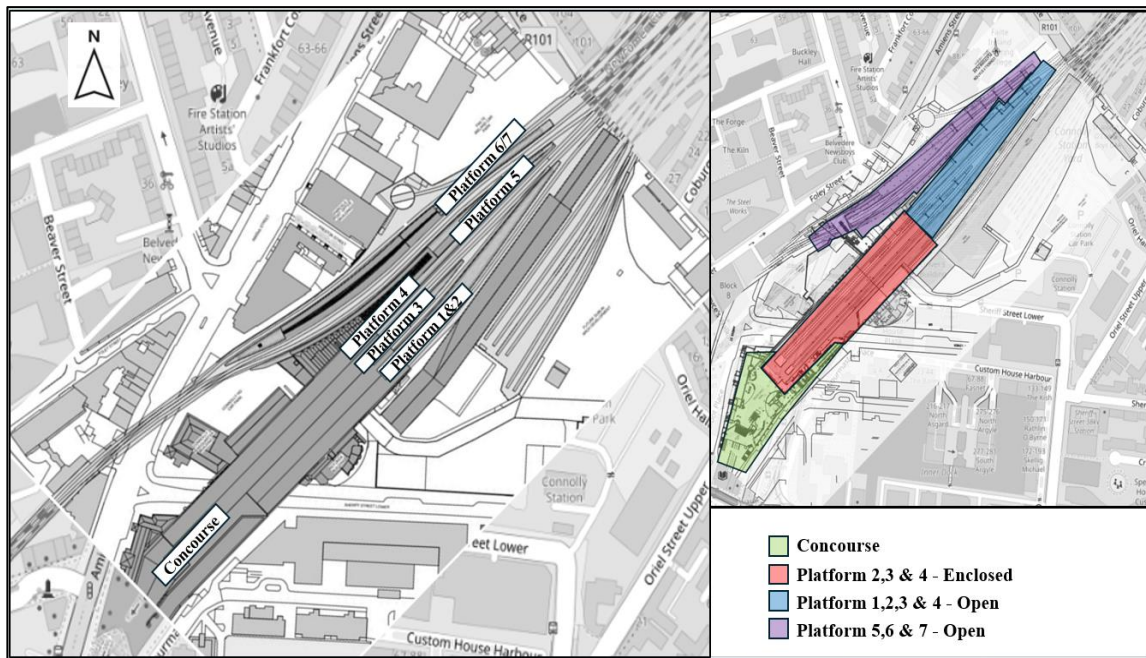


Figure 3.5. Layout of Connolly train station located in the city centre of Dublin, Ireland.

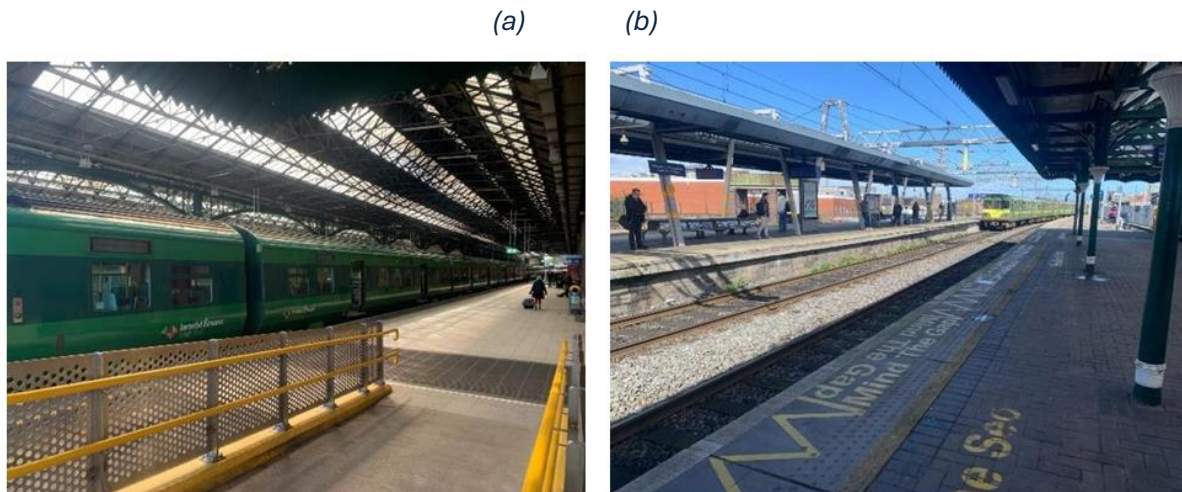


Figure 3.6. (a) Terminal platform at Connolly station. (b) Through platform at Connolly station.

3.3 Ireland EPA Air Quality Monitoring Stations

The EPA of Ireland operates a nationwide network of air quality monitoring stations to monitor and report ambient air quality levels across the country. These stations are employed in urban, suburban, rural, and traffic-influenced locations to capture temporal and spatial variations in air quality. Six EPA station data located in Dublin are used in this study. Details of the EPA station are presented in the Table 3.1. Figure 3.7 presents the location of the EPA stations used in this study.

Table 3.1. Details of the EPA stations used in this study.

Station Name	Abbreviation	Site Description	Pollutants Monitored	Distance from city Centre	Station Characteristics
St. John's Road West	St John's FMS	Traffic	PM _{2.5} , PM ₁₀ and NO ₂	~3 km southwest	Near busy roads
Ringsend	Ringsend FMS	Industrial	PM _{2.5} , PM ₁₀ , NO ₂ , and SO ₂	~4 km southeast	Close to port and industrial area
Pearse Street	Pearse FMS	Street canyon	PM _{2.5} , PM ₁₀ , and NO ₂	~1 km southeast	High traffic location.
Amiens Street	Amiens FMS	Traffic	PM _{2.5} , PM ₁₀ , and NO ₂	~1.5 km northeast	City centre location
Rathmines	Rathmines FMS	Residential	PM _{2.5} , PM ₁₀ , and NO ₂	~3 km south	Residential and mixed traffic (urban background)
Cabra Community College	Cabra FMS	Residential	PM _{2.5} and PM ₁₀	~4 km northwest	Residential and education area

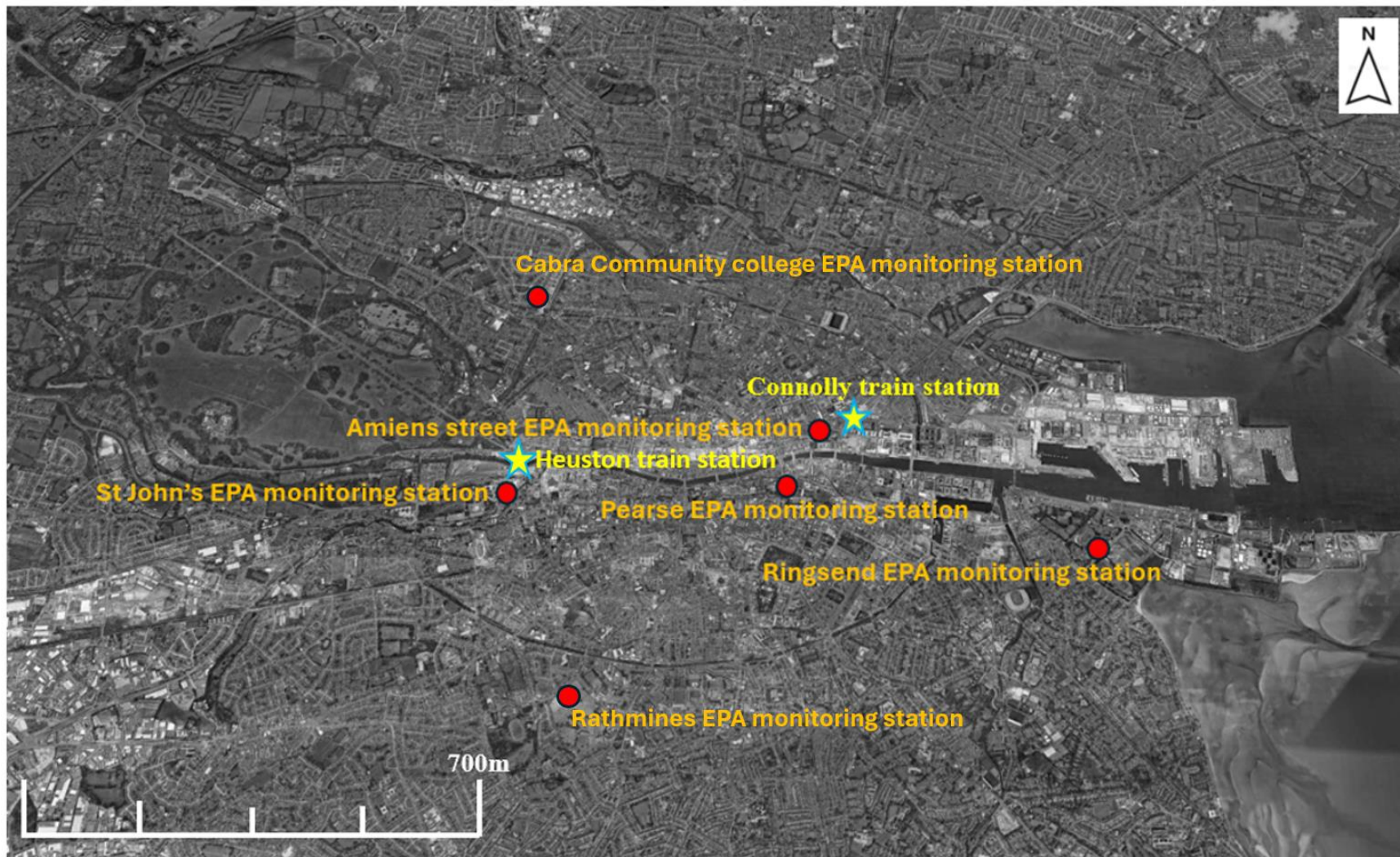


Figure 3.7. Locations of the EPA stations used in the study.

4. AIR QUALITY AND METEOROLOGICAL INSTRUMENTS

We employed different monitoring devices at various stages of the study. The instruments included a real-time continuous air-quality monitors, a high-volume sampler for PM measurement, and a weather station for recording meteorological variables. In addition to these instruments, a passive sampler was also used to measure NO₂.

4.1 Real-time continuous air quality monitors

4.1.1 SidePak AM520

The SidePak AM520 (manufactured by TSI Incorporated in Shoreview, Minnesota, USA) is a portable, battery-operated personal aerosol monitor PM concentrations in real time (Figure 4.1). It employs a light-scattering laser photometer to measure the mass concentration of PM. The instrument supports data logging and configured to measure particle concentration in 1-second resolution. The instrument was used from 11th November 2022 to 12th December 2022. Prior to sampling, the instrument was lab calibrated with emery oil calibration standard, and the photometric calibration factor was determined and adjusted in accordance with ISO 12103-1, A1 test dust. The instrument measures particulate mass concentrations over a range of 0.001–100 mg/m³, with a minimum resolution of 0.001 mg/m³. Instrument performance showed high agreement with reference measurements ($R^2 = 0.99$) and an accuracy of ± 0.04 mg/m³ (TSI Incorporated, 2016).



Figure 4.1. The TSI SidePak PM_{2.5} monitor.

4.1.2 ELOS outdoor station, Elichens

ELOS Outdoor Station devices (Elichens, <https://www.elichens.com/>) were used from May to December 2023 to monitor PM_{2.5}, and NO₂ (Figure 4.2). The ELOS Outdoor station is an autonomous, solar-powered, and low-cost air quality station. The instruments employ light-scattering optical sensors for PM_{2.5} measurements and an electrochemical sensor for NO₂. In addition to PM_{2.5} and NO₂, the devices also measure temperature, humidity, pressure, and noise. Five units were deployed for the above-mentioned period.

The optical particle sensors operate by directing a light beam through an air sample, where suspended particles scatter the incoming light. This scattered light is detected by a photodiode that produces an electrical signal proportional to the scattering intensity, from which particle size and concentration are estimated. NO₂ is quantified using an electrochemical sensor that detects electrical signals generated by oxidation–reduction reactions occurring at the sensor’s electrode surfaces. The magnitude of this signal is proportional to the ambient NO₂ concentration, enabling sensitive, real-time gas monitoring. These sensor technologies, however, have relatively limited lifespans, and their accuracy may be affected by environmental factors such as humidity, temperature, and site-specific conditions. For this reason, all devices were calibrated prior to installation. The PM_{2.5} sensor operates over a measurement range of 0–500 µg/m³, with an accuracy of ±5 µg/m³ (mean absolute error) and a sensitivity of 1 µg/m³. The NO₂ sensor operates over a range of 0–5 ppm, with an accuracy of ±5 ppb (mean absolute error) and a sensitivity of 1 ppb. The humidity sensor measures 0–100 %RH with an accuracy of ±3 %RH and a sensitivity of 0.1 %RH, while the temperature sensor covers 0–65 °C with an accuracy of ±1.0 °C and a sensitivity of 0.1 °C. Atmospheric pressure is measured over 300–1100 hPa with an accuracy of ±1.0 hPa and a sensitivity of 0.1 hPa, while environmental noise is monitored within 34–94 dBA with an accuracy of ±2 dBA and a sensitivity of 0.1 dBA (eLichens,2021).



Figure 4.2. Elichens outdoor air quality monitor.

4.1.3 Sonitus NO₂ monitor

The Sonitus (<https://www.sonitussystems.com/>) monitor was used from March to July 2024 to monitor NO₂ (Figure 4.3). The Sonitus NO₂ monitor is an autonomous and low-cost air quality monitor. The device employs an electrochemical sensor to measure NO₂ concentrations, similar to the previous device. It operates with a flow rate of 5.5 L min⁻¹, and readings are recorded at a 1-minute resolution. To minimize the effects of moisture and humidity, the system is equipped with a heated inlet and an integrated fan. Prior to field installation, the device was calibrated in the laboratory using zero and span checks. The instrument operates using mains power. In addition to NO₂, the devices also measure temperature and humidity. The sonitus NO₂ monitor operates over a range of 0–1500 µg/m³, with an accuracy of ±10 µg/m³ (mean absolute error) and a sensitivity of 2 µg/m³ (Alphasense, 2024).



Figure 4.3. Sonitus continuous NO₂ monitor.

4.2 Manual air quality monitor

4.2.1 PM high volume sampler

A high-volume aerosol sampler (DHA-80, Digitel Enviro-Sense) operating at a flow rate of 0.5 m³ min⁻¹ was used from April to May 2024 to collect 24-hr PM_{2.5} samples on filters (Figure 4.4).

The sampler operates on the principles of inertial impaction and aerodynamic separation. A large volume of air is drawn through a size-selective inlet with a defined cut point, causing particles with aerodynamic diameters above the cut point to impact on the inlet surfaces and be removed from the airstream. Particles smaller than the cut point ($< 2.5 \mu\text{m}$) remain entrained in the airflow and are subsequently collected on the final filter. The sampler operates over a flow range of $0.1 - 1.5 \text{ m}^3/\text{min}$, with a flow volume measurement accuracy of $\pm 2\%$ and a reproducible setting tolerance of $\pm 0.45\%$. The instrument maintains volume flow control accuracy below 5% of the measured reading and provides stable high-volume sampling for $\text{PM}_{2.5}$ (DIGITEL enviro-sense, 2017).



Figure 4.4. High volume aerosol sampler for $\text{PM}_{2.5}$ sampling.

4.3 Passive air quality monitor

4.3.1 Diffusion tubes

Passive diffusion tube samplers were used to measure NO_2 at various stages of the study (Figure 4.5). The sampler consists of a small plastic tube containing triethanolamine (TEA), which absorbs ambient NO_2 through molecular diffusion over the exposure periods. TEA converts NO_2 to nitrite, a stable form suitable for laboratory analysis. The accumulated nitrite is subsequently quantified in the laboratory using UV-visible spectrophotometry or ion chromatography. Diffusion tubes have a practical detection limit of approximately 1–2 ppb, analytical sensitivity of $\sim 1 \mu\text{g m}^{-3}$, and typical field accuracy within $\pm 10\text{--}20\%$ relative to reference chemiluminescence methods (Gradko International Ltd, 2012). NO_2 diffusion

tubes were commercially analysed by Gradko International Ltd. The samplers were supplied pre-prepared, exposed in the field, and then returned to the laboratory for determination of the collected nitrite and calculation of the NO_2 concentration.



Figure 4.5. Diffusion tubes for passive NO_2 sampling.

4.4 Weather station

A weather station (HOBO U30, Onset Computer Corporation, MA, USA) was used alongside the air quality instruments during the measurement campaign (Figure 4.6). The device measures wind speed (m/s), gust speed (m/s), temperature ($^{\circ}\text{C}$), humidity (%) and the direction of the wind (degrees). The device is battery powered and is designed to operate within a temperature range of -40 to 60°C (-40 to 140°F). Wind speed is measured over 0 – 76 m/s with an accuracy of ± 1.1 m/s or $\pm 4\%$ of reading and a sensitivity of 0.5 m/s, while wind direction is measured over 0 – 355° with an accuracy of $\pm 5^{\circ}$ and a sensitivity of 1° . Air temperature is measured over -40 to 75°C with an accuracy of $\pm 0.2^{\circ}\text{C}$ and a sensitivity of 0.02°C , whereas relative humidity is measured over 0 – 100% RH with an accuracy of $\pm 2.5\%$ RH and a sensitivity of 0.1% RH (Onset Computer Corporation, 2009).



Figure 4.6. Weather station for meteorological variables measurement.

5. PERFORMANCE EVALUATION AND CALIBRATION OF AIR QUALITY DEVICES

Part of this chapter has been published in Environmental Pollution (<https://doi.org/10.1016/j.envpol.2024.124903>). The candidate is the first author, and the content related to calibration of low-cost sensors in this paper is conceived, analysed, and written by the candidate.

This chapter presents the evaluation of the low-cost air quality devices (ELOS PM and Sonitus NO₂ monitor) by co-locating them with the EPA FMS (reference station) and deriving either correction factors or calibration models based on the observed measurement discrepancies between the devices and the reference station. Performance metrics such as Root mean square error (RMSE) and correlation coefficient (R^2) was used to evaluate the devices and the model. Reference data were downloaded from respective EPA FMS.

A staged validation strategy was adopted in this study to ensure both inter-device consistency and agreement with reference-grade monitoring data before and after field deployment. First, all ELOS devices were co-located at the EPA traffic monitoring station on Ringsend Road for 14 days (4–17 May 2023) to evaluate inter-device precision under high and variable traffic-related pollutant concentrations. This initial co-location allowed direct comparison among devices under identical environmental conditions before field deployment. Calibration models were then developed using reference measurements from the EPA station at St John's Road West Monitoring Station, selected because of its proximity to the main train station environment in Dublin and representative of the major study sites.

After deployment at the two study sites, Heuston Station and Connolly Station, the ELOS devices were again co-located, this time with the EPA city-centre monitoring station at Pearse Street for 10 days (24 September–10 October 2023), to evaluate post-deployment precision and assess calibration stability and measurement accuracy. Similarly, the Sonitus Systems NO₂ monitors were co-located with the EPA reference monitoring station at Pearse Street for 15 days (10–25 February 2024) to derive an adjustment factor prior to installation at the study site.

5.1 Co-location of ELOS Air Quality Monitors Prior to Deployment

Five ELOS device were used in this study. Before deploying them at the study sites, the devices were co-located with EPA station (reference station) for 14-days at a traffic site

(Ringsend Road) from 4th to 17th May 2023. to evaluate the precision of the devices. Figure 5.1 shows the co-location of the devices at Ringsend FMS. The devices recorded PM_{2.5} and NO₂ concentrations at 20-minute intervals, however, for analysis purposes, the data were averaged hourly. Figure 5.2 and Figure 5.3 compare the raw PM_{2.5} and NO₂ measurements from the ELOS devices with the Ringsend FMS reference values, respectively.

PM_{2.5} measurements across the ELOS devices, relative to reference station, exhibited good correlation ($R^2 = 0.85-0.87$) and moderate error (RMSE = 3.3-3.7 $\mu\text{g}/\text{m}^3$) (Figure 5.4). Among the ELOS devices, device A exhibited a strong association with reference station. Furthermore, PM_{2.5} measurements across the ELOS devices, relative to Device A, showed strong correlations ($R^2 = 0.95-0.97$) and relatively low errors (RMS E= 1.5–2.0 $\mu\text{g}/\text{m}^3$) (Figure 5.5). Linear adjustments were applied to PM_{2.5} values measured by the devices, using Device A as the reference, to further reduce error between devices. The calibration model was developed for the device A, which is used for calibrating all other devices as the PM_{2.5} measurement performance of all the devices were very similar.



Figure 5.1. Co-location of the devices with EPA monitor at Ringsend (4th to 17th May 2023).

NO₂ measurements exhibited poor agreement with the reference station, with very low correlation ($R^2 = 0.003-0.009$) and high errors (RMSE = 18–21 $\mu\text{g}/\text{m}^3$). In contrast, moderate ($R^2 = 0.57$) to good ($R^2 = 0.87$) agreement was observed among the ELOS devices themselves (Figure 5.3). Among the devices, Device A exhibited a strong correlation with Device B ($R^2 = 0.87$) and relatively low error (RMSE = 1.86 $\mu\text{g}/\text{m}^3$). Consequently, only Devices A and B were

retained for NO₂ measurements in this study. A calibration model for NO₂ was therefore developed using Device A and subsequently applied to Device B. Devices C, D, and E were excluded from NO₂ measurements.

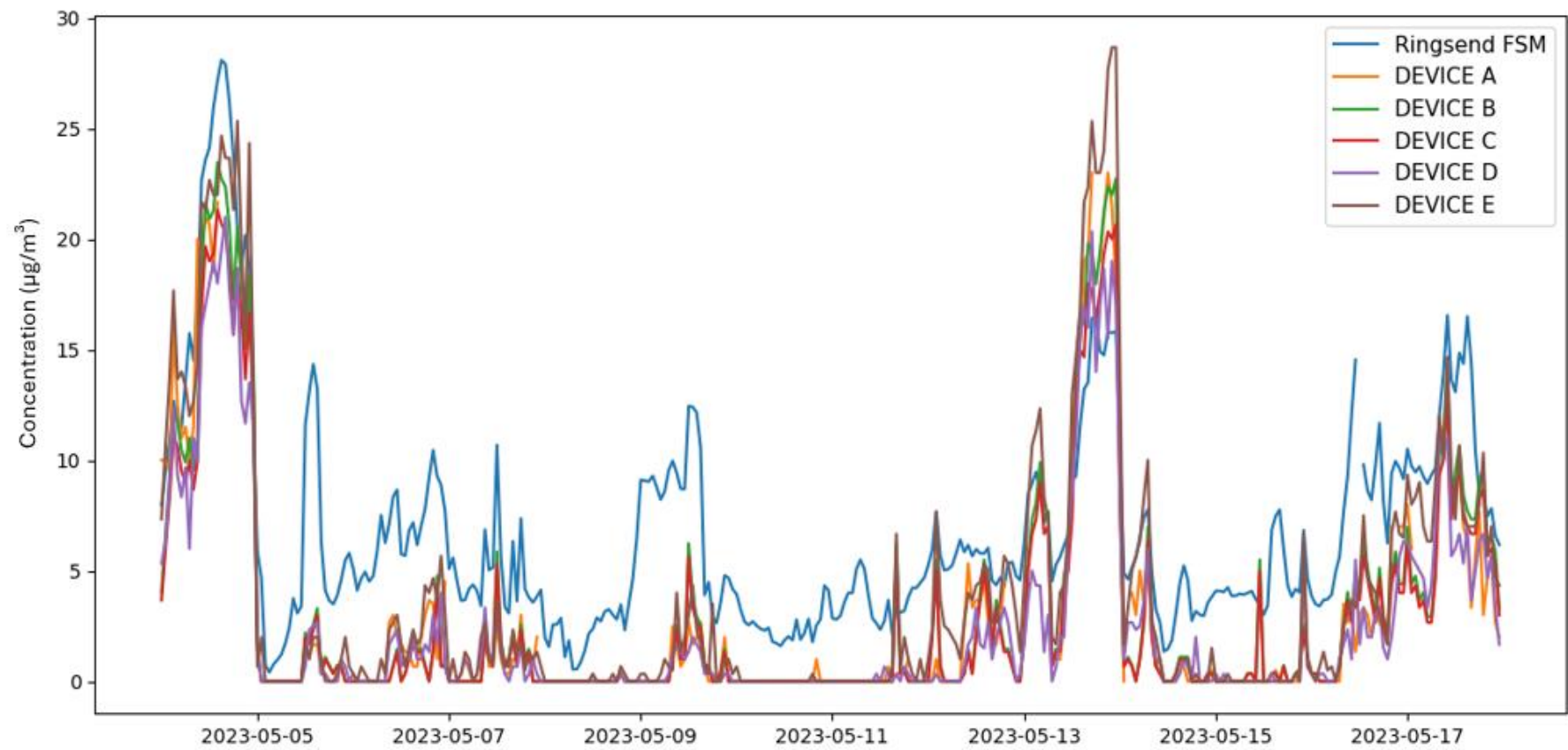


Figure 5.2. PM_{2.5} measurements from the ELOS devices with the Ringsend FMS reference values.

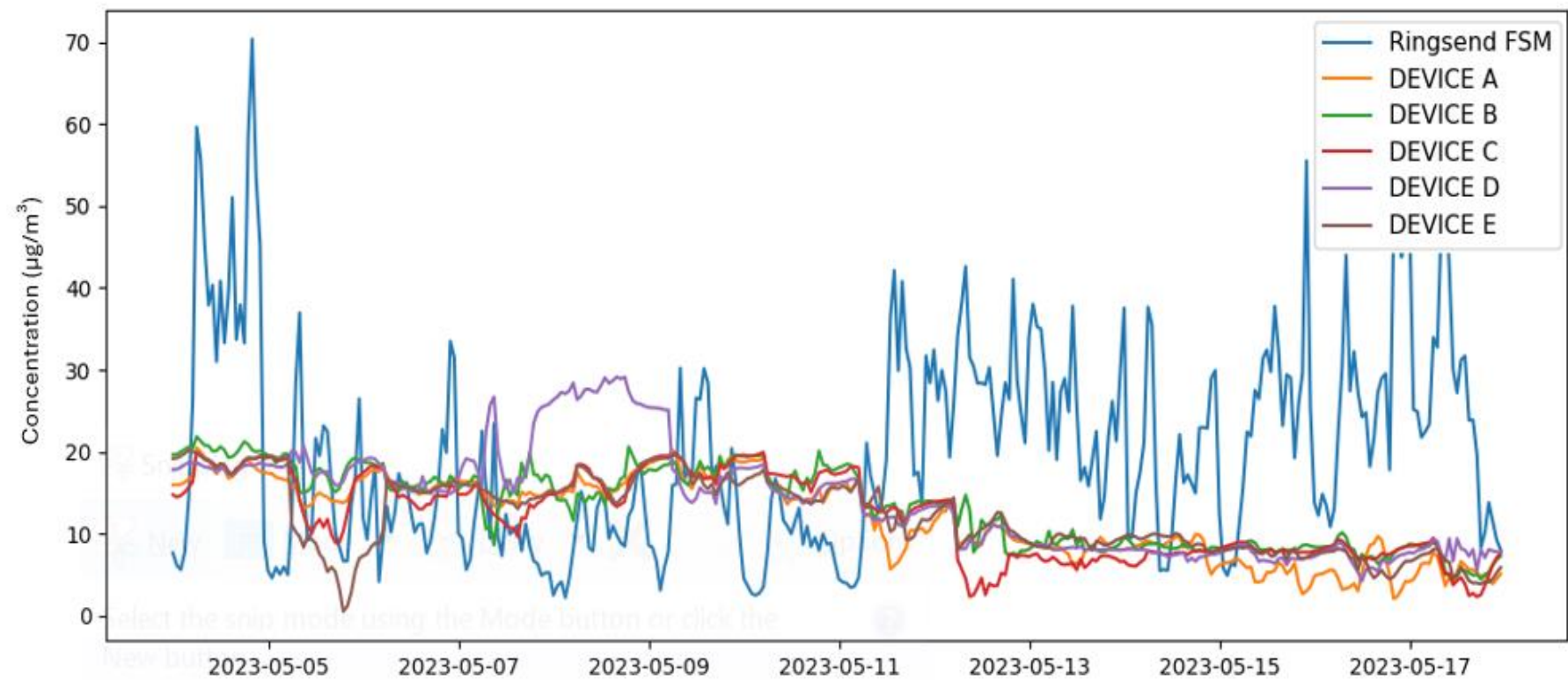


Figure 5.3. NO₂ measurements from the ELOS devices with the Ringsend FMS reference values.

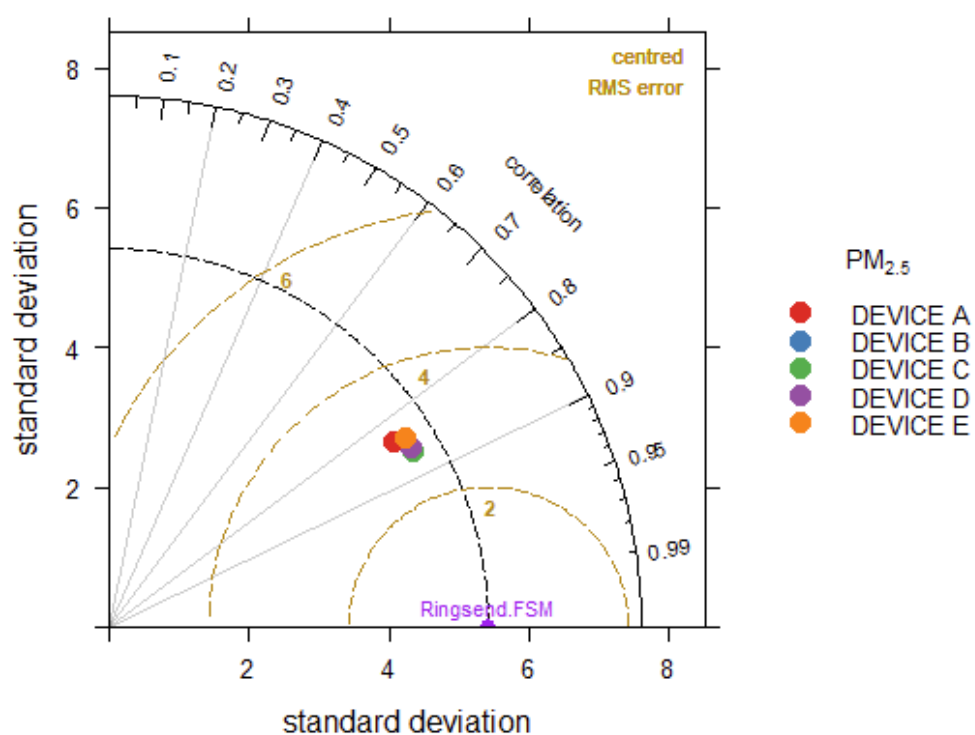


Figure 5.4. Performance of ELOS $PM_{2.5}$ measurement with the Ringsend FMS values (4th May - 17th May 2023).

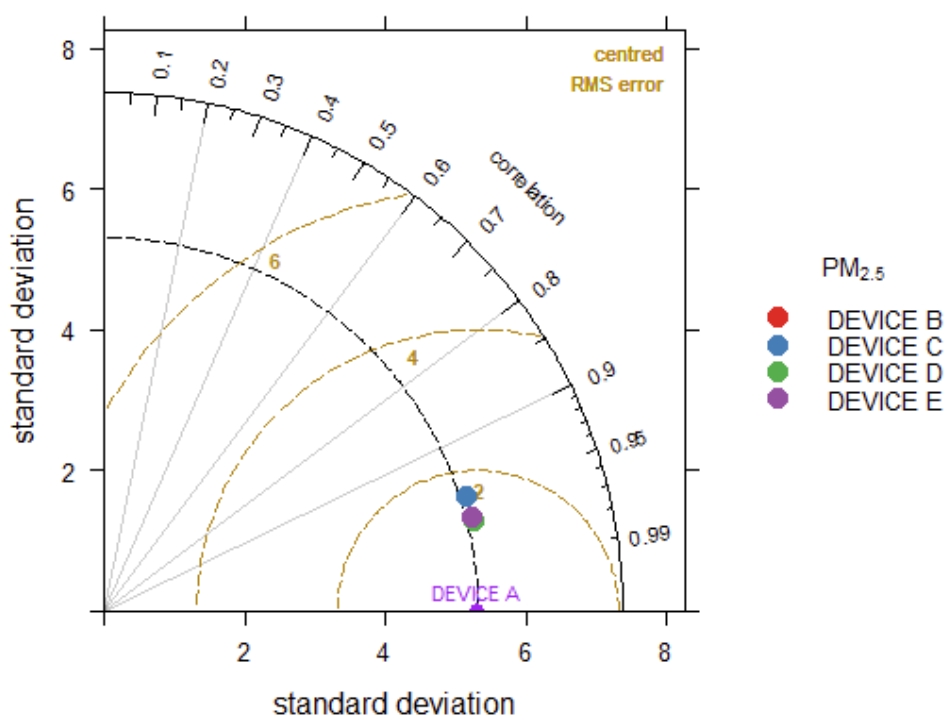


Figure 5.5. Performance of ELOS devices $PM_{2.5}$ measurements with the device A values (4th May - 17th May 2023).

5.2 Development of calibration model for ELOS Device A

We examined the raw data collected by the ELOS Device A relative to the St. Johns EPA FMS located at St. Johns Road for 28 days to develop the calibration model from 25th May to 26th June 2023. Hereafter, this EPA station is referred as St. Johns FMS.

The raw data was measured using Device A in reference to the St. Johns FMS. The average PM_{2.5} and NO₂ concentrations captured by Device A during the sampling period were found to underestimate the average concentrations measured by the reference monitor by 33% and 59%, respectively. In addition, Device A presented a significantly lower StDev for NO₂ of 2.8 µg/m³ compared to the St. Johns FMS with a StDev of 16.3 µg/m³. This suggests that the NO₂ sensor was less effective at capturing both high and very low NO₂ concentrations. Also, the Device A showed a high RMSE of 19.6 µg/m³ and no discernible linear correlation ($R^2 = 0.009$) for NO₂ in relation to reference monitor. These discrepancies commonly occur in NO₂ measurements using electrochemical sensors because NO₂ is primarily a chemically reactive pollutant, and the accuracy of the electrochemical sensors for NO₂ measurements is influenced by various factors such as interference, pollutant sources, cross-sensitivity, and changing environmental conditions (Nowack et al., 2021).

Conversely, StDev the value for the PM_{2.5} sensor (6.1 µg/m³) was similar to the St. Johns FMS (5.5 µg/m³), indicating similar performance in terms of capturing extreme concentration. The error and linear correlation between the sensor and the reference monitor for PM_{2.5} was found to be 3.7 µg/m³ and 0.76, which indicated that the PM_{2.5} sensor performance was in good agreement with that of the St. Johns FMS monitor.

5.2.1 Methodology

The study evaluated two distinct machine learning algorithms (XGBoost and random forest), which are commonly found in the literature for calibrating low-cost devices (Adong et al., 2022; B. Liu et al., 2021). XGBoost and random forest are the ensemble models but employ boosting and bagging technique, respectively (Pan et al., 2023). The PM_{2.5} calibration model developed for ELOS Device A was applied to all other ELOS devices, while the NO₂ calibration model developed for ELOS Device A was applied only to Device B.

5.2.1.1 Random Forest regression model

Random Forest is an ensemble machine-learning algorithm that combines multiple decision trees to produce a more accurate and stable prediction. It works by generating many trees using bootstrapped samples of the training data, while also randomly selecting subsets of features at each tree split. This randomness reduces overfitting and improves model generalization. For regression process, the final prediction is obtained by averaging the outputs of all trees, whereas classification tasks use dominant voting. Random Forest is effective at capturing nonlinear relationships, handles high-dimensional data well, and is relatively robust to noise and outliers.

5.2.1.2 Extreme Gradient Boosting (XGBoost) regression model

XGBoost is an advanced gradient-boosting algorithm designed for high performance, speed, and accuracy. Unlike Random Forest, which builds trees independently, XGBoost constructs trees sequentially, with each new tree trained to correct the residual errors of the previous ensemble. It incorporates regularization techniques such as L1/L2 penalties, shrinkage (learning rate), and tree pruning to prevent overfitting while improving predictive power. XGBoost efficiently handles missing values, nonlinear relationships, and interactions between features, and is known for its competitive performance in structured (tabular) data applications. Its optimized implementation makes it one of the most widely used algorithms in modern machine-learning workflows.

5.2.1.3 Model Training, Optimization, Evaluation and Feature Analysis

A k fold cross validation approach was adopted to evaluate the calibrating models. In this approach, the dataset is split into k fold, and the model is trained and tested k times, using a different fold serving as the validation set in each iteration. This approach is used to avoid performance overprediction, restricting leakage of data, and limiting prediction of past observation (Wang et al., 2023a). The Python packages scikit-learn (sklearn) and XGBoost were used to perform RF and XGBoost regression, respectively. RandomizedSearchCV function was employed to perform k fold cross validation and obtain the optimal hyperparameters for the models.

In the dataset, device reading of PM_{2.5} and NO₂, meteorological variables such as wind speed (m/s), wind direction, humidity (%), temperature (Celsius), and pressure (millibar),

engineered features such as hours of the day, day of the month, rate of change of temperature per hour, rate

of change of humidity per hour, and additional factors such as noise (Db), train schedule, and road traffic were considered as the explanatory features. Hourly wind conditions were collected from the HOBO U30 weather station installed at Heuston roof.

Table 5.1 presents the information of the variables used in the model. The reference monitor reading of PM_{2.5} and NO₂ (EPA station values) were treated as the response feature. Two calibration model was developed for PM_{2.5}, dataset with pollutant values less than or equal to median value and dataset with pollutant values above the median value to avoid overprediction of the response variables at lower concentration.

However, NO₂ calibration model was developed considering the whole dataset, as NO₂ sensor exhibited lower standard deviation value. For each fold, trained models are evaluated against the test dataset using performance metrics such as RMSE and correlation coefficient (R²).

Table 5.1. Variables used in the model.

Variables	Variable identity	Unit
Wind speed	Wind speed	m/s
Sine function of wind direction	Wind_direction_sin	dimensionless
Cosine function of wind direction	Wind_direction_cos	dimensionless
Raw PM _{2.5} sensor data	PM _{2.5}	µg/m ³
Raw NO ₂ sensor data	NO ₂	µg/m ³
Humidity	humidity	%
Temperature	temperature	Celsius
Barometric Pressure	pressure	hPa
Noise	Noise	decibel
Rate of change of temperature per hour	Temperature_Engineered	%
Rate of change of humidity per hour	humidity_Engineered	%
Sine function of month of the year	month_sin	dimensionless
Cosine function of month of the year	month_cos	dimensionless
Sine function of day of the week	day_of_week_sin	dimensionless
Cosine function of day of the week	day_of_week_cos	dimensionless
Sine function of hours of the day	hour_sin	dimensionless
Cosine function of hours of the day	hour_cos	dimensionless
No of vehicles passing through St. John's Road	Road_traffic	count/hour
Arrival & Departure in Heuston station	Rail_traffic	count/hour

The result from each evaluation is then averaged to derive the final evaluation metric for the model, and a similar procedure is applied to determine the model's hyperparameters. The Shapley Additive exPlanations (SHAP) method was used to sort the features based on their global impact and to compute the impact of each features on the model output of each sample test, highlighting the complex relation between the response and explanatory features (Wang et al., 2023a).

5.2.2 Performances of the calibration algorithm for ELOS device

We summarized the statistical performance (R^2 and RMSE) of the calibration models developed for ELOS Device A for $PM_{2.5}$ and NO_2 in Figure 5.6. The calibration models were applied to the test dataset from 20–27 June 2023 to assess model performance against selected evaluation metrics. After applying the calibration model, device measurements demonstrated good agreement with the reference monitor. Primarily both the algorithms provided good calibration results for both NO_2 and $PM_{2.5}$, while performance of the XGBoost model is slightly better than the RF model. Also, performance of the calibration models for $PM_{2.5}$ is better than NO_2 . The R^2 and RMSE for $PM_{2.5}$ calibration model ranges between 0.9-0.92 and 2.2-2.25, respectively, which indicates good reconstruction of PM concentration by the models. In general, PM calibration results tends to be better than gaseous pollutants, owing to good linear relationship between sensor raw data and reference monitor values (Nowack et al., 2021; Wang et al., 2023).

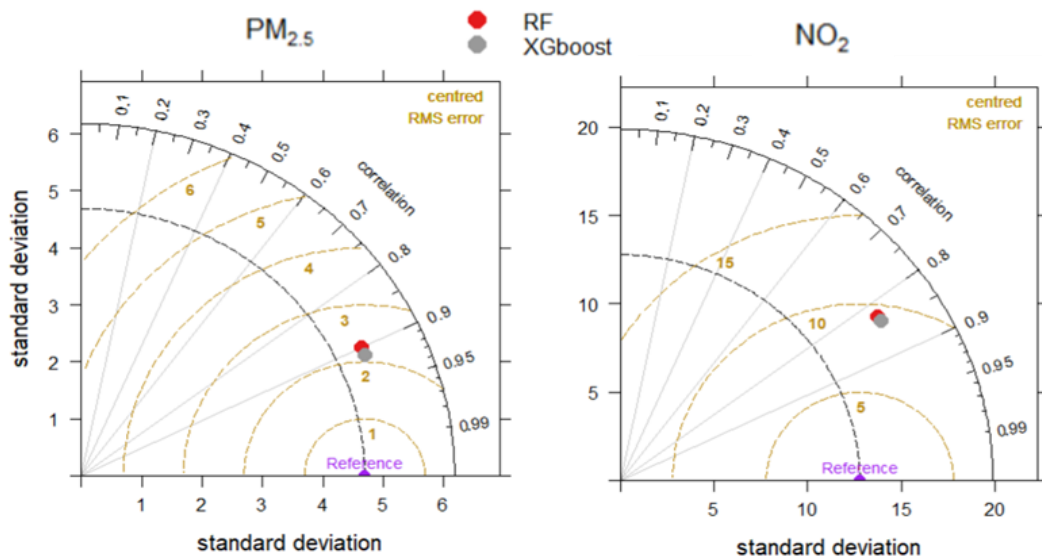


Figure 5.6. Performance of $PM_{2.5}$ and NO_2 calibration models during test period of 20-27 June 2023

The R^2 and RMSE for the NO_2 calibration model ranged between 0.82-0.83 and 9.1-9.25, respectively, which indicated a reasonable level of reconstruction accuracy for a gaseous pollutant like NO_2 . Machine learning models yield good calibration accuracy but sometimes overfit the training data, however significant temporal aggregation effects were not observed for the model's performance. Based on the performance of the model's, XGBoost was selected to calibrate both $\text{PM}_{2.5}$ and NO_2 . The time series of the modelled and measured device and reference NO_2 and $\text{PM}_{2.5}$ concentration are shown in Figure 5.7.

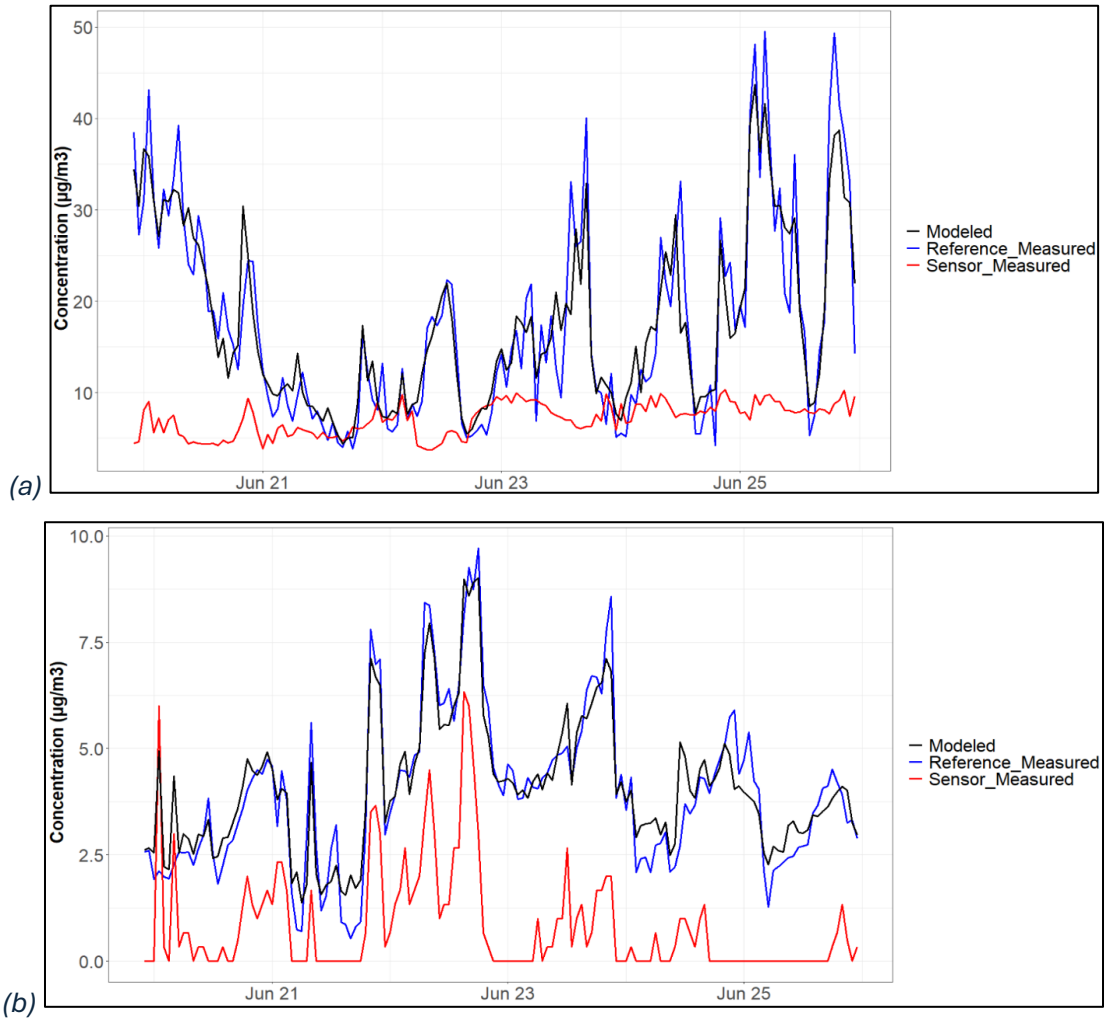


Figure 5.7. Time series of measured (sensor and reference) and modelled (using XGboost) (a) NO_2 and (b) $\text{PM}_{2.5}$ concentrations (20th – 27th June 2023).

5.2.3 Impact of features on model output

We investigated the impact of different features on best performing XGBoost model for $\text{PM}_{2.5}$ and NO_2 . The importance of each feature on model output is represented using SHAP summary plot, which consist of magnitude contribution of all points of

training dataset of each feature, expressed by their SHAP value (Wang et al., 2023). The explanatory feature with positive SHAP values has positive prediction on the model and vice-versa, and higher absolute SHAP value of feature denotes greater effect on the output. Features are ranked high to low based on the importance, with absolute SHAP values of all datapoints from high to low.

Figure 5.8 presents the violin SHAP summary plot for NO_2 and $\text{PM}_{2.5}$ respectively. In Figure 5.8 (a), wind speed has the highest feature importance on the NO_2 model with SHAP values increases at lower wind speed. The strong relation of positive SHAP values with lower wind speed clearly indicate that NO_2 is strongly influenced by local source. Other than wind speed, $\text{PM}_{2.5}$, pressure, rail traffic, road traffic, NO_2 raw sensor readings, days of the week are positively correlated with the reference NO_2 values. The wind sectors corresponding to negative sine functions have a significant impact on the positive SHAP values, indicating potential dominance of NO_2 sources in those directions. The effect of relative humidity, hours of the day, noise and temperature are not significant on NO_2 model.

The $\text{PM}_{2.5}$ model SHAP values presented in Figure 5.8 clearly shows that relationship between raw sensor reading, and model output is linear. Beside sensor reading, pressure is the second important feature that is positively correlated with reference $\text{PM}_{2.5}$. The positive relation with humidity indicates the presence of aerosol hygroscopicity in the atmosphere. The association between pressure and model outcome was recognised as non-linear, consistent with previous literature (Wang et al., 2023b). High air pressure is conducive in accumulation of $\text{PM}_{2.5}$ to form polluted weather, so the concentration of $\text{PM}_{2.5}$ increases. However, during maintenance of high PM concentration, it shows inverse association. It is noteworthy that air pressure is good predictor than good explainer for sensor readings. Other features do not have significant impact on $\text{PM}_{2.5}$ model. Since NO_2 calibration is strongly influenced by local factors such as wind speed, wind direction, and road traffic, the NO_2 model was applied only to the outdoor environment in the study and is applicable only for this location. These devices were not employed for NO_2 measurement inside the station.

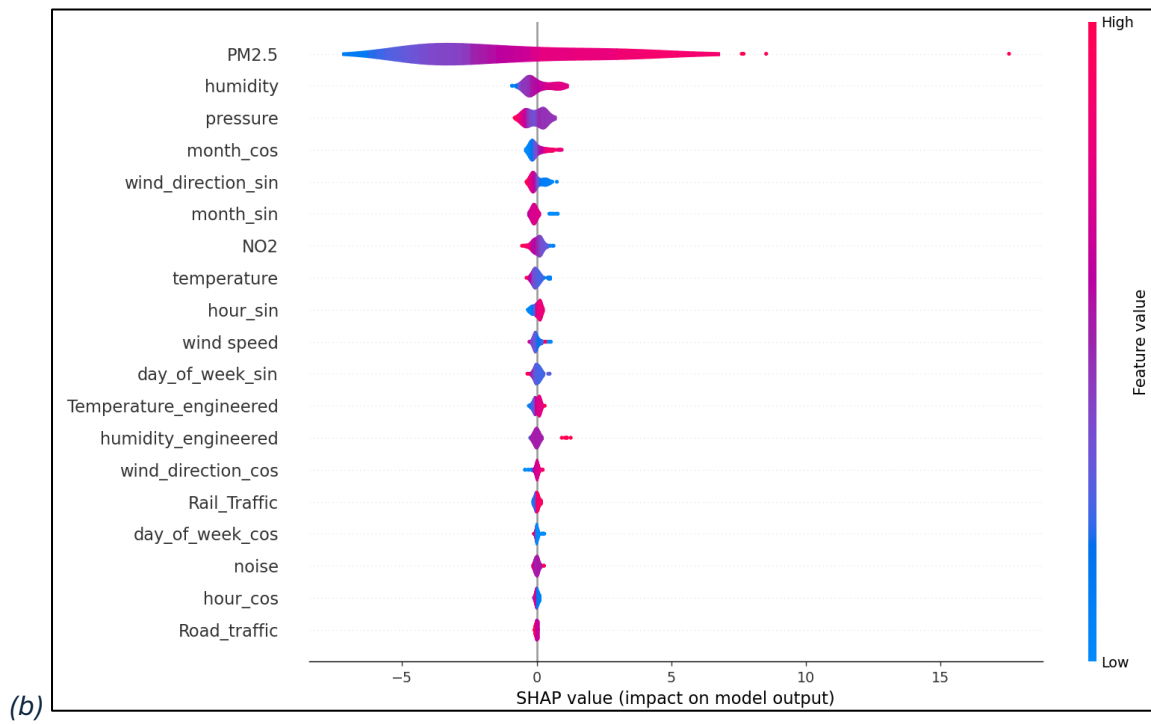
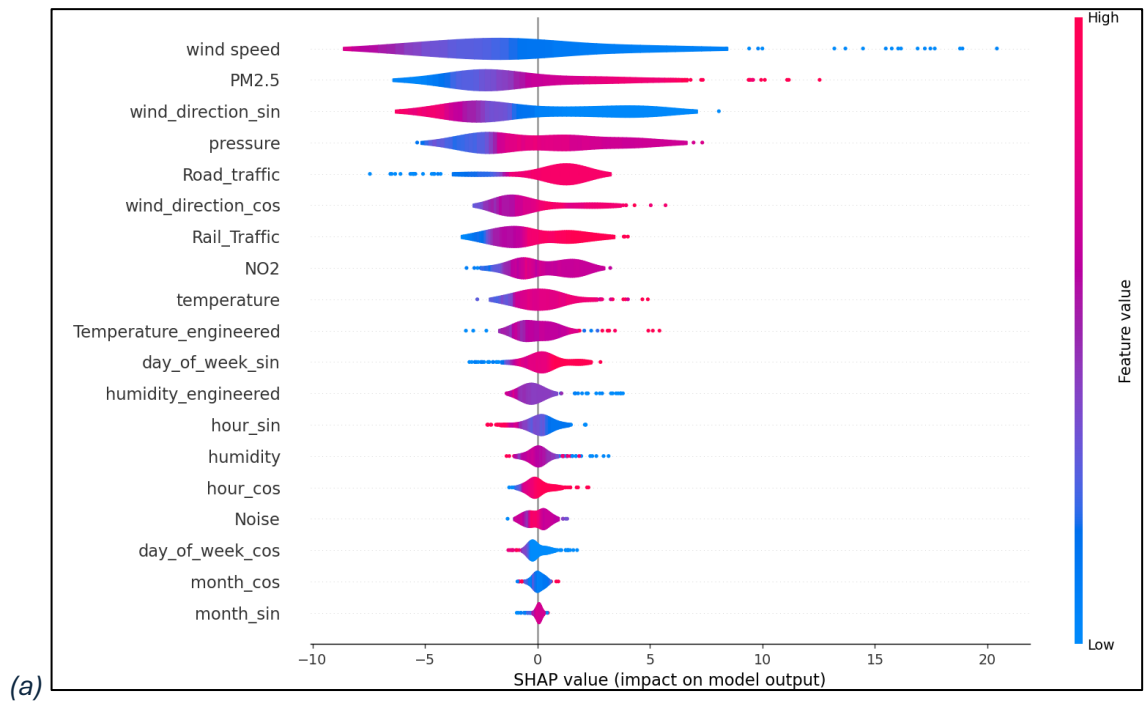


Figure 5.8. SHAP summary plot for (a) NO_2 and (b) $\text{PM}_{2.5}$ calibration models.

5.3 Co-location Assessment of ELOS Air Quality Monitors After Deployment

After deploying them at the study sites (both Heuston and Connolly terminals), the devices were co-located themselves for 10-days at a city centre site (Pearse EPA station) from 24th September to 10th September 2023 to evaluate the precision and accuracy of the devices. Hereafter, this site is referred as Pearse FMS. Post co-location of the devices validates inter devices performance and the performance of the developed calibration model. Figure 5.9 compare the calibrated PM_{2.5} measurements of the ELOS devices with the Pearse FMS reference values,

The calibrated PM_{2.5} measurements across the ELOS devices, relative to the reference station, exhibited good correlations ($R^2 = 0.91\text{--}0.93$) and moderate errors (RMSE = 1.5–1.7 $\mu\text{g}/\text{m}^3$). Furthermore, PM_{2.5} measurements from all ELOS devices exhibited strong agreement with Device A after deployment, with only slight drift observed, confirming that the developed calibration models remained applicable across all devices at all monitoring sites. Similarly, Device A also exhibited strong association with the Device for NO₂, however calibration model developed was not valid for this site.

5.4 Performance evaluation and correction factor for Sonitus NO₂ monitors

The Sonitus NO₂ monitors were co-located with the Pearse Street EPA air quality monitoring station for 15 days (10 February to 25 February 2024) to determine the adjustment factor before their installation at the study site. Unlike the ELOS NO₂ measurements, the Sonitus monitor showed good consistency with the EPA reference data, with an R^2 value of 0.71 and an error of 10.3 $\mu\text{g}/\text{m}^3$ (Figure 5.10). A linear adjustment factor ($\text{NO}_2 = ((0.8204 \times \text{device value}) + 29.09)$) was applied to correct the NO₂ concentrations.

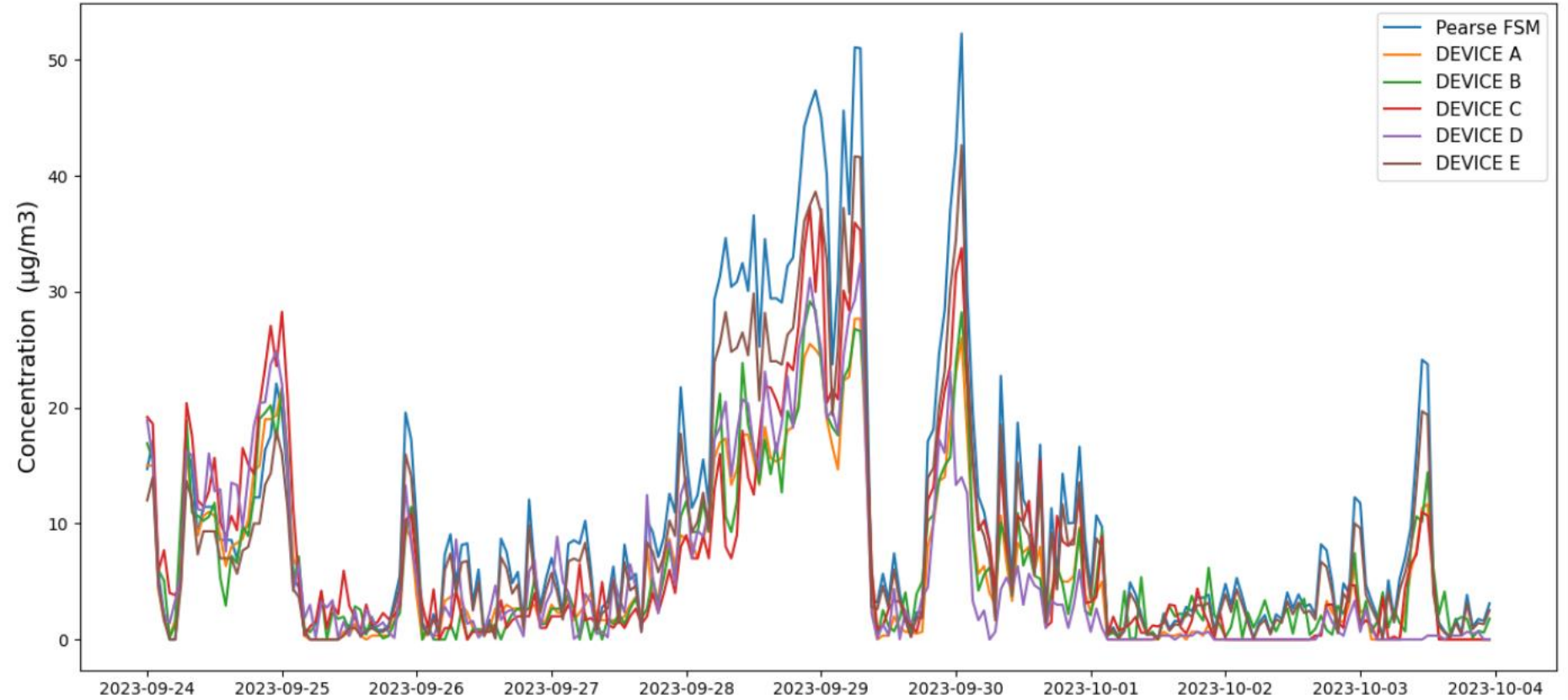


Figure 5.9. Calibrated $PM_{2.5}$ measurements of the ELOS devices with the Pearse FMS reference values (24th September to 4th October 2023)

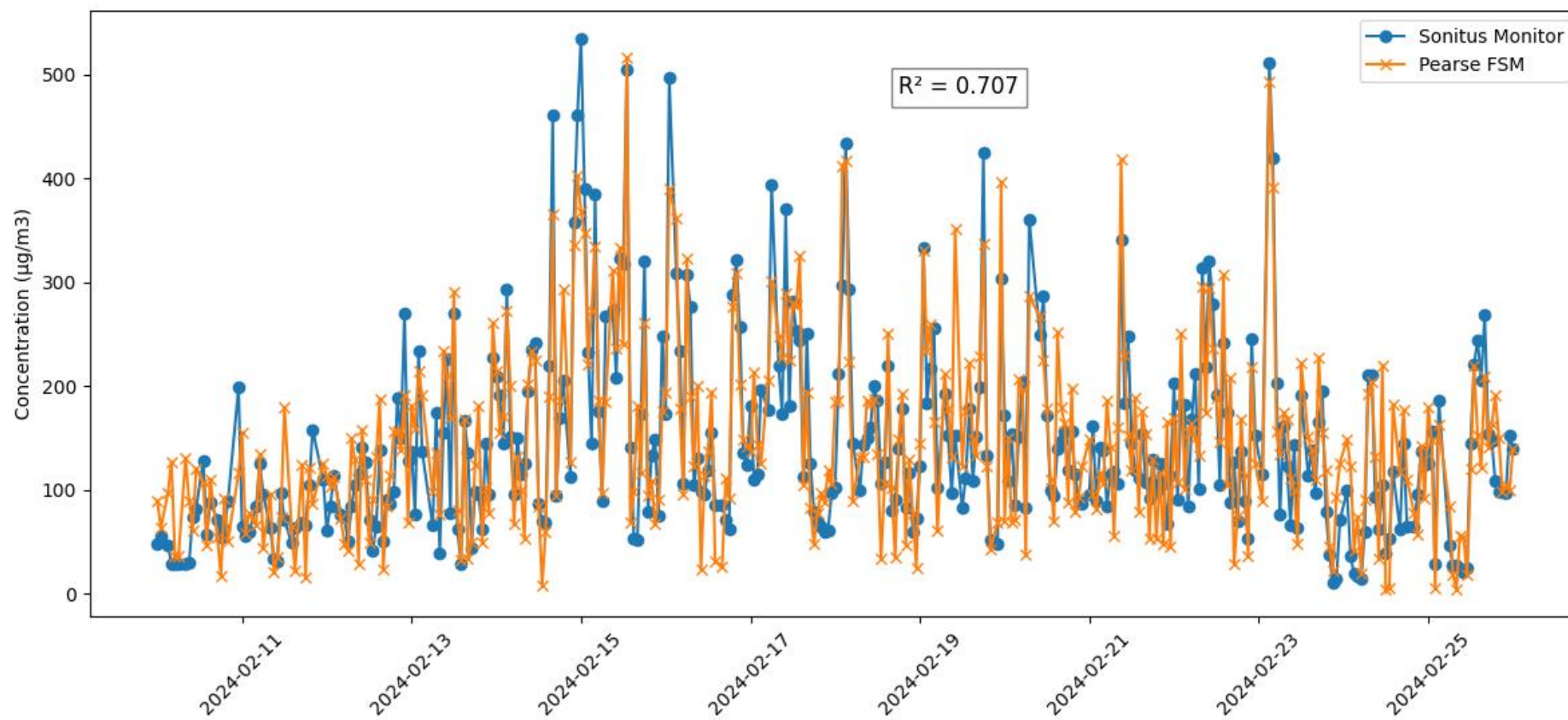


Figure 5.10. Performance of Sonitus NO₂ measurements with the Pearse FMS NO₂ values

5.5 Summary

PM_{2.5} measurements across the ELOS devices, relative to reference station, exhibited good correlation ($R^2 = 0.85-0.87$) and moderate error (RMSE = 3.3-3.7 $\mu\text{g}/\text{m}^3$). NO₂ measurements exhibited poor agreement with the reference station, with very low correlation ($R^2 = 0.003-0.009$) and high errors (RMSE = 18–21 $\mu\text{g}/\text{m}^3$).

Machine learning models (RF & XGBoost) to calibrate the PM_{2.5} and NO₂ measurements acquired by the ELOS devices. The performance of the XGBoost) model was slightly better than the RF model for both PM_{2.5} and NO₂. Local wind speeds presented the variable with the greatest impact on NO₂ model results, followed by equivalent PM_{2.5} concentrations, wind direction and pressure. The strong relation of lower wind speeds was observed for the NO₂ model which clearly indicated that NO₂ was strongly influenced by the local sources.

Linear relationship between the raw sensor readings and the PM_{2.5} model was identified, indicating that sensor readings have a significant effect on the model output. These results highlight that the NO₂ sensor requires more input data for accurate calibration compared to the PM_{2.5} sensor. Unlike ELOS device, the Sonitus NO₂ monitor showed good consistency with the EPA reference data, with an R^2 value of 0.71 and an error of 10.3 $\mu\text{g}/\text{m}^3$.

6. QUANTIFYING TRAIN AND ROAD TRAFFIC CONTRIBUTIONS TO $\text{PM}_{2.5}$ AND NO_2 NEAR HEUSTON TERMINAL

Part of this chapter has been published in Environmental Pollution (<https://doi.org/10.1016/j.envpol.2024.124903>). The candidate is the first author, and the content related to source apportionment in this paper is conceived, analysed, and written by the candidate.

This chapter presents the levels of $\text{PM}_{2.5}$ and NO_2 inside the Heuston terminal. It also focuses on detecting and quantifying the contributions of train and road traffic emissions to PM and NO_2 in the vicinity of the terminal using data-filtration techniques. The diffusion tubes used in this chapter were commercially analysed for nitrite and, consequently, NO_2 by Gradko International Ltd, UK.

6.1 Air quality assessment at Heuston

The measurements of NO_2 and $\text{PM}_{2.5}$ were undertaken from 25th May to 26th June 2023 at Heuston. The simultaneous multisite measurement of NO_2 was made using palmes-type passive diffusive tubes. These were exposed for 4 weeks at 19 locations inside and outside the station. A set of diffusion tubes were also co-located alongside the St. Johns EPA FMS. The results of these diffusion tubes were compared with St. Johns EPA FMS NO_2 gas analyser and a correction factor was determined using the DEFRA bias adjustment tool (DEFRA, 2011). The correction factor (0.89) was then multiplied with diffusion tube NO_2 measurements collected at the Heuston station. The $\text{PM}_{2.5}$ measurements were obtained using ELOS AQ devices C, D and E, and the measurements were corrected using the developed calibration model. The devices were installed at Platforms 2, Platform 3 & 4, and in the concourse area of terminal. Locations of the diffusion tubes and the ELOS AQ devices employed in the terminal are shown in the Figure 6.1.

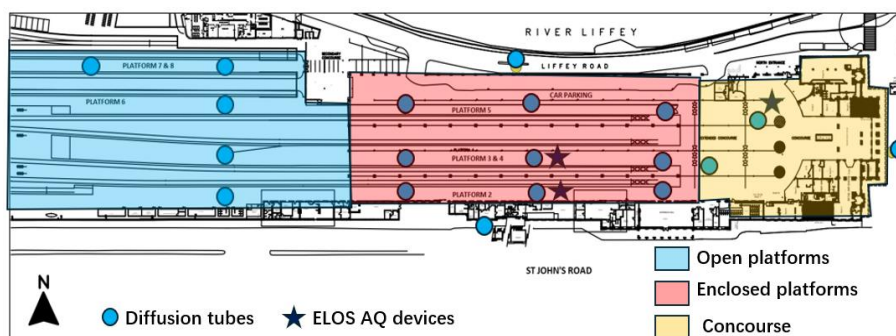


Figure 6.1. Location of the diffusion tubes and ELOS AQ devices installed at Heuston terminal during May-June 2023.

6.1.1 Measuring NO₂ and PM_{2.5} concentrations

Table 6.1 and Table 6.2 presents the summary of the NO₂ and PM_{2.5} concentrations measured over the study period at Heuston terminal, respectively. NO₂ concentrations differed significantly between indoor and outdoor locations at the station, with campaign-average levels ranging from 32 to 121 µg/m³. The highest concentrations were observed on Platform 2, ranging from 62 to 121 µg/m³, with high values found at the centre of the platform. All indoor locations exceeded the EU annual NO₂ guideline value of 40 µg/m³, except for one site in the concourse. In contrast, average PM_{2.5} levels over the measurement period ranged from 7 to 10.3 µg/m³, with high values observed in the concourse, however, average PM_{2.5} concentrations at all the locations were found well below the EU annual guideline value of 20 µg/m³. The 24-hour average PM_{2.5} values exceeded the WHO guideline value of 15 µg/m³ on only 3–4% of the monitoring days.

Table 6.1. Summary of average NO₂ levels measured over the study period at Heuston terminal (25th May- 20th June 2023).

Location	Exposure Time (hr.)	Concentration (µg/m ³)
North wall of Heuston station	622.0	31.9
Platform 5 enclosed Car Parking end	622.2	96.0
Platform 5 enclosed -front end	621.8	43.4
Platform 4 enclosed-front end	621.8	52.5
Platform 2 enclosed- front end	621.7	62.4
Platform 5 enclosed-Middle	619.9	58.7
Platform 4 enclosed-Middle	620.8	98.6
Platform 2 enclosed-Middle	620.9	121.3
Platform 5 enclosed-back end	619.8	56.7
Platform 4 enclosed-back end	620.7	77.6
Platform 2 enclosed-back end	620.6	76.3
Platform 5- Open	619.3	72.9
Platform 5- Open-back end	619.2	62.9
Platform 4- Open	620.6	74.1
Platform 2- Open	621.1	72.9
Concourse- Coca cola vending machine	619.5	36.8
Concourse-front steel column	619.2	44.9
Lamp post- front entrance	619.2	31.8
EPA station St. Johns road - 1	527.2	38.1
EPA station St. Johns road - 2	527.2	37.6
Blank	622.3	0.3
South wall of Heuston station	621.6	51.8

Table 6.2. Summary of PM_{2.5} concentrations measured at the study site.

Site	Average PM _{2.5} concentration (µg/m ³)	No. of days exceeding 24-hr WHO guideline value
Platform 2	9.3	1
Platform 3 & 4	7	1
Concourse	10.3	2

6.2 Source attribution to PM_{2.5} and NO₂ from train and road traffic near train terminal

6.2.1 Site Description

Adjacent to the Heuston train station is a continuous EPA monitoring site that is located along St John's Road station in Inchicore (St. John's FMS), and which is situated within 3 kilometres of Dublin city centre (Figure 6.2). This station observed the NO₂ exceedances in 2019 and therefore serves as a point of interest in determining the contribution of pollution from the railway station at the monitoring site. The station records hourly PM₁₀, PM_{2.5}, and NO₂ concentrations and is located opposite to a major road (St John's Road West) and Heuston railway station. St John's Road West is one of the major roads in Dublin connecting city the with the arterial M50 motorway via the N4 corridor to and from the city centre. The average traffic on this road in June ranged between 26,000-27,000 vehicles/day (Dublin City Council, 2023). Averaged over May-June 2023, Heuston had approximately 134 trains/day in the station between Monday-Saturday, reducing to approximately 73 trains/day on Sundays. All the trains from Heuston scheduled during the monitoring campaign were fuelled by diesel.

6.2.1.1 Monitoring Plan

The measurement of PM_{2.5} and NO₂ were carried out using ELOS AQ devices A & B. Device A was co-located with St. Johns FMS, while Device B was employed outdoor at roof level on the Heuston station building and measurements were collected simultaneously (Figure 6.2). PM_{2.5} and NO₂ concentrations were monitored continuously for a month from 25 May – 26 June 2023. Measurements were adjusted using developed calibration models for PM_{2.5} and NO₂. The weather station (HOBO U30) was installed at Heuston roof to collect the hourly wind speed and direction for the aforementioned period. The winds were predominantly from the NEE direction (26%) during this period (Figure 6.2). Additionally, another nearby national EPA FMS (Cabra community college) located approximately 2.1 km upwind of railway station was selected to act as a representation of the background air quality for PM_{2.5} (Figure 6.2). This site

is hereafter referred to as Cabra FMS. Cabra FMS is a residential site surrounded by parks and educational establishments, with no major air pollution sources in its neighbourhood during the study period.

6.2.2 NO₂ measurement using diffusion tube

A Palmes-type diffusion tube was co-located with the DEVICE B device on the Heuston roof to measure average NO₂ concentrations over the monitoring period of one month. The accuracy of the NO₂ diffusion tubes (10–12% error) is higher than the calibrated NO₂ device values (Mueller et al., 2017). To further reduce the bias associated with the calibrated values, the device B based NO₂ measurements were normalised using its average value (over the study period) after applying the calibration model and adjusted using average NO₂ value measured using diffusion tube. Additionally, a diffusion tube was installed in the northern wall of Heuston station to capture the upwind station background NO₂ concentration (Figure 6.2). The diffusion tube value is corrected using DEFRA bias correction factor (0.89).

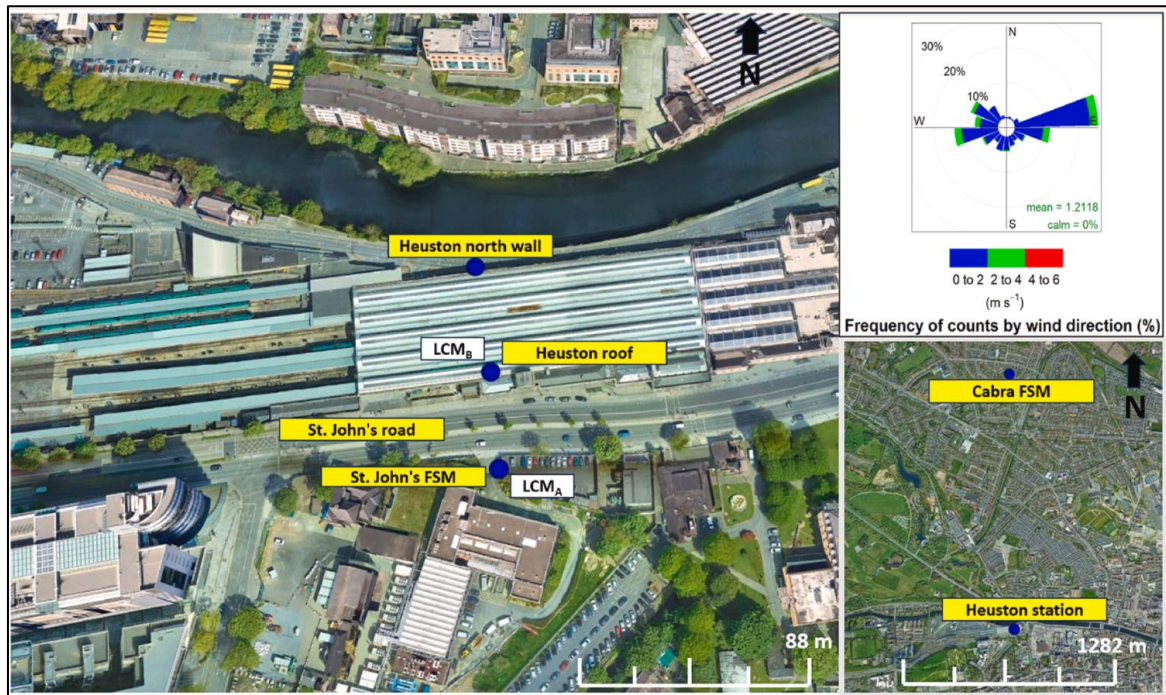


Figure 6.2. Layout of monitoring site and insert of wind rose (25 May – June 26, 2023) at Heuston railway station in Dublin, Ireland.

6.2.3 Source apportionment

A data filtration technique helped disaggregate the contribution of road traffic and railway station emission sources. Data filtration is a quantitative technique that can be used to detect the sources contribution based on specific periods of interest such as selecting hours of the day when traffic is high, filtering data corresponding to upwind and downwind directions of monitoring sites, or based on specific activity such as filtering data corresponding to specific traffic movements (e.g., aircraft LTO, ship hostelling and manoeuvring etc) (Carslaw et al., 2006; Merico et al., 2016) and transport characteristics (e.g., engine type, fuel type etc) (Schürmann et al., 2007). In this study, the pollutant concentrations were filtered based on corresponding upwind and downwind sectors of the Heuston railway station and St. Johns Road.

The road traffic emission contribution for NO₂ and PM_{2.5} were estimated by considering the hourly concentrations in the specific wind sector of 110–250° when the road traffic emissions was considered more likely to have an effect on NO₂ and PM_{2.5} concentrations (measured at Heuston roof) and by removing the background concentration by subtracting the pollutants concentration measured at St. Johns FMS (Table 6.3).

Table 6.3. Filtering technique employed at the sites.

Site	Sources to be estimated	Sources wind sector	Background site	Sources contribution
Heuston station roof	Road traffic	110-250 °C	St John EPA station	Road traffic = average pollutant concentration at Heuston roof - average pollutant concentration at background site
	Train emission	0-70 °C & 290-360 °C	NO ₂ - Northern wall of Heuston roof & PM _{2.5} - Cabra community college)	Train emission = average pollutant concentration at Heuston roof - average pollutants concentration at background site
St John EPA station	Train emissions	0-70 °C & 290-360 °C	-	Train emissions = average pollutant concentration at St John EPA station - Road traffic

Similarly, railway station emissions contribution for NO₂ and PM_{2.5} were estimated by considering the wind sector ((0–70°) & (290–360°)) where railway station emissions have

significant effect on NO_2 and $\text{PM}_{2.5}$ levels (measured at Heuston roof), after subtracting the background concentration (NO_2 - Northern wall of Heuston roof & $\text{PM}_{2.5}$ - Cabra FMS). However, the railway station emission contribution for NO_2 was not estimated explicitly as the upwind background NO_2 concentrations were reflective of the averaged value (measured using diffusion tube) over the monitoring period. At the St. Johns FMS, the railway station emissions contribution was estimated, after subtracting the previous estimated traffic contribution from the average $\text{PM}_{2.5}$ and NO_2 measured at St. Johns FMS. For estimating railway station emissions, only the hours during which trains were stationed at the platform with their engines running were included in the filtration analysis. Figure 6.3 shows the filtrating technique adopted at the site.

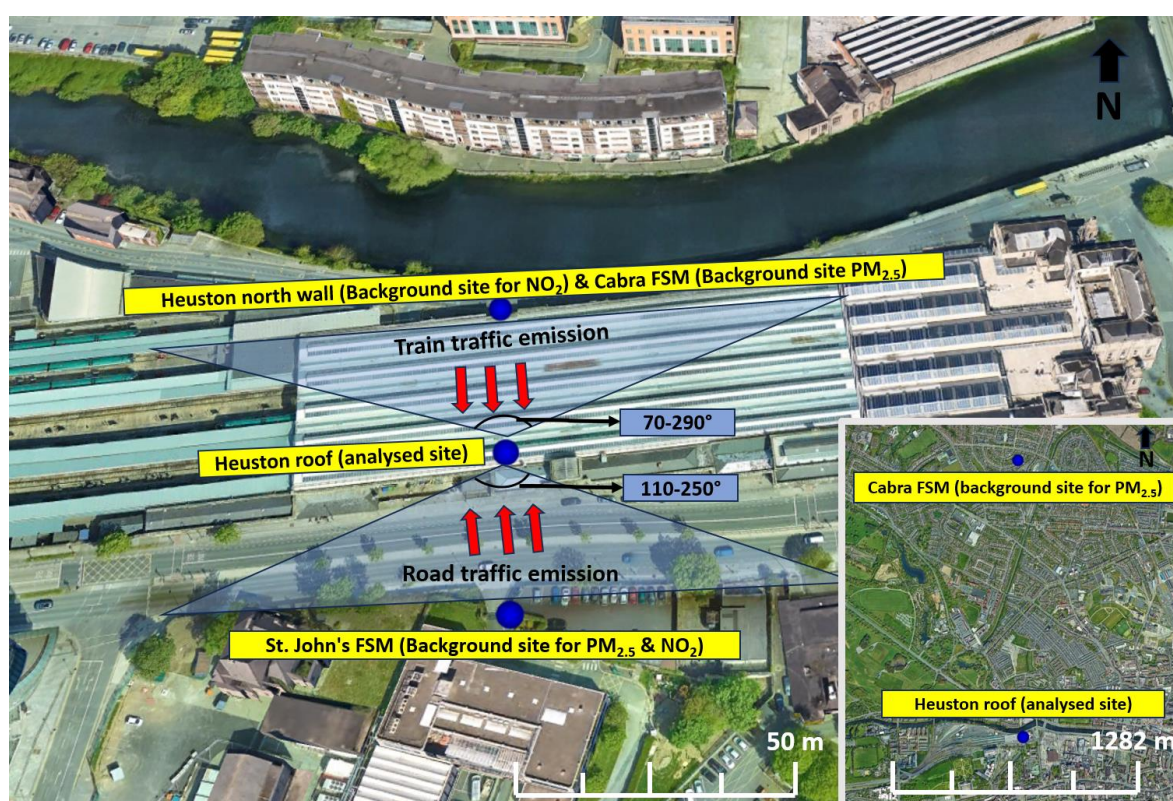


Figure 6.3. Filtrating technique adopted at the sites.

6.2.4 Bivariate polar plot

To interpret the dependency of pollutants on wind speed, the concentration of NO_2 and $\text{PM}_{2.5}$ measured at Heuston station roof and St. Johns FMS were associated with wind speed and direction using bivariate polar plots. Bivariate polar plots are a commonly employed method to discriminate between sources of pollutants emitted with significant levels of buoyancy

(e.g., industrial stack emissions, ships and aircraft plumes) (Carslaw et al., 2006). This method can also be employed to understand the complex relationships between wind speed and pollutants concentration. For instance, flow in an urban street-canyon where wind-blown particle re-suspension is important and where concentration of particle increases with wind speed (Carslaw et al., 2006).

6.3 Results & discussion

6.3.1 Concentrations profiles at different study sites

Table 6.4 presents the summary of the NO_2 and $\text{PM}_{2.5}$ concentration measured at the study sites. The concentration of $\text{PM}_{2.5}$ and NO_2 over the study period at St. Johns FMS were found to be 7.8 and 38 $\mu\text{g}/\text{m}^3$, respectively. While the concentration of $\text{PM}_{2.5}$ and NO_2 at Heuston roof were found to be 8.9 and 51.8 $\mu\text{g}/\text{m}^3$, respectively. The concentration of $\text{PM}_{2.5}$ and NO_2 at the upwind sites of railway station were found to be 5 and 31.8 $\mu\text{g}/\text{m}^3$, respectively. Measured $\text{PM}_{2.5}$ concentrations averaged over the study period were exceeding the annual WHO guideline values ($\text{PM}_{2.5} = 5 \mu\text{g}/\text{m}^3$, $\text{NO}_2 = 10 \mu\text{g}/\text{m}^3$) by 1.6–1.8 and 3.2–5.2 times respectively at the study site. However, $\text{PM}_{2.5}$ and NO_2 concentrations were well below the EU guideline values of 10 and 40 $\mu\text{g}/\text{m}^3$, respectively (except NO_2 level at Heuston roof). The diurnal variation of pollutants at the study sites showed that elevated $\text{PM}_{2.5}$ concentration was observed during the early hours of the day (01:00–05:00) and during morning (07:00–9:00) (Figure 6.4). The average $\text{PM}_{2.5}$ concentrations during these hours ranged between 5.2 and 9.9 $\mu\text{g}/\text{m}^3$, respectively.

The prevalence of low wind speed and low temperature at the site potentially led to PM accumulating and stagnating during these hours. The heterogeneous hydrolysis of NO_2 to nitrate is typically dominant during early hours of the day, and this may also add to elevated PM concentrations (Shanmuga et al., 2021). The diurnal variation of NO_2 showed a morning and evening peaks reflecting the schedule of traffic activities (Figure 6.5). The average NO_2 concentrations during these peak hours ranged between 30.3 and 50.7 $\mu\text{g}/\text{m}^3$, respectively. The weekday average concentrations ($\text{PM}_{2.5} = 7.8\text{--}9.3 \mu\text{g}/\text{m}^3$ & $\text{NO}_2 = 38.1\text{--}52.6 \mu\text{g}/\text{m}^3$) were slightly higher than the weekend average concentrations ($\text{PM}_{2.5} = 6.8\text{--}8.1 \mu\text{g}/\text{m}^3$ & $\text{NO}_2 = 35.6\text{--}49.3 \mu\text{g}/\text{m}^3$) at the study sites.

Table 6.4. Summary of NO₂ and PM_{2.5} concentrations measured at the study site.

Site	Average concentration		No. of days exceeding 24-hr WHO guideline value	
	PM _{2.5} (µg/m ³)	NO ₂ (µg/m ³)	PM _{2.5}	NO ₂ [*]
Heuston roof	8.93	51.76	2	30
EPA station	7.83	38.05	4	25
Upwind sites of Heuston station	5.02	31.8	-	-

* Hourly and daily averaged NO₂ values (obtained using calibrated sensor) are adjusted using diffusion tubes data.

6.3.2 Disaggregation of emission sources at St. Johns FMS

6.3.2.1 Contribution from road traffic

Table 6.5 presents the sources of NO₂ and PM_{2.5} at study site. Estimates of the road traffic contribution to NO₂ and PM_{2.5} were made by considering the wind sector from which road traffic was likely to considerably effect on concentrations. Removing background concentrations aided in disaggregation of local sources. The road traffic contribution was estimated by computing the mean concentration of measurements in the considered wind sector range (110–250°) and the measurement frequency was estimated as a proportion of total number of hourly measurements in that sector (Table 6.5). This estimated value represented an upper limit of traffic contributions because there were no major sources of NO₂ and PM_{2.5} between the background site (St. Johns FMS) and the analysed site (Heuston roof). An upper limit of traffic emission contributions to PM_{2.5} and NO₂ from St. John's Road was estimated to be 1.7 and 18.7 µg/m³, respectively. The proportion of measurements (both PM_{2.5} & NO₂) in this wind sector was estimated to be 46%. The mean PM_{2.5}/NO₂ ratio was estimated to be 0.09 (on a mass basis), which was consistent with the PM_{2.5}/NO₂ ratio (0.05–0.09) measured from street level road traffic emissions in European cities of Gothenburg and Umea, interpreting the source of road traffic (Ferm & Sjöberg, 2015).

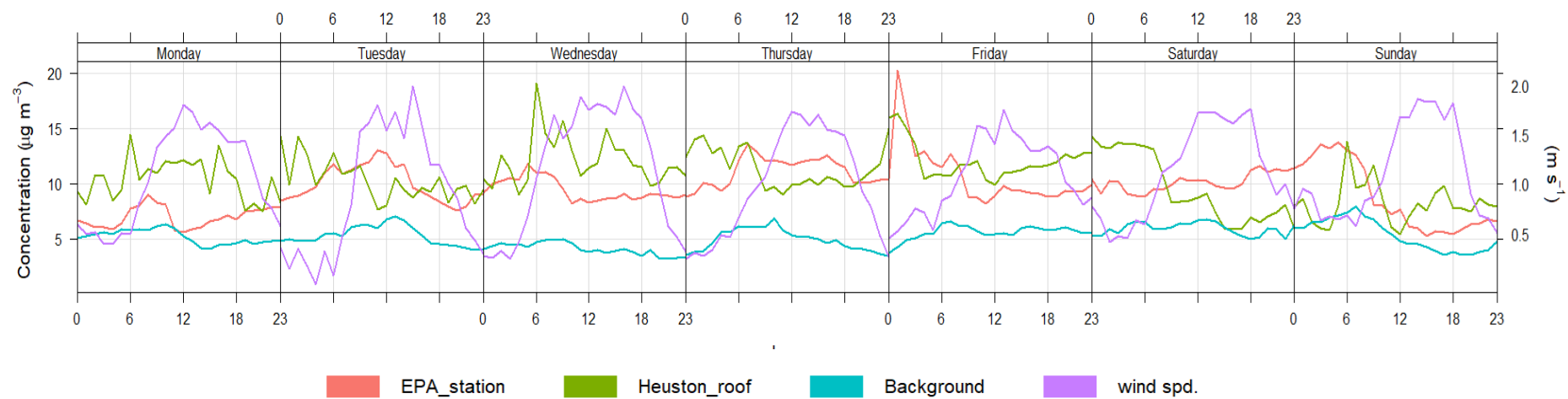


Figure 6.4. Diurnal and daily variations in $PM_{2.5}$ concentrations at the study sites.

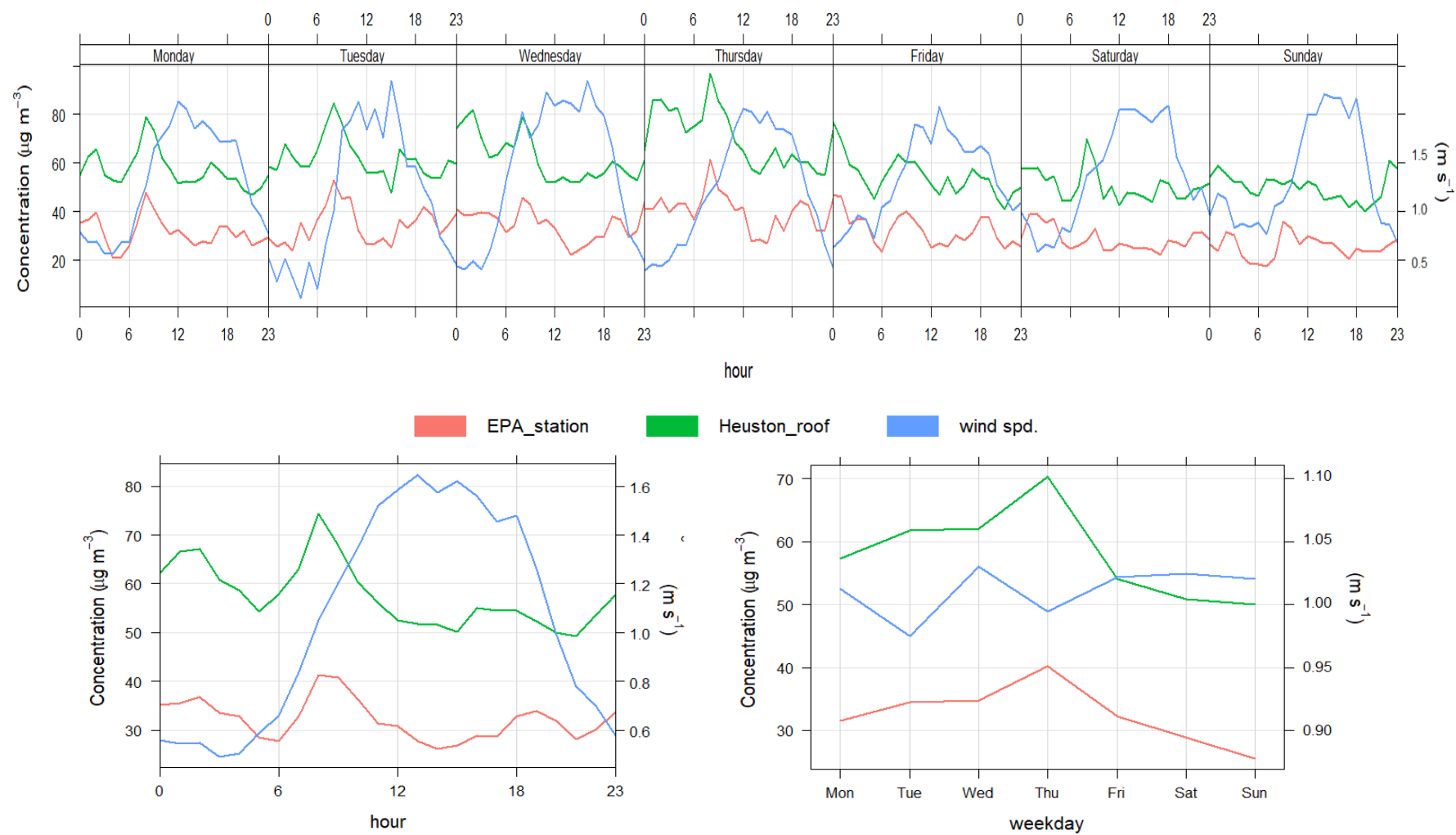


Figure 6.5. Diurnal and daily variations in NO_2 concentrations at the study sites.

6.3.2.2 Railway station contributions

In a similar way, the measurements were filtered based on wind sectors (0–70° & 290–360°) where railway station emissions were likely to have significant effect (Heuston roof), while also considering the hours of the day when trains are scheduled to run. The railway station emissions contribution to PM_{2.5} and NO₂ at Heuston station roof was estimated to be 6.3 and 36.7 µg/m³, respectively after removing the upwind pollutant concentration. However, NO₂ emissions from the railway station was not explicitly estimated, as upwind NO₂ concentration reflected the averaged value over the entire monitoring period (irrespective of wind sector). The proportion of measurements (both PM_{2.5} & NO₂) in this wind sector was 12%.

The estimated mean concentration of PM_{2.5} at St. Johns FMS (9.3 µg/m³) in the wind sector (0–70° & 290–360°) nearly aligns with the estimated mean concentration at the Heuston roof (11.8 µg/m³) within the same sector. This implies that the PM_{2.5} emissions from the railway station are effectually transported to the St. Johns FMS in this specific wind sector with slight dispersion. Therefore, the railway station emissions contribution to PM_{2.5} estimated at Heuston roof (6.3 µg/m³) is projected to be the same at St. Johns FMS. However, a similar trend was not observed for NO₂, making the results inconclusive for NO₂ dispersion.

The contribution of railway station emissions to NO₂ at the St. Johns FMS was estimated to be approximately 20.1 µg/m³, after subtracting the previously determined road traffic contribution from the mean NO₂ St. Johns FMS concentration in this wind sector (Table 6.5). It should be noted that the estimates include the upwind concentration of the railway station.

Table 6.5. Sources share of NO₂ and PM_{2.5} at study site.

Site	Sources	Source wind sector	Background site	PM _{2.5}	NO ₂
Heuston station roof	Road traffic	110-250 (46%)	St John EPA station	Site = 7.1 µg/m ³ Background = 5.4 µg/m ³ Road traffic share = 1.7 µg/m ³	Site = 42.1 µg/m ³ Background = 23.4 µg/m ³ Road traffic share = 18.7 µg/m ³
Heuston station roof	Railway station emission	0-70 & 290-360 (12%)	Heuston Northern wall & Cabra community college	Site = 11.8 µg/m ³ Background = 5.5 µg/m ³ Railway station share = 6.3 µg/m ³	Site = 68.7 µg/m ³ Background = 32 µg/m ³ Railway station share = 36.7 µg/m ³
St John EPA station	Railway station emission	0-70 & 290-360 (12%)	-	Site = 9.3 µg/m ³ Railway station share = 6.3 µg/m ³	Site = 38.8 µg/m ³ Railway station share = 20.1 µg/m ³

6.3.2.3 Effect of wind speed on pollutants source

The bivariate polar plots for pollutants at the study sites considering the wind sectors for which road and railway station emission are likely to have considerable effect on measured concentrations are shown in Figure 6.6.

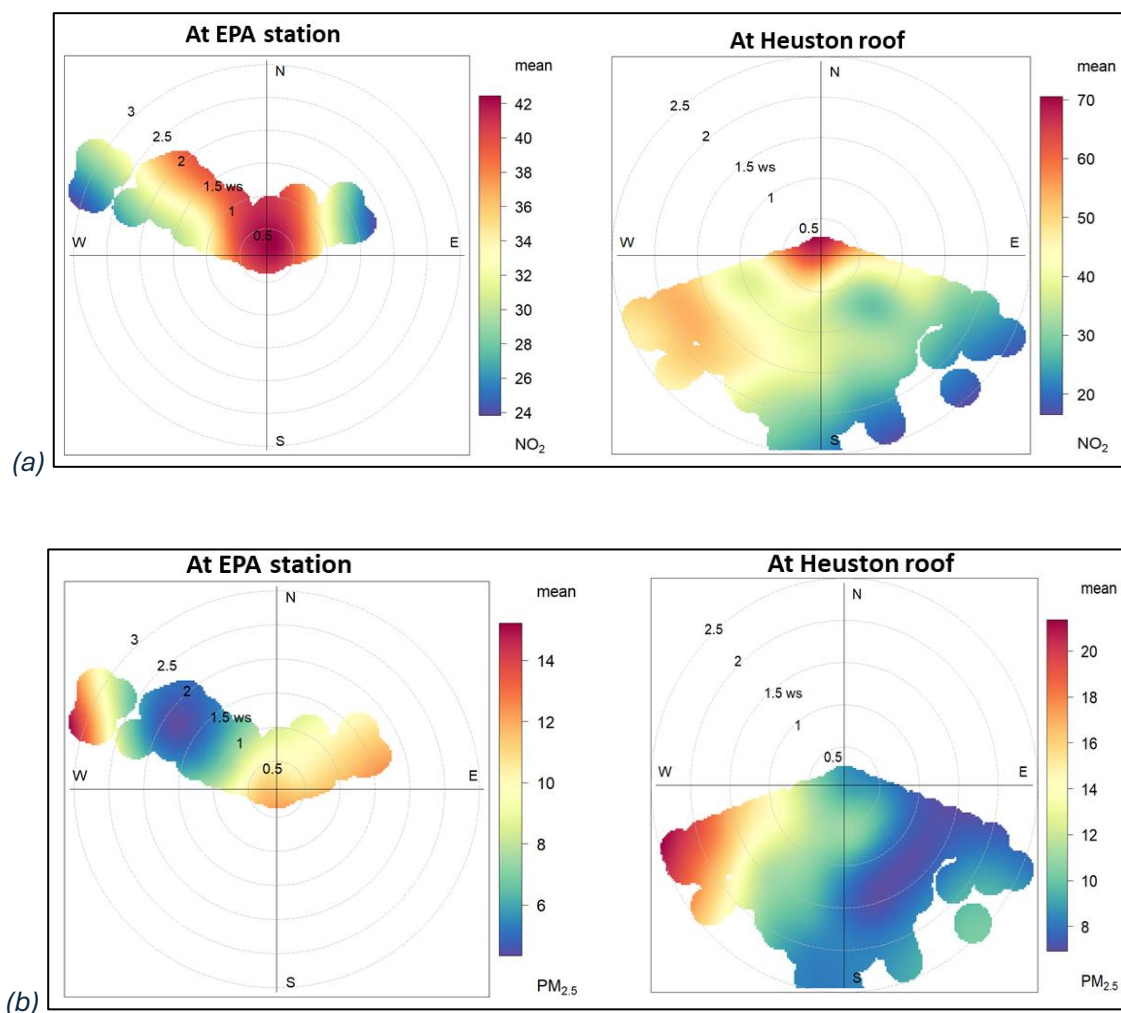


Figure 6.6. Bivariate polar plots for (a) NO_2 and (b) $\text{PM}_{2.5}$ at the study site.

At Heuston Station roof (considering wind directions in the sector $110\text{--}250^\circ$), the highest concentrations of NO_2 are observed with calm wind speed ($0\text{--}0.5\text{ m/s}$) and concentrations decrease with increase in wind speed (Figure 6.6 (a)). The average concentration of NO_2 ($42.1\text{ }\mu\text{g/m}^3$) lies predominantly in the lower wind speed range ($1\text{--}1.5\text{ m/s}$) which could possibly implicate local source (i.e., road traffic in this case) as a dominant source. In general, low wind speed in bivariate polar plot corresponds to local sources of pollutants and high wind speed helps in identifying long distant transport of pollutants (Uria-Tellaetxe & Carslaw, 2014; Xing et al., 2021). A similar pattern was observed in the NO_2 concentrations measured at St.

Johns FMS (considering concentrations in the sector 0–70° & 290–360°), however a slight spike in concentrations was observed at higher wind speed bins, likely owing to transport of pollutants from distant sources. The average concentration of NO₂ (38.8 µg/m³) was distributed over both high (>2 m/s) and low wind speed ranges (1–1.5 m/s), reflecting dominant contributions from both local sources (i.e., railway station and on-road emissions in this case) and distant background sources. The polar plots clearly support that the local traffic is one of the dominant sources of NO₂ at both St. Johns FMS and Heuston Station roof.

Concerning PM_{2.5}, concentrations at St. Johns FMS increases with calm wind speed condition (0–1 m/s) and decreases with increase in wind speed (1.5–2.5 m/s) (Figure 6.6(b)). The spike in concentration was observed at higher wind speed range (>2.5 m/s), where particles are transported to ground level through buoyancy effects (likely from the distant sources). The average concentration of PM_{2.5} (9.1 µg/m³) was noted in both low and high-speed ranges, indicating emission from local sources (on-road and railway station emissions) and distant sources. While average concentration of PM_{2.5} (11.1 µg/m³) at Heuston roof dominantly lies in the higher wind speed (>1.5 m/s) range indicating the upwind background as a dominant source.

6.3.3 Summary

Measurements at Heuston Station showed average NO₂ concentrations ranged from 32 to 121 µg/m³, with the highest levels on Platform 2 (62–121 µg/m³), particularly at the platform centre. All indoor locations exceeded the EU annual NO₂ guideline value of 40 µg/m³, except one concourse site. In contrast, PM_{2.5} concentrations were much lower, averaging 7–10.3 µg/m³, with the highest values in the concourse. PM_{2.5} levels at all locations were well below the EU annual guideline value of 20 µg/m³, and 24-hour PM_{2.5} exceeded the WHO guideline value of 15 µg/m³ on only 3–4% of monitoring days.

Source apportionment by data filtration method showed that railway station emissions as the main PM_{2.5} source, and road traffic as the main NO₂ source, when winds are from station wind sector. Bivariate polar plot also revealed the dominance of local sources in this sector for PM_{2.5} and NO₂. However, only 12% of the winds were from the direction of the station during the study period, which may not reflect the annual average conditions. The majority of measured wind conditions were upwind of the St. Johns FMS (46%), with upwind background NO₂ and PM_{2.5} being the major contributors to the St. Johns FMS.

7. PM_{2.5} AND NO₂ SOURCE CHARACTERIZATION AT HEUSTON TERMINAL VICINITY USING LONG-TERM MEASUREMENTS

This chapter focuses on estimating emissions from train and road traffic and on characterising PM_{2.5} and NO₂ sources in the vicinity of the terminal using an additive semi-parametric model based on long-term measurements. The PM_{2.5} & NO₂ data used in the chapter were downloaded from St. John's EPA FMS.

7.1 Methodology

7.1.1 Long term measurement of PM_{2.5} and NO₂ and meteorological parameter

Hourly PM_{2.5} and NO₂ data were collected from the St. John's FMS over a nine-month period from June 2024 to January 2025. Additionally, PM_{2.5} and NO₂ measurements were obtained from another national EPA FMS (Rathmines), located approximately 3 km from the St. John's FMS, for the same period. The Rathmines FMS was selected to represent upwind background AQ for PM_{2.5} and NO₂, as it is situated in a residential area with minimal influence from immediate traffic sources compared with urban traffic sites.

A weather station (HOBO U30, Onset Computer Corporation, MA, USA) was installed alongside the St. John's FMS to record outdoor meteorological parameters including wind speed, wind direction, temperature, and humidity at a 5-minute resolution, which were subsequently averaged to hourly values for analysis. Additional meteorological variables, such as cloud amount, cloud height, pressure, rainfall, and hours of sunshine, were obtained from the Dublin Airport weather station.

7.1.2 Train and road traffic data

Traffic volume data for St. Johns Road were obtained from Dublin City Council. The hourly composition of the vehicle fleet was obtained from a manual traffic survey carried out from 11th to 15th August 2025. The survey was carried out for the period 08:00 and 20:00, with different time periods surveyed on different days. Information such as vehicle counts by type was collected. For time periods that were not surveyed, the average fleet composition for the 08:00–20:00 period was used. Vehicle emissions depend primarily on fuel type and Euro class; however, obtaining this information for St. Johns Road was challenging. Therefore,

representative data on fuel type and Euro class distributions for urban traffic in Dublin for each year were taken from Mahesh et al. 2023

For cars in Dublin, Euro Class 6 vehicles constitute the largest share of the fleet (56%), followed by Euro Class 5 (35%) and Euro Class 4 (9%). Similarly, for Light Goods Vehicles (LGVs), Euro Class 6 accounts for 75% of the fleet, with Euro Class 5 and Euro Class 4 contributing 16% and 9%, respectively. The bus fleet is composed of approximately 70% Euro Class 6, 20% Euro Class 5, and 10% electric buses. In terms of fuel type, diesel cars make up the largest proportion of the Dublin car fleet (50.5%), followed by petrol (35.2%), hybrid (11.1%), and electric vehicles (2.12%). LGVs and buses predominantly operate on diesel. Information on train traffic, idling duration, engine idling speed, and engine power was obtained from Irish Rail.

7.1.3 Road and Train Emission

Hourly road transport emissions for each combination of vehicle type, Euro class, and fuel type were computed using the following Equation (7.1):

$$Emission_{pollutants} = \sum_{i=1}^N VKT \times EF_{ijk} \quad (\text{Eqn. 7.1})$$

where N is the total number of vehicles of type (i) per hour, VKT is the vehicle kilometres travelled (in this case, 1km) and EF_{ijk} is the emission factor for different vehicle types (i), which is based on the euro class of the vehicle (j) and fuel type (k) (Ligterink, 2017).

Hourly train emissions were estimated based on engine output power and idling duration of the train, as presented in Equation (7.2):

$$Emission_{pollutants} = \sum_{i=1}^N P_i \times ID_i \times EF_i \quad (\text{Eqn. 7.2})$$

where N is the total number of trains in an hour, P_i is the engine output power of each train(kW), ID_i is the idling time of each train (hr), EF_i is the emission factor (g/kWh). EU Stage IIIA railcar NO_x and PM emission factors corresponding to the output power range less than 130 kW were used, as the engine power of the train during idling was found to fall within this range (EU, 2004). Conversion factors of 0.13 and 0.80 were applied to the emission factors to obtain the NO_2 and $PM_{2.5}$ emission factors, respectively (EEA, 2019).

7.1.4 Emission factor adjustment for train emission

The longitudinal vent in the roof is the primary outlet through which pollutants from the train exhaust exit the Heuston train station. Emission factors of the pollutants at the roof level were determined using the emission ratio method. The emission ratio at the roof level is defined as the ratio of the concentration enhancement in the exhaust plume at the roof level to the concentration enhancement in the plume at the exhaust level, assuming that any chemical or physical loss of the pollutant is negligible. The emission factor derived using this approach remains valid for any measurements taken anywhere within the plume. We also assume an equal-dilution approximation for all pollutants measured, including particle-phase species.

7.1.5 PM_{2.5} & NO₂ measurement at roof & exhaust level

Measurements of PM_{2.5} and NO₂ were carried out using a ELOS Outdoor Station. Device A was installed on a station steel column approximately 3 m from the platform and 0.5 m above the exhaust height on Platform 2. However, the position of the trains exhaust plume varies by 1–2 m on either side depending on the exact stopping position of the train, making precise alignment challenging. Device B was installed on the rooftop directly above Device A just below the longitudinal vent, aligned vertically. PM_{2.5} concentrations were monitored continuously for three weeks from 26 June – 19 July 2023. Diffusion tubes were installed alongside these devices to measure NO₂ levels. Both the ELOS devices and the diffusion tubes were placed at the rooftop vent in such a way that they were not affected by outdoor pollution. These measurements give the average value of the pollutant's concentration at the exhaust level and the roof level over the monitoring period. Adjusted emission factor at the roof top of the station is calculated according to the Equation 7.3.

$$EF_{i(adjusted)} = EF_i \times \frac{C_x}{C_R} \quad (\text{Eqn. 7.3})$$

Where $EF_{i(adjusted)}$ is the adjusted emission factor the pollutant i at roof level, EF_i is the emission factor of the pollutant i, C_x is the average concentration of the enhancement in the plume at the exhaust level, C_R is the average concentration of the enhancement in the plume at the exhaust level at the roof level.

7.1.6 Additive semi-parametric model

To identify the variables influencing the NO₂ and PM_{2.5} concentrations at the St. John's FMS, pollutants concentrations are modelled using additive semi-parametric statistical model on a logarithm scale to capture the co-linear effects of variables (Equ.7.4) (Valotto & Varin, 2016). This model is commonly used in AQ studies because the distribution of air pollution concentrations is often positively skewed.

$$\text{Log}(P_t) = Z_t^T \beta + \sum_{i=1}^q S_i(x_{it}) + \epsilon_t \quad (\text{Eqn. 7.4})$$

where P_t is the pollutant concentration measured at hour t , Z_t^T is a vector of p covariates modelled parametrically at hour t , β is the regression coefficients showing the strength of each covariates, x_{it} are the q covariates modelled non-parametrically at hour t using smooth function S_i , and ϵ_t is a normal distributed error term with zero mean and variance σ^2 (Valotto & Varin, 2016). The analysis was performed using the Python library pyGAM, with the GammaGAM function for regression. The covariates included wind speed, wind direction, urban background concentrations, hours of the day, days of the month, temperature, humidity, pressure, hours of sunshine, rainfall intensity, cloud amount, cloud height, and road and train emissions. Wind direction, hours of the day, and days of the month were constrained as cyclic variables to account for their natural periodicity. All covariates were modelled as non-parametric, smooth functions. The grid search method was used to optimize the smoothing parameters by minimizing the generalized cross-validation (GCV) score. Lower the GCV score, better the performance of the model. Additionally, Partial Dependence Plots (PDPs) were generated to visualize the partial effect of each covariate on the model output on the logarithmic scale. The model's performance is evaluated using R^2 (log scale) and GCV score.

7.2 Results & Discussion

7.2.1 PM_{2.5} and NO₂ concentration at the study site

The mean concentrations of PM_{2.5} and NO₂ at the St. John's FMS during the period June 2024 to January 2025 were 7.8 µg/m³ and 31 µg/m³, respectively. At the upwind background site, the corresponding mean concentrations were 5.9 µg/m³ for PM_{2.5} and 14 µg/m³ for NO₂. Both PM_{2.5} and NO₂ concentrations remained well below the EU annual guideline values of 10 µg/m³ and 40 µg/m³, respectively. The diurnal variation of NO₂ exhibited distinct morning and

evening peaks, reflecting the temporal pattern of traffic activity. In contrast, PM_{2.5} showed pronounced nighttime peaks between 19:00 and 00:00, highlighting urban domestic heating as the dominant source during these hours (Figure 7.1). Seasonal variation showed that the highest concentrations occurred in winter, followed by autumn, while the lowest concentrations were observed in summer (Figure 7.2). Weekly concentrations were higher on weekdays and lower on weekends, corresponding to reduced traffic activity (Figure 7.3).

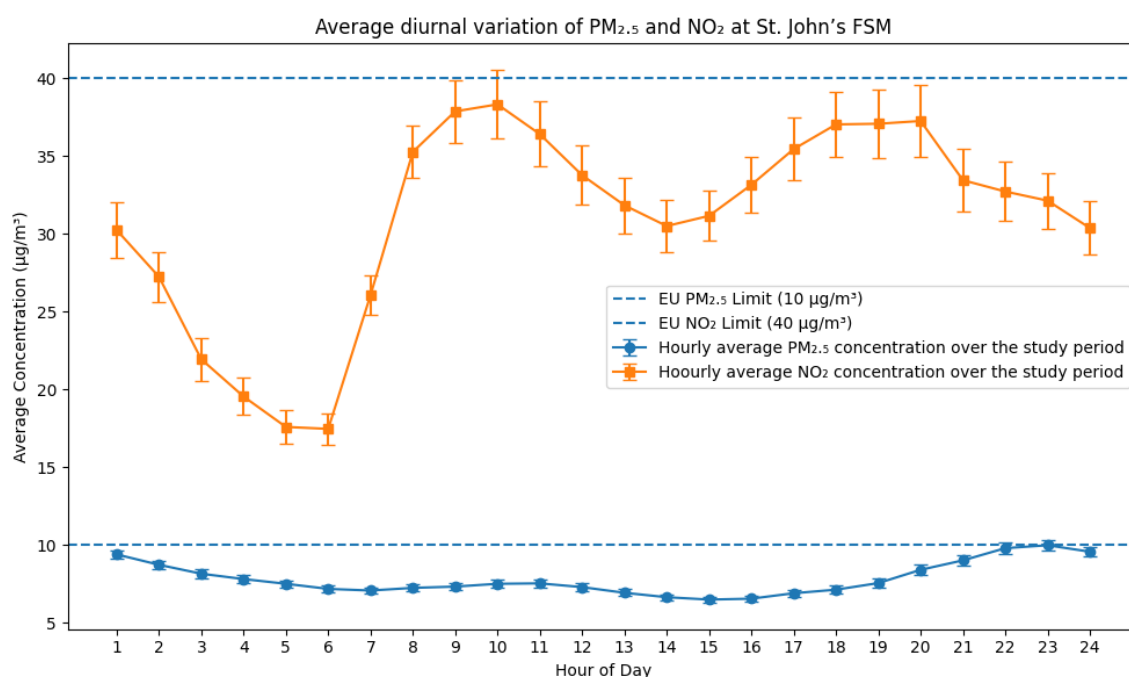


Figure 7.1. Diurnal variation of average NO₂ and PM_{2.5} at St. Johns FMS (June 2024 to January 2025).

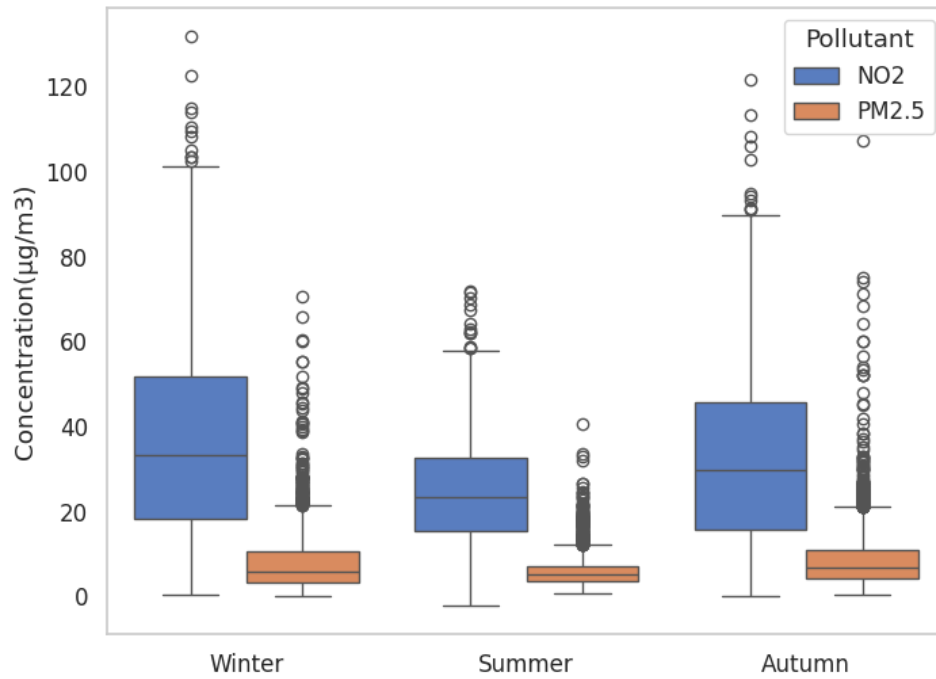


Figure 7.2. Seasonal variation of NO₂ and PM_{2.5} at St. Johns FMS (June 2024 to January 2025).

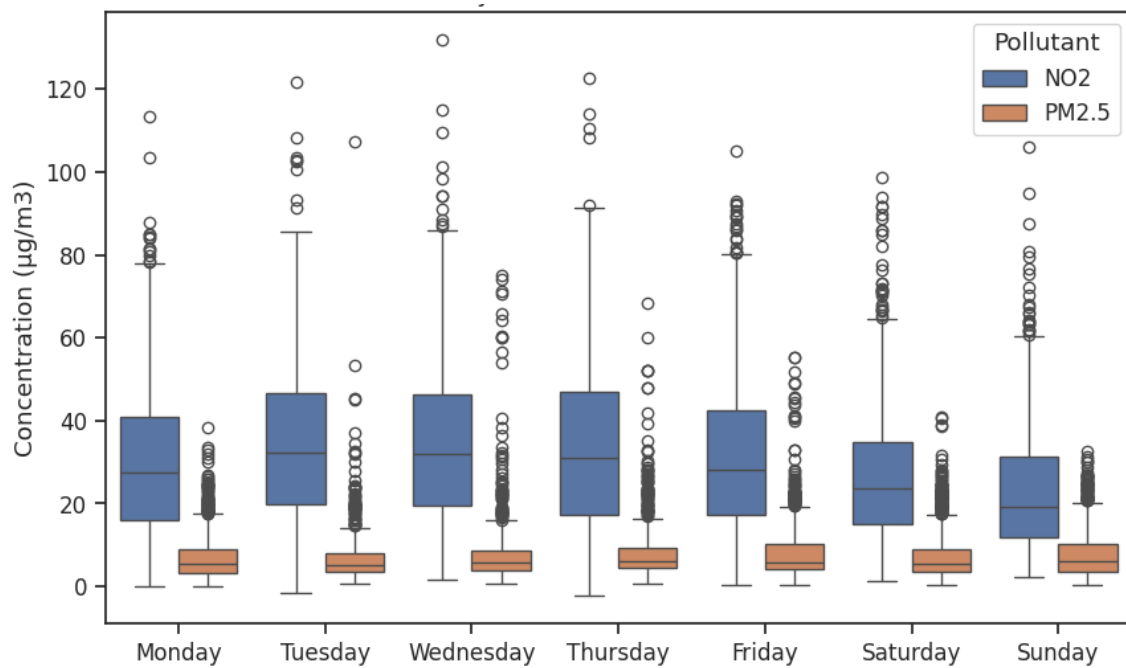


Figure 7.3. Weekly variation of NO₂ and PM_{2.5} at St. Johns FMS (June 2024 to January 2025).

7.2.2 Road fleet composition and associated emissions

The vehicle volume on St. Johns Road ranged from 19,550 to 22,000 vehicles per day, with peak hourly volumes between 2,000 and 3,500 vehicles. Figure 1 shows the average proportion of cars, LGVs, HGVs, and buses recorded during the survey campaign. Cars

constituted the largest share of the fleet (84%), followed by LGVs (11%), buses (4%), and HGVs (1%) (Figure 7.4).

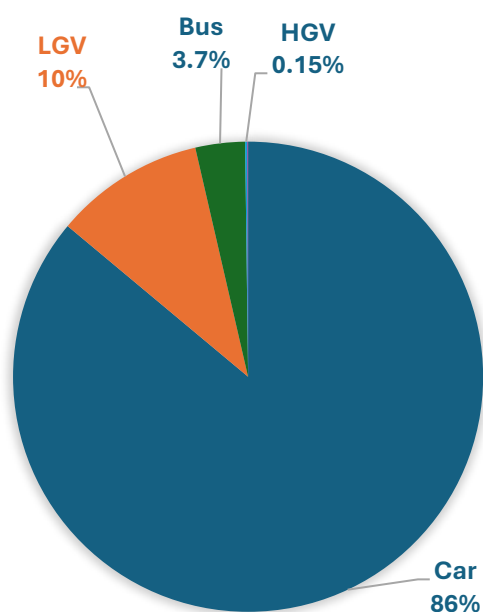


Figure 7.4. Composition of vehicle fleet at St. Johns Road.

Hourly NO_x and PM emissions for the 1 km stretch of St. Johns Road ranged from 33 to 266 g/hr and 1.1 to 13.7 g/hr, respectively, resulting in monthly emissions of approximately 110–130 kg of NO_x and 10–11 kg of PM. Among the transport fleet, Euro Class 5 diesel buses represent only 1.5% of the total fleet, contributed the largest share of both NO_x and PM mass emissions (38%), followed by Euro Class 4 diesel cars (20%) and Euro Class 5 diesel cars (18%) to PM and NO_x emissions (Figure 7.5). In contrast, petrol vehicles comprise approximately 35% of the fleet yet account for only 6% of the total PM and NO_x emissions.

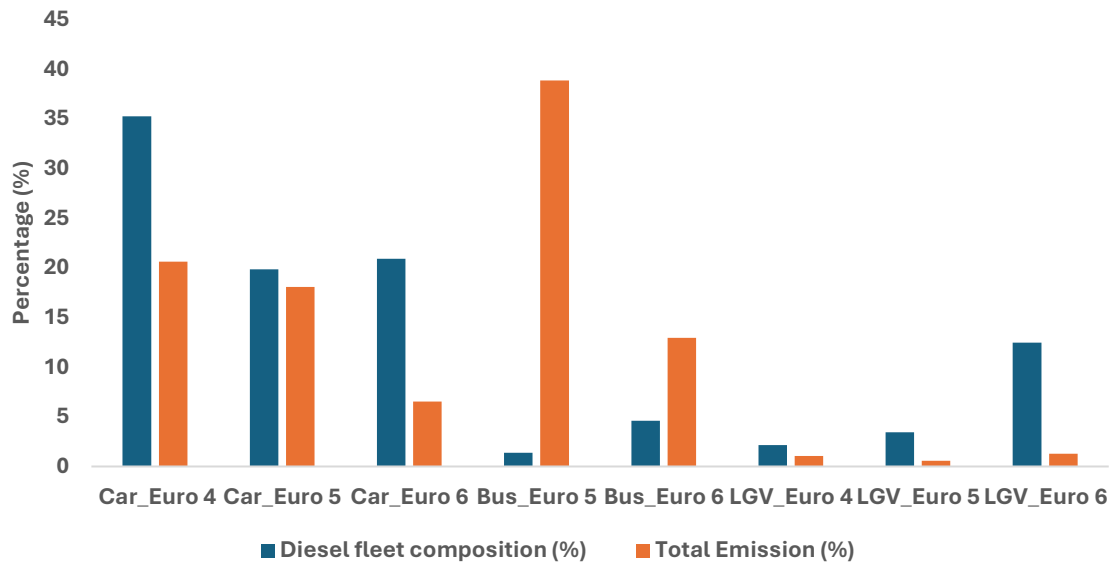


Figure 7.5. Percentage contribution of vehicle categories to both NO_x and PM mass emissions at St. Johns Road.

7.2.3 Train Emissions

Hourly train emissions of NO_x and PM ranged from 16–850 g/hr and 1.2–68 g/hr, respectively, resulting in monthly emissions of approximately 235–258 kg of NO_x and 18.4–20 kg of PM. Emissions were also observed during non-service hours (12 a.m. to 5 a.m.), when train engines remain running to supply heating and lighting required for cleaning and maintenance activities (Figure 7.6).

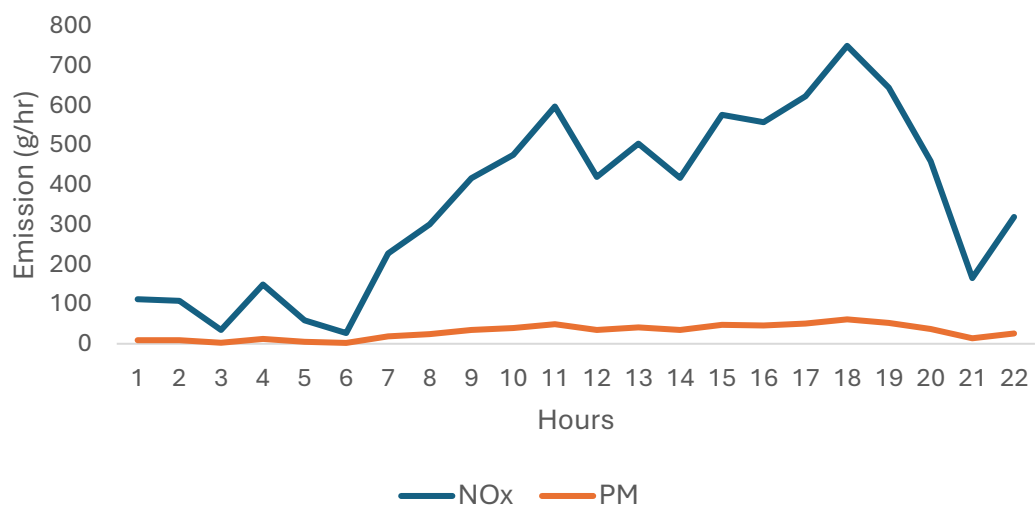


Figure 7.6. Diurnal variation of NO_x and PM emission from Hueston Terminal.

7.2.4 NO₂ and PM_{2.5} concentration at platform and roof level.

The average concentrations of NO₂ and PM_{2.5} at Platform 2 over the monitoring period were 116.6 µg/m³ and 21.37 µg/m³, respectively. At the station roof, the average concentrations of NO₂ and PM_{2.5} were 87.4 µg/m³ and 19.58 µg/m³, respectively. The emission ratio at the station roof were determined to be 0.91 for PM_{2.5} and 0.75 for NO₂. These ratios were multiplied to estimate NO_x and PM emissions from train at roof level, assuming that NO₂ and PM_{2.5} are proportional to NO_x and PM, respectively, at the source level.

7.2.5 Wind characteristics at St. Johns EPA FMS

Winds at the St. Johns EPA station during the study period (June 2024 to January 2025) were predominantly from the WSW sector (64%), with an additional 15% originating from the NEE sector (Figure 7.7). Only 8% of winds were from the sector (0–50° and 310–360°), where train and road emissions are dominant. Wind speeds at the site were mainly in the light-breeze range (1–2.5 m/s), and 17% of the winds corresponded to calm conditions (< 0.5 m/s).

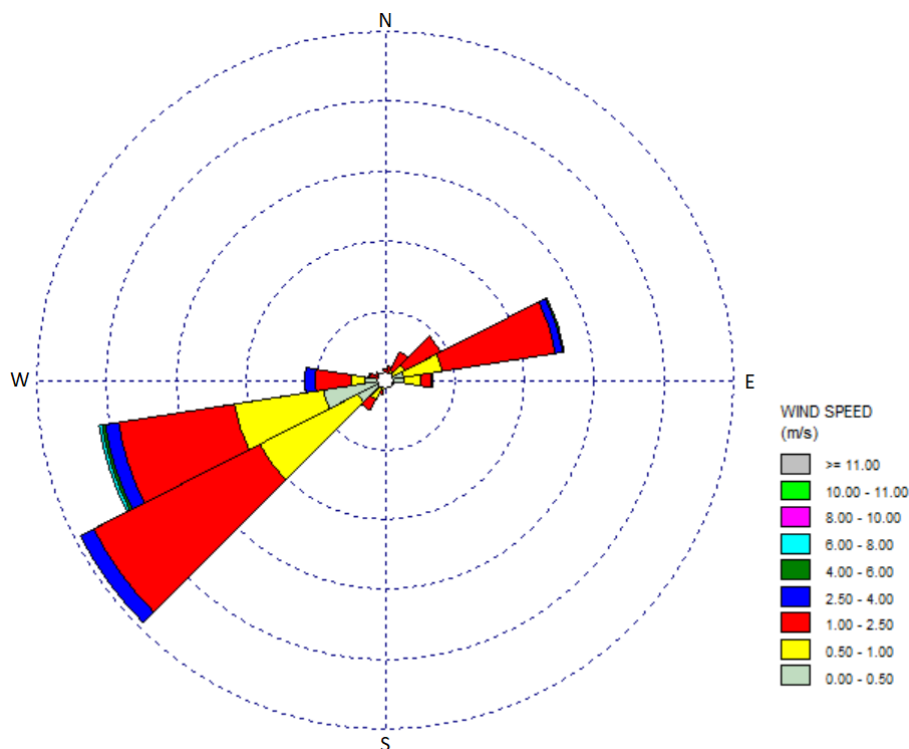


Figure 7.7. Wind characteristics at St. Johns FMS.

7.2.6 Performance of the model

The model performance was good for $\text{PM}_{2.5}$ ($R^2 = 0.81$, GCV = 28.8) and moderate for NO_2 ($R^2 = 0.73$, GCV = 37.2). The model identified background NO_2 , wind direction, and wind speed as the strongest drivers in predicting NO_2 concentrations during the study period, indicating that upwind background levels represent the major source influencing concentrations at the St. Johns FMS (Figure 7.8). Road and rail emissions, rainfall, and cloud amount showed moderate effects, whereas humidity and sunshine hours were not statistically significant. Model performance improved substantially when background NO_2 was included, with the R^2 increasing from 0.59 to 0.73, highlighting its importance as a predictor. Figure 7.10 presents the PDPs for the most influential variables.

The wind-related terms indicate that higher NO_2 concentrations are associated with reduced advection under low wind-speed conditions. The plots further show that increasing wind speed generally leads to a decrease in NO_2 concentrations; however, at higher wind speeds, an increase in concentration is observed, likely due to enhanced pollutant transport from upwind sources driven by buoyancy effects. Similarly, elevated NO_2 concentrations were observed for wind directions between 150° and 250° , corresponding to the predominant upwind sector for the site. Increased concentrations were also evident for wind sectors between 0° – 50° and 320° – 360° , suggesting the presence of dominant NO_2 sources along these directions.

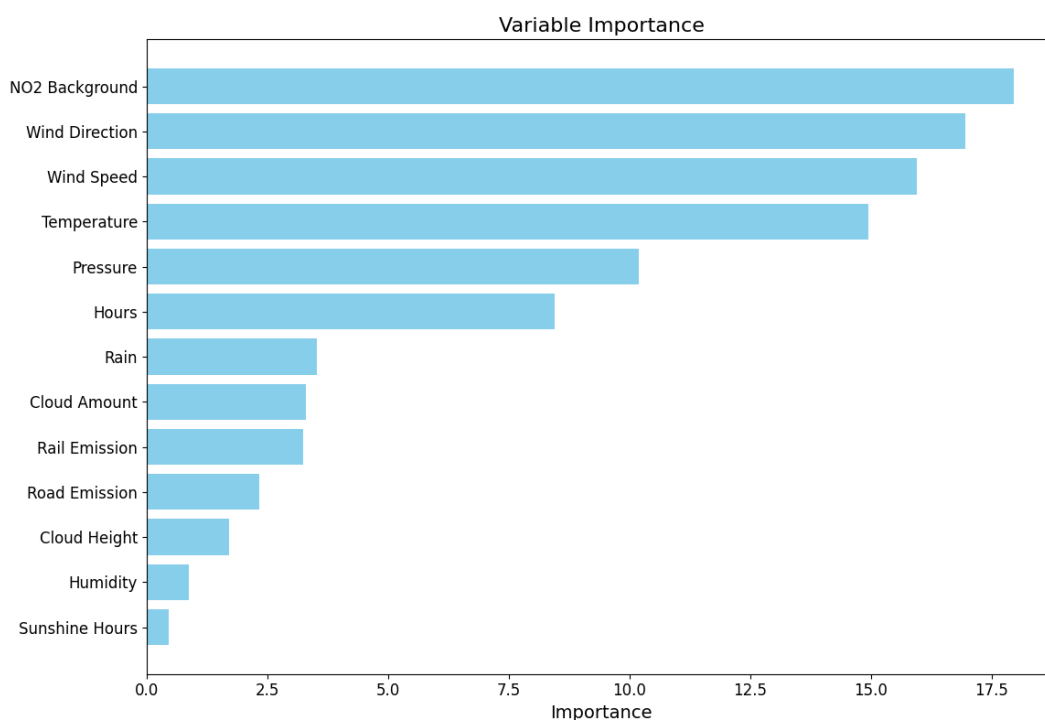


Figure 7.8. Variable of Importance for NO_2 identified by GAM model.

A clear linear relationship is observed between background NO_2 concentrations and NO_2 levels at the site, indicating that background NO_2 represents a major contributing source. However, at higher background NO_2 concentrations, NO_2 levels at the site decrease, likely due to changes in wind direction. The hourly term shows an increase in NO_2 concentrations from 00:05 to 11:00, followed by a decline between 11:00 and 15:00, a new growth from 17:00 to 20:00, and a sharp decrease during the night. This temporal pattern is consistent with the mean diurnal variation typically observed on weekdays in urban traffic-influenced environments, suggesting that background NO_2 is strongly associated with emissions from urban traffic sources.

Similarly, for $\text{PM}_{2.5}$, model identified background $\text{PM}_{2.5}$ as the most influencing feature followed by followed by temperature, humidity, wind speed and wind direction. Figure 7.9 presents variable of importance for $\text{PM}_{2.5}$ identified by the model. The PDP for important features for both $\text{PM}_{2.5}$ is shown in the Figure 7.11. Like NO_2 , $\text{PM}_{2.5}$ at the study site has a linear relationship with background $\text{PM}_{2.5}$ and strongly associated with the wind speed and wind direction, indicating that background $\text{PM}_{2.5}$ represents a major contributing source. Unlike NO_2 , $\text{PM}_{2.5}$ displays a distinct diurnal pattern, with pronounced peaks during nighttime hours (19:00–00:00), highlighting urban domestic heating as the dominant source. A smaller peak observed during the morning hours (07:00–10:00) is likely associated with traffic emissions.

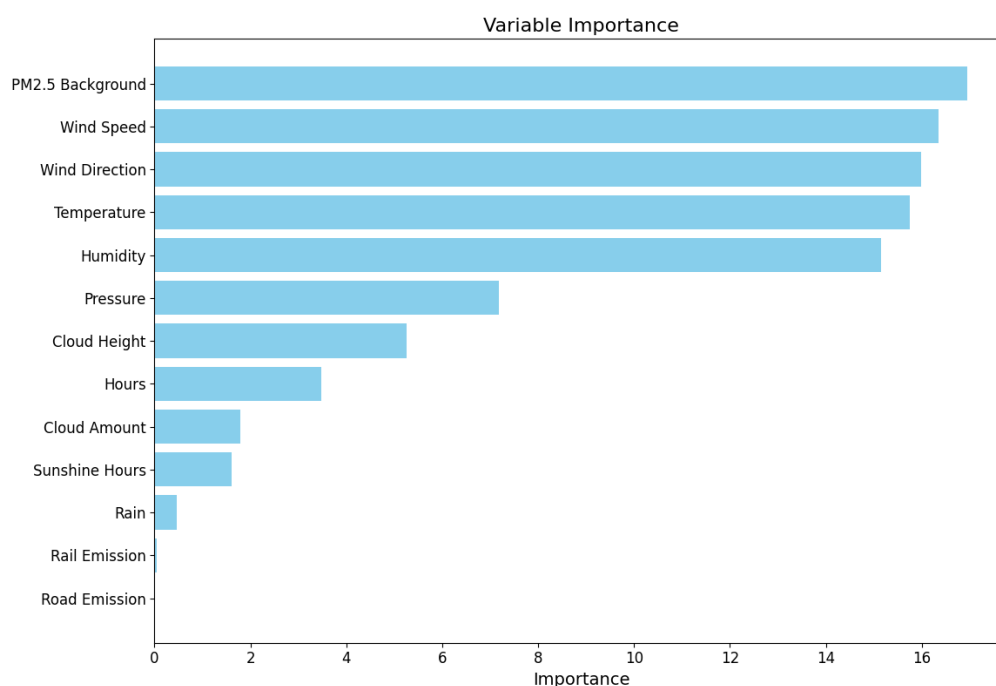


Figure 7.9. Variable of Importance for $PM_{2.5}$ identified by GAM model.

The temperature-related term indicates that $PM_{2.5}$ concentrations decrease with increasing temperature, consistent with findings reported in previous air quality studies. $PM_{2.5}$ concentrations increase with relative humidity up to approximately 50%, after which they decline as humidity continues to rise. This behaviour is due to hygroscopic growth of particles at moderate humidity, which enhances particulate mass, whereas at higher humidity levels, increased particle size promotes faster gravitational settling and removal, leading to reduced $PM_{2.5}$ concentrations.

Both $PM_{2.5}$ and NO_2 models results indicate that road emission from St. Johns Road and train emission from Heuston station are not the not the primary sources of air pollutants at this site.

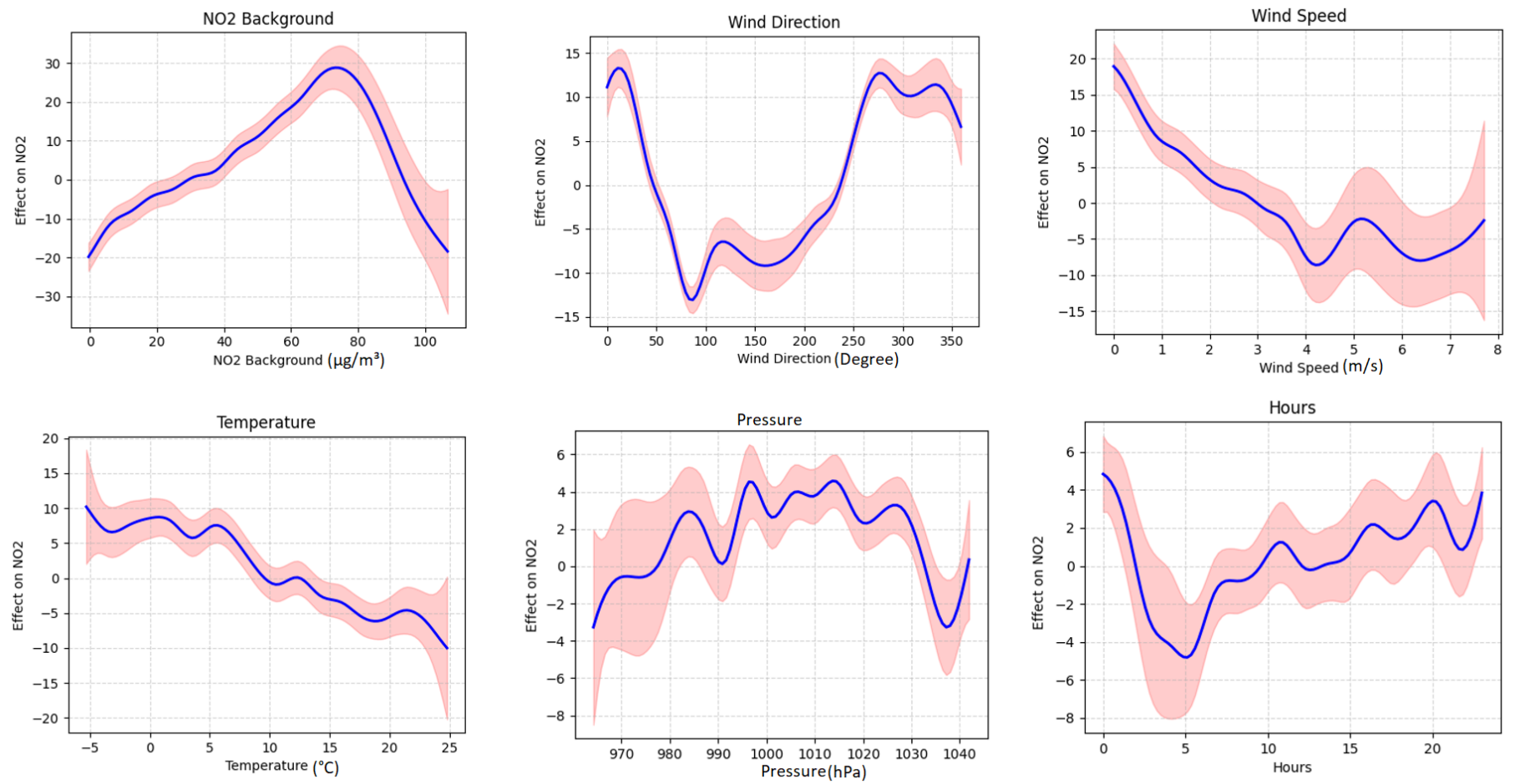


Figure 7.10. PDPs for the most influential variables of NO₂.

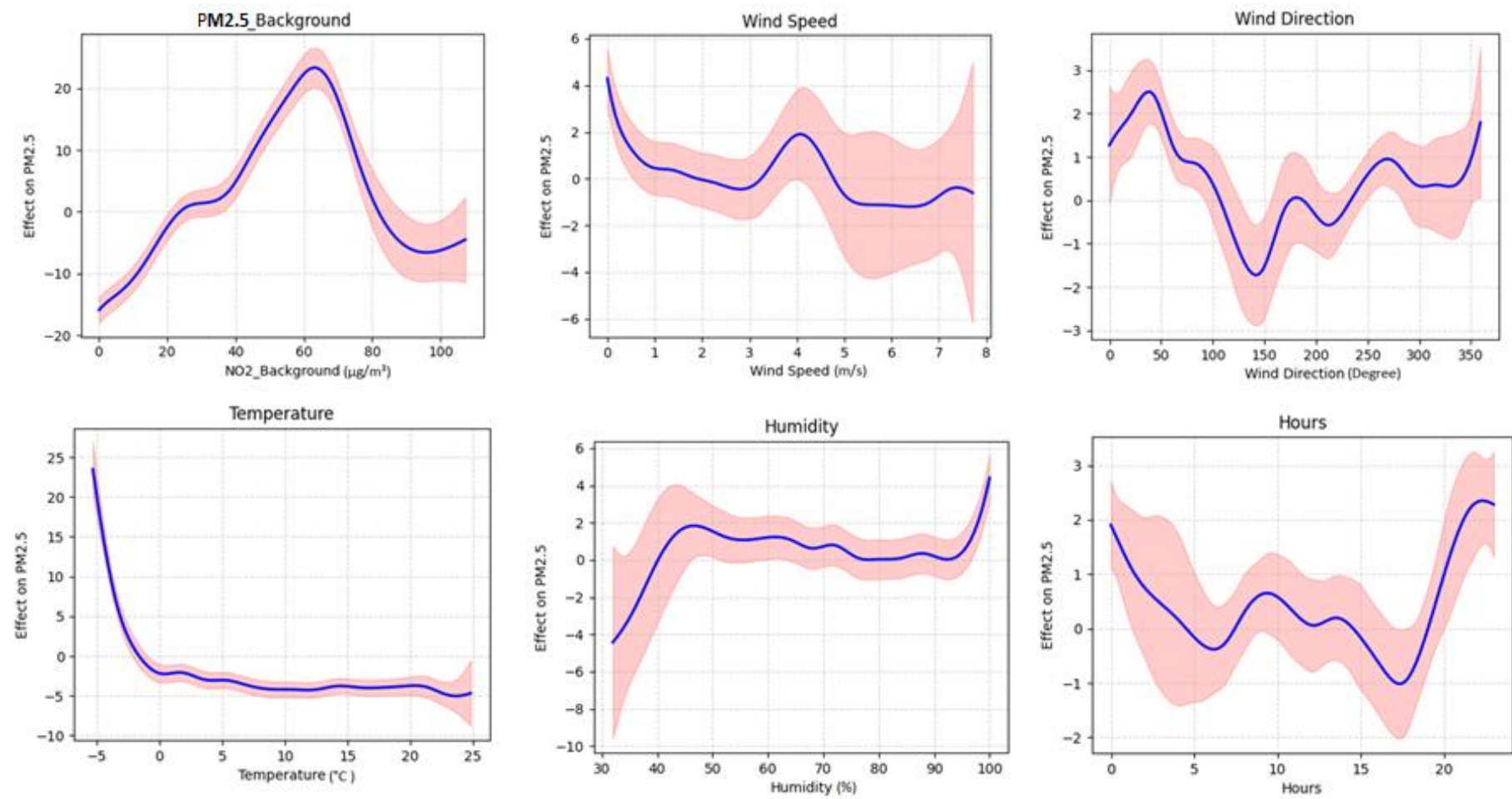


Figure 7.11.PDPs for the most influential variables of PM_{2.5}.

7.3 Summary

Air quality measurements at the St. John's FMS site between June 2024 and January 2025 indicate that mean concentrations of $\text{PM}_{2.5}$ ($7.8 \mu\text{g}/\text{m}^3$) and NO_2 ($31 \mu\text{g}/\text{m}^3$) remained well below the EU annual guideline values.

Road traffic emissions from St. John's Road, yielded a monthly total emission of approximately 110–130 kg of NO_x and 10–11 kg of PM. Rail emissions from Heuston Station were of similar magnitude, yielding a monthly total emission of 235–258 kg of NO_x and 18.4–20 kg of PM.

Winds were predominantly from the north-western sector (64%), with an additional 15% from the north-eastern sector, while only ~8% of winds originated from sectors directly influenced by road and rail sources ($0\text{--}50^\circ$ and $310\text{--}360^\circ$).

Despite substantial road and rail emissions from nearby St. John's Road and Heuston Station, wind analysis showed that these sources are infrequently upwind of the monitoring site. This finding is supported by the GAM results, which demonstrated good model performance for $\text{PM}_{2.5}$ ($R^2 = 0.81$) and moderate performance for NO_2 ($R^2 = 0.73$). For NO_2 , background concentrations, wind direction, and wind speed emerged as the strongest drivers of variability. For $\text{PM}_{2.5}$, background $\text{PM}_{2.5}$ was the most influential variable, followed by meteorological factors such as temperature, humidity, and wind conditions, highlighting the important role of regional background pollution impacting the local concentrations.

The combined observational and modelling results indicate that regional background pollution and meteorology, rather than local road or rail emissions, are the primary drivers of $\text{PM}_{2.5}$ and NO_2 concentrations at the St. John's FMS site during the study period.

8. ANALYSING THE IMPACT OF DIESEL TRAINS ON AIR QUALITY IN DUBLIN CONNOLLY

Part of this chapter has been published in Environmental Pollution (<https://doi.org/10.1016/j.envpol.2026.128029>). The candidate is the first author, and the content related to XGboost modeling in this paper is conceived, analysed, and written by the candidate.

This chapter presents the levels of $PM_{2.5}$ and NO_2 inside the Dublin Connolly. It also focuses on characterising the impact of train idling, along with other contributing factors such as train traffic, engine power and ambient conditions, on NO_2 levels within the station. The diffusion tubes used in this chapter were commercially analysed for nitrite and, consequently, NO_2 by Gradko International Ltd, UK.

8.1 Air quality assessment at Connolly

8.1.1 Methodology

The measurements of NO_2 and $PM_{2.5}$ were undertaken from 15th August to 21st September 2023 at Connolly. The simultaneous multisite measurement of NO_2 was made using palmestype passive diffusive tubes. Tubes were exposed for 5 weeks at 18 locations inside the station. A set of diffusion tubes were co-located alongside an EPA station air quality monitoring site (St. John's Road), the diffusion tubes results were compared with EPA NO_2 gas analyser, and a correction factor was determined using the well-established DEFRA bias adjustment tool (DEFRA, 2011). The correction factor (0.84) is then multiplied with all the diffusion tubes values to obtain the adjusted results. Continuous monitoring of $PM_{2.5}$ were collected out using the ELOS devices A, B, C, D and E. The devices were installed at Platforms 2, 3, 4, 6/7, and in the concourse area of Connolly train station. On each platform, the devices were positioned approximately halfway along the platform length. Locations of the diffusion tubes and the ELOS AQ devices employed in the terminal are shown in the Figure 8.1. Information on train traffic were collected from Irish rail for the above-mentioned period.

8.1.2 NO_2 and $PM_{2.5}$ concentrations

The 24-hour average $PM_{2.5}$ levels at the station, measured using ELOS devices, ranged from 3.2 to 32.6 $\mu g/m^3$, with elevated concentrations observed on enclosed Platforms 3 and 4

(Figure 8.2).

On enclosed Platform 2, the 24-hour average $PM_{2.5}$ concentration ranged from 7.8 to 16.0 $\mu g/m^3$. On enclosed Platforms 3 and 4, the 24-hour average $PM_{2.5}$ concentrations ranged from 11.7 to 53.1 $\mu g/m^3$ and 17.7 to 60.0 $\mu g/m^3$, respectively. The 24-hour average $PM_{2.5}$ concentration exceeded the World Health Organization 24-hour guideline value of 15 $\mu g/m^3$ during 90% of the monitoring period. The elevated concentrations on these platforms are attributed to the operation of DMU trains.

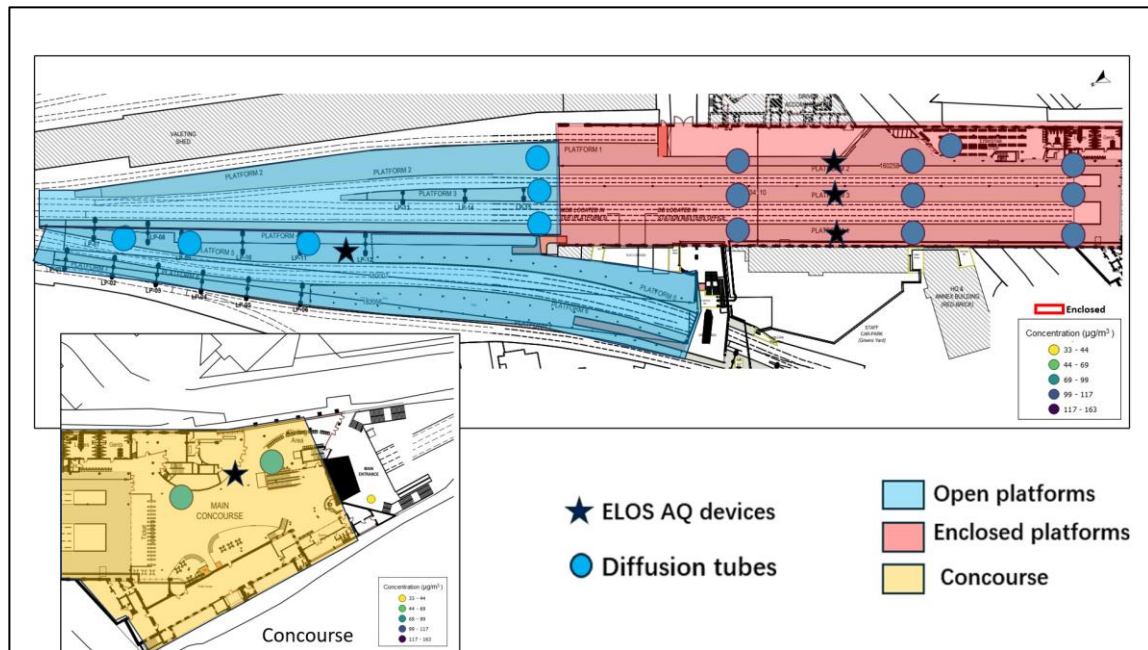


Figure 8.1. Locations of the diffusion tubes and the ELOS AQ devices employed in the terminal.

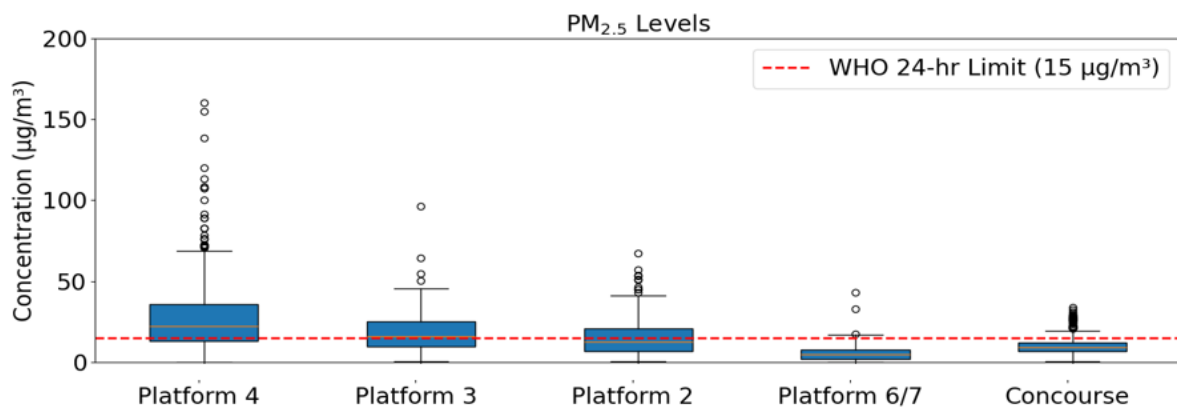


Figure 8.2. Average concentration of $PM_{2.5}$ over the monitoring period.

In contrast, lower 24-hr averages of PM_{2.5} levels, ranging from 3.18 to 7.89 µg/m³ were observed on Platforms 6/7, which are open and predominantly serve electric trains. The 24-hr average PM_{2.5} concentrations in the concourse area ranged from 3.3 to 7.78 µg/m³ and rarely exceeded the WHO 24-hour guideline values. Diurnal variation of PM_{2.5} showed higher concentration during periods of low train traffic (Figure 8.3). Additionally, PM_{2.5} concentrations on weekdays were slightly lower than those observed on weekends, possibly associated with the longer idling times of the trains (Figure 8.4).

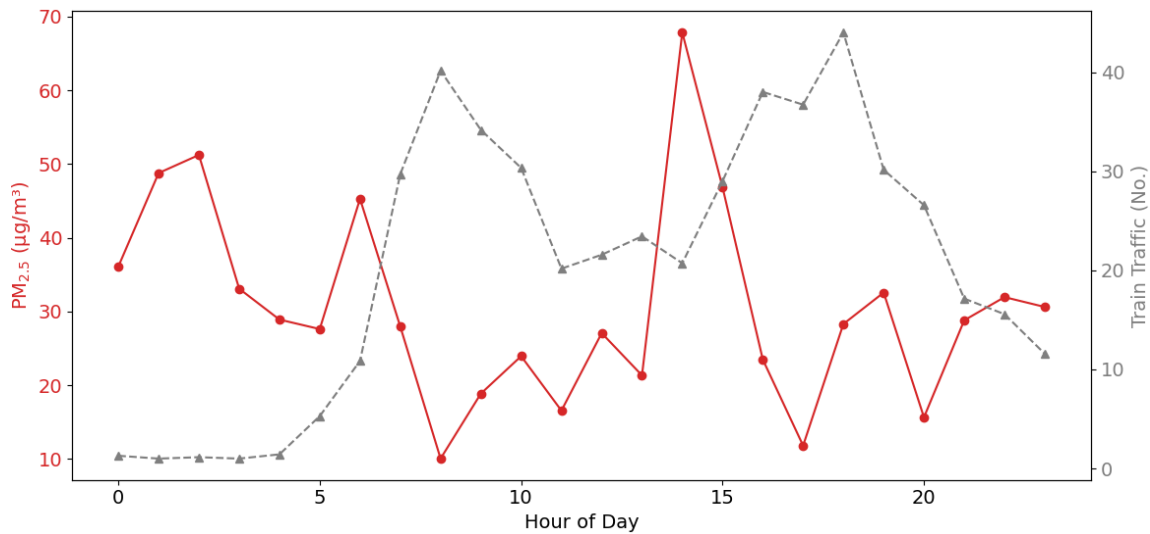


Figure 8.3. Diurnal variation of PM_{2.5} concentrations (averaged across all platforms) and train traffic (15 August to 21 September 2023).

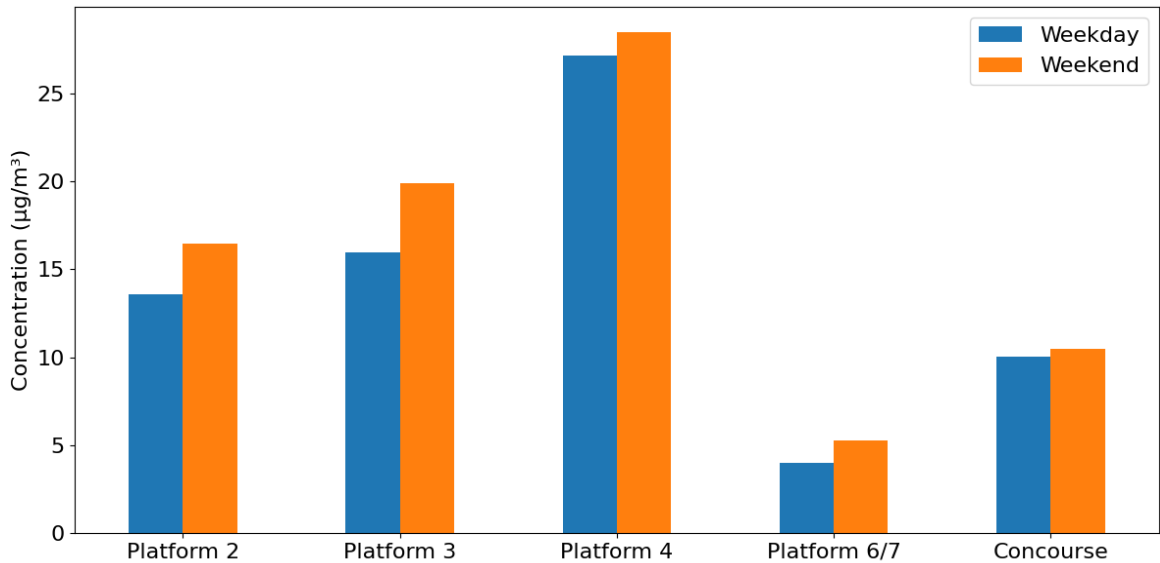


Figure 8.4. Average PM_{2.5} concentrations during weekdays and weekends at different monitoring locations in the train station (15 August to 21 September 2023).

8.1.3 Variation of NO₂ across Station

Table 8.1 shows the NO₂ concentrations measured using diffusion tubes at the station. Average NO₂ concentrations varied significantly between the enclosed and outdoor platforms. On the enclosed platforms, concentrations during the measurement campaign ranged from 83.0 to 162.7 µg/m³, with particularly high levels observed across the full length of the enclosed Platform 4. In contrast, NO₂ concentrations on the open platforms ranged from 40.5 to 71.5 µg/m³, with elevated levels observed at the open end of Platform 3. Concentrations in the concourse area ranged from 58.5 to 63.0 µg/m³, while the concentration at the station entrance was 32.6 µg/m³. Concentrations in the concourse area exceeded the EU annual NO₂ guideline value of 40 µg/m³, whereas the station entrance remained below this guideline value.

Table 8.1. Summary of average NO₂ levels measured over the study period at Connolly terminal (15th August- 21st September 2023).

Location	Time (hr.)	Concentration (µg/m ³)
St. John FMS (for bias factor)	959.2	28.1
St. John FMS (for bias factor)	959.2	28.2
Platform-2 enclosed- Front end	720.4	122.8
Platform-2 enclosed- Middle	720.3	120.7
Platform-2 enclosed- Back end	720.3	103.2
Platform-2- Open	720.2	67.7
Platform-2 enclosed- Waiting room	720.5	82.8
Platform-3 enclosed -Front end	720.8	97.8
Platform-3 enclosed -Middle	720.7	114.4
Platform-3 enclosed-Back end	720.7	106.2
Platform-3 Open	720.5	71.5
Platform-4 enclosed-Front end	720.9	99.8
Platform-4 enclosed-Middle	721	125.2
Platform-4 enclosed- Back end	719.6	162.6
Platform-4 Open	720	44.01
Platform 6 & 7 Open- Front end	719.9	44.3
Platform 6 & 7 Open- Middle	719.8	42.5
Platform 6 & 7 Open- Back end	719.6	39.9
Concourse-Stanley shop	720.2	63.2
Concourse-Ticket counter	720.2	58.5
Connolly entrance, camera pole	720.1	32.6
Blank	959.2	0.14

The scatter plot of $PM_{2.5}$ averaged over the diffusion tube NO_2 exposure period of all measured locations revealed stronger correlation between the NO_2 and $PM_{2.5}$, ($R^2 = 0.91$, $p < 0.001$). This suggests that both $PM_{2.5}$ and NO_2 share common sources, primarily from diesel emissions (Figure 8.5).

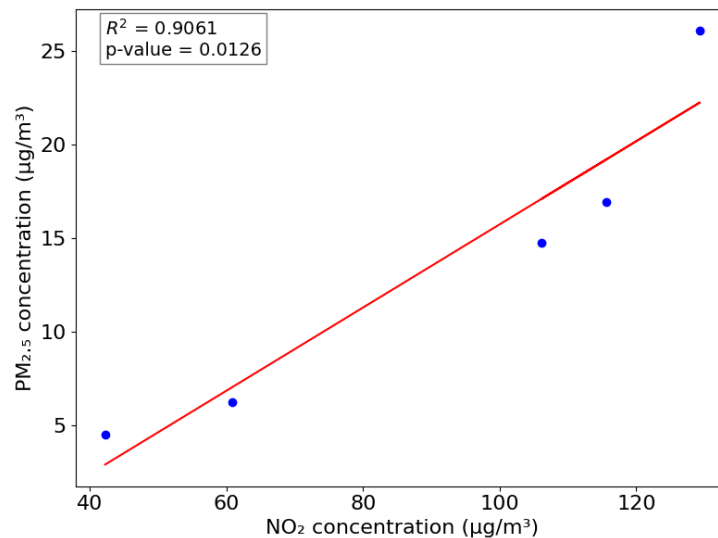


Figure 8.5. Scatter plot of average $PM_{2.5}$ and NO_2 concentrations period of all measured locations (15th August to 21st September 2023).

8.2 Analysing the impact of diesel trains on NO_2 levels in Dublin Connolly using XGBoost modelling

8.2.1 Methodology

8.2.1.1 Continuous NO_2 monitoring

The continuous NO_2 monitoring was carried out in middle of Platform 4 for a period of 90 days, from 01 March to 31 May 2024. This location on Platform 4 was chosen as it was identified with high NO_2 levels (based on the diffusion tubes results). NO_2 was measured continuously using an NO_2 monitor (<https://www.sonitussystems.com/>) which employs an electrochemical sensor to measure NO_2 concentrations in a 1-minute resolution. However, for analysis purposes, the NO_2 readings were hourly averaged. Similar to the $PM_{2.5}$ monitoring activity, the NO_2 monitor was co-located with the Pearse street EPA AQ monitoring station for 10 days to determine the adjustment factor before installing it into the station. Additionally, a diffusion tube was installed alongside the NO_2 monitor each month to evaluate its monthly average performance.

8.2.1.2 Meteorology data

A weather station (HOBO U30, Onset Computer Corporation, MA, USA) was installed in the open end of Platform 2 to record outdoor meteorological parameters for a period of one month (01 to 31 March 2024). The weather station was moved to the enclosed Platform 4 and installed along with the continuous NO₂ monitoring from 01 April to 31 May 2024. Data were collected at a 5-minute resolution and subsequently averaged to hourly values for analysis.

8.2.1.3 Train operational data

Information on train traffic, idling duration, engine idling speed, engine power, and fuel consumption were obtained from Irish Rail for the abovementioned period. Irish Rail operates two types of diesel trains at Connolly: Diesel Multiple Units (DMUs), where engines are incorporated into the carriages and multiple exhausts are found along the length of the train, and push-pull trains, where the train is operated by a locomotive at the front.

8.2.1.4 Statistical Analysis

The increment of the station concentration over the background level was used to quantify the contribution from internal sources, similar to the approach adopted by (Lenschow et al., 2001). The method assumes that station background concentration is similar to the outside background. In this study, we used data from an EPA monitoring station located on Amiens Street, directly outside Connolly Station, as the outside background. This station offers lower uncertainty at high time resolution, as both the railway station and the urban background are influenced by the same localized variations.

The study adopted the eXtreme Gradient Boosting (XGBoost) algorithm to evaluate the impact of various factors, including ambient conditions, train idling, and train traffic on NO₂ concentrations. XGBoost is an ensemble model that employs the boosting technique and is commonly used in the literature for predicting AQ and calibrating low-cost sensors (Le et al., 2025; Li et al., 2022; Qian et al., 2024). The model was evaluated using the *k*-fold cross-validation approach, where the dataset was divided into *k* folds. The model was trained and tested *k* times, with a different fold used as the validation set in each iteration. The RandomizedSearchCV function was used to optimize the model's hyperparameters. The analysis was performed using the Python libraries scikit learn and XGBoost to implement

regression.

The dataset included hourly NO₂ concentrations (measured from 01st April to 31 May 2024), adjusted by subtracting urban background NO₂ levels, as the response variable. The explanatory variables consisted of meteorological data (hourly wind speed in m/s and temperature in °C), as well as operational factors such as hourly train traffic, fuel consumption and average train idling time with the engine running. The models were trained using 1,440 data points, with 20% of the data reserved for testing, using a random state of 42 and 5-fold cross-validation. For each fold, the trained models were evaluated on the test dataset using performance metrics including RMSE and R². These metrics were averaged to derive the final evaluation scores for the model. Additionally, a PDPs was used to understand the marginal effect of each explanatory variable on the model's output, while averaging out the influence of all other variables. XGBoost regression was not performed for PM_{2.5} due to the unavailability of train activity data.

8.3 Results & Discussion

8.3.1 Continuous NO₂ Concentrations

The 24-hr average NO₂ concentrations at enclosed Platform 4 measured using an NO₂ monitor during the measurement period ranged from 135.6 to 169.8 µg/m³, exceeding the WHO 24-hour guideline value by 5.4 to 6.7 times. Diurnal variations in NO₂ levels were analysed in relation to train traffic and the idling time of trains (Figure 8.6).

It was observed that NO₂ concentrations were higher during periods of low train traffic, where trains experienced longer idling time before departure. Elevated idling time and consequent higher NO₂ levels were most prominent during the early morning hours (5:00–7:00 AM), late evening (10:00 PM–12:00 AM), and midday (11:00 AM–2:00 PM). Peak concentrations ranging between 309 to 429 µg/m³ were observed during these periods. Hourly average concentrations ranged from 220 to 257 µg/m³ when the total idling time of the trains exceeded 80 minutes. The average concentrations on weekends were 1.2 to 1.25 times higher than on weekdays, due to lower train frequency and consequently longer idling times (Figure 8.7).

The average NO₂ concentrations (165 µg/m³) over the monitoring period were significantly higher than outside background concentration (37 µg/m³), exceeding it by 4.45 times. The

temporal correlation coefficient between the station NO_2 and the outside NO_2 background was low and lacked statistical significance ($R^2 = 0.056$) (Figure 8.8). This supports the conclusion that indoor NO_2 concentrations on the enclosed platforms were strongly influenced by the local sources and independent of the outside background level. Furthermore, a decrease in NO_2 was observed when increases occurred in temperature and wind speed within the station.

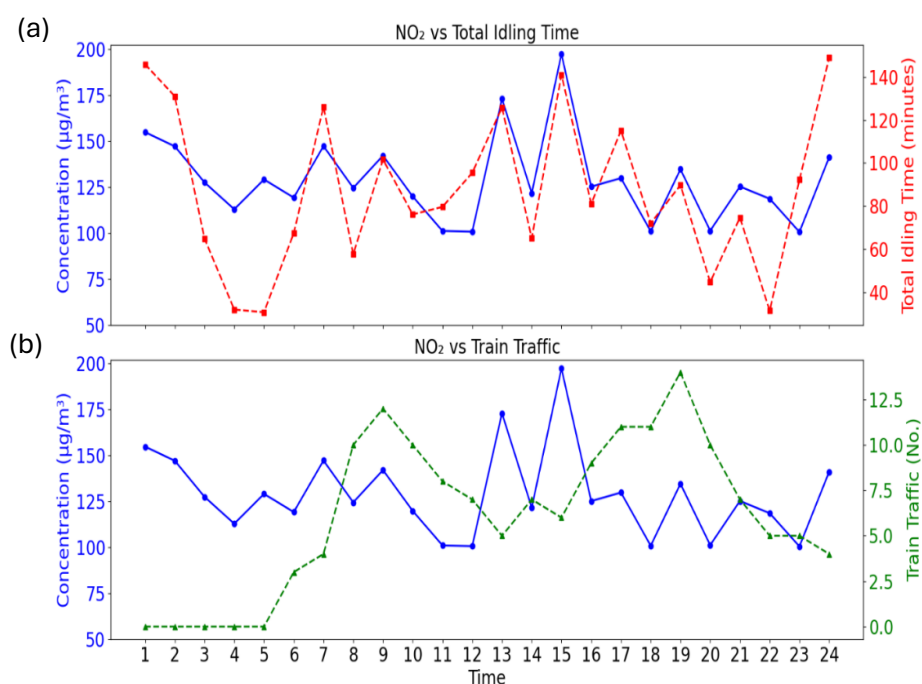


Figure 8.6. Average diurnal variations in NO_2 concentration over the study period as compared to the (a) total idling time and (b) train traffic.

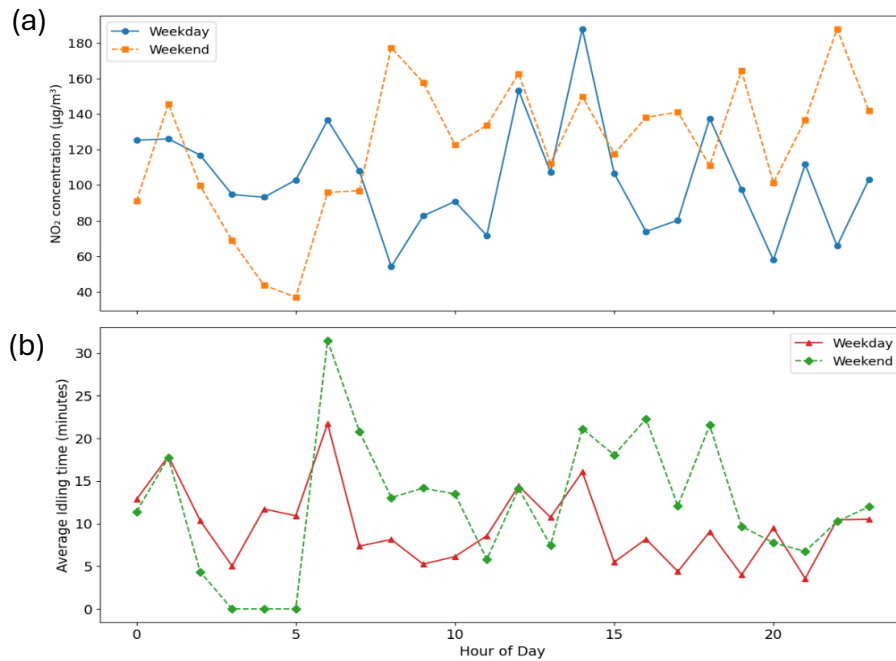


Figure 8.7. Average diurnal variation of (a) NO₂ concentrations and (b) average idling time for weekdays and weekends over the study period.

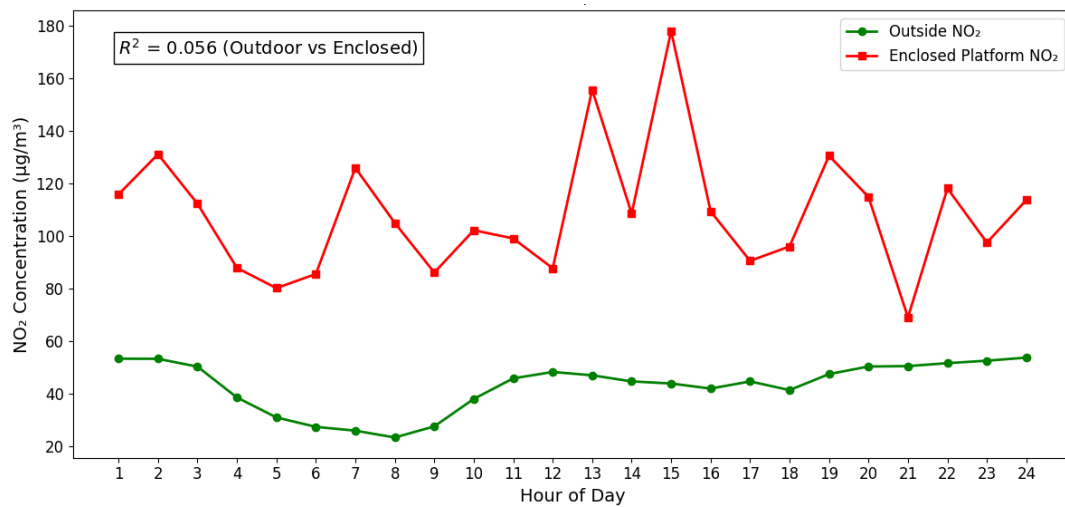


Figure 8.8. Average diurnal variations of NO₂ concentrations measured on the semi-enclosed (indoor) and outdoor platforms over the study period.

8.3.2 Impact of Meteorological Conditions

Meteorological variables at the station, both on the enclosed and outdoor platforms, were observed to vary depending on the time of day and train traffic. Warmer and windier conditions were observed during the midday hours at outdoor platforms (Figure 8.9).

On average, the indoor temperature in the enclosed station area was 2.81 °C higher than the

outdoor temperature, primarily due to train combustion activities. The average indoor wind speed in the enclosed area was 0.18 m/s, indicating predominantly calm conditions (i.e., < 0.5 m/s), and was approximately eight times lower than the outdoor wind speed (1.42 m/s).

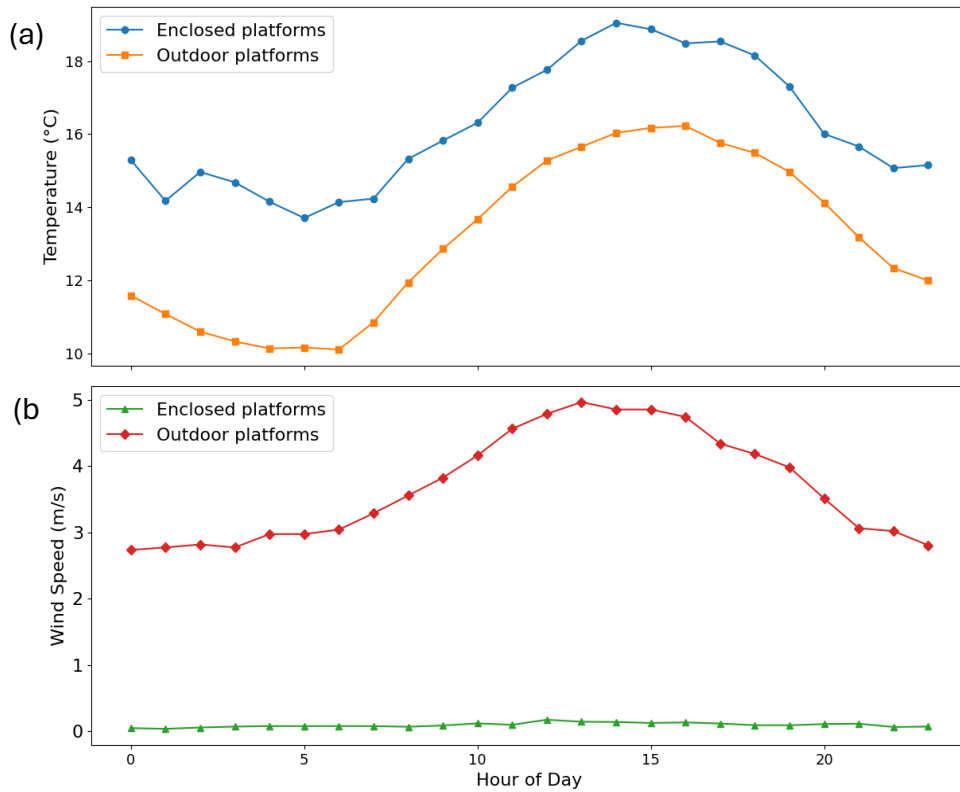


Figure 8.9. Average diurnal variation of (a) temperature and (b) wind speed measured on the semi-enclosed (indoor) and outdoor platforms over the study period.

8.3.3 XGBoost Modelling

To identify the controlling factors related to idling, several variables were excluded from the XGBoost model after the initial runs. These factors included fuel consumption, which was removed because it was directly correlated with idling time and did not enhance the model's performance. Wind direction was also excluded from the model, as indoor wind speeds in the enclosed station were predominantly reflective of calm conditions (less than 0.5 m/s), which did not produce meaningful prediction. The XGBoost model exhibited a moderate fit, with an RMSE of $15.12 \mu\text{g}/\text{m}^3$ and an R^2 value of 0.61 on the test data, which represented a reasonable reconstruction for a gaseous pollutant like NO_2 , given its sensitivity to multiple influencing factors including chemical reactions, interactions with other reactive pollutants, and dynamic environmental conditions. The model identified station ambient temperature

and average train idling time as the most influential factors in predicting NO₂ concentrations (Figure 8.10). Train traffic and wind speed were the variables with least importance.

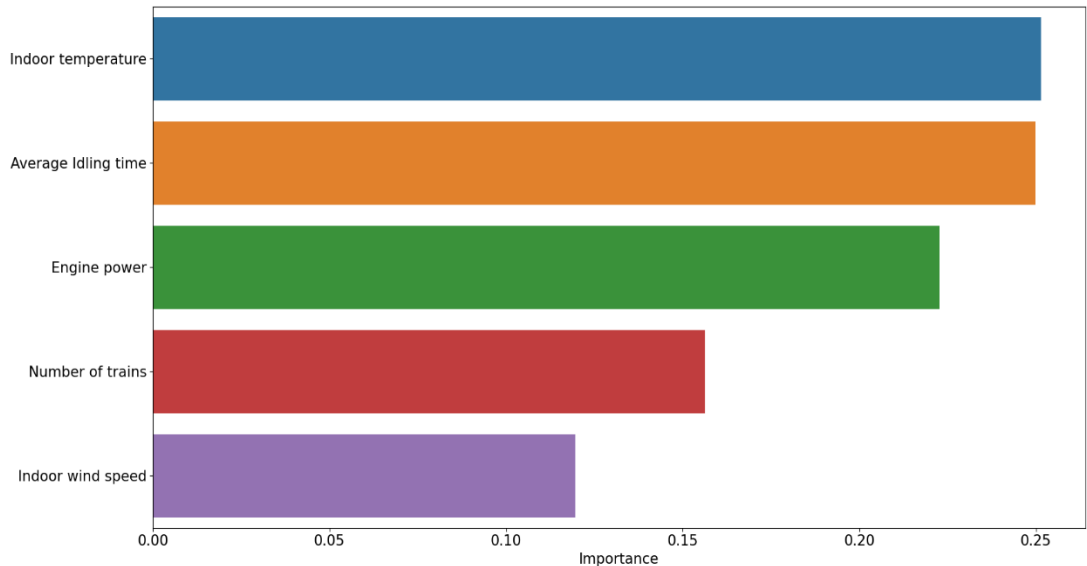


Figure 8.10 Variables of importances identified by the XGBoost modelling.

The PDP identified that NO₂ levels increased with a decrease in ambient temperature (Figure 8.11). However, meteorological parameters are independent of train management activities and therefore cannot be controlled within the station. Focusing on the idling time, which can be actively managed, PDP showed a steep increase in hourly NO₂ concentrations when the average idling time per train exceeded 10 minutes.

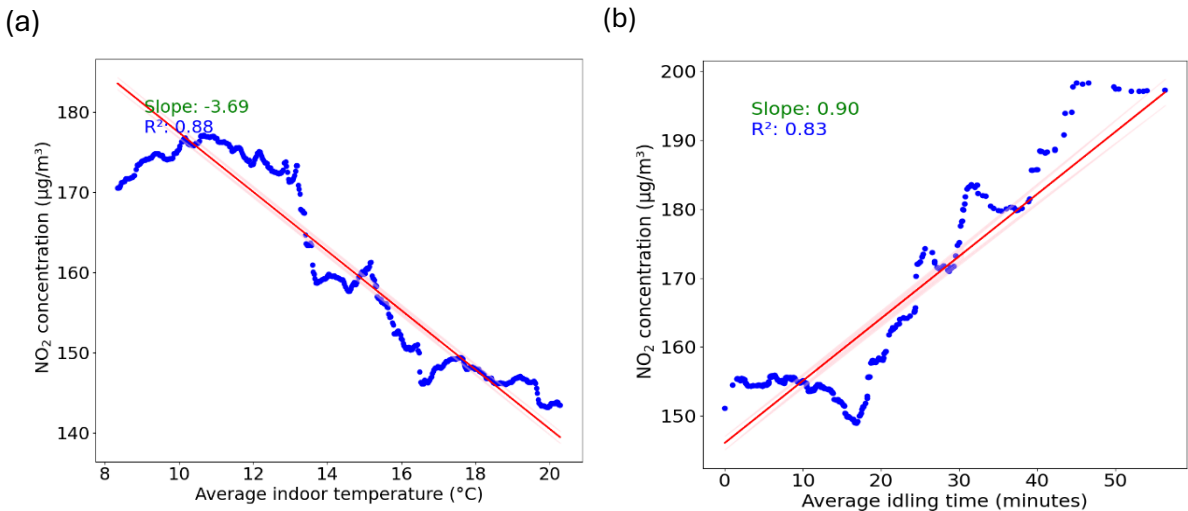


Figure 8.11. Partial dependence plot (PDP) for the average NO₂ concentrations against (a) average indoor temperature and (b) train idling time.

Conversely, a decrease in NO_2 levels were noted during periods of high train traffic, due to shorter idling time of the trains. Insights from the PDP suggest that reducing the average train idling time per train by two minutes could reduce NO_2 concentrations by approximately $2.5 \mu\text{g}/\text{m}^3$ per train. While wind speed was not identified as a key influencing factor, the PDP revealed that when wind speeds exceeded 0.2 m/s , a decrease in NO_2 levels was observed (Figure 8.12). This suggests that enhancing ventilation and increasing airflow within the station could also be a strategy to reduce NO_2 concentrations, in addition to managing train idling time.

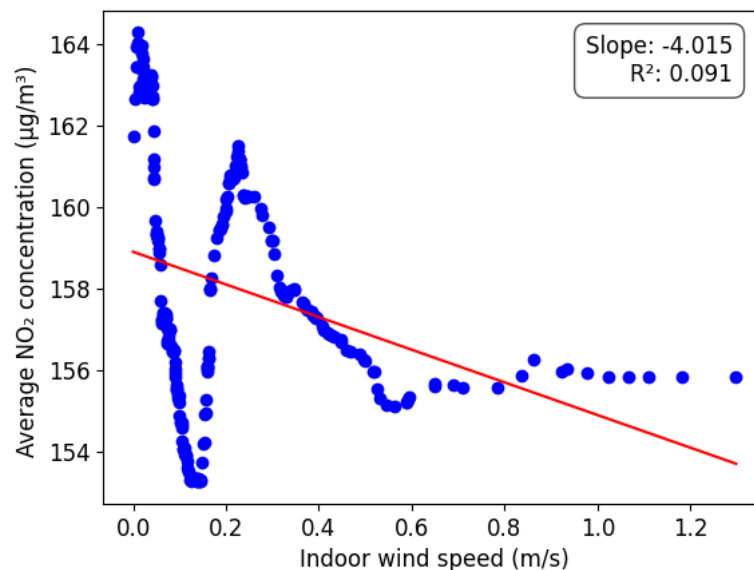


Figure 8.12. Partial dependence plot (PDP) for wind speed inside the train station compared to average NO_2 concentrations.

8.4 Summary

This chapter demonstrated the assessment of air quality using monitoring and identified the controlling factors of pollutant levels using XGBoost modelling at Dublin Connolly. The 24-hour average $\text{PM}_{2.5}$ measured ranged between 3.18 and $32.56 \mu\text{g}/\text{m}^3$, and 5.6 and $42.4 \mu\text{g}/\text{m}^3$, respectively. Higher $\text{PM}_{2.5}$ concentrations were observed on enclosed Platforms 3 and 4, which predominantly host DMU trains, exceeding the WHO 24-hour guideline value during 90% of the monitoring period.

NO₂ levels measured using diffusion tubes ranged between 40.5 and 162.7 µg/m³, with the highest concentrations recorded on enclosed Platform 4 during the exposure period. The 24-hour average NO₂ levels on enclosed Platform 4, measured using continuous monitoring, ranged between 135.6 and 169.8 µg/m³, exceeding the WHO 24-hour guideline value by a factor of 5.4 to 6.7.

The XGBoost model demonstrated a moderate fit, with an RMSE of 15.12 µg/m³ and an R² value of 0.61 on the test data. The model identified station ambient temperature and average train idling time as the most influential factors in predicting NO₂ concentrations. PDP suggested that reducing the average idling time of a train by 2 minutes could lower NO₂ concentrations by approximately 2.5 µg/m³ per train.

9. EFFECT OF IDLING ON FUEL CONSUMPTION AND EMISSIONS

This chapter focuses on estimating fuel consumption and emissions resulting from excessive train idling, as well as the potential economic savings associated with more efficient train operations. The analysis was performed using train operational data from Connolly Station obtained from Irish Rail.

9.1 Fuel Consumption & Associated Emissions

The effect of idling time and idling engine speed on fuel consumption and NO_x and PM emissions, was analysed. Hourly NO_x and PM emissions during idling were estimated based on engine output power and idling duration, as presented in Equation (1):

$$Emission_{pollutants} = \sum_{i=1}^N P_i \times ID_i \times EF_i \quad (\text{Eqn.9.1})$$

where N is the total number of trains in an hour, P_i is the engine output power of each train (kW), ID_i is the idling time of each train (hr), EF_i is the emission factor (g/kWh). EU Stage IIIA railcar emission factors corresponding to the output power range less than 130 kW were used, as the engine power of the train during idling was found to fall within this range (EU, 2004).

9.1.1 Effect of Idling on Fuel Consumption and Emissions

Longer idling times not only contribute to elevated pollutant levels within the station but also significantly increase fuel consumption. A train consumes approximately 22 litres of diesel per hour while idling. Based on the data collected during the study period (March to May 2024), it was estimated that idling activity resulted in the consumption of almost 13,000 litres of diesel per month (or 11 tons/month), generating equivalent emissions of approximately 130 kg/month of NO_x and 11 kg/month of PM.

An initial consideration noted the relationship between idling time and fuel consumption would suggest that reducing the average train idling time (with the engine running) by one minute could lower fuel use by approximately 0.3 litres per train (Figure 9.1(a)). Additionally, the relationship between idling engine speed and fuel consumption indicated that maintaining engine speed below 600 RPM reduces engine output power, thereby lowering both fuel consumption and emissions (Figure 9.1(b)). Therefore, two control strategies, related to idling, were considered and evaluated in terms of fuel savings and reduced gaseous and particulate emissions.

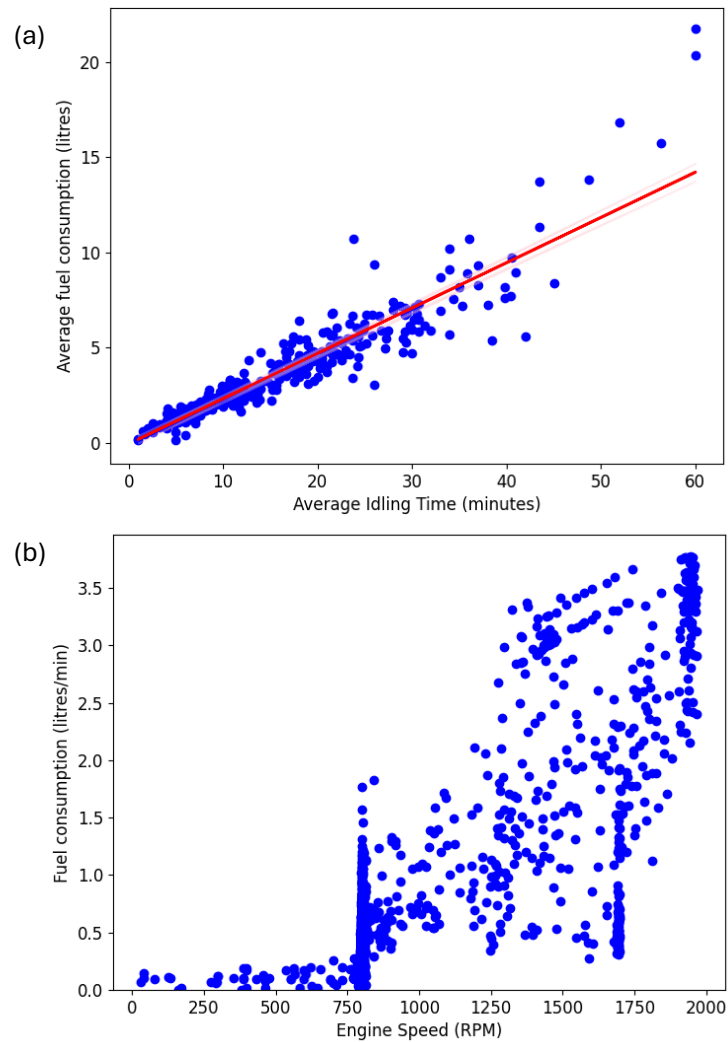


Figure 9.1. Relationship between average fuel consumption and average idling time at the station.

9.2 Assessment of control strategies

Two strategies were examined to evaluate the impact of reducing idling time and engine speed on fuel consumption and emissions: 1) shutting down train engines if the next scheduled operation is more than 30 minutes away and restarting the engine 15 minutes before departure. Shutting down engines when the next scheduled service is less than 30 minutes away poses operational challenges. Systems such as air brake pressure maintenance, carriage heating, and battery charging require the engine to remain running for at least 15 minutes prior to departure. Additionally, there is also a risk to service reliability, as the train may not restart on time; or 2) maintaining engine speed at or below 600 RPM during notch 0 can help minimize fuel consumption and emissions before shifting to notch 1. To calculate the monetary savings from the diesel fuel, average diesel pump prices are roughly

€1.72 per litre was used.

It was estimated that for control strategy 1, shutting down train engines during idling periods exceeding 30 minutes, could save approximately 3,530 litres (3 tons) of diesel per month. Similarly for control strategy 2, operating engines at idle speeds below 600 RPM during idling periods shorter than 30 minutes could result in an additional saving of an additional 3,530 litres (3 tons) of diesel per month. Overall, implementing a combination of these control strategies could reduce fuel consumption during idling by approximately 40–45%, while lowering NO_x emissions to 64 kg/month and PM emissions to 5 kg/month. The monetary savings correspond to the fuel savings of about approximately €12,140 per month if both strategies are implemented (Figure 9.2).

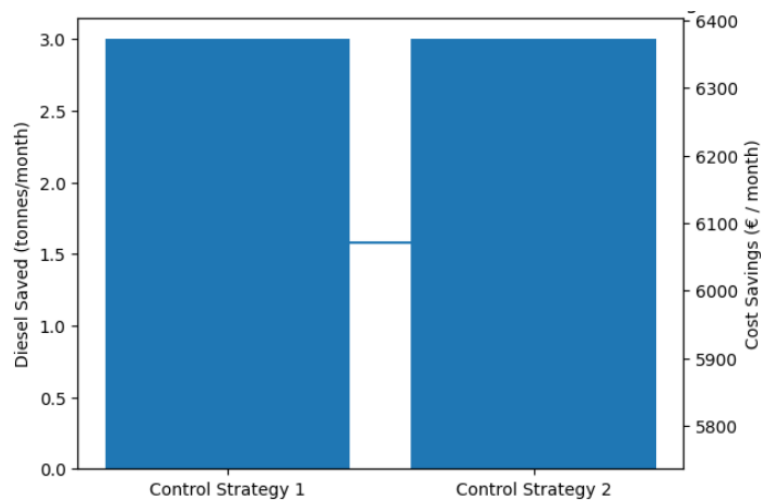


Figure 9.2. Diesel and cost savings resulting from the control strategies: (1) shutting down train engines when the next scheduled operation is more than 30 minutes away and restarting the engine 15 minutes before departure, and (2) maintaining engine speed at or below 600 RPM during idling.

9.3 Summary

Long train idling significantly increases fuel consumption and pollutant emissions, with trains consuming about 22 litres of diesel per hour while idling. During the study period (March–May 2024), idling led to nearly 13,000 litres (≈11 tonnes) of diesel used per month, producing roughly 130 kg of NO_x and 11 kg of PM monthly. Reducing idling time by one-minute saves about 0.3 litres of diesel per train, while keeping engine speed below 600 RPM further lowers fuel use and emissions.

Two control strategies were evaluated: (1) shutting down engines during idling periods over 30 minutes, and (2) maintaining engine speed below 600 RPM during idling under 30 minutes. Each strategy could save about 3,530 litres ($\approx$ 3 tonnes) of diesel per month and implementing both together could cut idling fuel consumption by 40–45%, reduce NO_x emissions to 64 kg/month and PM to 5 kg/month, and save approximately €12,140 per month in fuel costs.

10. CHEMICAL CHARACTERISATION OF PM_{2.5} AND QUANTIFICATION OF EXHAUST AND NON-EXHAUST SOURCES OF PM_{2.5} WITHIN THE CONNOLLY STATION

This chapter presents the chemical characterisation of PM_{2.5} and quantification of exhaust and non-exhaust sources of PM_{2.5} within the station using Positive Matrix Factorisation.

The elemental and ionic analyses presented in this chapter were carried out at the Trinity Centre for the Environment, Trinity College Dublin. Calibration of the analytical instruments had already been established as part of routine laboratory quality assurance procedures; therefore, instrument calibration was not undertaken as part of this study. Similarly, silica composition analysis was performed in the Department of Botany, where instrument calibration was also maintained under existing laboratory protocols. EC and OC analyses were conducted commercially at National Physical Laboratory, UK.

10.1 Methodology

10.1.1 Aerosol Sampling

The sampling of PM_{2.5} was conducted at Connolly station at platform 4 from 16th March 2024 to 30th April 2024. The sampler was placed in the enclosed section of Platform 4. The 24-hr PM_{2.5} samples were collected on 150 mm diameter Pallflex (Tissuquartz™) quartz fibre filters using a high-volume aerosol sampler (DHA-80, Digitel Enviro-Sense) operating at a flow rate of 0.5 m³/min. The PM_{2.5} concentrations were determined using gravimetric analysis. Each filter was weighed three times before and after sampling with a precision balance (OHAUS Adventurer Pro AV313) having a sensitivity of ±1 mg. Field blanks were included to account for any contamination of the filters during sampling. Prior to sampling and initial weighing, the filters were pre-heated at 500 °C in air using a furnace to eliminate volatile impurities and reduce carbon blank values, thereby improving the accuracy of the EC/OC analysis performed at a later stage. Figure 10.1 shows the weighing of the filter paper after sampling on the precision balance.

10.1.2 Chemical characterization

10.1.2.1 Analysis of elemental species

Elements were extracted using closed-vessel microwave digestion (Multiwave Go, Anton Paar GmbH). Filter samples were placed in PTFE-TFM digestion vessels and digested with an

extraction solution consisting of 5.55% HNO_3 and 16.75% HCl . Half of each filter was used for the extraction process. The elements Mg, Ba, Al, Na, P, Cr, K, Ca, Mn, As, Ni, Pb, Cd, Cu, Fe, and Zn were analysed using Inductively Coupled Plasma - Optical Emission Spectrometry (ICP-OES) (Agilent Technologies 5110) (Figure 10.2) following the Compendium Method IO-3.4 (USEPA, 1999).

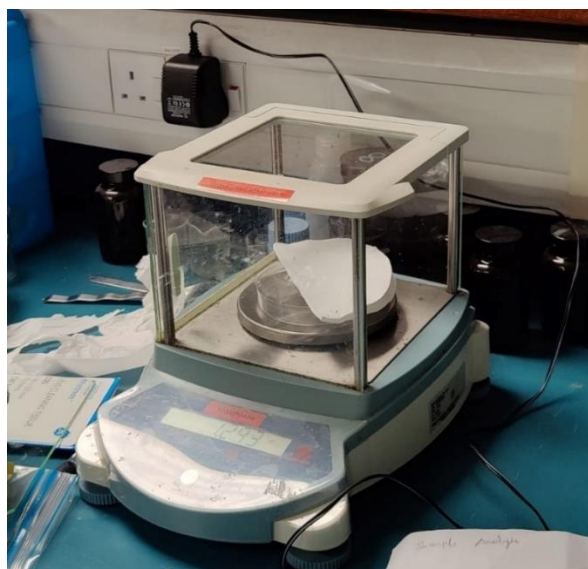


Figure 10.1. Weighing of the filter paper after sampling using precision balance Adventurer Pro AV313.

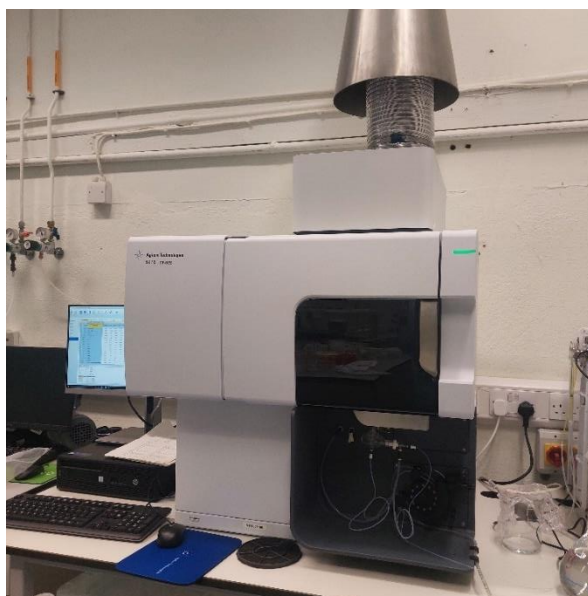


Figure 10.2. Inductively Coupled Plasma - Optical Emission Spectrometry for elemental analysis.

The instrument was calibrated using standards ranging from 0.01 mg/L to 10 mg/L and validated across this range prior to analysing the PM_{2.5} samples. Since HNO₃ and HCl cannot completely dissolve Si, its concentration was determined semi-quantitatively using handheld X-ray Fluorescence (XRF) (Niton XL2 Plus) according to the Compendium Method IO-3.3 ((USEPA, 2000). Laboratory blanks, field blanks, and blank extracts were analysed to account for potential contamination. The analysed elements were classified into two groups: crustal elements (Ca, Na, Mg, Al, Fe, K, and Si) and trace elements (Ba, Cr, Cd, Cu, Ni, As, Pb, and Mn).



Figure 10.3. X-ray Fluorescence for semi-quantitative measurements for elements.

10.1.2.2 Analysis of water-soluble ionic species

Water-soluble anions and cations were analysed following the standard operating procedure (USEPA, 2019). One-fourth of each filter was used for the extraction. Inorganic ions were extracted with deionized water in an ultrasonic bath, followed by filtration of the extract. The filtered extracts were analysed for cations (K⁺ and NH₄⁺) and anions (Cl⁻, NO₃⁻, and SO₄²⁻) using a Dionex ICS-1500 (Thermo Scientific) (Figure 10.4). The same procedure was applied to field blanks and laboratory blanks. Standards ranging from 0.1 to 10 mg/L were used to generate the calibration graph prior to analysis.

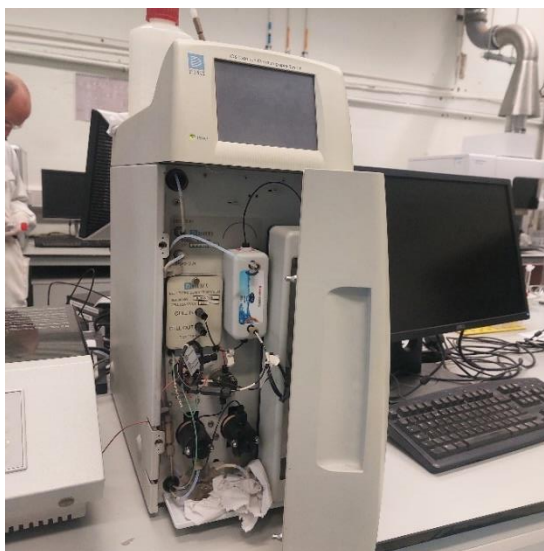


Figure 10.4. Ion chromatography for quantifying cations and anions

10.1.2.3 Analysis of elemental carbon (EC) and organic carbon (OC)

A 0.5 cm² area of the quartz filter was used for the estimation of elemental and organic carbon content (EC-OC). The total carbon (TC), elemental carbon (EC) and organic carbon (OC) composition of the samples were analysed using thermal/optical carbon analyser (DRI Model 2015, Atmos-lytic, Inc., Calabasas, CA, USA). The analysis was based on the IMPROVE_A protocol (Interagency Monitoring of Protected Visual Environments A): Thermal/ Optical Reflectance and Thermal/Optical Transmittance based measurements (Chow et al., 2007). OC fraction (OC1, OC2, OC3, and OC4) of the PM were quantified at 140, 280, 480 and 580°C respectively in a pure helium (He) atmosphere in the absence of oxygen. The EC fractions (EC1, EC2, and EC3) were estimated in an oxidizing atmosphere (2% O₂ and 98% He) at 580, 780, and 880°C respectively. For analysis and interpretation, OC and EC were expressed as the sum of their respective fractions.

10.1.3 Positive matrix factorization (PMF)

PMF is the factorization model is widely used in the source apportionment studies. PMF decomposes the input species concentration matrix into two matrices, factor profile (f_{kj}) and factor contribution (g_{ik}) in such a way that these matrices are non-negative (Paatero, 1997). PMF uses both species concentration and uncertainty in resolving the non-negative factor matrices (Paatero, 1997). The factor profiles and factor contributions are obtained by minimizing the objective function Q (Eqn.8.1) such that species with larger uncertainty values

have less influence, while species with smaller uncertainty values have greater influence on the weighted least-squares fit (USEPA, 2015).

$$Q = \sum_{i=1}^n \sum_{j=1}^m \left[\left((x_{ij} - \sum_{k=1}^p g_{ik} * f_{kj}) / u_{ij} \right)^2 \right] \quad (\text{Eqn.8.1})$$

where x_{ij} is the concentration of j^{th} species measured in the i^{th} sample, g_{ik} is the contribution of source k to i^{th} sample, f_{kj} is the fraction contribution of species j in the profile of source k and u_{ij} is the uncertainty associated with the concentration of species j in the i^{th} sample.

In this study, PMF analysis was performed using EPA PMF version 5 software. Bootstrap was done with 100 runs with a random seed, correlation threshold 0.6, block size 6. The following criteria were considered in obtaining the optimal solution: correlation coefficient between the measured and modelled $\text{PM}_{2.5}$ concentration (r^2) and bootstrap mapping for the base run. The measurement uncertainty is calculated as:

$$u_{ij} = \sqrt{(0.5 \times \text{MDL}_j)^2 + (0.1 \times x_{ij})^2}, \text{ if } x_{ij} \geq \text{MDL}_j \quad (\text{Eqn.8.2})$$

$$u_{ij} = \frac{5}{6} \times \text{MDL}_j, \text{ if } x_{ij} < \text{MDL}_j \quad (\text{Eqn.8.3})$$

where MDL_j is the minimum detection limit of the instrument for species j (Srivastava et al., 2021).

A high uncertainty was assigned to Si, calculated as 5% of the Si concentration plus the minimum detection limit of the instrument, since Si was estimated on a semi-quantitative basis.

10.2 Results and discussion

10.2.1 Concentration and Chemical composition of $\text{PM}_{2.5}$

The 24-hr $\text{PM}_{2.5}$ levels at the platform 4 ranged between 15.1 to 19.6 $\mu\text{g}/\text{m}^3$, exceeding the 24-hr WHO guideline value of 15 $\mu\text{g}/\text{m}^3$; however, levels were below the proposed 24-hr EU guideline value of 25 $\mu\text{g}/\text{m}^3$. Figure 10.5 presents the variation of 24-hr $\text{PM}_{2.5}$ concentrations over the monitoring period.

The chemical characterization of $\text{PM}_{2.5}$ showed that the mass is composed of 83–90% of carbonaceous matter (EC and OC), 8–12% of elemental species and 4–5% of ionic species (Figure 10.6). The concentration of elemental species is shown in the Figure 10.7. Among the elements, species from the exhaust emissions (Ca, Na, Ba, K, Mg) are abundant than the non-

exhaust species (Fe, Mn, Cu, Zn) (Kumar & Behera, 2024; Lu et al., 2015). The non-exhaust species originates from the mechanical wear from brakes, wheels, and rails. Since the train speed when arriving the station is in the range of 5–10 km/h, the required braking force and braked mass are low, and with the absence of a pantograph, the emissions of non-exhaust species are lower compared to those observed in subway systems (Heo et al., 2026; Russo et al., 2023). The species (Si, Al) associated with soil dust and the resuspension of crustal material due to commuter movements were also found to be abundant (Priyan et al., 2022).

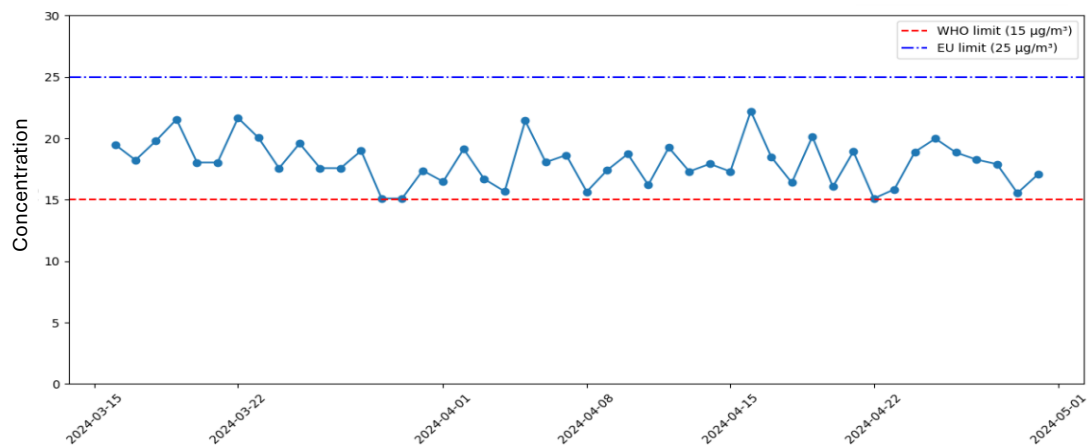


Figure 10.5. Variation of 24-hr $PM_{2.5}$ concentrations over the monitored period.

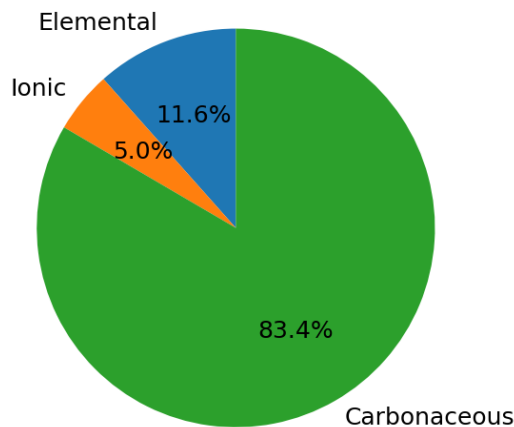


Figure 10.6. Chemical composition of $PM_{2.5}$.

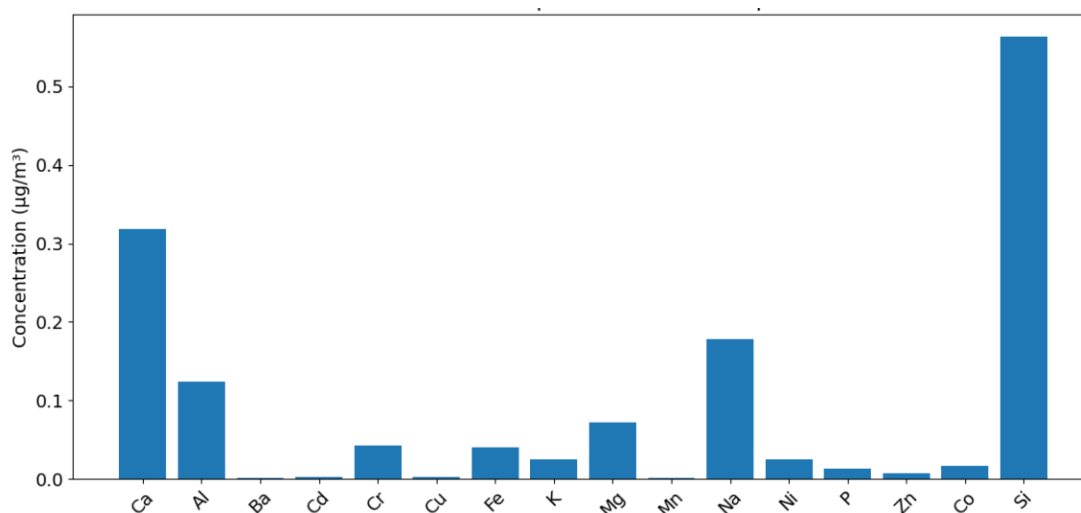


Figure 10.7. Average Concentration of Elemental species over the study period.

The concentration of ionic species is shown in Figure 10.8. Among the ionic species, Na^+ and Cl^- are the dominant species, primarily sea salt which are strongly observed in the coastal area. Average Cl^-/Na^+ ratio of 1.56 observed in this study is consistent with the ratio reported for sea salt in Dublin (Kirsten Fossum & Stig Hellebust, 2023). The inorganic secondary aerosol (NH_4^+ , NO_3^- , and SO_4^{2-}) levels were relatively low, indicating that conditions at the station were not favourable for nitrate and sulphate formation.

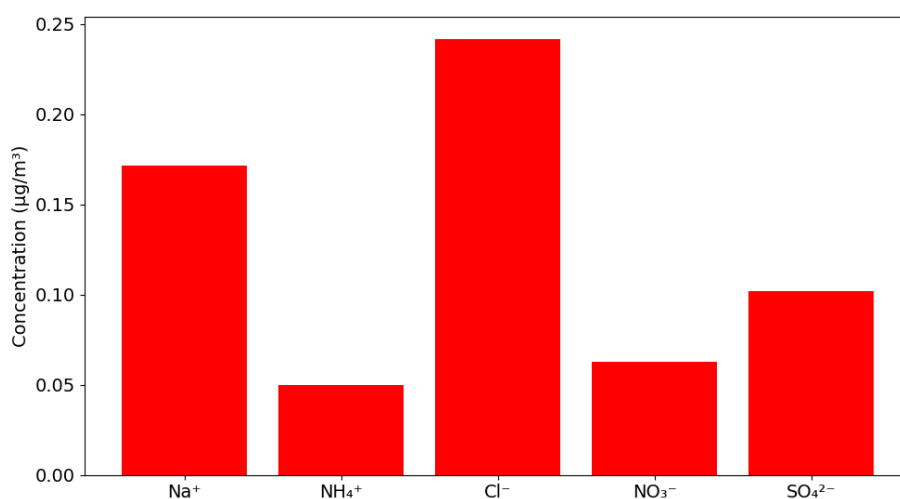


Figure 10.8. Average Ionic composition of $\text{PM}_{2.5}$ over the study period.

The Carbonaceous composition of $\text{PM}_{2.5}$ are shown in Figure 10.9. EC and OC are important tracers of diesel combustion; however, OC can also be formed through a series of chemical reactions in the atmosphere. The EC/OC (0.68) mass fraction indicates that idling train

operation was a greater contributor to $PM_{2.5}$ than transient train operation in the station (Shah et al., 2004). At idling, the engine operates at low temperature, resulting in incomplete fuel oxidation, increased hydrocarbon emissions, and condensation of semi-volatile organics, which lead to higher OC emissions, while the formation of EC (soot) particles is suppressed (Shah et al., 2004).

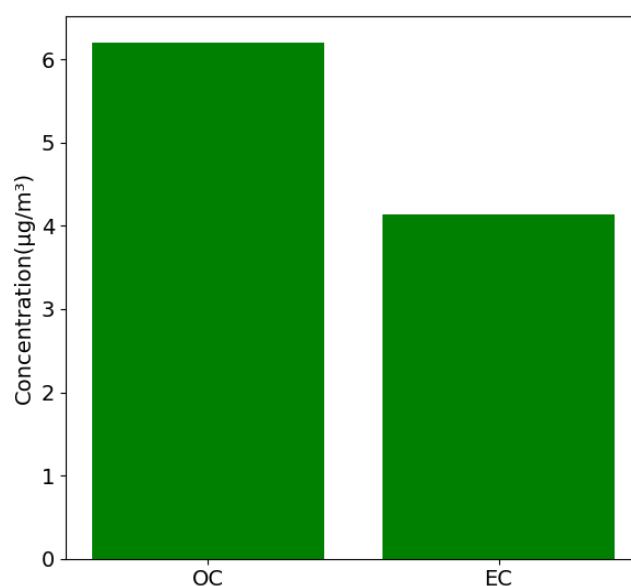


Figure 10.9. Average Carbonaceous composition of $PM_{2.5}$ over the study period.

10.2.2 Source apportionment of $PM_{2.5}$

A four-factor solution provided an acceptable fit, with all four factors being stable, and more than 80% of the bootstrapped factors mapping onto the corresponding base factors. The correlation coefficient ($r^2 = 0.87$) between modelled and measured $PM_{2.5}$ concentrations indicated good prediction performance.

Train exhaust (Factor 1) (Figure 10.10) is dominated by high contributions from crustal elements such as Ca (60–66%), Na (41–45%), and Mg (66–70%), along with ions such as NH_4^+ (29–32%) and NO_3^- (25–29%) and high carbonaceous matter (EC: 45–53% and OC: 42–55%), consistent with the profile reported by the USEPA diesel rail exhaust speciation (USEPA, 2006). The crustal elements are associated to the pyrolysis of lubricating oil, lubricant additives, catalyst materials, and engine wear during combustion. In addition, diesel fuel itself contains significant amounts of these elements, which are released during incomplete combustion (Hao et al., 2019). NH_4^+ and NO_3^- are possibly emitted from the selective

catalytic reduction process in the engine exhaust used to reduce NO_x emissions (Han et al., 2019).

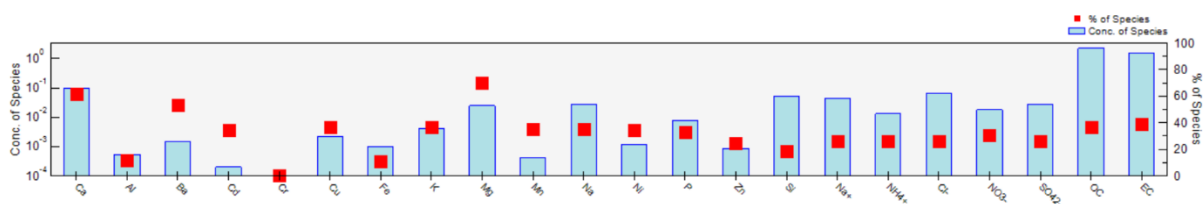


Figure 10.10. PMF resolved factor profile 1 (Train exhaust).

Train exhaust with non-exhaust sources (Factor 2) is characterized by high contributions from crustal elements such as Al (40–43%), K (50–53%), and Fe (53–56%), as well as trace elements including Mn (47–50%), Cu (49–53%), Ba (57–60%), Cr (66–68%), Cd (43–48%), and Zn (43–45%), along with carbonaceous matter (EC: 30–35% and OC: 32–35%) (Figure 10.11). The crustal elements are mainly associated with lubricating oil and diesel content (Hao et al., 2019). Among the trace species, Ba and Cr serve as markers of brake wear, Fe originates from wheel, rail, and contact surface abrasion as well as engine wear and fuel content, while Cd, Zn, and Cu are linked to engine wear, frictional components (e.g., gaskets and piston rings), and fuel composition (Russo et al., 2023; Salva et al., 2026). Owing to the linearity constraint and the strong correlation between train exhaust and non-exhaust sources, the model has difficulty quantifying them separately. However, considering Ba, Cr, and Fe as direct non-exhaust species, and given that non-exhaust sources do not contribute OC and EC, and subtracting these elements from this factor can help in quantifying the train exhaust contribution more precise.

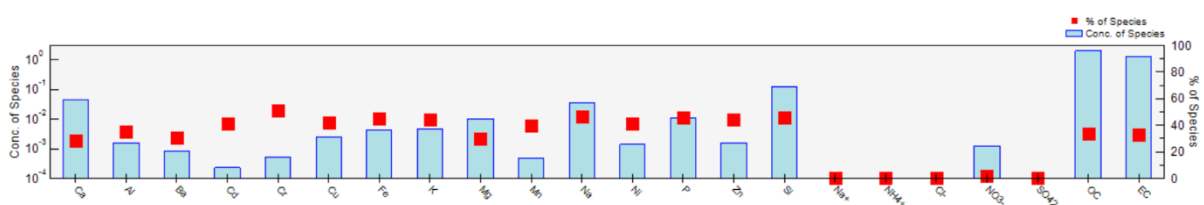


Figure 10.11. PMF resolved factor profile 2 (Train exhaust + non-exhaust).

The Secondary Organics and Inorganics (Factor 3) source profile is characterised by high contributions from ionic species such as NH₄⁺ (68–71%), NO₃⁻ (60–63%), and SO₄²⁻ (71–72%), with a smaller fraction of organic carbon (8–10%) (Figure 10.12). This source represents a

regional background to the train station. These ionic species are formed in the atmosphere through gas-to-particle conversion via homogeneous and heterogeneous aqueous- and gas-phase reactions of NO_2 and SO_2 . In the atmosphere, they primarily exist as $(\text{NH}_4)_2\text{SO}_4$ and NH_4NO_3 (Priyan et al., 2022).

In Dublin, the main source of SO_2 is residential space heating and shipping emissions from the port, while NO_2 mainly originates from road and non-road transport emissions. NH_3 emissions in the city are largely attributable to agricultural activities on the outskirts. In the profile, SO_4^{2-} formation is more prominent than NO_3^- . This is because $(\text{NH}_4)_2\text{SO}_4$ is less volatile and more stable than NH_4NO_3 . Additionally, nitrate formation is influenced by the availability of oxidants such as hydrogen peroxide and ozone (Priyan et al., 2022). A small fraction of organic carbon is also associated with this factor, likely formed through similar atmospheric pathways as NO_3^- and SO_4^{2-} , from the oxidation of precursor VOCs.

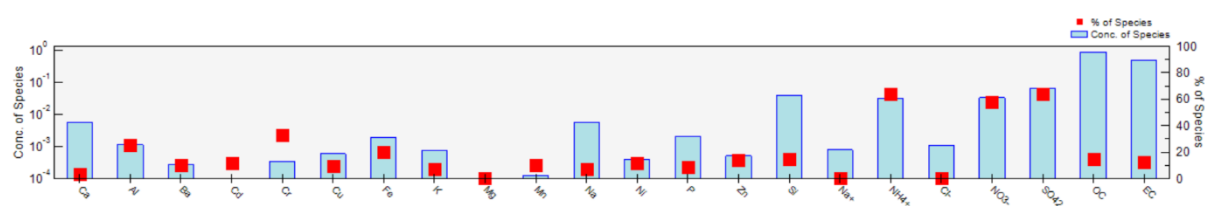


Figure 10.12. PMF resolved profile factor 3 (Secondary Organics and Inorganics).

Sea aerosols are another regional background source to the train station and one of the dominant natural sources in Ireland. This profile is characterised with high contribution from ionic species such as Na^+ (90-95%) and Cl^- (91-95%), which exist as NaCl in the atmosphere (Figure 10.13). These particles are generated through bubble bursting and wave breaking and transported into the inland by winds (Guazzotti et al., 2001).

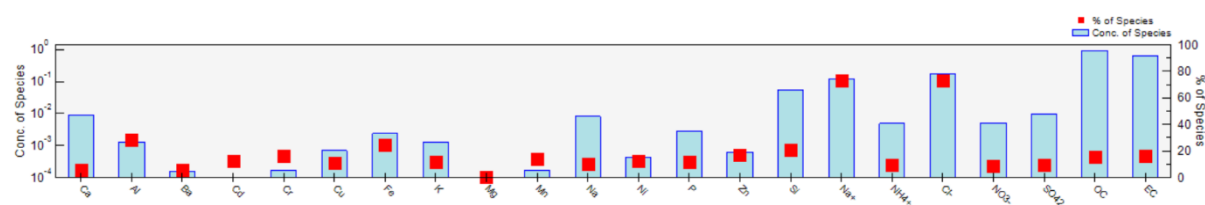


Figure 10.13. PMF resolved factor profile 4 (Sea aerosols).

Train exhaust is identified as the major contributor to the PM_{2.5} concentration (80-85%) inside the station followed by the secondary organics and inorganics aerosols (10-15%), sea aerosols (3-7%) and train non-exhaust (2-3%). Figure 10.14 show the shares of PM_{2.5} sources quantified inside Connolly terminal. Compared with the earlier Dublin ambient study by Gallagher et al. (2021), where solid fuel burning dominated PM_{2.5} at both roadside and city-centre locations (46–50%) followed by traffic-related sources (9-22%). While the enclosed train-station environment is dominated by rail activity, with train exhaust contributing 80–85% of total PM_{2.5}. This reflects that the confined microenvironment of the station, where continuous diesel train operations and limited dispersion enhance combustion-derived particle accumulation, unlike outdoor urban environments where pollutants are more widely dispersed. Further, secondary aerosols, sea aerosols, and train non-exhaust inside the station remain comparatively minor, whereas outdoor Dublin sites showed stronger influence from regional soil and sea spray.

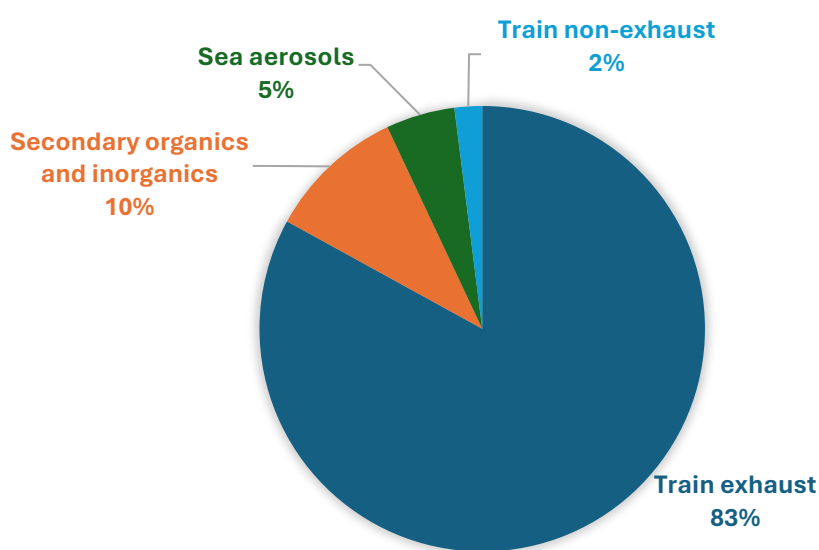


Figure 10.14. Shares of PM_{2.5} inside Connolly terminals.

10.3 Summary

The 24-hour PM_{2.5} concentrations at Platform 4 ranged from 15.1 to 19.6 µg/m³, exceeding the WHO guideline value of 15 µg/m³ but remaining below the proposed EU guideline value of 25 µg/m³. Chemical analysis showed that PM_{2.5} was dominated by carbonaceous matter (83–90%), followed by elemental (8–12%) and ionic species (4–5%). Exhaust-related elements

were more abundant than non-exhaust metals, reflecting low braking demand and train speeds within the station.

Na^+ and Cl^- were the dominant ionic species, indicating a strong influence of marine aerosols, with a Cl^-/Na^+ ratio consistent with sea salt in Dublin. Secondary inorganic aerosols were present at relatively low levels. The EC/OC ratio (0.68) suggested that idling train operations were the primary contributor to carbonaceous emissions. PMF analysis identified four stable sources, with good agreement between modelled and measured $\text{PM}_{2.5}$ ($r^2 = 0.87$). Train exhaust was the dominant contributor (80–85%), followed by secondary organics and inorganics (10–15%), sea aerosols (3–7%), and non-exhaust sources (2–3%).

11. HEALTH AND ECONOMIC IMPACTS ON RAIL COMMUTERS AND STAFF (DALY APPROACH)

This chapter presents short-term commuter and occupational PM_{2.5} concentrations, along with the associated health impacts assessed using the DALY approach and the corresponding economic losses.

11.1 Methodology

11.1.1 PM_{2.5} exposure assessment for commuter

The health risks associated with PM_{2.5} exposure were evaluated by assessing both carcinogenic and non-carcinogenic risks attributable to PM_{2.5}-bound heavy metals, including Cd, Cr (VI), Ni, and Co (Sirinara et al., 2024). These metals are known to pose significant adverse health effects, including increased risks of respiratory diseases, cardiovascular disease (CVD), chronic obstructive pulmonary disease (COPD), and elevated lifetime cancer risk (Sangkham et al., 2024). As the concentrations of these heavy metals were originally quantified as 24-hr averages (Chapter 10), they were adjusted to reflect short-term exposure conditions. The adjusted heavy metal concentration for short-term exposure is calculated using eqn.11.1.

$$C_{ia} = \frac{C_{im}}{C_m} * C_{pm} \quad (\text{Eqn.11.1})$$

Where C_{ia} adjusted heavy metal concentration for short-term exposure, C_{im} is the 24-hr average mass concentration of the heavy metals, C_m is the corresponding 24-hr average PM_{2.5} mass concentration and C_{pm} is the short-term PM_{2.5} mass concentration. The short-term PM_{2.5} mass concentration were obtained using personal monitoring.

11.1.2 Personal monitoring

Personal monitoring was conducted to assess short-term PM_{2.5} exposure experienced by commuters during peak hours at the station, before boarding the train. PM_{2.5} concentrations were measured using a real-time aerosol monitor (SidePak AM520, TSI Inc., Shoreview, MN, USA) with a 1-second resolution. Sampling was carried out from 11 November 2022 to 12 December 2022. A total of four samples were collected at each enclosed platform (Platforms 2 and 4) during the evening peak hours (5–8 p.m.) on different weekdays. Sampling locations

were positioned at the central sections of the platforms near seating areas, and each session lasted 10 minutes prior to the train's departure on the monitored platform.

11.1.3 NO₂ exposure assessment for commuter

The short-term NO₂ exposure experienced by commuters were obtained from the Sonitus NO₂ monitor (3rd March to 6th March 2024) installed at enclosed platform 4 for the evening peak hours (5-8 p.m.). Measurements were recorded at a 1-minute resolution. Short-term NO₂ concentrations were calculated by averaging the 10-minute readings prior to the departure of trains on this platform. Train departure times were obtained from the Irish Rail real-time API.

Short-term PM_{2.5} and NO₂ concentrations experienced by commuters were taken as the average concentrations measured while the train was idling on the monitored platform, excluding concentrations recorded during train arrival and departure.

11.1.4 PM_{2.5} exposure assessment for rail staff

Rail staff, including platform assistants, safety officers, security personnel, and cleaning and maintenance staff, typically spend 6-8 hours on station platforms and are therefore susceptible to continuous exposure to pollutants. Similar to the PM_{2.5} exposure assessment for commuters, carcinogenic and non-carcinogenic risks attributable to PM_{2.5}-bound heavy metals were calculated. The heavy metal concentrations were adjusted to reflect 8-hour occupational exposure conditions. The adjusted heavy metal concentrations for occupational exposure were calculated using Eqn.11. 2

$$C_{ja} = \frac{C_{jm}}{C_m} * C_{om} \quad (\text{Eqn.11.2})$$

Where C_{ja} adjusted heavy metal concentration for 8-hr occupational exposure, C_{jm} is the 24-hr average mass concentration of the heavy metals, C_m is the corresponding 24-hr average PM_{2.5} mass concentration and C_{om} is the 8-hr averages PM_{2.5} mass concentration for different shift periods: night shift (12:00 a.m.– 8:00 a.m.), day shift (8:00 a.m.– 4:00 p.m.), and evening shift (4:00 p.m.– 12:00 a.m.). The 8-hour averages PM_{2.5} mass concentration for different shifts were obtained from the ELOS outdoor station (15th August to 21st September 2023).

11.1.5 NO₂ exposure assessment for rail staff

The 8-hr average NO₂ concentrations for occupational exposure were obtained from the Sonitus monitor (3rd March to 31st March 2024), for abovementioned three different shift periods.

11.1.6 Exposure dose calculation

According to the human health evaluation manual (USEPA, 2011), the average daily exposure dose concentration (ADD_C) via inhalation were estimated using the following (Eqn.11.3)

$$ADD_C = \frac{C * IR * EF * EL}{BW * AL} \quad (\text{Eqn.11.3})$$

Where C is the pollutant concentration (µg/m³), IR is the inhalation rate of staff or commuters (m³/h), EF is the number of days per year that staff or commuters are exposed to the pollutant (days/year), EL is the duration of daily exposure (h/day), AL is the average exposure period for commuters and staff (365 days), and BW is the average body weight (Kg). EF and EL are considered as 230 days (Irish rail, 2024) and 8 hr (USEPA, 2011), respectively. The IR and BW are considered as 1.2 m³/h and 70 kg, respectively (USEPA, 2011).

11.1.7 Risk characterisation

According to International Agency for Research on Cancer (IARC), PM_{2.5} is classified as carcinogenic to humans and is also associated with non-carcinogenic health effects. PM_{2.5} contains heavy metals that can cause long-term health effects, including CVD, COPD and respiratory diseases and can penetrate deep into the lungs and enter the blood streams causing lung cancer and leukemia (IARC, 2013). While IARC classified NO₂ as non-carcinogenic, long-term exposure to NO₂ can contribute to CVD, COPD and respiratory diseases (IARC, 2013). According to the human health evaluation manual (USEPA, 2011), the non-carcinogenic risk is evaluated using hazard index (HI) (Eqn.11.4).

$$HI = \frac{ADD_C}{R_f D_{in}} \quad (\text{Eqn.11.4})$$

Where ADD_C (mg/kg-day) is the daily exposure dose of pollutant species (heavy metals and NO₂) and $R_f D_{in}$ (mg/kg-day) is the reference dose for inhalation for pollutant species. If aggregate HI of all pollutant species is greater than 1, it indicates a potential for non-carcinogenic health risk. Higher the HI values, higher the probability of causing non-

carcinogenic risk. If HI is less than 1, risk is insignificant. Reference dose for heavy metals and NO₂ are presented in the Table 11.1. While carcinogenic risk (CR) is evaluated using the following Eqn.11.5.

$$CR = ISF * ADD_C \quad (Eqn.11.5)$$

Where ADD_C is the daily exposure dose of pollutant species (heavy metals) (mg/kg-day) and *ISF* is the inhalation slope factor expressed as (kg·d)/mg. The tolerable CR is generally considered to range between 1 × 10⁻⁶ and 1 × 10⁻⁴. Aggregate CR value of all heavy metals exceeding 1 × 10⁻⁴ indicates a significant cancer risk. Inhalation for heavy metals are presented in the Table 11.2. HI and CR values were used to estimate the disability-adjusted life years (DALY). CR and HI values were assessed using the average exposure concentrations across all monitored days, with the highest average reported among platforms and shifts considered as the upper-limit exposure level.

Table 11.1.Reference dose for heavy metals and NO₂

Pollutant Species	Reference dose(mg/kg-day)	
Cd	1.71E-07	
Cr (IV)	5.14E-07	(USEPA, 2024)
Ni	3.43E-07	
Co	1.03E-07	
NO ₂	1.10E-02	(Gusti, 2019)

Table 11.2. Inhalation slope factor for heavy metals

Pollutant species	Inhalation slope factor ((kg·d)/mg)	
Cd	6.1	
Cr (IV)	42	(USEPA, 2024)
Ni	0.84	
Co	5.7	

11.1.8 Disability-adjusted life years (DALYs)

DALYs are a comprehensive metric used to quantify the burden of disease by accounting for years of life lost due to premature mortality and years lived with disability (Lo et al., 2023). DALYs represent the gap between an ideal health state, where individuals live to an age free from disease and disability and the current health status of a population (Lo et al., 2023). The difference between life expectancy and chronological age is a key influencing parameter, as

it reflects the duration of health impacts. DALYs were computed using Eqn.11.6 (Su et al., 2024).

$$DALY = n * \sum_i R * Q_i * W_i * L_i * P \quad (\text{Eqn.11.6})$$

where n is the number of exposure days, representing the total working days for staff or the number of days commuters used the train (days); R denotes the carcinogenic risk (CR) or non-carcinogenic risk ($HI \times 10^{-6}$); Q_i is the risk factor associated with disease type i (dimensionless); W_i is the impact factor of disease type i, ranging from 0 to 1 (dimensionless); L_i represents the impairment factor of disease type i; and P is the number of exposed individuals. The values of Q_i , W_i , and L_i are provided in Table 11.3. The value of P was assumed to be 1.

Table 11.3. Values for DALY related parameters (Su et al., 2024).

Type of health damage (i)	Q	W	L_i
Death	0.13	1	L_0
COPD	0.16	0.15	10
Cardiovascular disease (CVD)	0.16	0.24	L_0-5
Cerebrovascular disease	0.2	0.2	L_0-5
Acute respiratory infection	0.35	0.08	0.04
Leukemia	1	0.75	L_0

L_0 refers to the standard life expectancy, which is the difference between the average life expectancy and average age of the target population. The average life expectancy in Ireland is 83 years (CSO, 2016).

11.2 Results & Discussion

11.2.1 Commuter exposure concentration

Personal monitoring of short-term $PM_{2.5}$ concentrations experienced by commuters on the platforms ranged from 35 to 72 $\mu\text{g}/\text{m}^3$, with peak values reaching up to 250 $\mu\text{g}/\text{m}^3$. The average concentrations were found to be higher at Platform 4 compared to Platform 2. The average $PM_{2.5}$ concentrations during peak hours at platforms 2 and 4 are provided in Table 11.4 and Table 11.5. The monitoring results indicate that $PM_{2.5}$ concentrations were higher when DMU trains were present on the platform compared to pull-push trains. Also, elevated

concentrations were observed during train arrival and departure periods compared to periods when trains were idling. An example of the typical trend in concentrations observed at Platform 2 and 4 during idling and departure of a DMU train is presented in Figure 11.1 and Figure 11.2. Adjusted heavy metal concentrations at Platform 4 are presented in Table 11.6.

Similarly, the short-term NO₂ concentrations experienced by commuters on Platform 4 during ranged from 134 to 334 µg/m³ over the peak hours, with peak value reaching up to 554 µg/m³. NO₂ concentrations at Platform 2 during the peak period is presented in Table 11.7.

Table 11.4. PM_{2.5} concentrations during peak hours (5-7pm) at platform 2 at Connolly

Date	Train Type	Train activity	Average concentration (µg/m ³)	Trains on other enclosed platforms
21-11-2022	Diesel Pull-push	Departure	49	Yes
		Idling	35	
28-11-2022	Diesel Pull-push	Arrival	38	Yes
		Idling	41	
08-12-2022	Diesel Pull-push	Arrival	39	Yes
		Idling	37	
12-12-2022	DMU	Departure	77	Yes
		Idling	39	

Table 11.5. PM_{2.5} concentrations during peak hours at platform 4 at Connolly

Date	Train Type	Train activity	Average concentration (µg/m ³)	Trains on other enclosed platforms
21-11-2022	DMU	Departure	133	Yes
		Idling	65	
28-11-2022	DMU	Arrival	89	Yes
		Idling	67	
08-12-2022	DMU	Arrival	84	Yes
		Idling	62	
12-12-2022	DMU	Departure	137	Yes
		Idling	72	

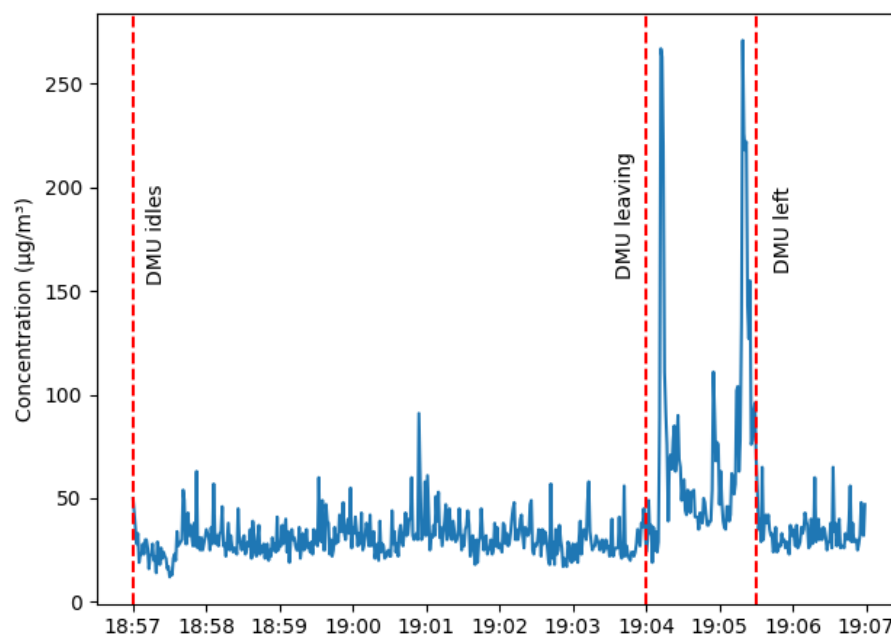


Figure 11.1. Profile of $\text{PM}_{2.5}$ concentrations measured on Platform 2 on Monday 12 December 2022.

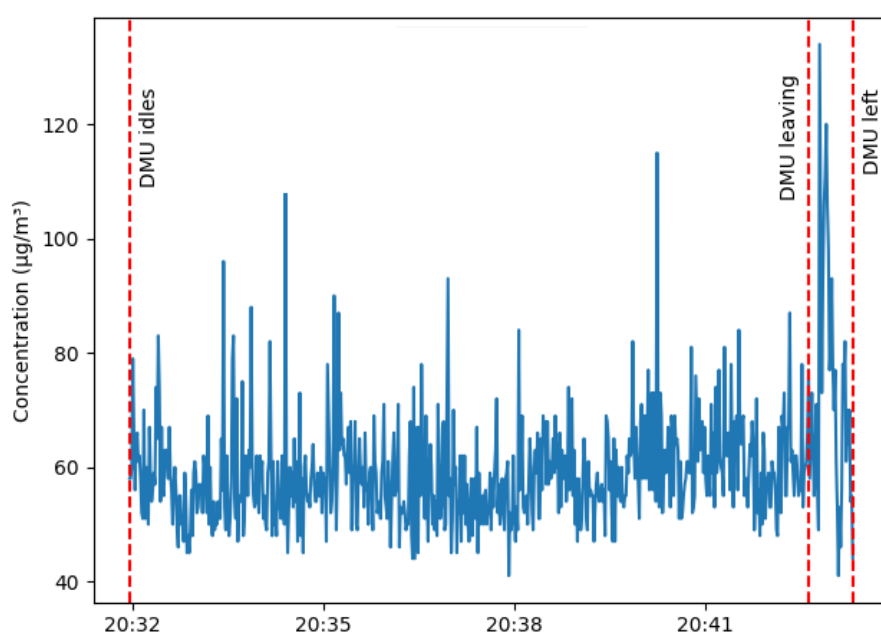


Figure 11.2. Profile of $\text{PM}_{2.5}$ concentrations measured on Platform 4 on Thursday 8 December 2022.

Table 11.6. Adjusted heavy metal concentrations for commuter exposure at Platform 4 (21st November to 12th December 2022)

Pollutant species	Concentration (ng/m ³)
Cd	6.9
Cr (IV)*	18.4
Ni	76.3
Co	49.2

*The Cr (VI) was considered as 1/7th of Cr (Peter et al., 2018)

Table 11.7. Short-term NO₂ concentration at Platform 4 at Connolly

Date	Train Type	Train Departure time	Average concentration (µg/m ³) *
03/04/2024	DMU-4 ICR	17:17:06	134
	DMU-4 ICR	18:57:24	198
04/04/2024	DMU-4 ICR	17:31:54	255
	DMU-3 ICR	18:17:06	278
05/04/2024	DMU-3 ICR	17:39:54	302
	DMU-4 ICR	18:36:48	332
06/04/2042	DMU-4x29000	17:28:06	257
	DMU-4 ICR	18:52:06	316

* Average concentration is the average of readings 10 minutes before the departure of the train

11.2.2 Rail staff Exposure concentration

The average PM_{2.5} and NO₂ concentrations for different shift on the platforms are presented in the Table 11.8. The PM_{2.5} and NO₂ exposure levels were higher during the day shift followed by evening and night shift. Similar to short-term PM_{2.5}, adjusted heavy metal concentrations for different shift for staff exposure were calculated. Adjusted heavy metal concentrations at Platform 4 for day shift are presented in Table 11.9 .

Table 11.8. Average PM_{2.5} and NO₂ concentration at different shift at Connolly

	PM _{2.5} (µg/m ³)			NO ₂ (µg/m ³)
	Platform 2	Platform 3	Platform 4	Platform 4
Night shift	10.1	13.6	18.5	161.5
Day shift	15.7	17.3	24.7	175.2
Evening shift	10.1	15.1	22.5	165.3

Table 11.9. Adjusted heavy metal concentrations for staff exposure at Platform 4 for day shift

Pollutant species	Concentration (ng/m ³)
Cd	3.18
Cr (IV)	8.42
Ni	35.1
Co	23.1

*The Cr (VI) was considered as 1/7th of Cr (Peter et al., 2018)

11.2.3 Non-carcinogenic and carcinogenic risk assessment

The inhalation-based non-carcinogenic and carcinogenic risks for commuters and staff associated with the exposure of PM_{2.5} at Connolly Station are presented in Table 11.10 and Table 11.11, respectively. The calculated carcinogenic risks associated with inhalation exposure to PM_{2.5}-bound multi-metals were 3.48×10^{-5} for rail staff and 4.36×10^{-6} for commuters, both of which are below the tolerable limit of 1×10^{-4} . In contrast, the non-carcinogenic risk was found to be significantly higher for staff (HI = 22.4). This indicates that the estimated exposure is 16.4 times greater than the acceptable reference level of 1, suggesting hazardous conditions in the station with potential long-term health effects, including CVD, COPD, and other respiratory diseases. Although the average PM_{2.5} concentrations during shift hours were below the EU 24-hour guideline value, the high heavy-metal content of PM_{2.5} originating from diesel train exhaust poses serious health risks to station staff.

Table 11.10. Estimated cancer and non-cancer risk of PM_{2.5} for Commuter at Connolly

Cancer risk				
	Concentration (µg/m ³)	ADD	Unit Inhalation factor	Cancer risk
Cd	6.9E-3	2.4E-08	6.1	1.5E-07
Cr (IV)	1.8E-2	6.5E-08	42	2.7E-06
Ni	7.6E-2	2.7E-07	0.84	2.2E-07
Co	4.9E-2	1.7E-07	5.7	1E-06
Total				4.3E-06
Non-cancer risk				
	Concentration (µg/m ³)	ADD	Reference dose	Non-Cancer risk
Cd	6.9E-3	1.7E-08	1.7E-07	0.1
Cr (IV)	1.8E-2	4.6E-08	5.1E-07	0.1
Ni	7.6E-2	1.9E-07	3.4E-07	0.55
Co	4.9E-2	1.2E-07	1E-07	1.3
Total				2.01

Table 11.11. Estimated cancer and non-cancer risk of PM_{2.5} for Rail staff at Connolly

Cancer risk				
	Concentration (µg/m ³)	ADD	Unit Inhalation factor	Cancer risk
Cd	3.2E-3	2.7E-07	6.10	1.7E-06
Cr (IV)	8.4E-3	7.2E-07	42	3E-05
Ni	3.5E-2	3E-06	0.84	2.5E-06
Co	2.3E-2	2E-06	5.7	1.1E-05
Total				4.8E-05
Non-Cancer risk				
	Concentration (µg/m ³)	ADD	Reference dose	Non-Cancer risk
Cd	3.2E-3	1.9E-07	1.7E-07	1.1
Cr (IV)	8.4E-3	5.2E-07	5.1E-07	1.02
Ni	3.5E-2	2.1E-06	3.4E-07	6.3
Co	2.3E-2	1.4E-06	1E-07	1.3
Total				22.8

The non-carcinogenic risk associated with PM_{2.5} exposure for commuters was slightly above the tolerable limit (HI = 2), indicating a moderate level of risk that remains a concern, particularly for sensitive groups such as individuals with asthma, the elderly, children, and those with pre-existing cardiovascular or respiratory conditions.

Similarly, the non-carcinogenic risk associated with NO₂ exposure for staff (HI = 1.36) was slightly above the tolerable limit (HI = 1) (Table 11.12), whereas no significant non-carcinogenic risk from NO₂ was identified for commuters. The total non-carcinogenic risk to staff from combined exposure to PM_{2.5} and NO₂ was estimated to be 24.4.

Table 11.12. Non-cancer risk of NO₂ for staff at Connolly

NON-CANCER RISK				
	Concentration (µg/m ³)	ADD	Reference dose	Non-Cancer risk
NO ₂	173	1.5E-2	1.1E-02	1.36

11.2.4 DALYs and monetary impacts for rail staff and commuter

The DALYs associated with combined exposure to PM_{2.5} and NO₂ for rail staff aged 25–60 years at Connolly station were estimated to range from 0.067 years (24 days) to 0.025 years (9 days) of healthy life lost per year over their lifetime. The lifetime average DALY for the staff is estimated to be 0.044 years (16 days) of healthy life lost per year, corresponding to an estimated monetary loss of approximately €9,731 per staff member per year, representing the value of lost healthy life (Figure 11.3). The estimated DALY indicates that the health burden associated with PM_{2.5} is greater than that of NO₂, even though PM_{2.5} levels were below the EU guideline values (Figure 11.4).

In contrast, the DALYs associated with combined PM_{2.5} and NO₂ exposure for commuters aged 18–60 years at Connolly Station were estimated to range from 0.003 years (1.5 days) to 0.001 years (0.5 days) of healthy life lost per year (Figure 11.3). The lifetime average DALY for the commuters is estimated to be 0.004 years (1 day) of healthy life lost per year, corresponding to a monetary loss of approximately €510 per commuter per year. When aggregated across the estimated 12,260 commuters using Connolly Station daily, this translates to a total economic loss of approximately €6.25 million per year.

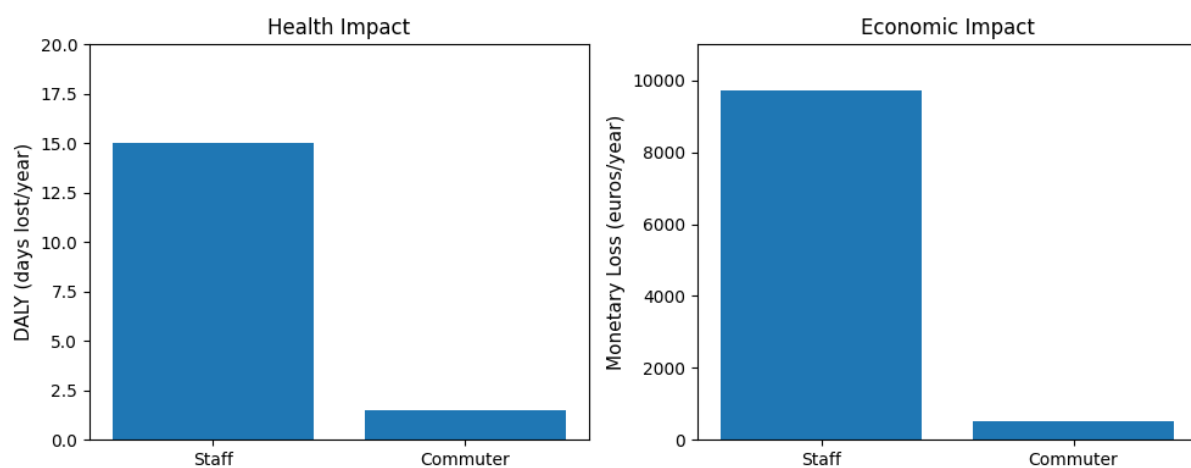


Figure 11.3. Estimated healthy life lost per year for staff and commuters and their corresponding monetary loss

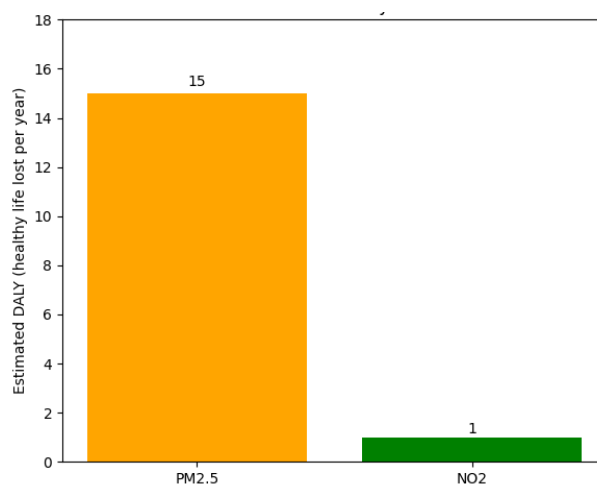


Figure 11.4. Estimated healthy life lost per year for staff by pollutants

11.3 Summary

Personal monitoring at Connolly Station revealed that commuters and rail staff are exposed to elevated concentrations of PM_{2.5} and NO₂, particularly when DMU trains are present. Short-term PM_{2.5} concentrations ranged from 35 to 72 µg/m³, with peaks up to 250 µg/m³, while Short-term PM_{2.5} NO₂ levels during train idling ranged from 134 to 260 µg/m³. Rail staff experienced higher exposures compared to commuters, with PM_{2.5} and NO₂ levels observed higher during the day shift.

Health risk assessment indicated that carcinogenic risks from PM_{2.5} bound heavy metals were below the tolerable limit for both staff (3.48×10^{-5}) and commuters (4.36×10^{-6}). However, non-carcinogenic risks were notably elevated for staff (HI = 22.4), indicating potential long-term health effects including cardiovascular and respiratory diseases. Commuters experienced moderate non-carcinogenic risk (HI = 2) from PM_{2.5} and minimal risk from NO₂. The combined exposure to PM_{2.5} and NO₂ resulted in a total non-carcinogenic risk of 24.4 for staff and negligible risk for commuters.

DALYs analysis estimated that staff could lose up to 0.04 years (15 days) of healthy life annually, with an average monetary loss of €9,731 per staff from the combined exposure of PM_{2.5} and NO₂. Commuters experienced a DALY loss of 0.004 years (1 day) per year, corresponding to a total economic impact of approximately €6.25 million per year across all daily users.

12. LIMITATIONS OF THE STUDY

12.1 Low-cost sensor and the calibration model

The ELOS NO₂ sensors showed poor agreement with the reference monitor, indicating limitations in their accuracy. The calibrated values from the machine learning models presented here are based entirely on meteorological parameters and PM_{2.5} concentrations recorded at the calibration site during the specific calibration period. As a result, the developed calibration model is site-specific and time-dependent, and therefore cannot be reliably generalised to other locations, seasons, or operating conditions. Furthermore, machine learning-based calibration models are sensitive to variations in environmental conditions and concentration ranges, which introduces uncertainty when applying the model beyond the conditions represented in the training dataset. This limitation is particularly important when extrapolating calibrated sensor outputs to different time periods or monitoring environments where pollutant concentrations may differ substantially from those observed during calibration.

In highly polluted environments such as urban roads and intersections, more frequent calibration or periodic co-location with a reference-grade analyser is required to maintain measurement accuracy. In addition, the lifespan of electrochemical low-cost NO₂ sensors is typically 12–24 months (Afshar-Mohajer et al., 2018), after which sensor sensitivity may decrease due to ageing, electrolyte depletion, and baseline drift, making sensor replacement necessary for reliable monitoring (Li et al., 2021). To improve measurement reliability, passive diffusion tubes should be deployed alongside the low-cost NO₂ sensors, as they provide independent time-associated concentration measurements that can be used to validate sensor performance over longer periods.

12.2 Uncertainties arising from different measurement periods

All concentrations and statistical analyses reported in this study correspond strictly to their respective monitoring periods. For continuous monitoring conducted both inside and outside the station, the collected data provide a relatively stable representation of pollutant behaviour during the monitoring period at each location; however, the measurements may still be influenced by seasonal variability. Therefore, the reported concentrations should not be interpreted as true annual averages. Although seasonal variability cannot be fully eliminated, these uncertainties do not affect the primary objectives or overall conclusions of the study.

For the personal monitoring campaign, the measured concentrations represent commuter exposure during the specific hours and days in which sampling was carried out. These values provide an estimate of short-term exposure under the prevailing environmental and operational conditions at the time of measurement. It is acknowledged that exposure levels may vary with temporal factors, seasonal changes, passenger activity, and train operations. Due to practical and logistical constraints, it was not feasible to conduct personal exposure monitoring over an entire year; therefore, the results should be interpreted as representative of the specific sampling period rather than as annual exposure estimates.

12.3 Uncertainties associated with DALY estimate

The DALY estimates reported in this study provide a scientifically reasonable indication of potential health burden. However, the absolute magnitude of the DALY values should be interpreted with caution (propagated error of 30-40%), considering the underlying assumptions and data limitations associated with the analysis. The main source of uncertainty arises from combining pollutant measurements collected during different years and over different monitoring durations. For example, commuter exposure estimates were derived from 10-minute monitoring data, whereas heavy metal concentrations were obtained from 24-hour particulate matter samples collected in a different year and subsequently adjusted proportionally to represent short-term exposure. This approach assumes that pollutant composition, train activity, and operational conditions remained comparable across the different sampling periods, which may not always be the case. Additional uncertainty is associated with the assumption that heavy metal fractions remain stable when converting 24-hour concentrations to shorter exposure durations.

13. CONCLUSIONS

Air pollution in urban railway stations, particularly those serving diesel-powered trains, is substantial and poses a growing public health concern. This thesis aims to identify and attribute train-related pollutant sources both in the vicinity of and within the terminal, and to examine how environmental conditions and operational characteristics influence pollutant concentrations inside the station. Furthermore, the study seeks to estimate the associated health impacts on commuters and railway staff, as well as the economic losses arising from inefficient train operations.

Based on the literature review of studies performed at THs such as ports and airports and given the limited number of studies at ground-level railway stations, the review highlights that statistical methods including bivariate polar plots, data filtration, and regression models are commonly employed to detect and quantify the contributions of THs to the local ambient environment. Data filtration, regression models, and bivariate polar plots are particularly suitable for analysing gaseous pollutants such as NO₂ and SO₂ when emissions originate from specific, localised sources. In contrast, speciated receptor modelling is more appropriate for PM and VOCs, which typically arise from multiple sources. All of these methods are applied in this study.

The literature review of health studies conducted at THs indicates that assessing health impacts in such environments is challenging due to the requirement for high-resolution health, demographic, and socio-economic data for surrounding populations, which are often difficult to obtain. Among the reviewed approaches, cancer and non-cancer risk assessment and the DALY metric are comparatively straightforward, as they do not require direct health data from exposed individuals. In this study, the DALY approach is applied to assess potential health impacts on commuters and railway staff.

With respect to the calibration of low-cost sensors, the literature indicates substantial variability in calibration approaches. Linear and multiple linear regression methods are the most commonly applied; however, they often perform poorly for gaseous pollutants, particularly NO₂, due to strong cross-sensitivities and environmental influences that limit linear model reliability. In contrast, multivariate and machine learning based techniques, including ANN, RF, SVM, SVR, and XGBoost, consistently demonstrate superior calibration performance for gaseous sensors. For particulate matter sensors, linear models generally provide moderate to good calibration accuracy.

Low-cost devices were used in this study to monitor $\text{PM}_{2.5}$ and NO_2 . Machine learning models (RF & XGBoost) to calibrate the $\text{PM}_{2.5}$ and NO_2 measurements acquired by the low-cost devices. The performance of the XGBoost model was slightly better than the RF model for both $\text{PM}_{2.5}$ and NO_2 . Local wind speeds presented the variable with the greatest impact on NO_2 model results, followed by equivalent $\text{PM}_{2.5}$ concentrations, wind direction and pressure. The strong relation of lower wind speeds was observed for the NO_2 model which clearly indicated that NO_2 was strongly influenced by the local sources. Linear relationship between the raw sensor readings and the $\text{PM}_{2.5}$ model was identified, indicating that sensor readings have a significant effect on the model output. These results highlight that the NO_2 sensor requires more input data for accurate calibration compared to the $\text{PM}_{2.5}$ sensor.

Source apportionment by data filtration method for a month measurement showed that railway station emissions as the main $\text{PM}_{2.5}$ source, and road traffic as the main NO_2 source, when winds are from station wind sector. Bivariate polar plot also revealed the dominance of local sources in this sector for $\text{PM}_{2.5}$ and NO_2 . However, only 12% of the winds were from the direction of the station during the study period, which may not reflect the annual average conditions. The majority of measured wind conditions were upwind of the St. Johns FMS (46%), with upwind background NO_2 and $\text{PM}_{2.5}$ being the major contributors to the St. Johns FMS.

An additive model was used to characterize pollutant sources at the St. John's FMS site using long-term air quality and wind measurements. Winds were predominantly from the north-western sector (64%), while only approximately 8% originated from sectors directly influenced by road and rail sources. The GAM modelling indicates that regional background pollution and meteorology, rather than local road or rail emissions, are the primary drivers of $\text{PM}_{2.5}$ and NO_2 concentrations at the St. John's FMS site during the study period.

A XGBoost modelling approach was adopted to characterise the impact of train idling, along with other contributing factors such as train traffic, engine power and ambient conditions, on NO_2 levels within the station. The model identified station ambient temperature and average train idling time as the most influential factors in predicting NO_2 concentrations. PDP suggested that reducing the average idling time of a train by two minutes could reduce NO_2 concentrations by approximately $2.5 \mu\text{g}/\text{m}^3$ per train.

Further, Analysis of idling time, speed, and fuel consumption indicates that shutting down train engines when the next scheduled operation is more than 30 minutes away, and restarting them 15 minutes before departure, combined with maintaining idle speeds below 600 RPM

during shorter idling periods (<30 minutes), could collectively save over 7,000 litres of diesel per month. Overall, these strategies could reduce fuel consumption by approximately 40–45% and lower NO_x and PM emissions by about 54% and save approximately €12,140 per month in fuel costs.

Chemical characterisation and source apportionment of PM_{2.5} was carried out within the station to apportion the exhaust and non-exhaust sources. Chemical analysis showed that PM_{2.5} was dominated by carbonaceous matter (83–90%), followed by elemental (8–12%) and ionic species (4–5%). Exhaust-related elements (Ca, Al, Na and Mg) were more abundant than non-exhaust metals (Cr, Cd, Fe and Zn), reflecting low braking demand and train speeds within the station. Na⁺ and Cl⁻ were the dominant ionic species, indicating a strong influence of marine aerosols. The EC/OC ratio (0.68) suggested that idling train operations were the primary contributor to carbonaceous emissions. PMF model identified train exhaust as the dominant contributor (80–85%), followed by secondary organics and inorganics (10–15%), sea aerosols (3–7%), and non-exhaust sources (2–3%).

Potential health impacts on commuters and staff were assessed for exposure to PM_{2.5} and NO₂. Commuters experienced a moderate non-carcinogenic risk (HI = 2). Staff experienced a high non-carcinogenic risk (HI = 24.4), indicating potential long-term health effects, including cardiovascular and respiratory diseases. The risk attributed to PM_{2.5} exposure was substantially higher than that associated with NO₂.

DALYs analysis estimated that staff could lose up to 0.04 years (15 days) of healthy life annually, with an average monetary loss of €9,731 per staff from the combined exposure of PM_{2.5} and NO₂. Commuters experienced a DALY loss of 0.004 years (1 day) per year, corresponding to a total economic impact of approximately €6.25 million per year across all daily users.

13.1 Recommendations for Future Work

Future research should focus on understanding micrometeorological conditions within enclosed train stations, particularly the effects of passive and active ventilation systems, to optimize air circulation. Additional research should examine strategies to minimize train idling times and optimize train schedules in order to reduce pollutant emissions, improve fuel efficiency, and limit exposure for staff and commuters. Further work is also needed to

characterize pollutant levels inside train carriages and to assess the potential health impacts on passengers traveling on diesel-powered trains.

The installation of platform screen doors and clean rooms equipped with air purification systems could further mitigate public exposure to $\text{PM}_{2.5}$ and NO_2 , particularly in enclosed platforms with high pollutant concentrations. Additionally, future work could explore the deployment of real-time air quality devices integrated with predictive machine learning models to enable dynamic ventilation management and operational adjustments.

Future work should also focus on investigating alternative low-emission train technologies, such as electrification or hybrid engines, as well as implementing urban traffic planning measures to reduce traffic congestion near stations, which could significantly contribute to lowering local air pollution.

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15.

16. APPENDICES



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LABORATORY ANALYSIS REPORT

NITROGEN DIOXIDE IN DIFFUSION TUBES BY U.V.SPECTROPHOTOMETRY

REPORT NUMBER R06704R
BOOKING IN REFERENCE R06704
DESPATCH NOTE 101974
CUSTOMER Trinity College Dublin Attn: Shanmuga Priyan
Botany Department
College Green
Dublin 2

DATE SAMPLES RECEIVED Ireland
13/09/2023

Location	Sample Number	Exposure Data			$\mu\text{g}/\text{m}^3$ *	ppb *	$\mu\text{g NO}_2$ on tube
		Date On*	Date Off*	Time* (hr.)			
EPA st.John's station -1	2266080	12/07/2023	21/08/2023	959.22	28.17	14.70	1.79
EPA st.John's station -2	2266079	12/07/2023	21/08/2023	959.20	28.21	14.73	1.80
Platform-4-Point 2	2266078	08/08/2023	07/09/2023	721.02	125.26	65.38	6.00
Platform-4-Point 1	2266077	08/08/2023	07/09/2023	720.90	99.88	52.13	4.78
Platform-3-Point 1	2266076	08/08/2023	07/09/2023	720.87	97.82	51.05	4.68
Platform-3-Point 2	2266075	08/08/2023	07/09/2023	720.77	114.42	59.72	5.48
Platform-3-Point 3	2266074	08/08/2023	07/09/2023	720.73	106.23	55.45	5.08
Platform-3-Point 4	2266071	08/08/2023	07/09/2023	720.55	71.50	37.32	3.42
Platform-2-sitting room	2266070	08/08/2023	07/09/2023	720.52	82.90	43.27	3.97
Platform-2- point 1	2266069	08/08/2023	07/09/2023	720.43	122.88	64.13	5.88
Platform-2- point 2	2266068	08/08/2023	07/09/2023	720.38	120.75	63.02	5.78
Platform-2- point 3	2266067	08/08/2023	07/09/2023	720.32	103.28	53.91	4.94
Platform-2- point 4	2266066	08/08/2023	07/09/2023	720.28	67.77	35.37	3.24
Concourse-Stanley shop	2266065	08/08/2023	07/09/2023	720.22	63.23	33.00	3.02
Concourse-Ticket counter	2266062	08/08/2023	07/09/2023	720.20	58.55	30.56	2.80
Connolly entrance, camera pole	2266061	08/08/2023	07/09/2023	720.17	32.69	17.06	1.56
platform-4-Point 3	2266060**	08/08/2023	07/09/2023	719.60	162.70	84.92	7.77
platform-4 point 4	2266059	08/08/2023	07/09/2023	720.02	44.05	22.99	2.11
Platform 6 & 7, Centre of struss	2266058	08/08/2023	07/09/2023	719.92	44.33	23.14	2.12
Platform 6 & 7,End of struss	2266057	08/08/2023	07/09/2023	719.88	42.51	22.19	2.03
Platform 6 & 7,Outside struss	2266056	08/08/2023	07/09/2023	719.83	39.98	20.87	1.91
Blank	2266073	12/07/2023	21/08/2023	959.22	0.14	0.07	0.01
Laboratory Blank				959.22	0.08	0.04	0.005

Comment: Results are not blank subtracted

Tubes marked ** were diluted to read within our UKAS accredited calibration range.

Results have been corrected to a temperature of 293 K (20°)

Overall M.U. $\pm 9.7\%$ Limit of Detection $0.031\mu\text{gNO}_2$ The reported expanded uncertainty is based on a standard uncertainty multiplied by a factor of $k=2$, providing a level of confidence of approximately 95%. Uncertainty of measurement has not been applied to the reported results.

Tube Preparation: 20% TEA / Water - Filter

Analysed on UV CARY2

Analyst Name Jennie Green

Report Checked By Adam Robinson

Date of Analysis 29/09/2023

Date of Report 29/09/2023

Analysis carried out in accordance with documented in-house Laboratory Method GLM7

Samples have been tested within the scope of Gradko International Ltd. Laboratory Quality Procedures. Results within this report relate only to samples as received. Data provided by the client and any subsequent calculations shall be indicated by an asterisk (*), these calculations and results are not within the scope of our UKAS accreditation. Any queries concerning data in this report should be directed to the Laboratory Manager Gradko International Ltd. This report is not to be reproduced, except in full, without the written permission of Gradko International Ltd.

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Report Number R06704R

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REPORT OFFICIALLY CHECKED

Gradko International Ltd
This signature confirms the authenticity of these results
Signed: L. Gates, Laboratory Manager



(A division of Gradko International Ltd.)

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LABORATORY ANALYSIS REPORT

NITROGEN DIOXIDE IN DIFFUSION TUBES BY U.V.SPECTROPHOTOMETRY

REPORT NUMBER R04791R
BOOKING IN REFERENCE R04791
DESPATCH NOTE 101833
CUSTOMER Trinity College Dublin Attn: Shanmuga Priyan
Botany Department
College Green
Dublin 2

DATE SAMPLES RECEIVED Ireland
23/06/2023

Location	Sample Number	Exposure Date On*	Exposure Date Off*	Time* (hr.)	µg/m ³ *	ppb *	µg NO ₂ on tube
Roof of Heuston station	2225827	25/05/2023	20/06/2023	622.33	87.43	45.63	3.61
North wall of Heuston station	2225826	25/05/2023	20/06/2023	622.00	31.91	16.66	1.32
Car Parking in North wall (Platform 5 middle)	2225825	25/05/2023	20/06/2023	622.18	96.05	50.13	3.97
Platform 5 Display	2225824	25/05/2023	20/06/2023	621.85	43.42	22.66	1.79
Platform 4 Display	2225823	25/05/2023	20/06/2023	621.82	52.51	27.41	2.17
Platform 2 Display	2225822	25/05/2023	20/06/2023	621.72	62.40	32.57	2.58
Platform 2 Third	2225833	25/05/2023	20/06/2023	621.43	103.41	53.97	4.27
South wall of Heuston station	2225832	25/05/2023	20/06/2023	621.55	51.76	27.01	2.14
Platform 2 Last	2225831	25/05/2023	20/06/2023	621.12	72.91	38.05	3.01
Platform 4 Middle	2225830	25/05/2023	20/06/2023	620.80	98.57	51.44	4.06
platform 4 Third	2225829	25/05/2023	20/06/2023	620.35	94.66	49.40	3.90
platform 4 Last	2225828	25/05/2023	20/06/2023	620.60	74.11	38.68	3.05
platform 5 Third	2225840	25/05/2023	20/06/2023	619.95	58.74	30.66	2.42
platform 7 front	2225839	25/05/2023	20/06/2023	619.58	67.52	35.24	2.78
platform 7 middle	2225838	25/05/2023	20/06/2023	619.43	69.17	36.10	2.85
platform 5 Last	2225837	25/05/2023	20/06/2023	619.35	72.85	38.02	3.00
Concourse- CocaCola vending machine	2225836	25/05/2023	20/06/2023	619.52	36.76	19.18	1.51
Concourse-front steel column	2225835	25/05/2023	20/06/2023	619.17	44.93	23.45	1.85
Lamp post- front entrance	2225845	25/05/2023	20/06/2023	619.17	31.79	16.59	1.31
EPA station st.Johns road - 1	2225844	29/05/2023	20/06/2023	527.20	38.05	19.86	1.33
EPA station st.Johns road - 2	2225843	29/05/2023	20/06/2023	527.22	37.56	19.61	1.32
"Blank" on tube, no barcode on arrival	2235126			622.33	0.34	0.18	0.01
Laboratory Blank				622.33	0.07	0.04	0.003

Comment: Results are not blank subtracted

Customer noted missing tube: 2225821.

Unlabelled tube not listed on exposure sheet was received. Number 2235126 was allocated & maximum exposure time was used.

Results have been corrected to a temperature of 293 K (20°)

Overall M.U. ±9.7%

The reported expanded uncertainty is based on a standard uncertainty multiplied by a factor of $k=2$, providing a level of confidence of approximately 95%. Uncertainty of measurement has not been applied to the reported results.

Tube Preparation: 20% TEA / Water - Filter

Analyst Name

Sania Choudhury

Limit of Detection

0.028µgNO₂

Analysed on UV CARY1

Report Checked By

Chris Andrew

Date of Analysis

03/07/2023

Date of Report

03/07/2023

Analysis carried out in accordance with documented in-house Laboratory Method GLM7

Samples have been tested within the scope of Gradko International Ltd. Laboratory Quality Procedures. Results within this report relate only to samples as received. Data provided by the client and any subsequent calculations shall be indicated by an asterisk (*), these calculations and results are not within the scope of our UKAS accreditation. Any queries concerning data in this report should be directed to the Laboratory Manager Gradko International Ltd. This report is not to be reproduced, except in full, without the written permission of Gradko International Ltd.

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Report Number R04791R

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REPORT OFFICIALLY CHECKED

Gradko International Ltd
This signature confirms the authenticity of these results
Signed: 
L. Gates, Laboratory Manager

