Understanding the variability in vehicle dynamics and emissions at urban obstacles

Aravinth Thiyagarajah
November 2015

Submitted in part fulfilment of the requirements for the degree of Doctor of Philosophy of Imperial College London

Centre for Transport Studies
Department of Civil and Environmental Engineering
Imperial College London

Declaration

The data collection activities detailed within this thesis were done in collaboration with Emissions Analytics Limited. All data processing, analysis, modelling and interpretation are my own work.

I hereby certify that I have personally carried out all the research detailed in this thesis. Any quotation from, or description of work of others is acknowledged by reference to the sources.

Aravinth Thiyagarajah

Abstract

Roadworks are a feature of the road network that can cause vehicles to deviate from their desired speed or trajectory. This may negatively impact traditional measures of network performance such as travel time, or result in changes to tailpipe emission rates. The impact of roadworks on tailpipe emission rates is of interest due to the harmful pollutants that are released during the combustion process. Pollutants such as nitrogen oxides (NO_x) are toxic to humans, and carbon dioxide (CO_2) is a greenhouse believed to influence human-induced global climate change.

In order to investigate methods of reducing the environmental impact of roadworks and other obstacles in the road network, modelling tools may be used. However, it is essential that the tools are appropriate for modelling these features of the road network. In order to assess the suitability of existing traffic and emission modelling tools, an understanding of the variability in vehicle dynamics and emissions at urban obstacles is first required.

In this thesis, a dataset that contains real-world tailpipe emissions and vehicle dynamics data, from vehicles in the vicinity of urban obstacles such as roadworks, is assembled. This is achieved using a portable emission measurement system (PEMS) and a high-resolution trajectory monitoring platform developed as part of this research. Through analysis of the acceleration behaviour and tailpipe emission rates at different urban obstacles and from different vehicles, an understanding of the variability is formed.

The findings from the analysis of behaviours observed in the vicinity of urban obstacles are then used to adapt existing traffic and emissions modelling tools. The error between measured and modelled emissions is shown to reduce from over 30% to under 12% for CO_2 emissions. Based on the findings of a roadworks case study, recommendations are made to policy makers and the modelling community.

Acknowledgements

First and foremost, I would like to thank my four supervisors, Professor Michael Bell, Dr Robin North, Professor Washington Ochieng and Professor John Polak. Without their guidance and support, my PhD experience would have been very different. Thanks are also due to Fionnuala Donovan, Jackie Sime and Amy Valentine who ensured the administrative side of the PhD was handled smoothly.

My colleagues and friends in CTS, Civil Engineering and Imperial have been a great source of inspiration and motivation over the past four years. I am especially grateful to those in 610 who were able to give me the nudge I needed during the more challenging times.

I would also like to thank PTV for providing access to Vissim and EnViVer, and Emissions Analytics for providing access to data and being so supportive of my research.

Finally, I would like to thank my friends and family for their continued encouragement and advice during the PhD process. In particular, my parents and Ashwinnie, who were always there during the ups and downs.

Contents

List of figures

List of tables

1. Introduction

The road network is not only a vital medium for surface movement of goods and people, but also a conduit for the distribution of essential services such as gas and electricity below ground. Roadworks are a necessity to ensure the road surface is maintained to an appropriate standard. In addition, they are required for the installation and maintenance of the various utilities that are buried beneath the road surface. Roadworks are also required when redeveloping a segment of the road network.

In the current Road Investment Strategy, the UK government plans to spend £15.2 billion on improving the road network in England over the next five years (Department for Transport, 2015c). This is in addition to the funding local authorities, private developers and utility companies have allocated for spending on highways. Whilst investment can be expected to benefit all road users once the works are complete, consideration needs to be given to the impact of the roadworks themselves.

Permanent and temporary interventions on the road network impact traffic and emissions. In London, UK, “there are in excess of 5000 roadworks taking place on any particular day” (Colin Buchanan, 2010). In order to manage the flow of traffic and for safety reasons, temporary traffic signals, speed humps or other traffic management infrastructure may need to be introduced (Department for Transport, 2009).This traffic management will result in additional acceleration events if the vehicle is forced to stop or change speed. For example, if the vehicle is forced to slow down to pass a speed hump or wait at a temporary traffic signal.

These additional acceleration (and deceleration) events are likely to have a minimal impact on traditional network performance indicators such as travel time or average speed. As the disrupted portion of the road network is usually small in relation to the whole trip. However, when other performance indicators such as passenger comfort, safety or vehicle emissions are considered, the roadworks may have a disproportionate impact.

The impact of a roadwork may be minimised by adopting a different roadwork configuration or coordination plan (London First, 2010). However, in order to explore these roadwork scenarios, tools for modelling the behaviour of vehicles and the potential impacts will be required. Before using these tools we must first be confident that these tools are able to accurately represent the behaviours observed in the vicinity of roadworks. Being able to accurately model the behaviours observed in the vicinity of roadworks and other interventions is the key motivation of this research.

There are several tools available for modelling the impact of a roadwork or other phenomenon found on the road network. Depending on the impacts that are to be assessed, a single modelling tool may be used in isolation or multiple models may be coupled together. For example, one model may be used to represent the behaviour of the vehicles as they travel through the network, and a second model may use this data as an input to estimate a potential impact. In order to ensure the potential impacts are estimated correctly, the data that is used as an input into the model must also be valid.

This introductory chapter outlines the motivation for the research investigation. Section 1.1 and 1.2 highlight the general focus of the research study. The key research issues are detailed and the research objectives are formulated before the thesis structure is summarised.

1.1. Impact of roadworks

The capacity of a road is defined as the maximum vehicular flow obtainable whilst using all available lanes, usually measured as vehicles per hour (Transportation Research Board, 2010). The demand is the number of vehicles desiring to travel on a section of road during a particular time period, also measured in vehicles per hour. As the demand on a particular road approaches its capacity, congestion can be expected. The introduction of a roadwork, such as filling a pothole, removes road capacity, potentially resulting in congestion if there is insufficient reserve capacity. Reserve capacity is the difference between the capacity of the road and the demand.

The negative impacts of traffic can generally be categorised into social, economic and environmental factors. A typical social impact of roadworks is increased public transport waiting time due to the additional congestion. An example of an economic impact of roadworks is lost revenue to local businesses due to access restrictions and a reduction in footfall. Whilst these impacts of roadworks are important, the focus in this research is the environmental impact of roadworks and particularly vehicle tailpipe emissions as explained in section 1.1.1.

1.1.1. Environmental and health impacts

Congestion is recognised to impact vehicle emissions and the environment. Both of which are becoming increasingly important to decision makers and road users due to the influence on air quality and human health (World Health Organisation, 2011), and the contribution to human-induced global climate change. Problems of poor air quality are especially significant in densely populated urban areas where human exposure to pollution is higher. The World Health Organisation (2011) states that 40 million people in the 115 largest cities in the European Union are exposed to air that exceeds air quality guideline values for at least one air pollutant.

Congestion impacts carbon dioxide (CO_2), a greenhouse gas that is believed to influence global climate change. Depending on the method of calculation, road transport contributes as much as 20-30% of total CO_2 emissions (DECC, 2012). Whilst it is difficult to estimate what proportion of these CO_2 emissions is attributable to the presence of roadworks, studies such as that by Huang et al. (2009) have shown that the presence of a roadwork can increase CO_2 emissions by up to 5.5% in a motorway environment. This figure is expected to be even higher in an urban environment due to most roads only having a single lane in each direction and it not being possible to temporarily increase road capacity by making the hard shoulder available.

Nitrogen oxide (NO) and nitrogen dioxide (NO_2), commonly referred to collectively as nitrogen oxides (NO_x), are another important local air pollutant associated with road transport. In 2013, road transport was estimated to have contributed just over a third of all NO_x emissions in the UK (DEFRA, 2014). NO_x is an important pollutant due to the gas being able to irritate sensitive lung tissue. This can exacerbate existing respiratory conditions such as asthma and in extreme cases result in premature death (Environmental Protection Agency, 2015). NO_x has also become a pollutant of significant interest in the media due to the violation of the Clean Air Act by Volkswagen (International Council on Clean Transport, 2015a). It has been reported that Volkswagen installed a 'defeat device' on certain diesel passenger cars that resulted in NO_x emissions 15-35 times higher than regulatory limits (International Council on Clean Transport, 2015b).

The focus of this research is on CO_2 and NO_x tailpipe emissions, however there are other pollutants emitted during the combustion process as discussed in section 2.1.

1.2. Vehicle dynamics

As outlined in section 1.1, roadworks have several potential impacts. However, the focus in this research is CO_2 and NO_x emissions. In order to use modelling tools to estimate the emissions, the model requires information about the vehicle dynamics, i.e. how the vehicle's position changes in space and time. There are several variables that could be used to represent the dynamic behaviour of a vehicle, for example average speed or duration of time active in the network. However, it is well established in the literature that vehicle acceleration is critical for accurately predicting vehicle emissions, as discussed further in section 1.2.1.

1.2.1. Vehicle acceleration

Vehicle acceleration is the rate at which a vehicle changes its speed with respect to time, normally measured in m/s^2. In his critical review of automotive test drive cycles and real-world emissions, Watson (1995) concluded that vehicle acceleration was the most important factor in explaining the variances in fuel consumption and emissions. Holmén and Niemeier (1998) showed a similar result and established that the intensity and duration of acceleration events produce significant differences in the emissions measured. The notion of vehicle acceleration being a critical component of understanding vehicle emissions is discussed widely in the literature, as found in Rouphail et al. (2001), Samuel et al. (2002), Darlington et al. (1992), Guensler et al. (1998) and Bachman et al. (2000). Therefore, it is proposed that the vehicle acceleration in the vicinity of roadworks should be another focus of this research as it is an important factor required to estimate vehicle emissions.

1.3. Research problem

In sections 1.1 and 1.2, the focus on vehicle acceleration and tailpipe emissions of CO_2 and NO_x in the vicinity of roadworks was outlined. In this section, the current research issues are briefly discussed further before being used to formulate the research objectives in section 1.4.

1.3.1. Vehicle dynamics and emissions data

In this introductory chapter the interest in roadworks is expressed, and the ability to accurately model them to explore ways of minimising their impact is presented as the motivation for this research. As discussed further in Chapter 2, roadworks are temporary and it is often not possible to define their precise location or the exact duration of the roadworks. Recognising the need to collect sufficient data to make robust conclusions, this introduces additional complexities.

In terms of the manner in which they influence vehicles, roadworks can be considered an "urban obstacle". This may be defined as anything that causes a vehicle to change speed and/or trajectory on the road network. This is a general characteristic of traffic management infrastructure, for example traffic signals and reduced speed areas. The mechanisms by which traffic management infrastructure affects the vehicle dynamics or tailpipe emissions are not expected to be different in the vicinity of a roadwork or else where on the network. It is therefore proposed that data is collected more widely on the road network and not just restricted to the vicinity of roadworks. The term "obstacle" will be used to define any event, object, traffic management infrastructure or roadwork that causes vehicles to change their speed.

In order to analyse vehicle dynamics and tailpipe emissions in the vicinity of urban obstacles, a method of collecting the required data will need to be developed. As will be discussed in Chapter 3, there are several methods for collecting trajectory information from vehicles, although not all are suitable for this study. Furthermore, some devices such as those that use the Global Navigation Satellite System (GNSS) have limitations that may require the development of a sensor platform. There are also a variety of methods available for collecting emissions data from vehicles whilst they are on the road network, each of which have their own merits as discussed in Chapter 3. A suitable method of collecting the required data is to be identified and must be compatible with the method of collecting vehicle trajectory data.

1.3.2. Vehicle acceleration

As outlined in section 1.2, there are several ways to represent the dynamic behaviour of a vehicle, however in this research, given the interest in vehicle emissions, the focus will be vehicle acceleration. In a modelling tool there are many different options for modelling the acceleration behaviour of vehicles. An assumption can be made that all vehicles are equivalent, and therefore a single mathematical formulation of vehicle acceleration can is used. Another option would be to assume all vehicles are different and have individual mathematical formulations of vehicle acceleration. The same can be said for obstacles and whether the acceleration behaviour at each can be considered equivalent.

To ensure the acceleration behaviour in the vicinity of urban obstacles is modelled correctly, the differences in the acceleration behaviour between different obstacles and between different vehicles will need to be understood. With an understanding of how the acceleration behaviour varies, ways of classifying obstacles and vehicles can be proposed so that they are modelled more appropriately.

1.3.3. Vehicle emissions

In section 1.1 it was explained that there are several potential impacts of roadworks, however in this research the focus is tailpipe emissions. In particular, CO_2 and NO_x emissions as they negatively impact the environment and human health. Similar to vehicle acceleration, there are different methods of modelling the emission rates of both pollutants. A single emissions factor can be assumed for all vehicles, or vehicle specific emissions factors that reflect differences in individual vehicle characteristics can be used.

In order to accurately model the tailpipe emission rates of CO_2 and NO_x in the vicinity of urban obstacles, an understanding of the differences between different vehicles and obstacles is required. With an improved knowledge of how emission rates vary, ways of grouping obstacles and vehicles to better represent the observed emissions rates can be proposed.

1.3.4. Improving existing modelling tools

The key motivation for this research is being able to accurately model the behaviours observed in the vicinity of urban obstacles such as roadworks. This requires being able to use the empirical data collected in the vicinity of urban obstacles to improve the performance of the models simulating vehicle behaviour.

In order to improve the existing modelling tools, there is a requirement that a method of adapting the models to better represent the observed behaviour is proposed. This will allow for the impact of obstacles such as roadworks to be assessed and methods to minimise their impact to be investigated.

1.4. Research objectives

In sections 1.1-1.3, the motivations for this research were discussed along with a definition of the research problem. In order to address the research problem, a series of research objectives have been defined, as detailed below. Section 1.5 explains how this thesis has been structured to meet the four research objectives.

1. Develop and validate a robust device for capturing vehicle dynamics that complements existing methods of measuring vehicle tailpipe emissions
2. Identify urban obstacles and then assess how the acceleration behaviour varies at different obstacles and between different vehicles
3. Understand how tailpipe emissions vary at different obstacles and between different vehicles to support emissions modelling
4. Propose a methodology for adapting traffic and emissions modelling tools to better represent the observed behaviours in the vicinity of urban obstacles

1.5. Thesis structure

This thesis contains seven chapters that are divided into several subsections including a chapter overview and conclusion.

Chapter 1: Introduction

This chapter outlines the motivations for this research and the areas that will be focused on. The research problems are summarised and this is used to define four research objectives.

Chapter 2: Understanding roadworks and urban obstacles

The second chapter explains how pollutant emissions are formed with a focus on vehicle power. A discussion on roadworks and how they relate to urban obstacles is also presented. The industry approach to roadworks in the UK is highlighted along with the requirement for improved modelling tools. Finally, there is a critical evaluation of existing research on vehicle acceleration and emissions at urban obstacles.

Chapter 3: Measurement of vehicle dynamics and emissions

Chapter 3 begins by examining the different methods of collecting acceleration and emissions data from vehicles whilst they are on the road network. A suitable emissions dataset is identified and the data collection procedure is discussed. A compatible trajectory monitoring platform is also developed to collect the required acceleration data. The chapter concludes with the data collection procedure implemented to support this research. This chapter addresses the first research objective.

Chapter 4: Understanding the variability in vehicle dynamics at urban obstacles

In this chapter a methodology for identifying obstacles in the trajectory data using changes in vehicle speed is proposed. Once obstacles are identified, the acceleration behaviour between multiple obstacles is assessed. A regression model is then introduced to assess the variation in acceleration behaviour between different vehicles. Finally grouping structures for obstacles and vehicles are defined to support the subsequent modelling activity. This chapter addresses the second research objective.

Chapter 5: Understanding the variability in vehicle emissions at urban obstacles

This chapter uses the tailpipe emissions dataset identified in Chapter 3 to understand the emissions associated with the obstacles identified in Chapter 4. The emission rate of CO_2 and NO_x in the vicinity of urban obstacles is assessed and differences are highlighted. A regression model is then used to identify vehicle characteristics that are significant in explaining the differences in emissions rates. Finally, grouping structures for obstacles and vehicles are defined to support the emissions modelling in the following chapter. This chapter addresses the third research objective.

Chapter 6: Modelling the variability in vehicle dynamics and emissions at urban obstacles

Chapter 6 uses the outputs from the previous chapters to improve the modelling of vehicle acceleration and emissions in the vicinity of urban obstacles. A methodology for using empirical data to redefine the acceleration behaviour model in a traffic microsimulation tools is presented. The procedure for defining new emissions classes that are more representative of the observed tailpipe emission rates is also explained. A real-world roadworks case study example is presented and the effects of model calibration are discussed. Finally, the policy implications and recommendations to traffic and emissions modellers are made.

Chapter 7: Conclusions and further work

The final chapter of this thesis summarises the conclusions from each chapter in the context of the research objectives. Limitations of this research are discussed and several areas of further work are specified.

2. Understanding roadworks and urban obstacles

In order to support this research on the variability in vehicle dynamics and emissions at urban roadway obstacles, a thorough understanding of the background to the problem is required. This chapter begins with a section that addresses how pollutants are formed by vehicles (section 2.1).

Roadworks are a feature of the road network that can cause changes in vehicle emissions as vehicles change speed or direction to navigate them. A background to roadworks and urban obstacles is presented in section 2.2. Current roadwork management techniques are also discussed in section 2.3. Finally, the limitations of existing research on roadworks and urban obstacles, with respect to vehicle acceleration and emissions, are discussed in section 2.4.

This chapter contributes to all research objectives addressed in later chapters by providing a solid foundation to the research problem. This thesis is structured such that the relevant literature is discussed in each chapter as required.

2.1. Pollutant emissions formation

The third research objective of this thesis is to understand the variation in vehicle emissions at urban obstacles. Therefore there is a requirement to understand vehicle power and how it relates to the release of pollutants by road vehicles. The factors that affect emission rates are then discussed before the focus on vehicle acceleration is justified.

2.1.1. Vehicle power

To support movement, a vehicle must produce sufficient power in order to overcome the resistive forces that act on it (Heywood, 1988). By considering the vehicle as a rigid body, the tractive force (F) supplied by the engine can be expressed as:

$$\boldsymbol{F = (mgC_u) + \left(\frac{1}{2}\rho C_D A v^2\right) + \left(mg\sin(\theta)\right) + (ma)}$$

Equation 2.1

where:

m is vehicle mass

g is gravitational acceleration

C_u is the coefficient of rolling resistance

ρ is the density of air

C_D is the coefficient of aerodynamic drag

A is vehicle frontal area

v is vehicle speed

θ is road grade

a is vehicle acceleration

The tractive force (F) supplied by the engine can be converted into a tractive power (P) by multiplying it by vehicle speed:

$$P = F \times v$$

Equation 2.2

$$P = (mgC_u v) + \left(\frac{1}{2}\rho C_D A v^3\right) + (mgsin(\theta)v) + (mav)$$

Equation 2.3

The first term in equation 2.3 is the power required to overcome the rolling resistance, the second term is the power required to overcome the aerodynamic drag, the third term is the power required to overcome gravity and the final term is the power used for motion. The first three terms can be considered as the external resistive powers. There are also internal resistive powers; these are the energy requirements needed for auxiliary devices such as lighting systems, entertainment systems and ventilation systems. If the tractive power supplied by the engine is equal to the sum of the resistive powers, the vehicle remains at rest or at a constant speed. If the tractive power is greater than the resistive powers, the vehicle accelerates. However, if the tractive power is less than the resistive powers, the vehicle will decelerate if already in motion.

The engine produces the tractive power by converting energy from a fuel source. The majority (>99%) of the vehicles in the UK use hydrocarbons such as petrol or diesel in the combustion process to produce energy for tractive power (Department for Transport, 2015a). Section 2.1.2 explains how the combustion of hydrocarbons such as petrol and diesel, for tractive power, results in the formation of pollutants.

2.1.2. Formation of pollutants

Vehicle fuels such as petrol and diesel are compounds that contain hydrogen and carbon atoms. In an ideal case, during the combustion process, the oxygen in the air is used to convert the hydrogen to water and carbon to carbon dioxide. In reality, this is not the case due to incomplete combustion, impurities in the fuel and the fact that the engine is not a perfect system (Heywood, 1988). There are several pollutants that are released into the atmosphere during the combustion of petrol and diesel. A description of the main pollutants including some discussion of the health and environmental impacts is presented in Table 2.1 (Stratford, 2010).

Pollutant	Description and impact
Carbon Dioxide (CO_2)	A gas that is found naturally in the atmosphere and in almost all circumstances has minimal impact to humans. However, it has been associated with climate change due to its effect on heat that is radiated from the Earth's surface.
Carbon Monoxide (CO)	A toxic gas that inhibits the human body's ability to effectively transport oxygen in blood around the body. At high concentrations, carbon monoxide can cause death and at lower concentrations can cause dizziness, nausea and a lack of concentration.
Nitrogen Oxides (NO_x)	A chemical compound formed during combustion that can be irritating to the eyes and cause various respiratory problems such as chest pains and lung damage.
Ozone (O_3)	A pollutant formed when a photochemical reaction occurs during the presence of ultraviolet light, hydrocarbons and nitrogen dioxide. The effect of this pollutant is worst on sunny days when ultraviolet rays are stronger and the ozone level on the Earth's surface is higher, causing inflammation of the airways and various respiratory problems.
Particulate Matter (PM)	Small particles found in exhaust fumes that once suspended in the air, are easily inhaled by those in close proximity to the source. Particles that are less than 10 micrometres in diameter are of greater significance as they can get trapped in the lungs and enter the blood stream.
Polynuclear Aromatic Hydrocarbons	Potent atmospheric pollutants formed as a by-product of fuel burning. Long-term exposure can lead to various cancers as PAHs have been proven to be carcinogenic and mutagenic. Pregnant women are at the greatest risk, as high

(PAHs)	prenatal exposure to PAHs is linked to childhood asthma and a low IQ.

Table 2.1 – summary of the typical pollutants released during the combustion process of petrol and diesel

2.1.3. Factors affecting emission rates

There are several factors that can affect the tailpipe emission rates of the pollutants outlined in Table 2.1. Zhang et al. (2013) summarises these factors into those that are due to the vehicle, driver and network conditions. Vehicle specific properties such as fuel type have been shown to affect tailpipe emission rates of pollutants such as CO and CO_2 as demonstrated by Almeida et al. (2015). Factors associated with the driver such as driving style and aggression have also been shown to affect pollutant emission rates (Sentoff et al., 2015). The network conditions can affect the amount of congestion and proportion of time vehicles queue, resulting in variations in tailpipe emissions as demonstrated by Bigazzi and Figliozzi (2012). Considering Equation 2-3, anything that increases the demand for power, increases the tailpipe emission rate.

This thesis focuses on network conditions, specifically roadworks and urban obstacles, as outlined in Chapter 1. As will be explained further in section 2.2, roadworks are network interventions that highway authorities and works promoters have control over. With an improved understanding of how these network interventions impact vehicle emissions, methods to minimise their impact can be investigated. Opportunities to control other factors that influence vehicle emission rates are harder to come by. For example, how aggressive a driver is difficult to control for, aside from driver training and penalties for overly aggressive behaviour.

Whilst vehicle specific factors such as fuel type or vehicle mass are not the focus of this study, they are investigated in the context of urban obstacles. In section 5.4, for example, a regression model is used to assess the significance of fuel type, Euro standard and vehicle mass in estimating tailpipe emission rates.

2.1.4. Vehicle acceleration

The term acceleration is used to describe the rate of change of speed, the second derivative of position. The acceleration of a vehicle is measured in m/s^2. As explained in section 1.2, it is important that vehicle acceleration is accurately represented in the tools used to model the dynamic behaviour of vehicles. Through an assessment of automotive test drive cycles and real-world emissions, vehicle acceleration has been shown by Watson (1995) to be the most important factor in explaining the variance in fuel consumption and emissions. Other studies such as those by Samuel et al. (2002) and Darlington et al. (1992) also discuss that vehicle acceleration is critical in understanding vehicle emissions. By reference to equation 2.3, when a vehicle is required to accelerate, the power demands on the engine are higher, and thus more fuel is combusted resulting in increased pollutant emissions. Considering that this research focuses on vehicle emissions at points on the network where vehicles are expected to accelerate, it is essential that vehicle acceleration be investigated.

As with vehicle emissions, there are several factors that can affect vehicle acceleration and these can be related to the vehicle, driver and network conditions. Typical vehicle characteristics such as engine size or maximum power output have been shown to affect vehicle acceleration (Rakha et al., 2004). For example, vehicles with a lager engine size can combust more fuel on each engine stroke, and therefore have more power available to overcome the resistive forces on a vehicle. Driver factors such as the reaction time, age and general aggressiveness have also been shown to affect vehicle acceleration (Ahmed, 1999). Belz and Aultman-Hall (2011) show that the driver age is statistically significant in estimating the speed and acceleration at which vehicles approach geometric features of the road network. Other studies such as Noland and Quddus (2006) show that making changes to the road network configuration that increase traffic smoothing and reduce the number of acceleration events lowers tailpipe emissions. Whilst the focus in this thesis is network features, specifically urban obstacles as outlined in Chapter 1, the significance of vehicle specific factors is discussed in section 4.4 through the use of a regression model.

In previous research such as Benson (1992), it has been preferable to categorise the operating mode of the vehicle into four mutually exclusive operating modes: acceleration, deceleration, idle and cruise. Frey et al. (2003) defined these states as:

Acceleration – vehicle acceleration is $>0.1 m/s^2$

Deceleration – vehicle acceleration is $<-0.1 m/s^2$

Idle – vehicle acceleration is between $-0.1 m/s^2$ – $0.1 m/s^2$ and vehicle speed is $<0.5 m/s$

Cruise - vehicle acceleration is between $-0.1 m/s^2$ – $0.1 m/s^2$ and vehicle speed is $\geq 0.5 m/s$

Frey et al. (2003) conclude that when vehicles are in an operating mode that requires a higher power demand, such as acceleration, vehicle emissions are higher. This method of defining operating modes simplifies the process of associating tailpipe emissions rates with what a vehicle is doing at a particular instance in time. For example, vehicles that spend a greater proportion of time in the acceleration operating mode are expected to have higher tailpipe emission rates. Whilst this method of defining operating modes makes it easier to understand tailpipe emission rates, it must be noted that these are broad categories. In this thesis, vehicle operating modes are supplemented with vehicle power based metrics as discussed in section 5.3. Furthermore, the accuracy to which the operating state can be defined is dependent on the measurement technology. In order to categorise the operating mode of the vehicle, accurate speed and acceleration data are required. Suitable ways of obtaining these data are presented in section 3.2.

2.1.5. Summary of pollutant emissions formation

In order to meet the power demands required for motion, a vehicle must generate power through the combustion of a fuel. The majority of vehicles in the UK use hydrocarbons as this fuel source. A by-product of the combustion process is the production of pollutants such as those presented in Table 2.1. The emission rates of pollutants such as CO_2 and NO_x are influenced by an array of factors. Vehicle acceleration has been shown in the literature to be critical in describing the dynamic behaviour of a vehicle when estimating vehicle emissions. In a study where the focus is modelling tailpipe emissions, it is important that the vehicle dynamics, particularly vehicle acceleration, is also accurately represented.

2.2. Roadworks and urban obstacles

In order to navigate a roadwork, a vehicle may be forced to change its speed or direction. This will result in additional acceleration events and thus will change the tailpipe pollutant emission rates. This section describes the background to roadworks and justifies why the focus of this research is on urban obstacles.

Roadworks (also known as "workzones" in the US) are required for road maintenance and sub-surface utility work. In this thesis, a roadwork is defined as any temporary intervention that removes capacity from the road network. Roadworks can be a major source of disruption when there is insufficient practical reserve capacity in the road network (London First, 2010). Due to the varying nature of roadworks, there are no explicit instructions on the configuration and coordination of roadworks. The Design Manual for Roads and Bridges (DMRB) (Department for Transport, 2012a), the Manual of Contract Documents for Highway Works (MCHW) (Department for Transport, 2012b) and the Traffic Signs Manual (Department for Transport, 2009) contain guidelines which focus on the safety requirements of the roadwork layout rather than the geometric layout. The Department for Transport (2008) has produced signal timing guidelines for contractors to assist with programming temporary traffic signals. However these guidelines are generic and again the focus is on safety.

When a works promoter requires access to the carriageway, a capacity reduction is introduced due to the presence of traffic restrictions such as speed restrictions, width restrictions or partial closure of a link. Associated with the traffic restrictions, it is often necessary to introduce temporary traffic management to ensure the safety of all road users and to manage traffic flow. As a result of this traffic management intervention, lower average speeds and vehicle flows, and increased vehicle delay and queuing are often observed, compared to the disruption free case.

There is a large body of research concerning capacity reductions, including roadworks, and their impact on network performance indicators. Typical network performance indicators include average vehicle speed, average delay and flow rate. Chung (2011), investigated how closing multiple lanes on a freeway due to roadworks would affect network performance. However, in this study, and others conducted by Hunt and Yousif (1994), and Ober-Sundermeier and Zackor (2001), it is possible to add capacity to the road network by reducing the lane widths and making the hard shoulder available. Whilst this research is relevant to the general research problem, it does not apply in dense urban areas where space does not allow for such redundancies. In an urban environment, many links are single lane and due to the presence of street furniture and other obstructions, temporary capacity additions are not feasible.

Research has also been conducted on how the introduction of roadworks affects vehicle tailpipe emissions (González and Echaveguren, 2012, Huang et al., 2009, Lepert and Brillet, 2009, Zhang et al., 2011). As with the research on the impact of roadworks on network performance, the studies focus on the highway environment. Whilst all the studies show an increase in tailpipe emission rates that justifies further research in this field, the results are not directly applicable in urban environments. For example, there are differences in the vehicle speed, with motorway speeds higher than 100km/h compared to lower than 50km/h in urban environments. Furthermore, in a motorway environment it is commonplace to introduce speed reductions several miles upstream of the roadworks to smooth the flow of traffic. In an urban environment this is not possible due to multiple alternative routes and presence of other traffic management such as a signalised junction.

There is a clear requirement to understand the impact of roadworks in urban environments on vehicle emissions. As highlighted in section 2.1, it is critical that the acceleration behaviour in the vicinity of roadworks is also understood due to its importance in estimating vehicle emissions. Furthermore, as highlighted in section 1.1, exposure to airborne pollutant emissions is higher in densely populated urban areas, making the potential health impacts even greater. With an understanding of the acceleration behaviour and tailpipe emission rates in the vicinity of roadworks, existing modelling tools can be improved to better represent the observed behaviours.

The remainder of this subsection outlines the different types of roadworks as defined in the UK. Data from a local authority is used to then narrow the focus to particular types of roadwork that can be planned for and where the capacity reduction is in place for the longest period.

2.2.1. Description of roadwork types

Roadworks have been categorised into five classes (Hawthorn, 2011):

- Minor works

- Standard works
- Major works
- Immediate urgent works
- Immediate emergency works

These definitions are used across the UK, including in London by Transport for London and highway authorities in all 33 London Boroughs. They can be further grouped by the roadwork notification as "planned disruptions" and "unplanned disruptions" as shown in Table 2.2. The planned classification applies when the authority responsible for a particular road has been informed prior to works commencing. The necessary traffic management procedures will have been put in place, and the required notifications to the public and other interested parties will have been sent out. With unplanned disruptions, the authority for a particular road has not been informed prior to the works commencing and the necessary procedures to manage traffic or notify interested parties will have not been initiated.

Roadwork notification	Class	Description	Example
Planned disruption	Minor	Limited impact on the carriageway, minimal or no traffic management required	Footway (pavement) repairs
	Standard	Works expected to impact traffic, traffic management required	Routine resurfacing
	Major	Works expected to impact traffic, traffic management required and consultation with neighbouring highway authorities	Streetscape redevelopment
Unplanned disruption	Immediate urgent	There is a risk to supply promoting the works	Burst water main
	Immediate emergency	There is a risk to life promoting the works	Gas main leak

Table 2.2 – roadwork categorisation in the UK with examples of each

The key difference between the two groups of roadwork types is the notification to interested parties and the traffic management procedures that are put in place. With the planned disruptions, typical traffic management infrastructure that could be deployed includes temporary traffic signals, vertical or lateral deflections and speed or width restrictions. With unplanned disruptions, the focus is to find the source of the problem, which may require multiple excavations. It is common for the whole road or a portion of the network to be closed. Once the source of the problem is found, a temporary fix is normally implemented and a planned roadwork is scheduled over the following days.

To determine whether the focus should be on more routine planned roadworks or unplanned roadworks, roadwork data from a local authority was studied as shown in section 2.2.2.

2.2.2. Roadwork activity for a local authority

Roadwork activity for each highway authority is recorded and reported as part of the Traffic Management Act Performance Indicators (TPI's) (2004). There are 19 TPI's in total that are split into the following categories: occupancy (13), inspection (2), reinstatement (2), and safety (2). The Royal Borough of Kensington and Chelsea (RBKC), a local authority in London, UK, provided data for four TPI's during 2012 as shown below:

TPI 1 – Works phases started – a count of all works phases started within a given quarter
TPI 2 – Works phases completed – a count of all works phases completed within a given quarter
TPI 3 – Days of occupancy – a count of the number of days that any works phases were active at any given time within a given quarter
TPI 4 – Average duration of completed work phases – the average duration in days for all those work phases that were completed within the quarter

A roadwork can have multiple works phases. However, between each phase, control of the road segment is handed back to the highway authority. For example, a works promoter may have one phase where an excavation is made and an inspection is conducted. The excavation would then be temporarily filled and the works promoter may return at a later date with the required equipment to conduct the repair. This is an example of a roadwork with two phases.

Table 2.3 shows a summary of the data obtained from RBKC for TPI 1 and TPI 3. The data are for 2012 split by quarter. During Q3, due to the 2012 Olympic Games hosted in London, restrictions on roadworks were introduced as part of Project Clearway.

Work phases started (TPI 1)	**Q1**	**Q2**	**Q3**	**Q4**	**Total**
Minor	1086	1189	784	878	3937
Standard	318	268	246	254	1086
Major	176	96	52	74	398
Immediate Urgent	232	360	386	322	1300
Immediate Emergency	96	112	107	132	447

(a)

Days of occupancy (TPI 3)	**Q1**	**Q2**	**Q3**	**Q4**	**Total**
Minor	2973	3147	2097	2368	10585
Standard	2011	1870	1597	1855	7333
Major	3391	1807	1161	1272	7631
Immediate Urgent	1469	1534	1148	1164	5315
Immediate Emergency	691	666	408	763	2528

(b)

Table 2.3 – number of works phases started (a) and days of occupancy for roadworks (b) in RBKC during 2012

From Table 2.3a, it can be seen that the highest number of works phases started is for minor roadworks across all four quarters. As shown in Table 2.3b, minor roadworks also have the highest number of days of occupancy in RBKC for every quarter apart from Q1. However, a key issue with the way occupancy is reported in the TPI's is that a roadworks phase always has a minimum length of one day. For example, a minor roadwork where a drain cover is replaced typically takes a few minutes, is reported as taking a full day. Whilst this limitation of roadwork reporting is being addressed through the development of a more advanced Roadworks Register, the current system does not allow for the extraction of data for subsequent analysis.

Using TPI 4, the average duration of completed work phases can be visualised as shown in Figure 2.1. It is clear that major roadworks have the highest average duration of completed work phases, with standard roadworks having the second highest average duration. This is despite minor works being reported with a minimum duration of one day. As mentioned above, the Olympic Games placed restrictions on roadworks during Q3, resulting in some roadworks taking longer to complete than normal.

Given that roadworks that are classified as standard or major are present on the road network for the longest, these types of roadworks are the focus of this thesis. From the available data, it is not possible to conclude that these types of roadworks have the greatest impact on vehicle emissions. However, the aim of this thesis is to improve the tools used to model roadworks and their impact. It is therefore justified that the focus is on roadwork types that can be planned for and have a sufficient duration that modelling them is an appropriate use of resources.

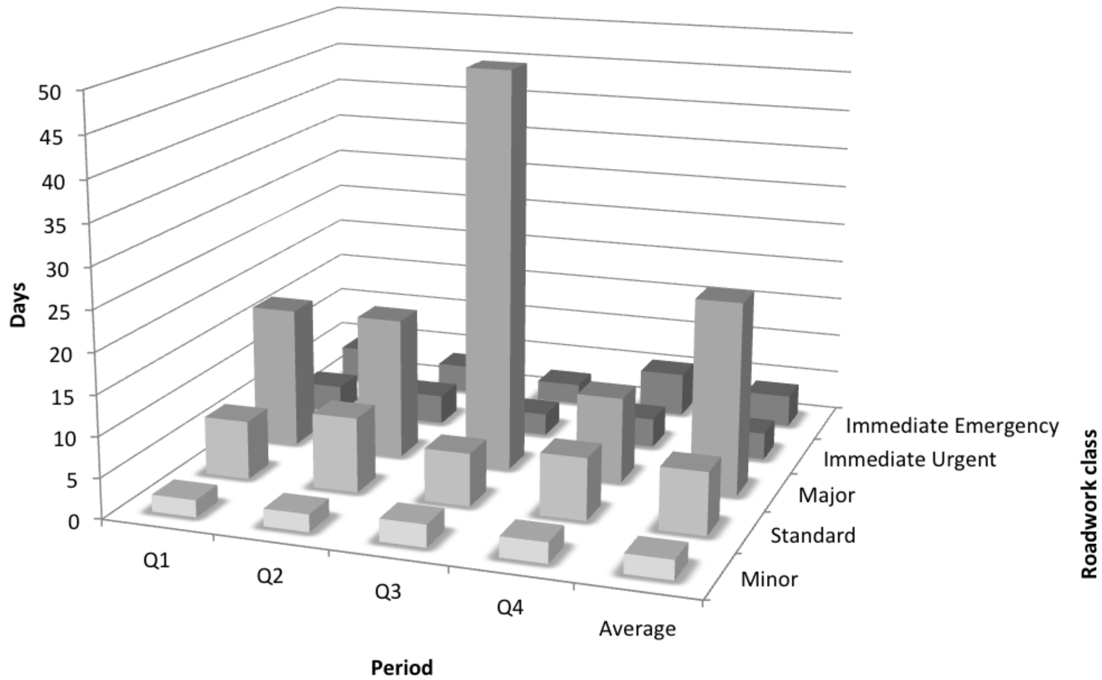


Figure 2.1 – the average duration of roadworks by roadwork class during 2012

2.2.3. Roadworks as a type of obstacle

When there is a roadwork that is classified as standard or major, traffic management such as temporary traffic signals or width restrictions may be introduced. When a vehicle encounters a roadwork, it is not the roadwork itself that causes a vehicle to change its speed or trajectory but the presence of traffic management. The mechanisms by which the traffic management affect the vehicle dynamics is not expected to differ, for example, between a temporary traffic signal upstream of a roadwork or at a signalised junction. Both will cause a delay to the vehicle if the traffic signal is red or due to the presence of a queue. Furthermore, whilst standard and major roadworks are planned, they can be rescheduled or cancelled due to operational or resource constraints. This increases the complexity of the data collection procedure, as a roadwork may not be physically present on the road network when it is expected to be there.

It is therefore proposed that the scope of this thesis, whilst focused on roadworks, considers all obstacles on the road network. An obstacle is defined in this thesis as any object or event that causes a vehicle to change its speed. An obstructed trajectory is therefore when an obstacle is present resulting in a vehicle deviating from its desired speed. This approach to the problem does not limit the research to traffic management only; potholes, pedestrians crossing the road, the presence of road signs and many other objects in the vicinity of the road may cause a vehicle to deviate from its desired speed.

It is noted that in this thesis, any changes in driver behaviour such as those caused by the unfamiliarity of the roadwork or aggression due to the additional disruption, are not considered. Whilst this is beyond the scope of this thesis, some of these changes in driver behaviour may be captured when random events such a car pulling out or debris on the road are encountered.

The approach of considering all roadway obstacles is expected to result in a more robust data collection procedure. The aim of this study, which is to improve the tools used to model roadworks and their impact, is still supported.

2.2.4. Summary of roadworks and urban obstacles

Roadworks remove capacity from the road network potentially impacting network performance and vehicle emissions. Previous research has investigated both of these impacts in a motorway environment. However, studies in an urban environment where the capacity of the roadwork network cannot be temporarily increased are lacking. A study of roadwork activity in a local authority in London, an urban environment, was conducted. It was determined based on the duration of the works; the focus should be on standard and major roadworks. Given that these are both planned roadworks, it further justifies that the focus is on roadworks where opportunities to minimise the impact of the roadwork exist. It was explained that it is the traffic management infrastructure in the vicinity of a roadwork that causes a vehicle to change its speed or trajectory. It was therefore proposed that the focus of this thesis should be on all obstacles on the road network, not just those associated with a roadwork.

2.3. Roadwork management techniques

The management of roadworks and other features of the road network that may negatively impact network performance, the environment, and human health are of interest to the global transport community. Whilst this section focuses on the UK and London, many of the concepts discussed are applicable in other parts of the world.

There are several stakeholders involved with a roadwork; the key stakeholders are the highway authority, works promoter, road users and local community. In order to gain a better understanding of the roadworks process, from the inception of the idea that access to the carriage way is required, to the point when possession of the carriageway is handed back to the highway authority, stakeholder interviews were conducted.

Nineteen stakeholder interviews were conducted with representatives from Transport for London (TfL), the Royal Borough of Kensington and Chelsea (RBKC), London Borough of Hounslow (LBH) and Vinci-Ringway (VR), as shown in Appendix B. The stakeholder interviews were structured as informal discussions either in person or via email to discuss the roadwork management approaches. The discussions with TfL focused on plans to charge works promoters to access the carriageway, by "renting" space. The Transport for London Lane Rental Scheme (TLRS) was introduced in June 2012 and is detailed in section 2.3.2.

The meetings with RBKC, a local authority in London, were about the London Permit Scheme that launched in 2010 and its effect on roadworks in the borough. The representatives from RBKC explained how the scheme had revolutionised roadworks and led to reductions in the number of recorded roadworks, as discussed further in section 2.3.2. The key concern with the scheme is the fees works promoters pay. They are based on the type of roadwork and do not consider the duration or environmental impact of the works. The research presented in this thesis is expected to result in more representative modelling tools that could be used to quantify the environmental impact of a roadwork. The estimated environmental impact could then be used to influence the permit fee structure.

The stakeholder discussions with LBH were shortly after they had been awarded an £800 million PFI Highway contract for the period 2013-2038. Vinci-Ringway was the appointed contractor with a planned expenditure of £100 million over the core investment period between 2013-2018. Given the number of planned roadworks due to take place over the coming years, LBH highlighted the need for tools to be able to accurately model roadworks. This would allow for opportunities for better roadwork coordination and configuration to be explored. These are key themes of the Mayor’s Code of Conduct for roadworks, as described in section 2.3.2.

In this thesis, through an understanding of vehicle acceleration and emissions in the vicinity of urban obstacles such as roadworks, an assessment of existing tools used to model them can be conducted. The fourth research objective of this thesis seeks to adapt existing modelling tools to better represent the observed behaviours. The expectation is that they will then be more suited to the task of modelling roadworks.

The key roadwork management techniques as highlighted during the stakeholder interviews are presented in the following subsections.

2.3.1. Roadworks in the UK

Within the UK, there are several pieces of legislation that cover roadworks and outline the rights that works promoters have, but also the restrictions that can be placed upon them by highway authorities. The New Roads and Street Works Act (NRSWA) (UK Government, 1991) which replaced the Public Utilities and Street Works Act (UK Government, 1950) is the key legislation that is followed. The NRSWA makes it clear that local authorities and works promoters have a legal right to excavate the carriageway and footway in order to access their assets to provide new connections and carry out maintenance. The NRSWA also has conditions to this legal right that mean a new road is protected from roadworks for a predetermined amount of time. Roadworks are only permitted during this period if new connections are required or there are emergency or urgent works.

In addition to the NRSWA, the Department for Transport has produced the Design Manual for Roads and Bridges (Department for Transport, 2012a), the Manual of Contract Documents for Highway Works (Department for Transport, 2012b) and several guidance documents (Department for Transport, 2012c). These manuals and documents highlight the various safety considerations that works promoters need to make, including lighting, signage, drainage and emergency services requirements. There are also some guidelines on minimum lane widths, temporary signal arrangements and taper lengths to ensure safety as vehicles navigate a roadwork. They do not however, offer guidelines on how roadworks should be configured or coordinated to minimise their impact.

2.3.2. Roadwork management in London

London is an example of an urban area where there are over 5,000 roadworks taking place everyday (Colin Buchanan, 2010). In London, there are two bodies responsible for managing the public highways, Transport for London (TfL) and the local highway authorities. TfL manages about 4% of the roads in London, many of which are major corridors or 'Red Routes' that collectively fall under the Transport for London Road Network (TLRN). The 33 London Boroughs manage the remainder of the roads in London, each with a Highways Team and Traffic Manager. The main schemes used in London by both TfL and local authorities to manage roadworks are discussed below.

<u>Mayor's Code of Conduct</u>

Roadworks are a topic that has been receiving increasing attention in London. A number of measures and initiatives have been delivered across London to tackle the problems associated with roadworks. In April 2009, the Mayor of London launched the first Code of Conduct for Roadworks (Greater London Authority, 2009). The code of conduct, signed by the major utility companies and supported by the National Joint Utilities Group (NJUG) promotes sharing plans for future works, working outside peak hours and improving the quality of reinstatements. The code of conduct was revised again in 2012 to include pledges that all works promoters in London are expected to follow (Greater London Authority, 2012).

<u>London Permit Scheme</u>

In January 2010, the London Permit Scheme (LoPS) (Transport for London, 2009) was launched with initial support from TfL and 15 of the 33 London Boroughs. The scheme forces all works promoters including the local authority, to require a permit to gain access to any part of the highway. In order to receive a permit for planned works, the works promoter must first submit a notice of the works to the relevant highway authority through an online system called EToN (Electronic Transfer of Notices). Within the works notice, the promoter must detail the purpose of the activity, works duration, precise location and a description of the methodology. Once submitted, between 3 days and 3 months ahead of the planned works, the Highways Team review the notice. There may be an exchange of comments (informal emails linked to EToN) that force the works promoter to use a different methodology, for example directional drilling to insert pipes rather than digging a trench. The Highways Team also look for opportunities for collaboration with other planned works and notify other utility companies that have assets in the same area if appropriate. Traffic management plans are drawn up and the relevant notices are sent out. The traffic manager makes the final decision on whether the permit is issued and the works promoter then pays the fees that vary depending on the class of the works. With unplanned works, immediate urgent works and immediate emergency works, the permit process is very similar. However, the EToN form is submitted retrospectively, within two hours of the works beginning.

In January 2011, after LoPS had been in operation for a year, TfL published an Evaluation Report (Transport for London, 2011b) which detailed many of the positives of the scheme. This included a 13% overall reduction in works numbers in 2010/2011 compared to 2009/2010 and a 32% reduction in the hours of serious and severe congestion caused by roadworks in the same period. There was a 147% increase in the number of recorded days of disruption saved through joint working and collaboration. This has resulted in more boroughs joining the scheme, with one of the last being the London Borough of Islington (2015) who joined in October 2015.

LoPS is an example of a scheme that can improve how roadworks are managed and minimises the disruption to the road user and the potential impacts of the roadwork. The limitation of the scheme, as found through discussions with RBKC, is that the permit charges are fixed depending on the class of works. They do not vary depending on the location of the works or even the duration of the works. Therefore, there is almost no benefit to the works promoter to use more efficient and possibly more expensive methodologies, tools or resources.

Lane Rental Scheme

The idea of charging works promoters to physically rent the space they require has been looked at many times, each time considering a different stakeholder. The Transport Research Laboratory published a report which, through various case studies, demonstrates that utility trenching can have a detrimental effect on the surface condition and underlying structure of highways (Transport Research Laboratory, 2009). They proposed a charging structure, which is based on the footprint of the works and the road class, with footways having the lowest unit charge and motorways having the highest. This would allow highway authorities to recoup the money they have to spend when the life of the carriageway is reduced due to poor reinstatement work or multiple trenches.

The first major lane rental scheme is the Transport for London Lane Rental Scheme (TLRS), which came into effect on the 11th June 2012. The scheme supports many of the objectives outlined in the Mayor's Transport Strategy (Transport for London, 2011e) and TfL's Network Operating Strategy (Transport for London, 2011c). The aim of the scheme is to promote works outside of the peak hours and avoid works at the pinch points. Pinch points are where works would constrain overall capacity of the wider road network, as mentioned in the TLRS Cost Benefit Analysis report (Transport for London, 2011d). The primary focus of the scheme is to minimise the impact to all road users by increasing journey time reliability across the network and reducing delay. Based on the London Congestion Analysis Project and other tools the Network Operations Team at TfL have at their disposal, a 3 band charging structure has been created (Transport for London, 2011a). The charging structure is based purely on the delay caused and does not account for the environmental impact of the works, though the timing and location of the works are taken into account (Transport for London, 2012). The scheme was last refreshed in 2014 with updated charges and locations where the scheme was active (Transport for London, 2014).

2.3.3. Summary of roadwork management techniques

In order to understand the current roadwork management techniques in the UK, with a particular focus on London, 19 stakeholder interviews were conducted. It was found that there are three main schemes in London: the Mayor's Code of Conduct; the London Permit Scheme; and the Transport for London Lane Rental Scheme. All three schemes aim to minimise the disruption to road users and the potential impacts of roadworks. This is achieved though best practices, better planning and charging works promoters to access certain parts of the road network. None of the schemes focus directly on the environmental impacts of the roadwork. However, a positive impact would be expected if the disruption due to roadworks was minimised or removed.

All of the stakeholders expressed an interest in developing a better understanding of how roadworks affect vehicle emissions. Representatives from the Planned Interventions team at Transport for London were particularly keen to see how the environmental cost of roadworks could be incorporated into the existing charging structures in LoPS and TLRS, as discussed in section 6.5. In order to model different roadworks scenarios, the tools used must be able to accurately model the behaviours observed in the vicinity of roadworks, the focus of this research.

2.4. Existing studies on vehicle acceleration and emissions at urban obstacles

For this research, there is a need to obtain vehicle acceleration and emissions data at urban obstacles. In section 2.2 it was explained that the focus of current research on the impact of roadworks on network performance and emissions was multilane highway environments. Whilst these studies improve our understanding of roadworks and their impact, the results are not directly applicable to urban environments. In urban environments, capacity cannot be temporarily introduced due to the presence of street furniture and other obstructions. Furthermore, there are differences in the vehicle speeds observed in multilane highway environments compared to urban environments.

There is existing research on how the presence of an urban obstacle impacts vehicle acceleration and tailpipe emission rates. However, whilst these studies are a valuable contribution to this field of research, the majority suffer from one or more of the following limitations:

- Number of vehicles on which the results are based
- Methodology used to calculate vehicle acceleration
- Methodology used to estimate vehicle emissions
- Range and number of obstacles studied
- Conditions under which the data is collected

These limitations are discussed below with reference to existing published studies. More specific reference to findings from existing studies is presented in discussion of the acceleration and emissions results in Chapters 4 and 5.

Number of vehicles

In order to assess the suitability of existing modelling tools, data is required to understand the variability in acceleration behaviour and tailpipe emissions in the vicinity of urban obstacles. It is therefore important that data from multiple vehicles is used to ensure the analysis is not specific to a particular manufacturer or vehicle technology. Furthermore, the larger the number of different vehicles used, the more representative the study will be of a particular vehicle fleet.

Studies such as Li et al. (2007) use an on board emissions measurement system to investigate how tailpipe emissions vary at a T-junction. A single Euro 1 vehicle was used, limiting the conclusions that can be drawn as acknowledged in the discussion of the results. Huang et al. (2013) used three vehicles fitted with portable emissions measurement systems to investigate how emissions vary as they complete an urban cycle in Shanghai, China. Whilst the study used vehicles powered by different fuel sources, it is difficult to conclude how representative a single petrol vehicle is of the overall petrol vehicle fleet. Huo et al. (2012) conducted a more comprehensive study where real-world emissions were monitored for 57 vehicles. However, the data was collected in three different cities and the test route in each city varied in length and the obstacles encountered. It is critical that data is collected for multiple vehicles that all navigate the same obstacles in order to assess the variability in vehicle acceleration and emissions.

<u>Acceleration measurement</u>

Vehicle acceleration can either be measured directly or estimated using other variables that describe the trajectory of a vehicle whilst on the road network. The different methods of measuring vehicle acceleration are discussed in section 3.2. The key issue with deriving vehicle acceleration from a variable such as vehicle speed is that a constant acceleration is assumed between two speed measurements. For example, with 1Hz GPS data, if a vehicle travels at 30mph (13.3m/s), the acceleration is assumed to be constant for ~13.3m. Whilst this may be suitable for certain applications, it is expected that the vehicle speed and thus acceleration will be highly transient in the vicinity of an urban obstacle (Noland and Quddus, 2006). Given that urban obstacles such as a pedestrian crossing are <13.3m in longitudinal length, any acceleration or deceleration events may not be reflected in the acceleration derived from 1Hz GPS speed data.

Mandavilli et al. (2008) conducted a study to understand how vehicle emissions at six roundabouts varied using a vehicle power based emissions model. Speed and acceleration data was obtained by processing video data from 360° video cameras located above each roundabout. Although this method allows data for multiple vehicles to be collected, manual processing of the video data is expected to have introduced considerable errors. Whilst these are not discussed in the work, other studies have shown errors in vehicle speed derived from video data to be ±7km/h on average (Karim and Dehghani, 2010). Another study by Mudgal et al. (2014) that was also focused on roundabouts, used a 1Hz GPS module to record vehicle speed, which was then used to derive vehicle acceleration. In order to have sufficient data in the vicinity of the obstacle to carry out the required analysis, the impact zone of the roundabout was extended 150m upstream and downstream of the roundabout. This is a key limitation of the study as behaviours not associated with navigating the roundabout may have been captured in the data used for subsequent analysis. Some studies such as Hu et al. (2014) have been able to successfully derive vehicle acceleration in the vicinity of a signalised junction using an optical sensor. However, to ensure accuracy in acceleration estimates, the sensor has a field of view of only 7.5m. Whilst this field of view may be suitable for certain urban obstacles such as debris on the road, it is not suitable for a signalised junction or roundabout. The optical sensor would not be able to "see" all entry/exit points for the junction or roundabout, limiting the data collected to only certain traffic streams.

For this research it is essential that a method of collecting vehicle acceleration data that does not suffer from the limitations outlined above is identified. The different measurement options and the chosen solution are explained in section 3.2.

<u>Emissions measurement</u>

As with vehicle acceleration, tailpipe emissions can either be measured directly or estimated using data that describes the trajectory of the vehicle. Considering that the motivation of this research is to be able to accurately model behaviours observed in the vicinity of urban obstacles such as roadworks, empirical data is required. Many studies collect trajectory data at urban obstacles such as junctions or roundabouts using GPS. This data is then used as an input into an emissions model, as demonstrated by Guo and Zhang (2014) and Fernandes et al. (2015). Whilst these studies give an indication of the expected emission rates, they do not validate the emissions model or comment on its suitability. In order to meet the objectives of this research, it is crucial that emissions measurements are obtained in the vicinity of urban obstacles.

There are several methods of collecting real-world emissions data. The different methods are described in section 3.3 with a discussion of their suitability to this research. In addition to the measurement technique employed, it is important that information about the vehicles from which measurements are obtained is known. Pu and Yang (2014) conducted a study using a roadside air quality monitor and then developed emissions factors as a function of vehicle speed. Information was only collected about the vehicle type (e.g. bus or passenger car), so it was not possible to assess the impact of vehicle specific characteristics. In this thesis, in order to adapt emissions modelling tools so that they are more representative of the scenarios that are being modelled, it is essential that vehicle specific information be collected. This will allow for an improved understanding of the variability in vehicle emissions, as required to meet the third research objective of this thesis.

Number of obstacles

Collecting real-world vehicle acceleration and emissions data is a resource intensive exercise. Access to vehicles, drivers and monitoring equipment can have a high financial cost. The data collection activity can span several weeks and months to ensure a sufficient sample size is collected. The resources required have often been the justification for focusing on a limited number of obstacles or obstacle types.

Daham et al. (2005) conducted a study to quantify the effects of traffic calming measures on emissions. A test route was defined where seven speed humps on a single road were investigated. Whilst this study provides real-world emissions data for a particular urban obstacle, it was collected with a single vehicle on one road and only focused on vertical deflections. Another category of obstacle related investigation is where alternative traffic management strategies are compared. For example a comparison of how a signalised junction and roundabout affect network performance and emissions, as demonstrated by (Höglund, 1994, Akçelik, 2006, Chamberlin et al., 2011, Gokhale, 2012). Whilst these studies consider more than one obstacle, they are still limited in their scope.

For this research it is important that a test route is defined where there is a potential for vehicles to be obstructed by different traffic management, objects and events. This will allow for a more comprehensive investigation of the variability in vehicle acceleration and emissions at urban obstacles. Whilst not all obstacles on the test route will be studied, methods of selecting those that have a higher probability of resulting in an obstructed trajectory will be discussed in section 4.2.4.

Test conditions

The environment in which the study is conducted is the final limitation of existing work on vehicle acceleration and emissions that is considered in this section. The conditions under which the data is collected can influence the results obtained. Some studies therefore try to exclude external factors that may influence vehicle acceleration and the resultant emissions. For example, using private roads or closed tracks can remove the effect of congestion. Others have used a chassis dynamometer to replicate a drive cycle obtained from real-world driving to ensure repeatability (Myung et al., 2014). Bella and Silvestri (2015) used a driving simulator to assess driver behaviours such as vehicle acceleration at pedestrian crossings in order to have more control over crossing events.

Whilst using closed tracks, dynamometers and driving simulators allows for more control of the heterogeneity observed in the real-world, it is not clear whether the observed behaviours are realistic. For example, with the study by Bella and Silvestri (2015), if the driver were to hit a simulated pedestrian, the consequences are very different to if it were to happen in real life. This could have resulted in changes in driver behaviour, for example overly aggressive accelerations in the vicinity of simulated pedestrian crossings.

In order to understand the variability in vehicle dynamics and emissions at urban obstacles, it is important that this research is conducted in an environment where the facets of “normal” vehicle and network operation are present. Whilst the results from on-road tests can be influenced by factors such as the weather or local congestion, measures to control these effects can be put in place, as discussed in section 3.4.

2.4.1. Summary of limitations with existing studies

A critical review of existing studies that focus on how urban obstacles affect vehicle acceleration and tailpipe emissions was conducted. It was found that the most studies had limitations in the way that the data were collected or the methodology employed. Some studies drew conclusions from data that was based on a single vehicle or a single obstacle. Others derived vehicle acceleration from 1Hz vehicle speed data or by processing video data to extract vehicle movements. Whilst these methods are acceptable in other circumstances, considering the highly transient vehicle speed and acceleration in the vicinity of an urban obstacle, these methods are not considered appropriate. In order to estimate the emissions associated with vehicles navigating an obstacle, several studies used emissions models without any assessment of their suitability or attempt to validate them. Finally, some studies simplified the data collection procedure by using tools such as driving simulators. Whilst these allow for the heterogeneity to be controlled, they may result in unrealistic behaviours.

There is a clear need to conduct this research where real-world vehicle acceleration and emissions data is collected from multiple vehicles in the vicinity of urban obstacles. This will allow for the variability between different vehicles and obstacles to be assessed, and will also support the subsequent modelling exercise in Chapter 6.

2.5. Summary of research direction

In this chapter it was explained that the majority of the vehicles in the UK combust hydrocarbons in order to meet the power demands required for motion. During the combustion of hydrocarbons such as petrol or diesel, several pollutants are emitted by the vehicle. There are several factors that affect the pollutant emission rates, however vehicle acceleration was explained to be critical.

Roadworks are a feature of the road network that can result in additional acceleration events due to the congestion caused by temporarily removing road capacity. Several studies have investigated the impact of roadworks in motorway or highway environments. However, work in urban environments where temporary capacity additions are not feasible, is limited. Through a review of roadwork activity data in a local authority, standard and major roadworks were identified as those that had the longest average duration and could benefit from roadwork modelling. The mechanisms by which traffic management is expected to affect a vehicle are not expected to be different in the vicinity of a roadwork or elsewhere on the road network. Therefore, it is proposed that data should be collected at all obstacles in the road network, regardless of whether it is a roadwork.

Current roadwork management techniques in the UK, with a particular focus on London, were presented. It was found through 19 stakeholder interviews that there are three main schemes: the Mayor's Code of Conduct, the London Permit Scheme and the Transport for London Lane Rental Scheme. Whilst all three schemes aim to minimise the disruption to road users, none of them focus on the environmental impacts of roadworks. Through discussions with the stakeholders, it was identified that being able to accurately model the behaviour of vehicles in the vicinity of roadworks would support the business case for incorporating the environmental costs of roadworks into the charging structures of existing schemes.

Finally, existing studies on urban obstacles and how they affect vehicle acceleration and the resultant tailpipe emissions were reviewed. It was found that the majority of studies had limitations with the amount of data that was collected and the methodologies employed. It was identified that there is a need to collect real-world emissions and acceleration data in the vicinity of multiple urban obstacles with different vehicles. The methodology for the data collection exercise is discussed in Chapter 3 along with a detailed description of the hardware developed and identification of a suitable emissions dataset.

3. Measurement of vehicle dynamics and emissions

In Chapter 2 it was explained that in order to meet the power demands required for motion, vehicles combust hydrocarbons. During this process, several harmful pollutants are released into the atmosphere. Roadworks and urban obstacles are features of the road network that can induce additional acceleration events, which have been shown to influence vehicle emissions, and are therefore of interest. In order to accurately model the behaviour of vehicles in the vicinity of urban obstacles so that methods to minimise their impact can be investigated, vehicle dynamics and emissions data are required. This chapter explains how the data required to understand individual vehicle dynamics and tailpipe emissions were collected. This addresses the first research objective:

Develop and validate a robust device for capturing vehicle dynamics that complements existing methods of measuring vehicle tailpipe emissions

The chapter begins by examining the alternative methods of acquiring individual vehicle trajectories and measuring real-world vehicle emissions. The Emissions Analytics dataset and its limitations are assessed and the development of a high-resolution sensor platform is detailed. Finally, the full data collection platform is presented, along with the pre-processing routines.

3.1. Background

As discussed in Chapter 2, there is a requirement to collect data on vehicle dynamics and tailpipe emissions in the vicinity of urban obstacles. In Chapter 1, it was explained that the motivation of this research is to be able to accurately represent the behaviours observed in the vicinity of roadworks in modelling tools. The vehicle dynamics data are necessary to investigate whether the acceleration behaviour of vehicles is appropriately represented in traffic modelling tools. Similarly, the tailpipe emissions need to be measured to assess whether emissions modelling tools are capable of accurately modelling pollutant emissions in the vicinity of urban obstacles.

The dynamic behaviour of a vehicle can be described by changes in its position in space and time. When a vehicle is navigating a roundabout for example, there will be lateral and longitudinal accelerations potentially requiring multiple measurement devices to be integrated. Section 3.2 explains the different infrastructure and vehicle based measurement options for obtaining individual vehicle trajectories.

As explained in section 2.1, in order to move, vehicles require sufficient power to overcome the internal and external resistive powers. The majority of vehicles do this through the combustion of hydrocarbons such as petrol or diesel. A result of this process is the production of various pollutants harmful to human health and the natural environment, such as NO_x and CO_2. Section 3.3 presents the laboratory based and real-world measurement options for quantifying the tailpipe emissions rates of various pollutant species.

A dataset that contains both vehicle dynamics and tailpipe emissions data in the vicinity of urban obstacles will support the subsequent analysis to understand the variability between different vehicles and obstacles (Objectives 2 and 3). The outputs from this analysis can then be used to inform how the modelling of urban obstacles such as roadworks should be conducted (Objective 4).

3.2. Vehicle dynamics

The dynamic behaviour of a vehicle is how the vehicle's position in space and time changes over the interval being considered. A vehicle's trajectory is an alternative way of describing the dynamic behaviour whilst it travels on the road network. For this thesis, there is a requirement that individual vehicle trajectories are recorded as they navigate urban obstacles. The trajectory data should contain at least the vehicle's position with respect to time. The first derivate of which provides velocity and the second derivate provides vehicle acceleration. Whilst vehicle acceleration can be derived from changes in vehicle position or speed, it is also possible to measure acceleration directly, as discussed in section 3.2.2.

There are two broad categories for obtaining vehicle trajectory data, infrastructure based measurement and vehicle based measurement. Infrastructure based measurement options are discussed in section 3.2.1 and vehicle based measurement options are discussed in section 3.2.2.

3.2.1. Infrastructure based measurement

Infrastructure based measurement of vehicle trajectories relies on hardware being installed in the vicinity of the section of road that is to be monitored. These devices are either used as a pair to track a vehicle between two points, as explained in section 3.2.1.1 or are capable of tracking a vehicle whilst it is in the sensor's field of view, as explained in section 3.2.1.2. Devices such as inductive loops and magnetometers are not considered in this study. They can be used to identify the presence of a vehicle and in some cases the type of vehicle (Abdulhai and Tabib, 2003). However, they are unable to provide individual vehicle trajectory data and thus do not meet the requirements of this research.

3.2.1.1. Paired devices

Paired devices are those that track a unique signature of the vehicle, for example, the vehicle registration mark, a Bluetooth address or a cellular transmission from within the vehicle (Jie et al., 2011). Automatic Number Plate Recognition (ANPR) cameras are able to identify a vehicle using its vehicle registration mark (Axer et al., 2012). When ANPR cameras are used in a pair, one being upstream of the monitoring location and one being downstream, a vehicle's trajectory can be obtained. The output from the cameras would be two time-stamped readings from when a particular vehicle crossed the field of view of each camera. With a known distance between the two fixed ANPR cameras, the time mean speed can be calculated.

Whilst a measure of average speed can be used for characterising network performance, it is not suitable for estimating vehicle acceleration. Due to only having two point measurements, it is impossible to measure acceleration, as it is assumed that the vehicle travels at a constant speed between the two measurement points. Whilst this may be true, it is highly unlikely given the presence of traffic management infrastructure, other vehicles and changes in road grade. Dividing the area of interest into several zones and having multiple measurement points could improve upon the speed estimates. However, this is normally not feasible due to the cost of implementation. Furthermore, in urban areas, there are multiple routes through the network that a vehicle could take; requiring assumptions to be made about the route vehicles take.

3.2.1.2. Field of view devices

An alternative to paired devices is to use a device that is capable of taking several measurements whilst a vehicle is in its field of view. For example, a traditional video camera recording multiple frames per second would capture the motion of vehicles as they pass the camera's field of view. The drawback of using a traditional video camera is the computational cost and accuracy associated with processing the video in order to extract the vehicle trajectories and then estimate vehicle acceleration (Barcellos et al., 2015).

More advanced cameras and optical traffic data sensors that are capable of automatically tracking vehicles are also available on the market. Whilst these cameras do not have the same processing requirements as traditional cameras, the setup procedure involves a complex calibration process, which often requires the road to be temporarily closed to traffic. An example of an optical traffic data sensor is the 'Smart Eye' (Bauer et al., 2007). A study was conducted with colleagues at Imperial College London and the Austrian Institute of Technology where a Smart Eye was mounted on a gantry near a signalised junction (Hu et al., 2014). The Smart Eye was capable of providing individual trajectories for vehicles as they passed the traffic signal, which were then used to calculate vehicle acceleration.

With devices that track a vehicle whilst it is in the sensor's field of view, there is a trade off between the mounting height of the device and resolution of the trajectory data. Whilst mounting the device higher allows it to 'see' more of the network, the resolution of the trajectory data reduces as a pixel represents a larger spatial area. In Hu et al. (2014), a Smart Eye was mounted 5.6m above the road surface, which resulted in a field of view of only 7.5m. Given that trajectory data for multiple obstacles are required, a single Smart Eye or similar traffic data sensor would not be sufficient. Although deploying multiple sensors is an option, the cost implications and the requirement to have to temporarily close the road would limit the scope of this research.

3.2.1.3. Suitability of infrastructure based measurement

As explained in Chapter 2, trajectory data from individual vehicles is required in order to extract acceleration data that can be used to understand the variability between different vehicles at different obstacles. The infrastructure based measurement options have the advantage of being able to provide data for multiple vehicles within a relatively short period of time. However, there are issues with the number of devices that would be required and the data resolution.

Another option for collecting vehicle trajectory data is to use a vehicle based measurement solution as described in section 3.2.2.

3.2.2. Vehicle based measurement

The measurement device used must be able to record individual vehicle trajectories as vehicles navigate urban obstacles. The trajectory data should also include at least the vehicle's position with respect to time, from which vehicle speed and acceleration can be derived. There are several vehicle based measurement platforms available on the market. The most basic system that meets the requirements of this study is a system that relies on a global navigation satellite system (GNSS), as discussed in section 3.2.2.1. More complex systems where the GNSS data are augmented with data from other sensors in a single package are discussed in section 3.2.2.2.

3.2.2.1. Standard systems (Single GNSS receiver)

The most basic form of a vehicle based measurement system that allows for individual vehicle trajectories to be recorded, is one that is capable of receiving signals from a GNSS, for example the NAVSTAR Global Positioning System (GPS). To use GPS, the vehicle must be fitted with a device that is able to receive GPS signals as explained by Guochang (2007). The receiver requires the “visibility” of at least four satellites, which are used to determine the vehicle’s 3-D position and time. Using the signals from satellites, the receiver is able to output messages that include coordinated universal time (UTC), longitude, latitude, altitude, speed over ground (SoG) and several other parameters as well as accuracy metrics, as detailed by Hofmann-Wellenhof et al. (2007).

Recording the GPS messages whilst a test vehicle travelled on the road network would provide the data required to understand vehicle acceleration in the vicinity of urban obstacles. The positioning information would be used to locate the vehicle on the network and associate a particular behaviour with a certain obstacle, for example a traffic signal. Vehicle acceleration could be calculated by differentiating the speed over ground data with respect to time. With the acceleration and positioning information for multiple vehicles, the data required for the subsequent analysis would be present.

As highlighted above, a standalone GPS receiver could be used in this thesis. However, there are a few potential problems that would limit the scope of this research as discussed below:

<u>Navigational performance</u>

The navigational performance of a GPS receiver can be assessed using four parameters: accuracy, integrity, continuity and availability (Ochieng and Sauer, 2002). The data for this thesis is to be collected in an urban environment where buildings, trees and other infrastructure can obstruct the open-sky view of the GPS receiver. This is expected to negatively impact the navigational performance of the GPS receiver and also lead to issues such as multipath (ESSP, 2015). Langley (1997) estimates that these issues can result in positioning errors in excess of 25m.

Some of the navigational performance issues can be minimised by using more advanced receivers that support Satellite Based Augmentation Systems (SBAS), tracking of several satellites on different frequencies or can be coupled with inertial measurement units (IMU). The use of these augmented systems is discussed in section 3.2.2.2.

<u>Data resolution</u>

The GPS receivers found in most modern devices operate at a maximum frequency of 1Hz, which is suitable for most applications such as route guidance and timing. However, when these data are used for trajectory analysis, it means that there is a data point each second. Considering that the speed limit in the UK in urban environments is typically 30mph or 13.3m/s, this translates to a data point recorded about every 13.3m. Assuming a speed hump is 1m in longitudinal length, a data resolution of 1Hz is not sufficient to capture the acceleration behaviour of the vehicle upstream and downstream of the speed hump. Therefore, a system with a higher resolution is required to capture trajectory information required for this study. Even when considering that a speed hump results in an average reduction in the 85th percentile speed of 16kph or 4.44m/s (Harvey, 1992). This would mean a vehicle travelling at the speed limit would reduce its speed to about 9m/s (20mph) when in the vicinity of the speed hump. Therefore, a device operating at 10Hz would be suitable in most circumstances. However, Nyquist-Shannon sampling theorem states the sampling frequency should be at least twice the frequency of the signal being captured/reproduced (Petracovici and Rosenblatt, 1999) – so a device operating at 20Hz would be more appropriate. This therefore means that the solution used to measure vehicle acceleration in the vicinity of urban obstacles should have a resolution of at least 20Hz.

Calculated acceleration

The acceleration that is obtained using GNSS is not measured directly, but calculated using the speed over ground (SoG) parameter that is based on Doppler shift in the pseudo range signals from the satellites. This means that any acceleration values are accelerations in the direction of travel and cannot be decomposed into the three component accelerations. This poses a limitation when more in-depth analysis of the acceleration data is conducted. For example, it would not be possible to distinguish whether a vehicle was unobstructed by the presence of the bus stop (no bus present) or whether the vehicle changed lanes to go around the bus (bus waiting at bus stop). This information would be important when trying to characterise the acceleration behaviour in the vicinity of a bus stop.

An alternative to calculating acceleration would be to measure it directly using an accelerometer. Accelerometers typically work by either detecting changes in electric charge when a piezoelectric crystal is stressed or changes in capacitance. The magnitude of the change can be related to acceleration in a particular direction. Combining an accelerometer with a GPS receiver would allow for a more accurate acceleration data to be collected, whilst the GPS data could be used to associate the accelerations with a particular urban obstacle.

In summary, a system comprising of a single GNSS receiver and recording platform would be capable of acquiring the data required to assess the acceleration behaviour of vehicles in the vicinity of urban obstacles. However, there are problems associated with using such a system that would limit the scope of this investigation and potentially undermine the results. A system where a GNSS receiver is augmented with data from additional sensors or a system where multiple devices are used simultaneously may be better suited to this research as discussed in the following sections.

3.2.2.2. Augmented systems

There are several solutions that address the shortcomings of the system outlined in section 3.2.2.1, namely navigational performance, data resolution and how acceleration data are derived.

The benchmark for obtaining positioning and navigation information for a moving body is to use an integrated GNSS/inertial navigation system (INS) (Abbott and Powell, 1995). A GNSS/INS system combines an inertial measurement unit (IMU) and inertial navigation equations with a GNSS receiver. The IMU contains a series of gyroscopes and accelerometers that are capable of measuring acceleration and rate of turn in all three dimensions. Using an on-board processor, when the GNSS receiver is unable to acquire accurate positioning information, the INS is able to compensate to ensure accurate positioning and navigation information is output.

The iMar iTraceRT-F200 is an example of an integrated GNSS/INS system that could be used in this thesis to collect the required data (iMar Navigation, 2012). The INS is able to compensate when the accuracy of the GPS data is compromised. The data acquisition frequency is 200Hz on the accelerometer channels and acceleration is measured directly in all three axes. This system is not without its limitations; these include a complex setup procedure, a heavy computational cost associated with processing the output data and finally the financial cost of the system.

An alternative is to use a GNSS receiver that is able to receive GPS signals, but also compensate for errors using Satellite Based Augmentation Systems (SBAS) or Precise Point Positioning (PPP) (El-naggar, 2011). Whilst these receivers do not measure acceleration directly, they have better positioning and navigation performance compared to a standard GPS receiver and can be configured to acquire data faster. The u-blox NEO-7P range of receivers support differential GPS

(DGPS) using SBAS, PPP and a data acquisition rate of 10Hz (u-blox, 2015). The issue with the u-blox series is the requirement of a laptop to process and store the data. The Leica GS-10 has on-board storage and is able to receive signals on a greater range of frequencies. However, it has a complex roof mounting system that requires the vehicle to have roof bars (Leica Geosytems, 2015).

All of the solutions discussed so far rely on a single GNSS receiver/antenna assembly. There are systems that use multiple roof-mounted antennas with known offsets between them. A processing system is then able to combine the positioning measurements from multiple antennas to better estimate the vehicle's acceleration and rotation. With these systems, the accuracy of the GPS signal is very important, as any positioning errors will have a negative impact on the output data. VBOX provide a range of devices such as the VBOX 3i that are used for the testing of vehicle dynamics. However, most of these tests occur on racetracks in open sky environments (Racelogic, 2015a). As the data for this research are to be collected in an urban environment, the presence of trees, buildings and other objects is likely to result in positioning errors, making such a system unsuitable.

Another solution would be to use a system where data from the vehicle's on-board computer is augmented with a GNSS receiver. For example, a VBOX Pro can be connected to the vehicle's computer via the CAN Bus interface to record high-resolution vehicle dynamics data (Racelogic, 2015b). The key issue with accessing vehicle information via the CAN bus interface is that the data available will vary between manufacturers and may not always be reliable.

Whilst the augmented systems presented in the section are an improvement upon the single GNSS receiver system presented in 3.2.2.1, they all have limitations that would affect the data collected for use in this study.

3.2.2.3. Suitability of vehicle based measurement

Two broad types of vehicle based measurement solutions were presented, a standard system that uses a single GNSS receiver and a more complex device that augments the GNSS data with other sensors. Both types of solutions meet the overarching requirement of this research, which is to be able to record individual vehicle trajectories as vehicles navigate urban obstacles. However, as shown in the review on existing studies (section 2.4) and explained in section 3.2.2.1, a system that is based on a 1Hz GNSS receiver does not output data at sufficient resolution to accurately understand acceleration behaviour. A solution such an integrated GNSS/INS system would meet the requirements of this study. However, there are other limitations such as the complexity of the setup procedure and data processing requirements.

3.2.3. Summary of vehicle dynamics measurement

As explained in this section, there are two broad categories for obtaining vehicle trajectory data as a vehicle navigates urban obstacles, infrastructure based measurement and vehicle based measurement. Whilst an infrastructure based measurement solution allows data to be collected from multiple vehicles simultaneously, the key limitation is that either several devices would be required to collect data at a range of urban obstacles, or the device would need to be constantly moved.

A vehicle based measurement solution is more appropriate for this research considering data are required from vehicles as they travel on the road network navigating multiple obstacles. Whilst data can only be collected from a single vehicle, unless multiple devices are used, the data obtained are of a higher resolution and acceleration can be measured directly with an augmented system. Of the augmented solutions presented, an integrated GNSS/INS system would be best suited to this study. Traditional GNSS/INS systems such as the iMar iTraceRT-F200 have a complex setup procedure and a heavy computational cost associated with processing the output data. A solution where a GNSS receiver is combined with an accelerometer is required for this study; the development of a suitable device is discussed in section 3.5.

3.3. Emissions measurement

As discussed in Chapter 2, in order to propel a vehicle, an energy source is required. The majority of vehicles in operation on the road network today use either petrol or diesel as this fuel source. In the UK, 83% of registered vehicles are passenger cars, with 36.2% diesel, 63.7% petrol and less than 0.1% powered by alternative fuel sources (Department for Transport, 2015d).

During the combustion of petrol and diesel several pollutants are released into the atmosphere. Oxides of nitrogen that are released during the combustion of fossil fuels are harmful to human health as they are associated with respiratory diseases and reduced lung function (Environmental Protection Agency, 2015). Carbon dioxide is also released during the combustion process, a gas that is harmful to the environment and has been associated with climate change (Bollen and Brink, 2014).

Frey et al. (2003) described the operation of a vehicle as being in one of four mutually exclusive 'operating modes': idle, cruise, acceleration or deceleration. Operating modes that require more power, such as acceleration, consume fuel at an increased rate and therefore, have higher pollutant emissions rates. Obstacles on the road network that result in an obstructed trajectory induce additional acceleration events as the vehicle tries to return to its desired speed. Hence, there is an increased rate of fuel combustion in the vicinity of an urban obstacle and as a consequence, higher pollutant emission rates.

The third objective of this thesis is to understand the variability in vehicle emissions between different vehicles at different roadway obstacles. Therefore there is a need to collect vehicle emissions data in the vicinity of roadway obstacles and there are two key methods. The first is to use data derived from laboratory based tests and the second is to collect data whilst the vehicle is in real-world operation. The two data collection methods are discussed in further detail in the following subsections.

3.3.1. Laboratory based measurement

Laboratory based emissions testing typically involves either running the vehicle on a chassis dynamometer or the engine on an engine dynamometer whilst the exhaust gases are collected in a sample bag. Depending on the system used, the concentration of different pollutants is either measured during the test by drawing samples of the exhaust gases before they enter the sample bag or after completion of the test by taking measurements from the sample bag. The latter option would not be suitable for this study as the measurements obtained would be for the full drive cycle completed by the vehicle (Pelkmans and Debal, 2006). For this research, the emissions associated with a particular acceleration event or at particular point in time are required.

Governments and emissions testing organisations primarily use dynamometer based testing whilst completing regulatory emissions testing for passenger vehicles (Sileghem et al., 2014). In the European Union, all vehicles are subject to emissions testing with the New European Drive Cycle (NEDC), soon to be replaced by the World harmonised Light vehicles Test Procedure (WLTP) in late 2015/early 2016 (UNECE, 2015). Whilst there are several benefits of using a laboratory based testing approach such as greater control over atmospheric conditions, test repeatability and comparability between multiple vehicles, the NEDC testing procedure has attracted criticism (Demuynck et al., 2012).

Aside from the test cycle not being representative of real-world driving, the test procedure is unable to represent changes in road grade and varying atmospheric conditions (Franco et al., 2013). Furthermore, as a dynamometer is used to simulate the resistive power imposed on the wheels of the vehicle, coast-down tests are completed to obtain driving resistance values. It has been found that these tests are conducted under artificially favourable conditions resulting in lower emission rates compared to real-world operation (Mellios et al., 2011).

For this research, it is essential that the emissions data are representative of the emissions expected during real-world operation. Therefore, whilst a laboratory based measurement approach may offer better test repeatability due to the controlled conditions, a field based measurement approach is required.

3.3.2. Real-world measurement

Using a real-world emissions measurement technique allows for data to be collected from vehicles whilst they are travelling on the road network and exposed to facets of real-world operation that are difficult to replicate in a laboratory environment. For example, it is hard to reproduce the highly transient operation of a vehicle as it travels through a city centre exposed to multiple roadway obstacles (Franco et al., 2013).

There are four key methods of obtaining real-world operation emissions data: remote sensing, chase measurements, tunnel studies and on-board measurement. The suitability of each method to this research is discussed in sections 3.3.2.1 - 3.3.2.4.

3.3.2.1. Remote sensing

Remote sensing is where a measurement station is deployed close to the traffic stream and as a vehicle drives past, measurements are taken. The monitoring equipment takes multiple readings of the ratios of pollutant concentrations as each vehicle passes, along with background concentration readings. The main advantage of remote sensing or roadside monitoring is that data from a large number of vehicles can be obtained over a relatively short period of time (Carslaw and Rhys-Tyler, 2013). If the measurement system includes an Automatic Number Plate Recognition (ANPR) camera, specific details about each vehicle can be matched to the emissions measurement (Rhys-Tyler and Bell, 2012).

The requirement of the emissions measurement technique used is that data from individual vehicles can be collected. At certain obstacles such as a roundabout, there may be multiple lanes or a queue of vehicles may form. With a remote sensing technique it would be difficult to identify the emissions associated with a particular vehicle (Burgard et al., 2006). Furthermore, all the measurements are taken at a particular location on the network and therefore, it is not well suited to this research where measurements are required at multiple obstacles on the network. Whilst the measurement system could be redeployed once sufficient data have been collected, the difficulty in identifying the emissions associated with a particular vehicle is still a problem. Remote sensing is therefore not considered to be suitable for this research.

3.3.2.2. Chase measurements

In chase measurements, a vehicle containing a mobile emissions laboratory follows the vehicle for which emissions data are required. The chase vehicle measures the concentration of pollutants from the vehicle being followed, and is able to attain a level of accuracy similar to that found in laboratory based testing (Bergmann et al., 2009).

The main drawback of using chase measurements is that the chase vehicle and the test vehicle must be separated by a minimum of 10m (Morawska et al., 2006). Chase measurements are usually conducted on closed test tracks where it is possible to maintain the required separation distance. In an urban environment where the data for this research are required, it would be difficult to maintain a 10m minimum separation distance in the presence of other road traffic. In addition, attempting to maintain a 10m minimum separation distance may influence the behaviour of the vehicle being monitored and thus result in unrepresentative results. Furthermore, there is a risk of contamination from other vehicles in the vicinity. Therefore, this approach is not suitable for this thesis.

3.3.2.3. Tunnel studies

Tunnel studies as the name suggests, involve the measurement of pollutants as vehicles pass through a tunnel. The concentration of pollutants of interest is measured at the entrance and exit of the tunnel along with the airflow. Multiplying the difference in concentration between the entrance and exit by the airflow, it is possible to obtain estimates for the total amount of pollutant produced by the vehicles in the tunnel.

Whilst the tunnel studies provide valuable data for estimating aggregate real-world emissions, they are not suitable for this research. Firstly, it is not possible to obtain emissions data for a specific vehicle unless only one vehicle is in the tunnel. Secondly, tunnels are typically free of roadway obstacles such as traffic signals and speed humps. Meaning it would not be possible to collect emissions data in the vicinity of a roadway obstacle, as required for this study.

3.3.2.4. On-board measurement

On-board measurement of vehicle emissions involves the use of a Portable Emissions Measurement System (PEMS) installed within the test vehicle. The PEMS unit is connected directly to the vehicle’s exhaust pipe and can therefore measure instantaneous emissions of a range of pollutants. As the monitoring system is within the vehicle, it can be connected to the vehicle’s on-board diagnostics (OBD) system. This will allow for the collection of additional data about the current state of the vehicle. This includes information such as throttle position, engine speed, engine temperature, filter status and several other parameters which maybe of interest when analysing vehicle emissions.

The accuracy of modern PEMS units is similar to that of laboratory grade systems which makes them suitable for in-depth emissions analysis as proposed in this research (Franco et al., 2013). The key limitation of using a PEMS unit is the additional load that is placed on the test vehicle. The unit typically weighs 30-70kg not including batteries and other test equipment which may skew the test results on smaller vehicles (Franco et al., 2013). However, for consistency in the testing procedure, the same weight could be added to each vehicle, which is the equivalent of approximately one passenger.

In order to address concerns associated with how the added mass of the PEMS unit may bias the test results, a prototype Emissions Monitoring Unit (EMU) was developed with colleagues in the Transport and Environmental Analysis Group at Imperial (Thiyagarajah et al., 2013). The unit connected directly to the tailpipe and was capable of estimating the mass flow rate of carbon dioxide. This was achieved through instantaneous measurement of the flow rate and carbon dioxide concentration, as shown in Figure 3.1. The device was tested on multiple vehicles as part of the RAC Foundation Future Car Challenge in 2011 and 2012 (North et al., 2012). Whilst the 1kg device appeared to agree with measurements from a traditional PEMS unit, further validation tests were required to address concerns about the flow measurement. It was determined that the EMU was not suitable for this research, however on-board measurement remains the best available solution to meet the objective of this study. The identification of a suitable PEMS data set is discussed in section 3.4.

Figure 3.1 – in-house developed Emissions Monitoring Unit (EMU)

3.3.3. Summary of emissions measurement

As discussed in section 3.3.1, a laboratory based measurement approach is not suitable for this study as it is difficult to replicate the exact test conditions that would be present during real-world operation. There are several real-world measurement options as presented in section 3.3.2.

However, the only suitable option for characterising the vehicle emissions at urban roadway obstacles is on-board measurement. Using a PEMS unit puts an additional load on the vehicle due to the weight of the test equipment. Whilst attempts to solve this issue were sought, ultimately the additional load would be the equivalent of having a passenger in the rear of the vehicle, which is not uncommon. With this is in mind, using a PEMS unit to collect the data required for this study would be the best solution given the current options.

In section 3.2.3 it was concluded that a vehicle based measurement solution would be the best option for obtaining vehicle trajectory information. Using PEMS would complement an augmented system such as a GNSS receiver combined with an IMU. The identification of a suitable dataset that involves the use of these measurement techniques is discussed in section 3.4.

3.4. Acquired PEMS dataset

To conduct this research, it would be possible to collect the vehicle trajectory and emissions data independently. However, access to a portable emissions measurement system (PEMS) would be required, along with a fleet of vehicles that are representative of the UK vehicle parc. Hiring the PEMS equipment and vehicles for testing would be very expensive and financial constraints would limit the scope of the research in terms of the number of vehicles tested. Opportunities to rent or loan vehicles directly from vehicle manufacturers were explored. However, the installation of the PEMS equipment would violate the terms of the rental agreement and insurance policy. Furthermore, the OBD connection port is usually not accessible on rented vehicles as it is used for sending diagnostic information and tracking information back to the vehicle owner. Given the constraints of independent testing, it was decided to collaborate with a vehicle testing organisation, Emissions Analytics.

Emissions Analytics Limited is an independent emissions testing and data analysis consultancy based in London, UK and California, US. Emissions Analytics conducts regular vehicle emissions testing for several vehicle manufacturers, research organisations, commercial organisations and private individuals (Emissions Analytics, 2015b). Emissions Analytics also have a long-term relationship with 'What Car?' magazine in the UK and 'Motor Trend' in the US where they test every vehicle that is reviewed in the magazine. Further details on the test procedure, data structure, data integrity and limitations of the dataset are discussed in the following subsections.

3.4.1. Background

Since beginning testing in 2012, Emissions Analytics have an inventory of emissions data for over 700 modern passenger cars in the UK on the same test cycle. Specific details about the testing procedure and the dataset are discussed in the following subsections in order to assess the suitability of the dataset for use in this research.

3.4.1.1. Test setup

Emissions Analytics have two PEMS units that they use during routine testing to collect instantaneous emissions data, data from the vehicle's on-board diagnostics (OBD) system and trajectory information. Both PEMS units, the SEMTECH-DS and SEMTECH-ECOSTAR, are manufactured by Sensors Inc. and have successfully been used for on-road emissions testing, as demonstrated in Chen et al. (2007), Johnson et al. (2009) and Weiss et al. (2012).

During testing, a flow tube is connected to the vehicle's exhaust pipe from which samples of the exhaust gases are drawn and fed to the gas analysers, as shown in Figure 3.2. A Garmin GPS-16 GNSS receiver is connected to the monitoring equipment for collecting GPS data, and a weather station is used to monitor local atmospheric conditions. A connection is also made to the vehicle's OBD port for collecting data from the on-board computer. A laptop running the Sensor Tech-PC software is used to initialise, monitor and collect the data from the PEMS unit.

The key difference between the SEMTECH-DS and SEMTECH-ECOSTAR is the range of pollutants that can be measured. The configuration of the SEMTECH-DS allows for data to be collected on the following pollutant species: carbon monoxide, carbon dioxide, nitrogen oxide, nitrogen dioxide and hydrocarbons. However, during typical operation, hydrocarbons are not measured due to the additional batteries required to operate the flame ionisation detector (FID). The configuration of the SEMETECH-ECOSTAR only allows for data to be collected on carbon monoxide and carbon dioxide.

The use of two different measurement systems is not expected to influence the measurement data as both systems are calibrated using span gases before and after every test, as explained in section 3.4.3. For this research, CO_2 and NO_x data is required and therefore the SEMTECH-DS is the preferred system. However, the actual system used depends on availability. For vehicle tests where the SEMTECH-ECOSTAR is used, the analysis of tailpipe emissions is restricted to CO_2 only.

Figure 3.2 – the flow tube connected to a test vehicle during emissions testing (Emissions Analytics, 2015a)

3.4.1.2. Test procedure

Upon receiving a vehicle, an initial inspection is carried out to ensure the vehicle is safe for on-road testing. This involves several checks ranging from checking no dashboard warning lights are lit to checking the tyre pressures are within the manufacturer specified range. Once the technicians are satisfied the vehicle is safe and ready for testing, its exact configuration is recorded. This includes specific details about the tyre type and brand, to the trim options and optional extras on the vehicle (e.g. roof bars). The vehicle is then weighed using four pressure sensitive pads. The vehicle is aligned so that each wheel is on a pad and the mass on each pad is recorded along with the total mass of the vehicle.

The various components that make up the PEMS unit are then installed inside the rear of the vehicle, this comprises of two 12V batteries, the SEMTECH module, heated lines to connect to the exhaust flow meter and cabling to connect the devices together. On the exterior of the vehicle, the flow tube is installed on a bicycle rack just above the rear bumper, rubber hosing is used to connect the exhaust pipe(s) to the flow tube, the GPS module is mounted on the roof and the weather station is attached close to the rear windshield. Finally, before the equipment is turned on, the SEMTECH module is connected to the vehicle's OBD port and the test laptop.

With all the test equipment installed on the vehicle, the initialisation procedure is commenced. The setup is checked for leaks (including the exhaust pipe itself), zero and span checks are conducted on the gas analysers with test gases and the whole system is purged. The vehicle's on-board computer is reset to the manufacturer default settings and the 'driving mode' is set to normal.

If all the tests and checks are successful, vehicle testing can begin. The testing involves some stationary tests to assess the impact of auxiliary devices on emissions, before completion of a pre-defined test route – discussed further in section 3.4.1.4. After completing the test, the data are checked for errors and to ensure that the speed and timing requirements for each test segment have been met. Finally the vehicle is reweighed before all the test equipment is removed and the vehicle is returned to its original state.

Emissions Analytics follow a strict testing procedure for every vehicle test, which results in consistency and reproducibility in the emissions testing. These are essential for this research, as imprecisions in the testing procedure will undermine the subsequent analysis on the variability in vehicle dynamics and emissions. The integrity of the dataset and limitations are discussed further in sections 3.4.3 and 3.4.4.

3.4.1.3. Test vehicles

The vehicles that Emissions Analytics use for testing in the UK are those that have been supplied to 'What Car?' magazine for review. All of the vehicles are supplied either directly by the vehicle manufacturer or through a marketing company. The vehicles tested are all production vehicles that are available for purchase in the UK.

The vehicles are typically either petrol or diesel fuelled. However, a few hybrid petrol and hybrid diesel vehicles have also been tested. All of the vehicles meet either the Euro 5 or Euro 6 European emissions standards and can be considered to be modern as they were manufactured in 2012 or later.

As most of the vehicles are press vehicles from the vehicle manufacturers, they are well maintained and appropriately serviced. The vehicles usually have an odometer reading between 2,000 and 15,000 miles so are considered new, but beyond the engine 'break-in' period. All of the test vehicles are considered to have an average or above average level of maintenance. The vehicles tested in the UK consist of 700 models from over 40 different manufacturers and include the most popular vehicles based on UK sales data (Emissions Analytics, 2015c).

Given that only Euro 5 and Euro 6 vehicles are tested, the scope of this research will be limited to modern vehicles only. Euro 5 and Euro 6 vehicles represent about 50% of the UK vehicle parc and this is expected to increase in the future (Department for Transport, 2013). Furthermore, the methods that are employed in this research are applicable to other PEMS datasets where data for vehicles conforming to older European emissions standards is available.

3.4.1.4. Test route

The Emissions Analytics test route is composed of multiple sub-trips that can be categorised into urban and extra-urban segments. The test route typically takes 2.5 hours to complete and includes several short breaks between test segments to ensure the equipment is securely mounted and operating as expected.
The London based test route begins with two urban segments where speeds of up to 30mph can be reached. Whilst data is collected at this stage, it is generally discarded as the tailpipe emission rates may not be representative of those during normal vehicle operation – this is referred to as 'cold start emissions' in the literature. Whilst cold start emissions do contribute to problems of local air quality, the focus in this research is hot emissions. The first two urban segments take about 30 minutes to complete, after which the engine is considered to be 'hot' and this can be verified by monitoring the engine coolant temperature.

The next test segment is the extra-urban run on a motorway where speeds of up to 70mph can be reached. As highlighted in Chapter 2, the focus of this thesis is urban obstacles due to the differences in how roadworks are managed and the higher human exposure to pollutant emissions. The data collected on the motorway are therefore unlikely to be used in this thesis.

Following from the motorway segment, there are three urban segments that take about 75 minutes in total to complete. A part of the test route is repeated in these segments and allows for some repeatability testing to be conducted. The urban segments have a speed limit of 30mph. However, due to the presence of various obstacles such as traffic signals, speeds humps, pedestrians and bus stops, vehicles generally do not reach the speed limit – as shown in section 4.3.

Overall, the London based test route involves a range of speeds and passing multiple roadway obstacles as required to meet the research objectives of this thesis. In order to have some control over the external factors that may affect the route, the test is only conducted when there are no road closures or other events that may severely impact journey times. Similarly, the testing period is restricted to one of two time slots in the day to ensure the general traffic conditions remain similar and are not influenced by the AM peak for example. The testing is also only conducted in dry weather where there is no standing water – again this is to ensure there is more control over the external factors that may affect the vehicle emissions and dynamics. This is important for this research as the focus is on how urban obstacles affect vehicle dynamics and emissions, not other factors such as the weather and local traffic.

3.4.1.5. Test drivers

How different drivers operate a vehicle can have a significant impact on the vehicle dynamics and the resultant emissions (Sentoff et al., 2015). In order to ensure the vehicle tests are comparable, Emissions Analytics have a strict driver-training programme that all technicians must undertake before conducting any testing for the company. The training programme guides the technicians on how to follow the 'Emissions Analytics driver profile', for example when to change gear and how aggressively to accelerate.

The standard testing procedure for Emissions Analytics is to have two technicians in the vehicle during the test. One monitors the PEMS data, whilst the other focuses solely on operating the vehicle. Having two technicians in the vehicle helps to ensure the vehicle is driven in a consistent manner. The trajectory data after each vehicle test is also evaluated to assess whether a technician is deviating from the pre-defined driving style, for example accelerating too aggressively or coasting.

Regular driver training programmes and peer-evaluation help to maintain a similar driving style across the technicians. Changes in driver behaviour are therefore, not considered to be an influencing factor in the variability in vehicle dynamics and emissions between different test vehicles in the Emissions Analytics dataset. Given that the focus of this thesis is how urban obstacles affect vehicle dynamics and emissions, it is important that there is consistent driver behaviour. Investigating how changes in driver behaviour affect vehicle dynamics and emissions is beyond the scope of this study.

3.4.1.6. Suitability of the dataset

From reviewing the Emissions Analytics test setup up, the procedure used would be suitable for this research with some modification, this is explained further below.

The carbon monoxide, carbon dioxide and hydrocarbon data are collected using a non-dispersive infrared sensor that has a range of 0 - 80,000ppm with an accuracy of ± 3% (Sensors Inc., 2010). The non-dispersive ultraviolet sensor used to measure the oxides of nitrogen has a range of 0 - 2,500ppm and an accuracy of ± 3% (Sensors Inc., 2010). The trajectory data are recorded using a 1Hz GPS module that would not be suitable as explained in section 3.2.2.1. However, a device that meets the requirement of this research could be used, the development of which is discussed in section 3.5. Other data from the weather station and the vehicle's on-board diagnostics system may be useful when characterising the vehicle dynamics and the resultant emissions.

Regarding the overall testing, the test procedure is rigorous which ensures the data obtained will be robust and accurate. The vehicles used are passenger cars available in the UK and are of a suitable age and level of maintenance. The test route includes several urban segments containing a variety of urban obstacles that would be of interest in this research. Trained technicians operate the test vehicles and follow a prescribed 'Emissions Analytics driver' profile.

There are however, some limitations of using the Emissions Analytics dataset; these are discussed in section 3.4.4.

3.4.2. Data structure

After completion of a test, assuming the speed and timing requirements for each test segment have been met, the data are input into Sensors Inc. post-processing software, SENSOR Tech-PC. The software initially scans the raw data to check if there are any faults or warnings, for example, loss of a particular channel or measurements outside of the senor's range. If no faults or warnings are found in the data, the end user can then enter specific details about the vehicle and also the test setup – this is used to calculate delay between the flow measurement in the flow tube and the measurements by the gas analysers. Once all the details have been entered into the postprocessor, the processed data is output as an XML file and a CSV file.

The CSV file contains all the time aligned processed data for the test in a series of columns as well as all of the test information input into the post processor as a header. The structure of the CSV file differs depending on which SEMTECH unit is used and which version of the post processing software is used. The CSV file contains all of the data from the flow tube, gas analysers, GPS module, weather station, vehicle's on-board diagnostics systems and calculated fields such as mass flow of pollutants.

In order to use the data in this thesis, some additional post processing will be required to extract the relevant header information and the required columns of data, this will be done using a simple Python code.

3.4.3. Integrity and error sources

As discussed in section 3.4.1.6, the Emissions Analytics dataset could be used in this thesis, however the integrity of the data and any potential errors need to be identified.

As highlighted in section 3.4.1, Emissions Analytics have a rigorous testing procedure that aims to produce repeatable and consistent testing conditions for all of the vehicles tested. The test equipment is regularly serviced in line with the manufacturer's recommendations to ensure accurate measurement. The gas analysers are calibrated at the start and end of each test with a known concentration of a particular test gas. For example, zero checks are conducted on the gas analysers with bottled 'zero air' – a gas containing less than 0.1PPM of total hydrocarbons. Similarly, span checks are conducted with quad-blend of gases where known concentrations of CO, CO_2, NO and HC are measured by the gas analysers. The zero and span checks before and after each test ensure the accuracy of the emissions measurement during the vehicle testing.

The vehicle dynamics, in particular the acceleration behaviour and the resultant emissions can be influenced by a range of factors excluding the vehicle itself and the event causing the acceleration event. For example, the driver behaviour, the weight of the vehicle and test route are all factors that affect the operation of the vehicle, and therefore, the vehicle acceleration and emissions. Emissions Analytics control for all of these factors by training their drivers to follow a particular driving profile, an equivalent weight is added to each test vehicle (including driver weight) and the same test route is maintained for all tests. Some factors such as the weather and congestion are more difficult to control for. Regarding the weather, Emissions Analytics have a strict policy of conducting testing only when there is no precipitation and no standing water on the road surface. To control for the varying levels of traffic, Emissions Analytics use two testing time-slots, which lie outside of the peak hours and are less susceptible to recurrent congestion. Furthermore, after the completion of each test, the average speed and time taken to complete each test segment is assessed. Test segments that do not meet the strict requirements are repeated to ensure each vehicle is exposed to similar levels of congestion.

Other factors that are more difficult to control for include the fuel that is used in the test vehicle and any modifications by the vehicle manufacturer. Before the vehicles are delivered for testing, they are fuelled by the vehicle manufacturer or by a third party. The vehicles are fuelled in accordance with the manufacturer’s recommendations. However, it can be expected that there are minor differences in the fuel blend between different suppliers and depending on the season. To take into consideration the specific fuel mix, samples would need to be laboratory tested. In addition, the fuel would need to be run through the vehicle for long enough for the vehicle’s engine control unit (ECU) to optimise the fuel delivery based on the specific fuel composition (Millo et al., 2015). This is beyond the scope of this research and the only consideration for fuel is whether the fuel type is petrol or diesel and whether it is a hybrid engine.

All the vehicles that are tested are supplied as equivalent to a vehicle that could be purchased by a typical consumer. Emissions Analytics carry out a detailed inspection prior to any testing to check for any manufacturer defects in the exhaust system. They also check whether the vehicle has been modified to improve the performance during the testing – e.g. disconnecting the alternator. Some modifications such as reprogramming the ECU or modifying the suspension settings for example, may not be picked up during their inspection. Whilst all efforts have been made by technicians to ensure the vehicle testing procedure is fair and representative, this is a potential error that may affect the quality of the data used in this study.

3.4.4. Limitations of dataset

The Emissions Analytics dataset contains trajectory and vehicle emissions data for multiple vehicles in the vicinity of urban roadway obstacles. There are however, some limitations with the dataset as discussed below.

Emissions Analytics technicians follow a prescribed driving style when operating the test vehicles and this is checked by reviewing the test segment timings and speeds. Whilst this means that the different vehicles are operated in a consistent manner, it is likely that there are certain driving behaviours prevalent in the general population of drivers that are not captured in the test. For example, extreme acceleration or deceleration events would be missing in the dataset. For this thesis, the focus is to assess whether existing modelling tools are representative of behaviours observed in the vicinity of urban obstacles, particularly the acceleration behaviour model. In an ideal case, it would be possible to validate all of the components of the model that describe the behaviour of a vehicle. However, this is beyond the scope of this thesis.

The Emissions Analytics data to be used in this thesis have all been collected in London, UK on a particular test route. The test route, while confidential, has been designed to include a mixture of different urban and extra-urban segments in order to capture the combination of roads a typical UK driver may encounter. Whilst there are differences in the mix of roads a driver may encounter in the UK and around the world, it would not be feasible to collect sufficient data from all these roads to accurately represent the behaviours. However, the methods and tools created to support this research activity could be applied globally with any trajectory and vehicle emissions dataset. The use of additional PEMS datasets is discussed as one of the further work opportunities in section 7.2.

Another limitation of using the Emissions Analytics dataset is that the data is collected using modern light duty passenger vehicles. Given that the aim of this research is to assess the suitability of existing modelling tools, it is justified that the focus is on light duty passenger vehicles that make up 83% of the UK fleet (Department for Transport, 2015d). The vehicles tested also all meet the Euro 5 or Euro 6 emissions standard, which currently represents 52.9% of the UK fleet and is projected to increase with time (Department for Transport, 2013). Data from heavy duty vehicles or vehicles that meet the older European Emissions standards would allow for an improved assessment of the existing vehicle and emissions modelling tools. However, this is beyond the scope of this thesis.

As mentioned previously, the vehicle trajectory data collected as part of the Emissions Analytics testing procedure is from a 1Hz GPS module. Whilst this data is adequate for general positioning and timing data, it is not suitable for calculating vehicle acceleration in the vicinity of urban obstacles when travelling at the speed limit, as highlighted in section 3.2.2.1. Given the second objective of this thesis is to assess the variability in acceleration behaviour in the vicinity of urban obstacles, better trajectory data is required. A trajectory monitoring platform that meets the requirements of this research is discussed in section 3.5.

3.4.5. Summary of PEMS dataset

This research requires vehicle trajectory and emissions data from multiple vehicles in the vicinity of urban roadway obstacles. Using a third party source for the data overcomes many of the difficulties in obtaining the test vehicles and a portable emissions measurement system. Emissions Analytics have access to a range of modern vehicles and have developed a robust testing procedure that could provide the data required for this research. Their existing test route includes a range of obstacles, which would be of interest when assessing the variability in acceleration behaviour and the resultant emissions in the vicinity of urban obstacles.

Despite the limitations of the dataset discussed in section 3.4.4, the dataset is suitable for meeting the research objectives of this thesis. The only exception is that the vehicle trajectory data is collected at 1Hz. However, the use of an additional monitoring system would solve this problem, as discussed in section 3.5.

3.5. Hermes development

As discussed in section 3.4, the Emissions Analytics dataset would be suitable for use in this research as it contains trajectory and vehicle emissions data in the vicinity of urban roadway obstacles. The key limitation of the data, as highlighted in section 3.4.4, is that the trajectory data are derived from a 1Hz GPS receiver. As explained in section 3.2 where the different vehicle based trajectory measurement solutions were reviewed, a solution based on a single GNSS receiver was found to be not suitable for this study.

This section discusses how this limitation has been addressed through the installation of an additional data collection platform. The justification, design, calibration and validation of the device are discussed in the following subsections. “Hermes” is the commercial name given to the monitoring platform that was developed as part of this research. The data from the device are also due to be published under this name alongside the emissions data in the UK and US.

3.5.1. Justification

Several devices that are capable of recording detailed vehicle trajectory information exist on the market. For example, an augmented system from iMAR that couples a GPS module with accelerometers and gyroscopes was discussed in section 3.2.2. The issue with using such a system as part of a regular testing programme is the complex mounting that is required and the need for an additional laptop to acquire and store the data.

Emissions Analytics have two PEMS units, both of which allow for a connection to the vehicle’s on-board diagnostic systems using the Closed Area Network (CAN) interface. The vehicle’s on-board diagnostic (OBD) system collects data from all of the sensors on the vehicle and uses this as an input into the vehicle’s safety systems, but also for monitoring the vehicle’s performance and adjusting comfort levels based on the user requirements. Given that the vehicles tested by Emissions Analytics are all modern vehicles, the vehicles are more than likely to have a GPS module along with accelerometers and gyroscopes. The information from the vehicle’s OBD is polled using PIDs (Parameter IDs). The most commonly used PIDs are found in the Society of Automotive Engineers standard J/1979. However, vehicle manufacturers define many other PIDs that are vehicle/manufacturer specific (SAE STANDARD, 2002). The PIDs required to obtain data from a vehicle's in-built GPS module, accelerometers and gyroscopes is currently not covered by the standard. In order to use the vehicle's on-board sensors for the trajectory data, the vehicle manufacturers would need to disclose the required PIDs. However, this is unlikely to happen as these are normally classified.

Considering the limitations of the existing third party devices for capturing a vehicle's trajectory and the constraints of Emissions Analytics' testing procedure, a series of requirements were defined, as explained in the following section.

3.5.2. Requirements

As outlined in section 3.2, there is a need to collect trajectory data from individual vehicles as they navigate urban obstacles. Considering the requirements of this research and those of Emissions Analytics, seven requirements for the trajectory monitoring platform are defined as shown in Table 3.1. The development of a device that meets the seven requirements would mean that data required for this research could be collected in partnership with Emissions Analytics.

	Requirement	**Description**
1	GNSS receiver and accelerometer	• GPS module should operate at 20Hz for timing, speed and positioning data • Dual axis accelerometer to measure lateral and longitudinal acceleration
2	Self contained monitoring platform	• Platform should contain the necessary hardware to acquire, process and store data from connected sensors • A laptop or external device should not be required during normal operation • Should be capable of being powered by batteries, no power connection to vehicle
3	Robust platform	• Hardware should be able to withstand knocks and drops expected during a typical test • Housing should be waterproof if it is to be installed on exterior of vehicle
4	No interference with existing setup	• Additional monitoring equipment should not interfere with safe operation of vehicle or any existing monitoring equipment, for example interference with other GPS antennas

		• No additional load should be placed on vehicle, i.e. connection to vehicle for power or increased drag due to large frontal surface area
5	In-vehicle monitoring	• The monitoring unit should contain the necessary hardware so that the data can be monitored in real-time mid-test • This should be a low energy wireless connection using a standard data transfer protocol without the requirement of specialist hardware or software
6	Straightforward setup procedure	• Installation and setup of the monitoring platform should be simple and require no specialist training • The monitoring platform should be rigidly connected to the vehicle without requiring any permanent modification of the vehicle
7	Integrate with existing processing systems	• The data file output from the monitoring platform must be easily integrated with existing Emissions Analytics data processing systems • The current system uses CSV (comma-separated value) files and the package R to process the data

Table 3.1 – requirements of Hermes monitoring platform

3.5.3. Design and build

This subsection details the design procedure of the high-resolution trajectory data collection platform, Hermes. As mentioned previously, the Hermes unit is being used as part of Emissions Analytics' regular testing procedure in London, UK and California, US. A wearable form of the monitoring platform that uses the same internals but in a different packaging has also been created and is in the early stages of testing in California.

3.5.3.1. Processing board

In order to meet the second requirement in Table 3.1, the sensor platform needs to be supported by an on-board processor to ensure it is a self-contained monitoring platform. The processor must be capable of acquiring, processing and storing the data from the sensors that are connected to it.

Very early on in the design stage, it was decided that the Arduino platform would be used to due to the open-source hardware and software. Prior experience with the Arduino platform and the multitude of open source libraries also helped support this decision (Arduino, 2015).

Initially the Arduino MEGA 2560 processing board with an ATmega2560 processor was selected for use in this monitoring platform. The main reason for selecting the MEGA was due to the 16MHz CPU speed and the 256KB of flash memory. The majority of the Arduino processing boards have only 16KB or 32KB of flash memory. This limits the complexity of the code and the size of the memory buffer. The MEGA also has 54 digital inputs, 16 analogue inputs, as well as 4 UARTs (hardware serial) ports. This is sufficient considering the sensors and output devices planned for this monitoring platform. The board can be powered either via the type B USB connector with a 5V power supply or via the DC-in connector with 7-12V. The board can be also used to power the auxiliary devices that are connected to it via 3.3V or 5V output pins.

Based on the specification of the MEGA 2560, the processing board was considered fit for use as part of the monitoring platform. Upon purchasing a MEGA and conducting some laboratory based testing, it was found that the board was unable to operate at the required 20Hz. The MEGA was programmed to loop through three dummy sensors to acquire, process and store data. In order for the platform to operate at 20Hz, each complete loop needed to be completed in under 0.05s. However, it was found that each loop was taking about 0.12s, resulting in data sampled at 8Hz.

The most computationally expensive part of the operation was the processing stage where the raw data was converted from either bit–values or raw numbers into meaningful data. Removing this stage from the processing loop resulted in a loop time of about 0.03s (33Hz). Whilst in most scenarios it would have been acceptable to simply acquire and store the raw data, and then post-process the data to get meaningful data – this would have conflicted with requirement 5, the ability to monitor the data in real time.

Given the key limitation of the MEGA2560 was the processor speed, the Arduino DUE which has the same physical footprint of the MEGA but a faster processor was selected. The DUE has an AT91SAM3X8E processor that operates at 84MHz, 5.25 times the speed of the MEGA, and double the flash memory at 512KB. The other key difference between the MEGA and the DUE is that the DUE has a board operating voltage of 3.3V rather than 5V. This means the input from all the auxiliary devices connect to the board must be 3.3V or a voltage level-shift is required.

When the full version of the test code with the data processing operation was uploaded to the DUE, the loop time was just under 0.03s, well within the 0.05s requirement to ensure the monitoring platform could output 20Hz data. With this in mind, the Arduino DUE was selected as the processing board for use in the data collection platform.

3.5.3.2. GNSS receiver

A GNSS receiver is required to receive timing, speed and positioning data as stated in Table 3.1 as requirement 1. The timing data are used to match the vehicle trajectory data collected with the trajectory monitoring platform with the other data collected during the Emissions Analytics tests, in particular the data from the SEMTECH unit. Collecting the speed and positioning data, is duplicating the function of the GPS module connected to the SEMTECH unit. However, it allows for the Hermes data to be interpreted independently. This is important because the different data resolutions between the Hermes and SEMTECH unit will mean that the data from one source will either have to be aggregated or interpolated to synchronise with the other. Depending on the technique used, averaging or interpolation errors may be introduced into the dataset, for example smoothing errors when the Hermes data is aggregated as discussed in section 5.2.1.

Given the need to install a GPS module in the high-resolution data collection platform, a device compatible with the Arduino DUE was sought. There were three hardware considerations: the connection to the DUE, operating frequency and GPS antenna. The DUE has four UART ports that support data transfer using the RS-232 standard and the board can output 3.3V. With this in mind, a GPS module with a serial interface and an operating voltage of 3.3V or less was sought. The GPS module also needs to have an operating frequency of at least 20Hz to ensure that there is a unique time, speed and position for every acceleration measurement (as explained in section 3.2.2.1). The final hardware consideration is that the GPS module allows an external antenna to be connected to it rather than having an in-built antenna. Whilst an external antenna increases the size of the packaging, it introduces more flexibility in the mounting location of the Hermes unit. Ideally, the GPS antenna would be placed on the roof of the vehicle or close to the windshield for optimal signal quality.

With the above hardware requirements, there were only a few GPS modules available that could be easily purchased in the UK and the US. The SparkFun Venus evaluation board, which is based on the Venus638FLPx chipset, was chosen due to its price and stock availability. The board meets the requirements set out above (SkyTraq Technology, 2011).

3.5.3.3. *Acceleration*

The acceleration of a body can either be measured directly using an accelerometer or can be derived based on speed or time and position. As discussed in depth in section 3.2.2.1, the acceleration that is derived from speed obtained via the GPS module is the acceleration in the direction of travel. Using one or more accelerometers allows for the acceleration to measured in a particular direction.

In order to characterise the acceleration behaviour of vehicles in the vicinity of urban obstacles, two accelerometers are required. One would be parallel to the vehicle's longitudinal axis, and the other perpendicular to it, parallel with the transversal axis. The longitudinal acceleration would be required when characterising a stop-line acceleration event. The lateral acceleration would be required when characterising the acceleration event associated with passing a roundabout or changing lanes due to the presence of an obstruction.

Accelerometers are typically available in three configurations: single-axis, dual-axis or triple-axis. Whilst two single-axis accelerometers could be used, given that the accelerometers would be perpendicular to each other, a dual or triple-axis accelerometer would be better suited to simplify the hardware design. The price difference is negligible between dual and triple-axis accelerometers; therefore a triple-axis accelerometer was sought. The acceleration in the vertical axis could be used to provide additional insight when there is a vertical deflection, for example when going over a speed hump.

A MMA7361 triple-axis accelerometer was selected and connected to the Arduino DUE. The accelerometer had a measurement range of either ±1.5g or ±6g depending on the configuration. The accelerometer requires an input of 3.3V and outputs three voltages corresponding to each of the measurement axes. For example, if the device was configured to ±1.5g, a reading of 0V equates to -1.5g, 1.65V equates to 0g and 3.3V equates to +1.5g. Using the analogue inputs on the DUE, the voltage can be read using the ADC (analogue-digital converter) and transformed into a measure of acceleration. During laboratory based testing, the MMA7361 was able to detect acceleration events, however it was very sensitive to noise on the input voltage. A deviation in the input voltage of just 0.05V would result in an error of 0.045g or 0.446m/s. Given that the typical range of accelerations expected from a vehicle would be less than ±5m/s, this is unacceptable.

Therefore, it was decided that a digital accelerometer, whilst considerably more expensive, would be better suited to this research. Especially given the focus is on understanding the variability in vehicle dynamics in the vicinity of urban obstacles.

The LSM9DS0 is an example of an IC (integrated circuit) that contains a triple-axis accelerometer that communicates digitally with the processing board, rather than using a series of voltage outputs. The LSM9DS0 was purchased on a breakout board created by SparkFun, and is able to output the data using the I^2C (Inter-Integrated Circuit) protocol or SPI (Serial Peripheral Interface) bus. The LSM9DS0 requires an input voltage of between 2.4V-3.6V and is able to operate at up to 400KHz, well in excess of the 20Hz requirement.

In addition to a triple axis accelerometer that can be programmed to a specified measurement range, the LSM9DS0 also contains a triple axis gyroscope and triple axis magnetometer. With nine degrees of freedom, the inertial measurement unit (IMU) is able to describe the behaviour of a vehicle in even greater detail. The gyroscope allows for the measurement of the angular rate of change, i.e. the rotation around a particular axis. This can be used to calculate the pitch, roll and yaw of the vehicle, which may help to support the interpretation of the acceleration data. The magnetometer allows for the measurement of the magnetic field in the three axes, and could be used to find the orientation of the IMU using the earth's magnetic field.

Furthermore, the LSM9DS0 features an embedded self-test feature to check the ranges of the various sensors, improving the confidence in the data that is obtained from the IMU. There is also an embedded temperature sensor that is able to correct the output of the sensors in real-time to account for any fluctuations in ambient temperature.

3.5.3.4. Data storage and output

In order for the data collection platform to meet requirement 2 in Table 1, the unit needs to be self-contained and therefore, not require an external device to record the data. Similarly, to meet requirement 5, the platform needs to contain the necessary hardware so that the data can be output in real-time for in-vehicle monitoring.

The on-board data storage requirement can be met through the use of a solid-state storage media, for example a micro SD (secure digital) card. The use of a removable storage media means that the card can be replaced very easily if required.

In order to support real-time monitoring of the high-resolution trajectory data, a wireless connection is required between the monitoring platform and the device being used to monitor the data. Whilst there are several wireless standards that could be used, Bluetooth was chosen due to its availability on most modern smartphones, tablet devices and laptops. Bluetooth typically has a range of 10m and is able to transmit data at up to 721Kbps; only about 3Kbps would be required for this application. A generic 3.3V Bluetooth module that could be connected to the DUE via the serial interface was selected. The module can be paired with any device that can receive serial data over Bluetooth.

3.5.3.5. Mounting and packaging

The mounting of the data collection platform is critical to ensure that the data collected are representative of the vehicle's behaviour. For example, if the monitoring unit was left on the rear seat, it is likely that the measured accelerations would be lower than what the vehicle was actually doing due to damping provided by the cushioning in the seat. In order to obtain representative measures of the vehicle's behaviour, in particular acceleration, the monitoring unit needs to be rigidly mounted to the vehicle's body.

There are several methods of rigidly mounting an accelerometer to the body of a vehicle and this is a well-established area of research. The three key mounting methods involve using either a stud, adhesive or a magnet (Dytran, 2007). The test vehicles that will be used in this research are loaned to Emissions Analytics on the principle that they are returned in the same condition that they arrived in. Using a stud connection between the monitoring unit and the vehicle would involve drilling a hole in the body of the vehicle which would simply not be feasible – despite it being the preferred method of connection due to the rigidity. Using an adhesive connection either directly to the monitoring unit or via an adhesive mounting pad, is another way of rigidly mounting an accelerometer. However, this method may result in permanent damage to the test vehicle. The final option is to use a flat magnet that can be attached to any ferrous component of the vehicle's body. The magnetic force needs to be greater than any external forces that would be applied to the monitoring unit. Where this is true, the monitoring unit is considered to be rigidly mounted.

Using magnets to rigidly attach the monitoring unit to the vehicle is the only option that results in no damage or permanent modification of the vehicle. However, the use of magnets generally limits the placement of the monitoring unit to the exterior of the vehicle, as there are very few ferrous components inside the vehicle that are exposed. Furthermore, it is preferable to have a consistent mounting location in every vehicle to ensure that the bias due to mounting location is either minimised or removed. In automotive racing, the seat rails are typically used to mount accelerometer and gyroscopes as they are rigidly connected to the vehicle's chassis. However, upon inspection of a few of Emissions Analytics' test vehicles, it was found that the seat rails are not exposed or accessible on all vehicles.

With this in mind, it was decided that the monitoring unit would be mounted on the exterior of the vehicle. Opportunities to mount the unit underneath the vehicle or on side of the vehicle were sought. However, the ground clearance between vehicles varied significantly and many of the vehicles had non-ferrous side panels. The bonnet was considered also. However, this was dismissed due to concerns about the monitoring unit being a distraction to the driver, but also due to the potential for high frequency noise from the engine bay. It was decided that mounting the monitoring unit on the roof of the vehicle would be best, and preferably in line with the 'c-pillar'. This is where the roof meets the rear windshield or boot lid, and is usually made from a ferrous material. Placing the monitoring unit closer to the front of the vehicle would be an issue with vehicles that have a sunroof or a panoramic glass roof.

Having specified the hardware requirements, the mounting type and preferred mounting location, the final step in the design process was to define the packaging. Given the monitoring unit was to be mounted on the roof and potentially exposed to the rain, a waterproof housing was required. An ABS plastic box with an ingress protection (IP) rating of IP65 was selected. The box also had four mounting holes on the exterior that the magnets could be attached to and several mounting points on the inside for connecting the various components to.

3.5.3.6. Processing code

The Arduino development platform is composed of open source hardware and software. The Arduino DUE can be programmed through the Arduino IDE (Integrated Development Environment), which is based on C++. The IDE is used to write, compile and upload the 'sketch' to the hardware (Arduino, 2015).

The full code written to acquire the data from the various sensors and output the processed data to the SD card and to a monitoring device connected via Bluetooth is contained in Appendix C. In order to outline the general structure of the code and the key processes, a pseudo version of the code is presented below.

<u>Hermes pseudo code</u>

1. Initialise serial interfaces and set baud rate for the USB programming port, GPS module and Bluetooth module
2. Initialise IMU, define data acquisition rate and ranges for the accelerometers, gyroscopes and magnetometers
3. Check SD card is accessible and create new text file for data to be written to
4. Set starting loop time to current time
5. Clear temporary string that GPS data will be written to
6. If GPS messages are available, process messages to extract required data and store it in the temporary GPS data string
7. Clear temporary string that IMU data will be written to
8. Acquire the data from the accelerometer, convert the raw values into g-forces and store it in the temporary IMU data string
9. Acquire the data from the gyroscopes, convert the raw values into angular velocities and store it in the temporary IMU data string
10. Acquire the data from the magnetometers, convert the raw values into gauss and store it in the temporary IMU data string – later removed due to interference from magnetic mounts
11. Open the file created in step 3, write data from temporary GPS data string and temporary IMU data string, close file
12. Set loop end time to current time
13. Acquire data from the GPS module and encode
14. If the difference between the loop end time and the loop start time is greater than 0.049 seconds (20Hz), return to step 4. If the difference is less than 0.049 seconds, return to step 13.

3.5.3.7. Final Hermes design

Having described the design choices and chosen hardware in the previous sub-sections, this section outlines the final design and configuration of the Hermes box. References are also made to the requirements presented in section 3.5.2.

The Arduino platform was chosen for the Hermes monitoring unit due to the open-source nature of the hardware and software. The Arduino DUE processing board was selected, as it was the only board that had the range of inputs required for this application, whilst also having the processing power needed to output data at 20Hz. The SparkFun Venus evaluation board, which contains the Venus638FLP GPS module, was chosen to meet the timing and positioning requirements. The evaluation board was configured to operate at 20Hz and the following data are recorded: UTC time, latitude, longitude, ground speed, course angle and altitude. The LSM9DS0 IMU breakout board was selected for the acceleration measurement due to the triple-axis accelerometer and was set to acquire data at 20Hz (ST Microelectronics, 2013). The accelerometers were configured to a measurement range of +/- 2g, 0.061mg/LSB (translates to +/- 19.62m/s^2, 5.98x10^{-4} m/s^2). The gyroscopes were configured to a measurement range of +/- 245dps, 8.75mdps/digit. The magnetometer was disabled due to interference between the senor and magnetic mounts.

In addition to the GPS module and IMU, a SD card breakout board and Bluetooth module were connected to the Arduino DUE. The SD card breakout board interfaces with a removable micro SD that is used to store the processed data in the CSV file format. The Bluetooth module is configured to output the processed data in real time as serial data stream.

All of the hardware is packaged in a waterproof plastic component box that is magnetically mounted on the roof of the vehicle. There is sufficient room in the component box to install a battery pack to power the Hermes unit. However, in order avoid having to charge an additional battery after each vehicle test, Emissions Analytics requested that the unit was powered by a 5V 1A feed from one of their batteries in the vehicle. Figure 3.3 shows the final design of the Hermes monitoring unit with all of the key components labelled.

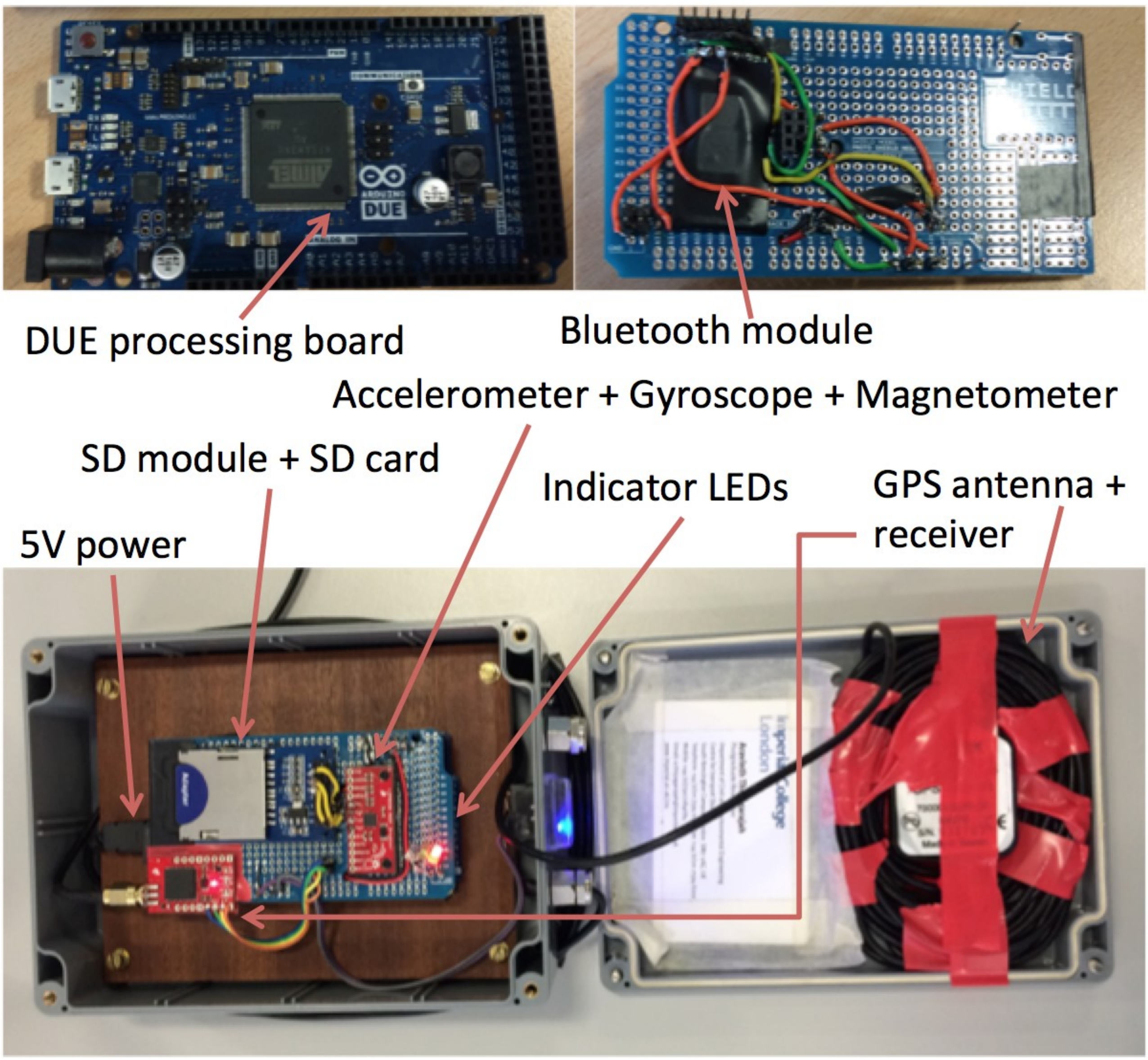


Figure 3.3 – diagram to show final Hermes monitoring platform

3.5.4. Setup calibration and error corrections

In order to ensure the accuracy of data output from the Hermes platform there are a series of steps undertaken at the start of each vehicle test and in the data post-processing routine. Section 3.5.4.1 explains the setup calibration procedure employed to ensure that the Hermes monitoring platform is correctly aligned with the vehicle's coordinate axis. Section 3.5.4.2 explains how errors in the data, particularly noise were mitigated.

3.5.4.1. Setup calibration

The Emissions Analytics technicians are instructed to place the Hermes unit on the roof of the test vehicle inline with the c-pillar, where the roof meets the boot lit or rear windscreen. The unit is placed in the centre of the roof or as close to the centre if the is an obstruction, for example a radio antenna, and the magnetic feet are aligned with the lip of the roof. Whilst efforts are made to ensure the unit is horizontal and aligned with the vehicle's longitudinal axis, there is an opportunity for misalignment that needs to be corrected for.

When the monitoring unit is horizontal and at rest, the only acceleration that should be measured is gravity in the Z-axis. Accelerations in the longitudinal (Y-axis) and lateral (X-axis), as shown in Figure 3.4, should be zero unless the unit is misaligned. The misalignment in the horizontal plane is a combination of the slope on the ground, slope on the vehicle's roof and any slope in the Hermes unit itself. The slope on the roof and Hermes unit remains constant during the test. However, the slope of the ground changes throughout the test. Therefore, by measuring the gradient of the ground using an inclinometer at the start of each test and noting the initial acceleration values whilst the vehicle is at rest, the data can be corrected. The Hermes data is corrected using a transformation matrix as part of the post processing routine. This is the standard method for correcting accelerometer data as presented in Botero et al. (2014).

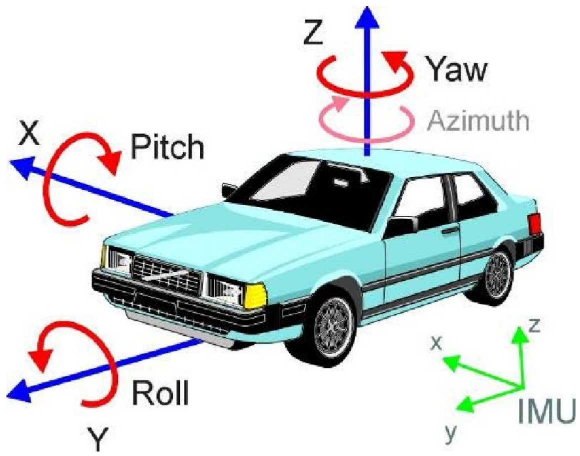


Figure 3.4 – vehicle coordinate system used throughout this study (iMar Navigation, 2012)

Once the above transformation has been made, the X-Y plane is horizontal and Z-plane, which is perpendicular to the horizontal, is aligned with the vertical plane. However, the Y-axis of the Hermes unit may not be aligned with the Y-axis of the vehicle, i.e. there is a small rotation around the Z-axis. Whilst the magnetic feet of the Hermes box are aligned with the lip of the roof, a misalignment between the Y-axis of the Hermes unit and vehicle is typically around 5 degrees. Assuming a maximum longitudinal acceleration of 5m/s^2 and a misalignment of 10 degrees, the error in the measured acceleration would be up to 0.065m/s^2 or 1.5%. This is a relatively small error, however, it can easily be corrected for in a post processing routine.

When the vehicle is travelling in a straight line on level ground, the acceleration in the X-axis should be zero and the rotation around the Z-axis (yaw) will also be zero. By using the data to find where the yaw is zero (typically on the motorway segments of the test route), the vehicle can be said to be travelling in a straight line. The X-Y horizontal plane is then rotated around the Z-axis using a transformation matrix so that the acceleration in the X-axis is zero.

By applying the two calibration steps discussed above, the X-Y measurement plane is horizontal and the Y-axis of the measurement unit is aligned with the longitudinal axis of the vehicle. Given that the X and Z axes are perpendicular to the Y axis, they are also therefore aligned with the vehicle's lateral and vertical axes.

3.5.4.2. Error corrections

With an inertial measurement platform there are three main error sources that need to be considered and corrected for: aging, drift and noise (Groves, 2013). These three errors are discussed in turn with reference to how they have been addressed in this particular application.

<u>Aging</u>

Aging of a MEMS device is where changes in temperature, humidity, pressure or other stresses on device can result in sub-optimal performance of the device. For example, the measurement range maybe reduced or biased. The LSM9DS0 IMU used in the Hermes monitoring unit features a self-test mode that is initiated during the sensor initialisation process at the start of each test (as mentioned in section 3.5.3.6.). The self-test mode is able to check the ranges of the sensors by applying a known electrostatic test force (ST Microelectronics, 2013). If the magnitude of the error exceeds 0.1%, the IMU will send an error message to the DUE that will be logged in the data file. The on-board temperature sensor is used to apply a temperature correction prior to any data being output using a factory defined response curve. This ensures the accuracy of the sensor platform between -40 to +80°C.

<u>Drift</u>

Drift mainly affects the gyroscopes in the IMU and is where for example, the device is rotated through 360 degrees but the final bearing based on the measured data is not the same as the initial bearing. Drift is a low frequency error and can be corrected for using GPS data or another reference device and a Kalman Filter (Abdel-Hafez, 2012).

In this thesis, the data from the gyroscopes is only used to determine when there is a rotation around a particular coordinate axis; the absolute values from the gyroscope are not used. The drift correction cannot be applied in real-time due to the additional processing requirements that cannot be met by the Arduino's processor. Given that the absolute values from the gyroscope are not used in this thesis, it is justified that that a drift correction is not applied. The GPS data including the bearing angle are recorded should the drift correction need to applied offline.

Noise

Noise is another error source that can affect the data obtained from the Hermes measurement platform. The noise in the data is from a combination of measurement noise generated by the IMU itself and noise in the domain that is being measured, for example high frequency noise from the engine bay or tyres. There are several methods of reducing noise from IMU data with differing levels of complexity. The noise obtained from accelerometers and gyroscopes at measurement frequencies used in this study (20Hz) is approximately white (Groves, 2013). Therefore a Kalman Filter, low pass filter or a moving average filter could be used as demonstrated by Kim et al. (2012). Kim et al. (2012) show that with a single device similar to the IMU used in this study, the accumulated error was of the same order of magnitude when a moving average filter or Kalman filter were used. Figure 3.5 shows the implementation of a 10-point moving average to filter the noise as recommended by the IMU manufacturer (Sparkfun, 2014) due to the low computational complexity whilst still being effective. The plots on the left of Figure 3.5 show the raw gyroscope data (black) and the plots on the right show the data after the implementation of the filter (red). It can be seen that the noise in the dataset has been reduced, most visible on the plots of the gyroscope data in the Z-axis. The noise has been reduced from an average magnitude of >50dps to <10dps and from >0.5m/s^2 to <0.1m/s^2 for the gyroscopes and accelerometers respectively. The disadvantage of using any averaging technique to reduce noise from data is that peak events may be smoothed out. However, this does not appear to be the case in this scenario as confirmed by the subsequent validation tests (section 3.5.5).

After performing the setup calibration steps discussed in section 3.5.4.1 and the error corrections discussed in this section, the data from the Hermes monitoring unit can be used to collect vehicle trajectory data in the vicinity of urban obstacles. Section 3.5.5 explains the validation of the Hermes unit with a high-grade inertial navigation system.

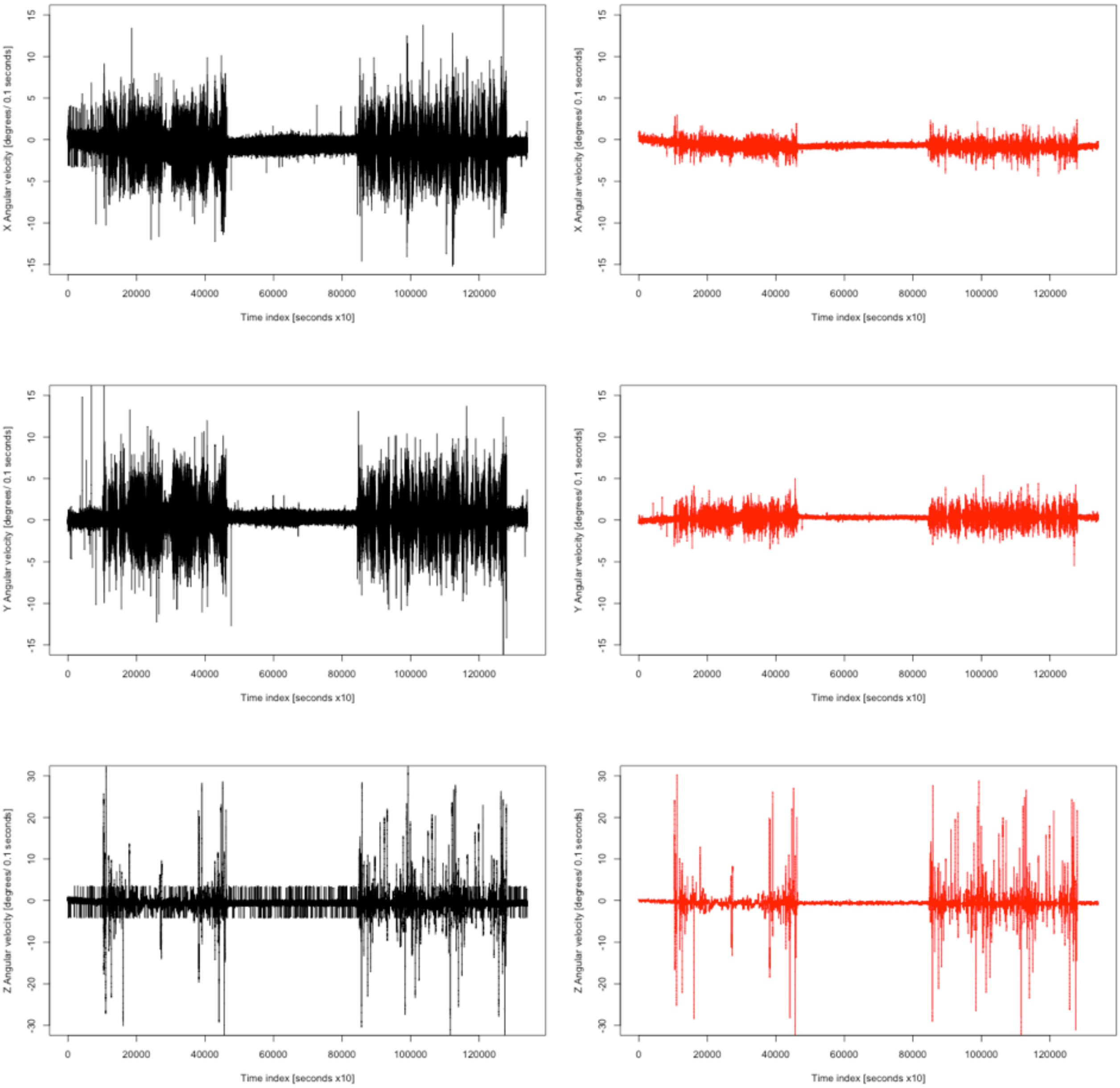


Figure 3.5 – the effect of the moving average filter on the gyroscope data to remove noise

3.5.5. Validation

In order to assess the performance of the Hermes monitoring unit several validation tests were conducted with an integrated GNSS/INS system. This is essential to ensure the measurement regime is fit for purpose. The validation tests were initially conducted using an Imperial test vehicle before partnering with Emissions Analytics to conduct tests on vehicles fitted with PEMS equipment. The subsections below explain a typical validation test that was conducted on 1st July 2014.

3.5.5.1. *Validation test setup*

To validate the performance of the Hermes monitoring unit, more specifically the outputs from the GPS module, accelerometers and gyroscope, a back-to-back comparison was conducted with an integrated GNSS/INS system. As explained in section 3.2.2.2, this is the benchmark for obtaining positioning and navigation information for a moving body, as an IMU, GNSS receiver and inertial navigation equations are combined into a single measurement platform. An iMar iTraceRT-F200 was used as the reference device to assess the performance of the Hermes monitoring unit.

A 2014 Volkswagen Passat was used for the validation test with the SEMTECH-DS PEMS unit. The technicians treated the validation test as a normal emissions test and therefore the standard test procedures outlined in section 3.4.1 were followed. The only difference was that the iMar and Hermes monitoring units were installed on the roof of the test vehicle with magnetic mounts (Figure 3.6) and that an additional laptop was placed in the vehicle to record data from the iMar.

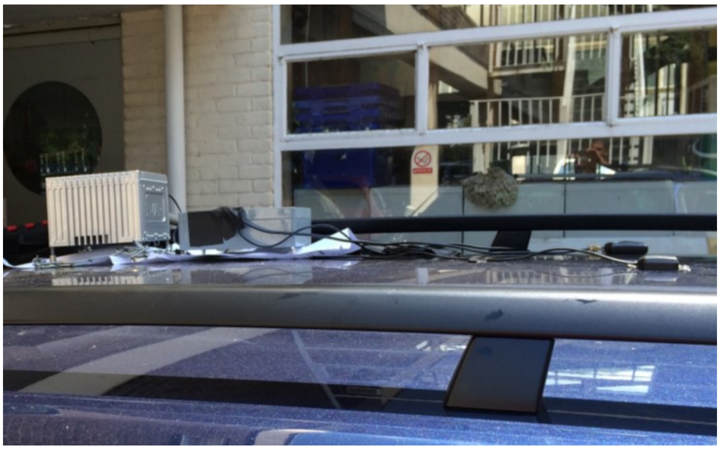


Figure 3.6 – the Hermes trajectory monitoring unit and reference iMar INS installed on the roof of a test vehicle

The iMar was configured to record the raw GPS, accelerometer and gyroscope data to the test laptop using the NovAtel Connect software package. The data from the sensors in the Hermes unit was stored locally to the on-board solid-state storage as explained in section 3.5.3.4. The full London test route as described in section 3.4.1.4 was completed and the data was analysed as explained in the following section.

3.5.5.2. *Validation methodology and results*

The data collected by the Hermes monitoring unit comes from two sources, the GPS receiver and the inertial measurement unit (IMU) – each of these data sources needs to be validated in turn. To assess whether the data obtained from each measurement device is indeed the same, the Student's t-test is used. The statistical test compares the population means of two related samples, μ_1 and μ_2, to assess whether they are drawn from the same population.

$$H_0: \mu_1 = \mu_2$$

$$H_1: \mu_1 \neq \mu_2$$

If the p-value obtained from the test is <0.05, the null hypothesis that there is no significant difference in the population means must be rejected.

GPS data

There are several parameters obtained through the GPS receiver including timing, positioning and speed data. The positioning and speed data are critical for this thesis, especially when the Hermes data is used independently of the SEMTECH data that also contains positioning and speed data.

In order to validate the positioning data, the latitude and longitude measurements obtained from both devices could be compared. The positioning data from the iMar has a precision of up to 0.02m and is output at 200Hz (iMar Navigation, 2012). The positioning data from the GPS module in the Hermes platform has a precision of up to 1m and is output at 20Hz (SkyTraq Technology, 2011). Whilst it would be possible to directly compare the latitude and longitude measurements, rounding the iMar data to a 1m precision and attempting to adjust the data resolution would result in additional errors. A more appropriate method would be to use the accuracy measure Positional Dilution of Precision (PDOP). The PDOP is the combined positioning error in the horizontal and vertical components, the lower the PDOP the better the positioning estimate (Langley, 1999). Table 3.3 shows the average PDOP obtained from both devices during the validation testing. A PDOP value of less than 4 is considered to be excellent and sufficiently accurate for all applications apart from those that a safety critical (Zogg, 2002).

Test segment	iMar Mean PDOP	Hermes Mean PDOP
Full test cycle	2.1	2.2
Urban segments	2.5	2.9

Table 3.2 – PDOP values obtained from the iMar and Hermes units during validation testing

The PDOP is influenced by both the positioning of the satellites relative to the GPS receiver and the visibility of the satellites. For example, trees and tall buildings limit the receiver's 'open-sky view' and thus result in a higher PDOP value. As the GPS and IMU data are tightly coupled by the iMar, the PDOP is lower for both the full test cycle and urban segments when compared to the

Hermes PDOP. On the urban segments of the test route, which will be the focus in this study, there are more obstructions that negatively impact the PDOP compared with the motorway environment. However, the mean PDOP is still less than 4 meaning the positioning data obtained from the Hermes GPS module can be used with confidence.

The speed data that is obtained from the GPS receiver, also commonly referred to as speed over ground, is calculated using the Doppler shift in the pseudo-range signals obtained from the satellites. Whilst some GPS modules are able to output or calculate a dilution of precision metric for speed (Chalko, 2009), the GPS modules in this study do not support this. In light of this, the speed data from the iMar was averaged over a 0.05s to match that of the Hermes unit and the t-test was conducted. A p-value of 0.971 was obtained; meaning the null hypothesis the means are drawn from the same distribution must be accepted. This result was expected as the error associated with speed over ground measurements is typically 0.1-0.2m/s (Witte and Wilson, 2004). The difference in average speed over the test cycle was also calculated to be 0.17m/s, equivalent to a difference of 1.76%. Given the results of the statistical test and minimal difference in average speed, it can be said that the Hermes is able to produce similarly accurate estimates of vehicle speed when compared to a reference system such as the iMar.

<u>IMU data</u>

The tri-axial accelerometer and tri-axial gyroscope found on the LSM9DS0 IMU is delivered calibrated from the factory. However, the accuracy of a low cost MEMS (micro-electro-mechanical system) compared to that of the higher-grade sensors found in the iMar is significantly lower (iMar Navigation, 2012). In order to compare the data from the two devices, the coordinate system of both devices was translated to a common origin using the software package Inertial Explorer. The accelerometer and gyroscope data was then output at 20Hz for comparison. The p-values obtained from the t-test were 0.022, 0.047 and 0.039 for the accelerometer data in the X, Y and Z directions respectively. The p-values obtained from the t-test were 0.034, 0.027 and 0.032 for the gyroscope data in the X, Y and Z directions respectively. As the p-values obtained from the t-test are less than the significance level of 0.05, the null hypothesis that the data is drawn from the same population must be rejected. The data is said to be drawn from different distributions.

The result that the IMU data obtained from the Hermes platform and iMar are drawn from different distributions is expected. The Hermes unit uses a low cost MEMS IMU (<£100), where as the iMar uses a high grade accelerometer with a fibre-optic gyroscope and is significantly more expensive (>£50,000). Using the Hermes data for navigation purposes would be inappropriate, as the positioning error would be of the order of 20-30% as found in studies using similar devices (Goodall et al., 2013). However, the use of MEMS accelerometers for measuring accelerations or vibrations is common in the literature, for example Spelta et al. (2010), Sun et al. (2013) and Lee (2013). Similarly, the use of MEMS gyroscopes for measuring pitch, roll and yaw is common, for example Kawahara (2008) and Reze and Osajda (2013).

The motivation for developing the Hermes platform was to be able to collect trajectory data, specifically acceleration data, from a moving body at 20Hz. The accuracy of the accelerometers can be assessed through calculation of the difference in the magnitude of acceleration from both devices. Over the full test cycle, the maximum error was $0.233m/s^2$ and the mean error was $0.09m/s^2$. Given typical stop-line accelerations of about $3m/s^2$ (Hu et al., 2014), this is equivalent to a 3% error. By way of comparison, the error associated with the acceleration based on the 20Hz speed measurement obtained from the GPS receiver can be calculated. It was found that the mean error was $0.834m/s^2$, equivalent to a 27.8% error, considerably high than the direct measurement of acceleration.

Whilst the results of the statistical test do not show the data obtained from the Hermes IMU is drawn from the same population as the iMar data, the prior use for MEMS based sensors in similar vehicle applications justifies the use of the Hermes unit. Furthermore, this is a considerable improvement over using a GPS based acceleration value, even when the data is collected at 20Hz.

Considering the results from the validation tests, the Hermes monitoring unit is suitable for the intended use of collecting trajectory data in the vicinity of urban obstacles. Section 3.6 summarises the data collection platform that will be used for this study.

3.6. Data collection procedure

Individual vehicle trajectory and emissions data in the vicinity of urban obstacles is required to support this research and the analysis in subsequent chapters. The emissions data will be obtained using a portable emissions monitoring system (PEMS) that will be installed onto test vehicles by Emissions Analytics. The high resolution trajectory data will be collected using the in-house develop Hermes monitoring unit that will also be installed by the Emissions Analytics technicians. Section 3.6.1 explains the data pre-processing routine and final data outputs from both measurement devices.

3.6.1. Data pre-processing and output

<u>PEMS data</u>

After the completion of a vehicle test, the data from the PEMS unit is initially run through the SENSOR Tech-PC post-processing software that checks for any errors in the data, time aligns the data from the various sensors and finally outputs a CSV file. Before the data can be used to support analysis in this study, there are several further processing steps that need to carried out as explained below:

1. Filename renaming – due to the use of two different PEMS units and differences in the versions of the SENSOR Tech-PC post-processing software, the data files are named in an inconsistent manner. A simple AppleScript is used to standardise the filenames by removing unusual characters and spaces, and also to append a unique vehicle identifier.
2. Restructuring data file – the structure of the data file output by the SENSOR Tech-PC post-processing software varies depending on the PEMS unit that was used as the range of pollutants that can be monitored differs, this changes the number of columns in a data file. In addition, the ordering of these columns also varies depending on the software version used and the sequence that certain sensors are connected to the PEMS unit. To create a consistent file structure for the subsequent analysis a Python script was written. The script scans the header information, identifies the location of the required columns from a pre-defined list and then copies these columns into a new file in a specified order.
3. Metadata matching – additional data about the test vehicles and the test itself were provided by Emissions Analytics in a separate CSV file. In order to use this data in the subsequent analysis, it needed to be matched to the data file containing the PEMS data.

This was implemented using an R script that uses the vehicle registration mark and test date to match the metadata to the corresponding PEMS data file and append the data. Due to errors in recording the vehicle registration mark, this step could not be fully automated.

Having completed the above processing steps, the resultant data file contains the required outputs from the PEMS unit with the metadata in a consistent file structure. This data file is then imported into R to carryout the analysis described in Chapters 4 and 5.

<u>Hermes data</u>

Upon completion of a vehicle test, the Hermes data file is downloaded from the unit before being renamed with the vehicle registration mark. The data file is then input into an R script where the following actions are performed:

1. File check – the structure of the file is checked to see if the timing, positioning, acceleration and gyroscope data are present for the duration of the test – an error message is written into the filename on instances where this check fails.
2. File renaming – the file is renamed using the date obtained from the GPS output to help with identifying the file.
3. Setup calibration – the setup calibration procedure explained in section 3.5.4.1 is executed. This involves the correction of the misalignment of the horizontal plane and the rotation of the horizontal plane to correspond with the vehicle's coordinate axis.
4. Error corrections – the error corrections explained in section 3.5.4.2 are carried out to reduce noise errors.
5. Metadata matching – similar to the processing of the PEMS data file, the vehicle registration mark and test date are used to match the metadata to the corresponding Hermes file.

After completion of the above processing steps, the Hermes data file can be used to assess the variability in vehicle dynamics in the vicinity of urban obstacles as shown in Chapter 4.

This section has presented the data collection platform that will be used to collect the data required to support this research and data pre-processing steps required. For each vehicle test, there will be two CSV files, one containing the PEMS data and one containing the Hermes data. These two data files could be matched and this is discussed further in Chapter 5.

3.7. Conclusions

In this chapter the different methods of collecting real-world vehicle trajectory and emissions data were identified and assessed. It was determined that a solution where GPS data are augmented would be required for collecting trajectory data needed to support this research. It was also concluded that the use of a portable emissions monitoring system would be the most appropriate solution to collecting the data required for this study.

Having considered the feasibility of collecting these data independently, the suitability of the Emissions Analytics data and testing procedure was evaluated. Emissions Analytics were able to provide robust real-world emissions data, however the 1Hz trajectory data was not suitable for studying vehicle accelerations. A device capable of measuring vehicle dynamics in the vicinity of urban obstacles, Hermes, was designed, built and tested.

With a monitoring platform composed of the Emissions Analytics portable emissions monitoring system and Hermes unit, the data required for this research can be collected. Therefore, this chapter meets the first objective of this research activity, which was to ‘develop and validate a robust device for capturing vehicle dynamics that complements existing methods of measuring vehicle tailpipe emissions’.

The data collected using the monitoring platform described in this chapter can be used to support the analysis on the variability in the vehicle acceleration and tailpipe emissions that is presented in Chapters 4 and 5 respectively.

4. Understanding the variability in vehicle dynamics at urban obstacles

In Chapter 3, the use of a portable emissions monitoring system (PEMS) was explained to be the most appropriate method for collecting real-world tailpipe emissions data whilst vehicles are in the vicinity of urban obstacles. The vehicle dynamics data could be obtained from the PEMS unit using the connected GPS receiver. However, it was explained that this would not be of sufficient resolution to meet the objectives of this research. Therefore, the Hermes trajectory monitoring platform was developed to collect the required data. The Hermes dataset is used in this chapter to understand the differences in acceleration behaviour in the vicinity of urban obstacles. This addresses the second research objective:

Identify urban obstacles and then assess how the acceleration behaviour varies at different obstacles and between different vehicles

This chapter begins by presenting a methodology for identifying urban obstacles and obstructed trajectories using a speed based technique. The characteristics of the obstacles identified are then described by reference to a digital map. In order to understand the variability in acceleration behaviour between different obstacles, the behaviour at each obstacle is described using vehicle activity and operating mode. To understand the variability between different vehicles, a regression model is used with vehicle characteristics as the explanatory variables. With an improved understanding of the variability, ways of categorising vehicles and obstacles based on acceleration behaviour are presented. These grouping structures are used to support the subsequent modelling in Chapter 6.

4.1. Overview

As discussed in Chapter 2, in this thesis, an obstacle is considered to be any object or event that causes a vehicle to change its speed in order to continue on its desired trajectory. An obstacle may therefore, take the form of traffic management infrastructure such as a traffic signal, or a physical obstruction such as a double-parked vehicle or debris on the carriageway. Encountering an obstacle results in an obstructed trajectory.

For the purpose of this research, an obstructed trajectory is defined as where a deviation from the desired speed has been observed. This deviation in speed results in one or more acceleration events, where a positive acceleration event is an acceleration $>0.1m/s^2$ and a negative acceleration (deceleration) event is an acceleration $<-0.1m/s^2$, as defined by Frey et al. (2003). A vehicle increasing its speed to catch a green traffic signal is an example of an obstacle resulting in a vehicle deviating from its desired speed and accelerating. A vehicle reducing its speed to navigate a vertical deflection (e.g. speed hump) is an example of where an obstacle results in a vehicle deviating from its desired speed and decelerating.

It section 2.1.4 it was explained that whilst in operation, a vehicle can be categorised into one of four mutually exclusive operating modes: acceleration, deceleration, idle and cruise. Frey et al. (2003) explain that when a vehicle is in an operating mode where the power demand is higher, such as acceleration, tailpipe emissions are also expected to be higher. The acceleration behaviour has also been shown to be the most important factor in explaining the variance in fuel consumption and emissions (Watson, 1995). Therefore, it is important that the positive acceleration events in the vicinity of urban obstacles are better understood for a better representation of the real-world behaviours in existing traffic models.

The analysis in this chapter uses data collected using the Hermes data collection platform described in section 3.5. During the data collection exercise, it was not always possible to attach the monitoring unit along the vehicle's central axis due to the presence of antennas and other fittings on the vehicle. Not placing the unit on the vehicle's longitudinal axis affects the magnitude of the lateral acceleration. This is because the lateral accelerations differ if they are measured along the centre of the vehicle or on the edge of the roof. Due to a lack of information about the exact placement of the Hermes unit in relation to the vehicle's central axis, the focus will be on the longitudinal accelerations. Furthermore, for this thesis, the longitudinal accelerations are more important given this is the primary direction of travel. This incorrect placement does not affect the longitudinal acceleration as the pitch is considered to be negligible as demonstrated by Ryu and Gerdes (2004).

The following section explains how obstacles that resulted in obstructed trajectories were identified in the Hermes data to support the subsequent analysis.

4.2. Identification of urban obstacles

Chapter 3 explained that Emissions Analytics would collect the data required to support this research as part of their routine testing. Section 3.6 discusses how the Emissions Analytics test setup was modified to include the Hermes data collection platform in order to obtain high-resolution vehicle trajectory data.

The Emissions Analytics test cycle is typically 2.5 hours long and is composed of multiple urban and motorway segments. In this thesis, the focus is on urban areas as this is where roadway obstacles are more common. Urban areas are also where humans have greater exposure to the harmful pollutants associated with road transport due to the close proximity to the emissions source (World Health Organisation, 2011).

The following sub-sections explain how a representative urban test cycle was selected from the Emissions Analytics test route. Two methods of identifying obstacles in the road network are detailed before obstacles are identified for investigation in this thesis.

4.2.1. Urban test cycle

The Emissions Analytics test cycle is composed of multiple test segments that may be completed multiple times and not necessarily in the same order. Therefore, in order to make fair comparisons between the different vehicle tests, the same urban test cycle needs to be extracted using GPS based positioning information. The main criteria for selecting the urban test cycle are the presence of a variety of potential urban obstacles that every test vehicle navigates at least once.

From reviewing the test cycle with Emissions Analytics technicians, a 10km urban cycle[1] common to two of the three urban test segments with hot emissions was identified. The urban cycle contains a mix of urban roads, from quiet residential streets to a busy high street. The cycle also contains an array of urban obstacles including signalised junctions, roundabouts, pedestrian crossings, bus stops, speed humps and other traffic calming measures.

---

[1] Due to a confidentially agreement between Emissions Analytics and Imperial College London, the disclosure of the test cycle is not permitted.

The simplest method of extracting this urban cycle from the dataset would be to first define the coordinates of a bounding box that covers the full urban cycle. Using the GPS data, each vehicle trajectory file could be processed to filter out any data points that do not fall in the bounding box, leaving only the data points on the test cycle. The limitation of this method is that it does not discriminate between incomplete and complete runs of the test cycle. It also does not consider whether the test cycle is completed multiple times. Furthermore, this method assumes the vehicle did not use alternative roads that fall into the bounding box.

A more accurate, but more computationally expensive method is to define the start and end coordinates of the test cycle and extract a continuous trajectory. This ensures that only complete runs of the cycle are extracted and also allows for multiple runs of the cycle to be separated. The extracted trajectory is then checked to see if a series of defined waypoints are crossed. This ensures the vehicle did not deviate from the defined route. This method of extracting the urban test cycle, as shown in Figure 4.1, was implemented using an R script. The test cycle has not been overlaid on a map due to a non-disclosure agreement with Emissions Analytics

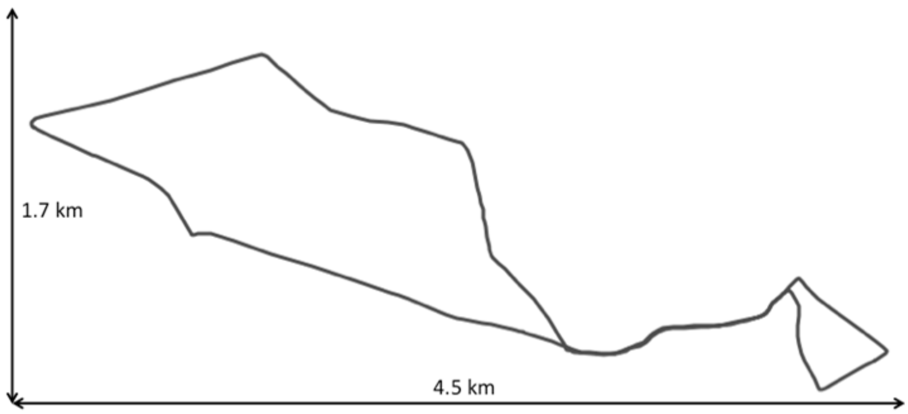


Figure 4.1 – the urban test cycle extracted from the Emissions Analytics test route

With data for multiple vehicles following the same urban test route, comparisons of the acceleration behaviour at different urban obstacles can be made. There are two methods of identifying an obstacle in the trajectory data. The first is to define the physical location of the obstacle, and the second is to use the deviation from desired speed. Both methods are discussed in sections 4.2.2 and 4.2.3 respectively.

4.2.2. Position based obstacle identification

The position based obstacle identification method involves defining the geographical coordinates of obstacles on the urban test cycle using a digital map. The latitude and longitude data contained within the trajectory file for each run can then be used to select the rows of data that correspond to a particular obstacle. The extracted rows of data can then be used to conduct the analysis on acceleration behaviour associated with a particular obstacle.

There are two limitations with this method. The first is that the assumption that the defined obstacle results in an obstructed trajectory. For example, a pedestrian crossing is an obstacle on the road network that could result in a vehicle slowing down or coming to a complete stop when a pedestrian is present. However, if the pedestrian crossing is not utilised due to a lack of pedestrians, it will not result in an obstructed trajectory. The second limitation is the assumption that the obstruction and obstructed trajectory occur in the same physical space. Using the same example of the pedestrian crossing, if there is good visibility and sufficient road space, a vehicle may slow down or stop several metres upstream of the crossing. Therefore, using this method could result in missing certain obstructed trajectories as they occur away from the physical obstruction.

Considering these limitations, an alternative method of finding obstacles that does not rely on definition of the physical location of the obstacle is proposed, as explained in section 4.2.3.

4.2.3. Speed based obstacle identification

The urban test cycle defined in section 4.2.1 has vehicles starting and finishing at the same point in the network and travelling on the same route. Therefore, if there is an obstacle 100m into the test route, all vehicles encounter this same obstacle once they have travelled 100m. The time into the cycle at which vehicles encounter the obstacle is different due to differences in vehicle speed.

The test route can be split into multiple segments of a pre-defined length where the data that fall into each into each segment are for a particular section of the test route. When there is an obstructed trajectory, by definition, there is a deviation from the desired speed – i.e. an acceleration or deceleration event. An acceleration event is where the vehicle speed for the current time interval is greater than the speed of the previous time interval. A deceleration event is where the reverse is true.

By calculating the number of acceleration and deceleration events in each segment of the test route, across the fleet of vehicles to be studied, it is possible to determine locations in the network where obstructed trajectories are most common. These locations can then be related back to physical obstacles on the road network. This is achieved using the coordinates of the segment and a digital map, or through notes made during the test, for example a broken down vehicle on the test route.

This method addresses the two limitations of the position based obstacle identification method outlined in section 4.2.2. The assumption that an obstacle results in an obstructed trajectory is not made. It is also not assumed that an obstruction results in an obstructed trajectory in the same physical space. This method also allows for the identification of obstacles that may not always be present in the network, for example, a double-parked vehicle or debris on the carriageway. Using this obstacle identification technique will provide the data required to support the second research objective of this thesis, which is to be able to understand the variation in acceleration behaviour in the vicinity of urban obstacles.

4.2.4. Implementation of speed based obstacle identification

The speed based obstacle identification has been implemented with the Hermes data by using an R script where the trajectory data for each run of the test route is binned into segments of a defined length. The distance travelled along the test route is calculated using the speed from the GPS data and the cumulative sum is used to assign parts of the trajectory to a particular segment bin. For example, if the segment length is defined to be 10m, the data associated with the first 10m of the trajectory falls into the first bin, the data from the next 10m falls into the second bin and so on. For each segment bin, it is then possible to calculate the number of time steps the vehicle is in one of the following operating modes using the GPS ground speed: acceleration, deceleration, cruise and idle.

The segment length is a variable that can be defined with a range of about 0.67m to the length of the cycle, 10km. The 0.67m lower threshold is derived from the 20Hz data acquisition frequency and a maximum vehicle speed of 13.33m/s based on the 30mph speed limit enforced on the urban test cycle. Dividing the theoretical maximum speed by the data acquisition frequency, the minimum resolution of the calculated distance is 0.67m (13.3/20), excluding any measurement errors.

As the test cycle is urban and assuming consistency in street planning and design, the number of acceleration events is expected to be proportional to the length of the segment. The larger the segment, the greater the distance travelled and therefore, the more likely that an obstacle is encountered. This is demonstrated in Figure 4.2, where the trajectory data for one vehicle was split into segments of different lengths. The segment length was varied in 1m increments between 1-20m and then set to 25m and 50m.

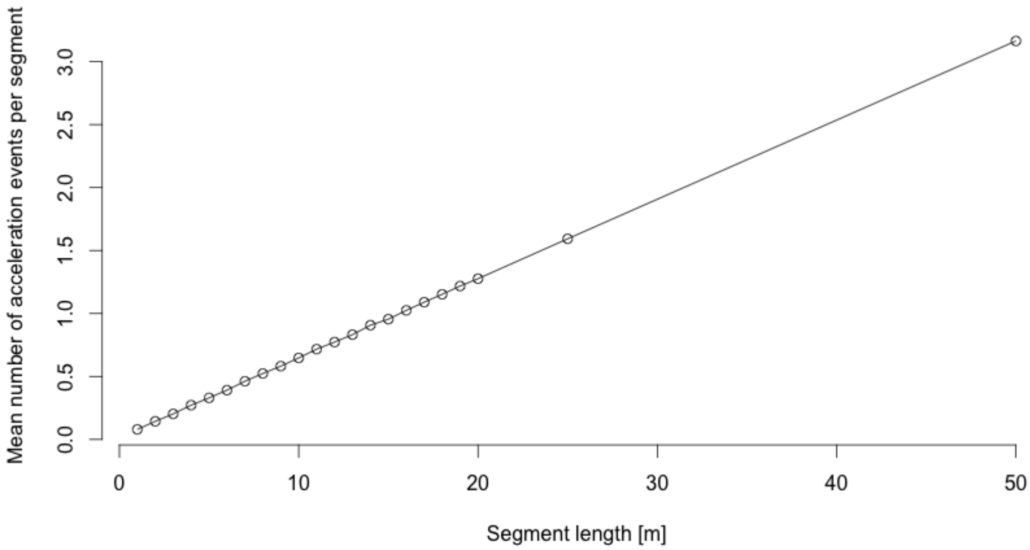


Figure 4.2 – linear relationship between segment length and the number of acceleration events per segment

With a correlation coefficient of 0.972, there is a positive linear correlation between segment length and the mean number of acceleration events per segment. The choice of segment size only becomes an influencing factor when the obstacles that fall into those segments have a separation distance of less than the segment size. For example, in a scenario where two obstacles are spaced 10m apart, if a segment size of less than 10m is defined, the obstacles will always fall into different segments.

However, the impact of an obstacle may be across multiple segments due to the "impact zone" of an obstacle as defined in Mandavilli et al. (2008). The impact zone is the area upstream and downstream of an obstacle where the obstacle is expected to influence driver behaviour. Due to the visibility or presence of a queue, a vehicle may start accelerating at a different point on the network, despite still being in the vicinity of the same obstacle. For example, at a signalised junction, if there is a queue of vehicles upstream of the junction, the point on the network where the vehicle starts accelerating is dependant on its queue position. Similarly, due to the presence of visual obstructions such as parked vehicles, the point at which the driver knows it is safe to pass a pedestrian crossing will vary. Thus there will be several segment bins in the vicinity of the obstacle that have a high number of positive acceleration events. Whilst a segment size that is equal to or less than the minimum separation distance between two obstacles should be chosen, the impact of an obstacle may be spread over multiple segment bins.

The urban test cycle contains a range of potential obstacles including signalised traffic signals, pedestrians crossings, roundabouts and speed humps. The proximity between these obstacles varies depending on the section of the urban cycle that is selected. For example, speed humps and speed cushions are spaced more closely on residential streets compared with the connecting higher-capacity roads. The critical spacing for obstacles on the urban test route is between a pedestrian crossing facility and junction, which is 5m (Department for Transport, 1995). Therefore, a segment size of 5m is selected, and with a 10km urban test cycle, this corresponds to 2000 segment bins.

High resolution Hermes data are available for 55 individual vehicles[2], from which 164 runs of the urban test cycle have been extracted. Every vehicle has completed the test cycle at least twice, with the majority completing the test cycle three times. This is presented in Figure 4.3 where the distribution of runs completed is shown.

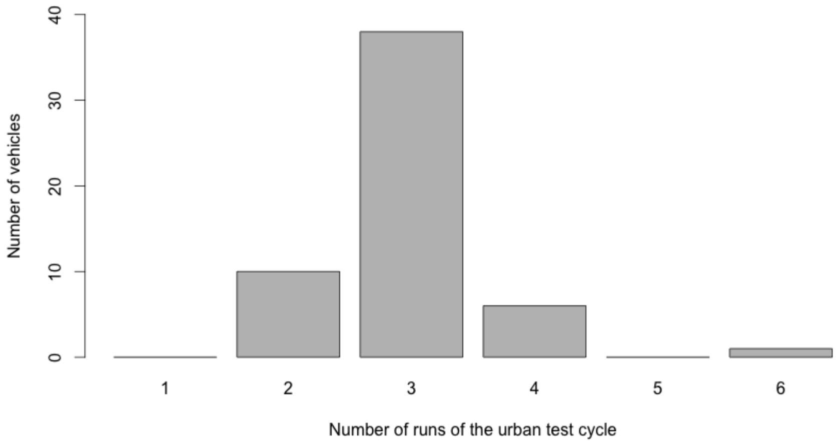


Figure 4.3 – distribution of urban test cycle runs

[2] Due to a non-disclosure agreement, the exact vehicle details cannot be presented, however the distribution of certain vehicle characteristics such as engine size are presented in section 4.4.

As discussed in section 4.2.3, obstacles that result in obstructed trajectories can be identified by finding where a vehicle deviates from its desired speed, i.e. there is an acceleration or deceleration event. When two or more obstacles are close, a vehicle may alternate between the acceleration and deceleration engine operating modes without being idle or reaching the cruise phase. Despite using small segment bins, this makes identifying which obstacle caused the deviation in vehicle speed more difficult. The solution is to consider either only positive acceleration or only negative accelerations when identifying the obstacle. Given that vehicle emissions is a focus of this thesis, only positive accelerations are used to identify obstacles. This is because of it being an operating mode where the power demand is higher, and therefore emission rates are expected to be higher (Frey et al., 2003). The limitation of this approach is that despite acceleration and deceleration events normally being paired, there are situations where only one occurs. For example, an increase in the speed limit would result in an acceleration event without a corresponding deceleration event. For the test route used in this thesis, the speed limit remains constant at 30mph. Therefore, this is not a limitation of the approach that is expected to influence the obstacles identified in this thesis.

For every vehicle and every segment bin, the number of positive acceleration events has been calculated using the speed data derived from the GPS module. Figure 4.4 shows the total number of acceleration events across the 164 test cycle runs for each segment bin.

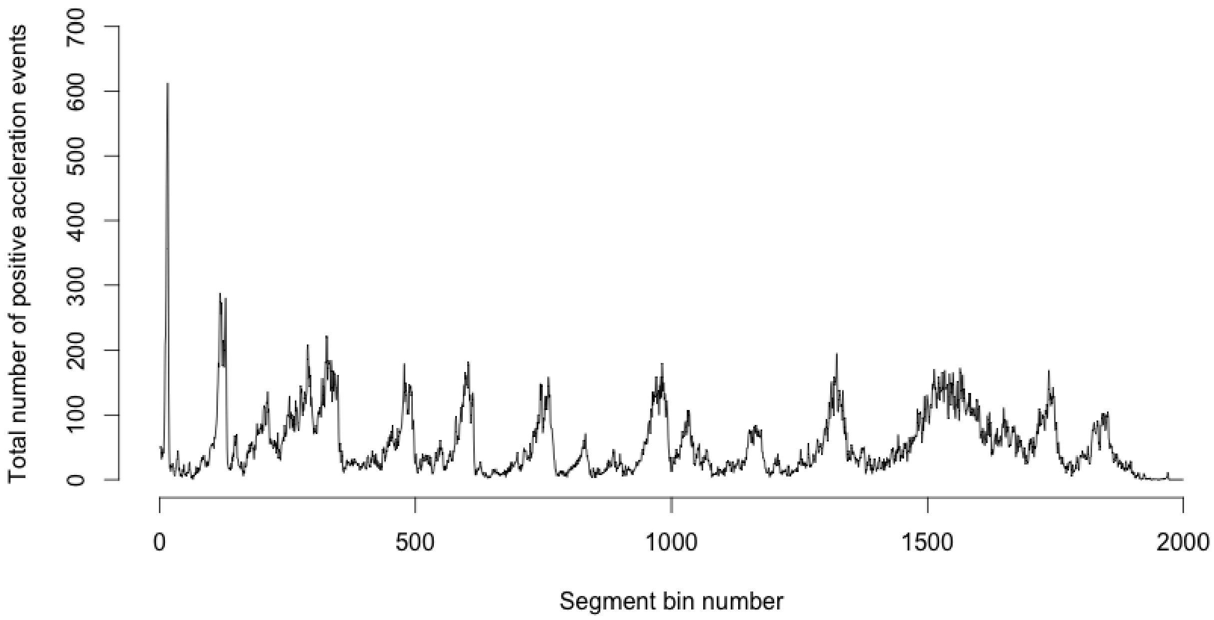


Figure 4.4 – total number of positive acceleration events across all test runs for each segment bin

From Figure 4.4 it can be seen that there are peaks in the data that correspond to segment bins where the number of acceleration events is higher than the mean number of acceleration events per segment bin (49.7). These peak segment bins are not in isolation. The surrounding segment bins also have a high number of positive acceleration events, which is explained by the "impact zone" of an obstacle.

The 50 bins with the highest number of acceleration events were selected. This corresponds to the top 2.5% of bins and 10.2% of all the positive acceleration events. They have been sorted into ascending order and adjacent bins are shown on the same line in Figure 4.5.

11 12 13 14 15 16 17

115 116 117 118 119 120 121 122 123 124 125 126 127 128 129 130

289 290 291 292

324 325 326 327 328 329 330 331 332 333 334 335

478

602 603 604

982

1323

1513

1529

1534

1564

1737

Figure 4.5 – top 50 segment bins with the highest number of acceleration events

From reviewing the 50 bins with the highest number of acceleration events, there are five cases where three or more adjacent bins are present (as highlighted above in bold). The impact zone of an obstacle is likely to be larger than the longitudinal length of the obstacle itself. This explains the presence of consecutive bins (noting the segment bins are 5m in length). There are a further eight bins which appear in isolation when only the highest 50 bins are selected. However, when the top 100 bins are selected, their adjacent bins appear.

A complementary method of determining the segments most likely to contain obstacles is to calculate the proportion of runs with a positive acceleration event in a particular segment bin, as shown in Figure 4.7. The general trend of the graph is very similar to Figure 4.4, which shows the total number of positive acceleration events across all the segment bins. There are five cases where at least 40% of the runs had one or more acceleration events in a particular segment bin as shown in Figure 4.6.

10 11 12 13 14 15 16 17
113 114 115 116 117 118 119 120 121 122 123 124
324 325
602 603
968 969 970

Figure 4.6 – segment bins where at least 40% of runs had one or more acceleration event

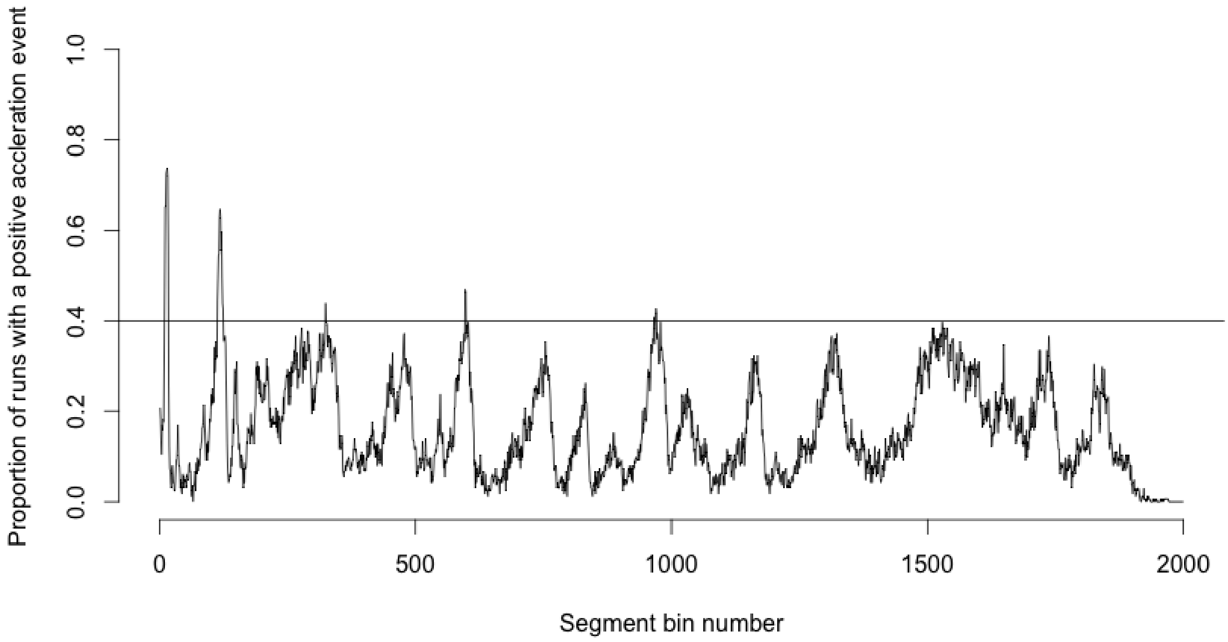


Figure 4.7 – proportion of runs with at least one positive acceleration event in any segment bin

The approach where segment bins are selected based on the absolute number of acceleration events, does not take into consideration the distribution of acceleration events in a particular segment bin across all the test runs. Using an approach based on the distribution of acceleration events fails to account for the number of acceleration events in a particular test run. By combining both approaches, the segment bins that are selected are those with a high number of acceleration events that are common across all the test runs.

There are four obstacles that were identified when both approaches were applied to the trajectory data. These are studied further in subsequent analysis. The number of obstacles to be studied could be increased by either increasing the number of 'top' segments in the first approach or lowering the threshold for the number of runs where an acceleration event occurs in a particular segment bin in the second approach. In this thesis, the impact of four obstacles on the variability of vehicle dynamics and the resultant emissions is studied. The investigation of a larger number of segment bins and thus obstacles is recommended for future work.

4.2.5. Urban obstacles used in this thesis

From the analysis in section 4.2.4, four obstacles were identified for further investigation. Using the positioning information associated with the data in each of the segment bins and a digital map, the obstacles leading to an obstructed trajectory are detailed in Table 4.1.

The segment bins that were identified to contain a high number of acceleration events across all the test runs were found to correspond to physical infrastructure. To test the effectiveness of the speed based obstacle identification methodology, the segment bins with the lowest number of acceleration events across all the test runs were also investigated. It was found that the segment bins were typically mid-link and there was no clear physical obstacle in the vicinity based on a digital map. It is assumed that the acceleration event was due to debris on the road or due to other vehicles on the road, for example a vehicle parking. The speed based identification method makes no assumption about the magnitude of the acceleration, only where accelerations are more common. By selecting the segment bins with the highest number of acceleration events across all the test runs, the subsequent analysis will be more robust as it is based on more data.

Obstacle identifier	Segment bins	Length of impact zone	Obstacle type	Description
A	11-17	35m	Speed cushion	This traffic calming measure is located on a two-lane road that leads onto several residential streets and private roads. The speed cushion is in a pair, with one speed cushion in each lane. The road has on-street parking which reduces the width of the opposing lane.
B	115-130	80m	Signalised junction	This traffic management measure is located at the intersection of a crossroads. The 4-arm junction has a signal plan that is programmed with two-stages and a late cut-off to accommodate vehicles turning right. The manoeuvre followed by all vehicles on the test route is straight ahead.
C	324-335	60m	Mini roundabout	This traffic management measure is located at the centre of a three-armed junction. All three roads have two lanes. The manoeuvre followed by all vehicles on the test route is straight ahead (2nd exit). The approach to the roundabout that vehicles on the test route use has a staggered pedestrian crossing 26m upstream of the stop line.
D	602-604	15m	“Keep clear” zone	This traffic management measure is a 40m “keep clear” zone outside private businesses and a fire station. Vehicles are advised not to enter the zone unless their exit is clear to ensure access is maintained to the off-street premises. The “keep clear” zone is just after a sharp bend in the carriageway.

Table 4.1 – obstacles identified in the urban test cycle for subsequent acceleration analysis

4.3. Variability in acceleration behaviour at different urban obstacles

This section presents the analysis conducted to assess how the acceleration behaviour at the four obstacles identified in section 4.2.5 varies. In sections 4.3.1-4.3.4 the acceleration behaviour at each obstacle is analysed using the distribution of speeds and accelerations before the vehicle operating mode is investigated. In section 4.3.5, the Kolmogorov-Smirnov test is used to determine whether there is inter-obstacle variability.

4.3.1. Analysis of acceleration behaviour at Obstacle A (speed cushion)

Obstacle A is a traffic calming measure on an urban road that has a speed limit of 30mph. The purpose of the speed cushion is to reduce speeds due to presence of several hidden entrances to private roads and businesses. The road also has on-street parking that reduces the width of the opposing lane. However, drivers following the test route have priority.

As shown in Table 4.1, the length of the impact zone is 35m with the first 9m being upstream of the obstacle, the next 3m being the speed cushion and the remaining 23m being downstream of the obstacle. The length of the impact zone is determined by multiplying the number of consecutive segment bins by the length of each segment bin (5m).

Figure 4.8 shows the distribution of speeds and accelerations extracted from the 164 runs of the test cycle whilst vehicles were in the 35m impact zone. The speeds range from 0-13.12m/s, with a median speed of 9.61m/s. 86% of the data points fall between 7-12m/s indicating that the majority of the vehicles were able to navigate the obstacle by just reducing their speed and not coming to a complete stop. Those that did come to a complete stop are likely to have either encountered a short queue or were waiting for another vehicle to complete a parking manoeuvre in the opposing lane. The median speed of 9.61m/s represents a 28% reduction in vehicle speed from the speed limit of 13.33m/s (30mph). As can be seen from the distribution of acceleration events, 95% of the acceleration events are between -2m/s^2 and +2m/s^2. This is expected, as there were only four runs of the test cycle where the vehicle was idle, hence few harsh acceleration or deceleration events to/from rest. The vehicle activity plot at the bottom of Figure 4.8 shows the vehicle activity generated from the 17,000 data points that fall into the zone of influence of Obstacle A. The main cloud of data points is between 6-13m/s and -2-2m/s^2 as seen in the speed and acceleration distribution plots. This is inline with the findings from similar studies by Barbosa et al. (2000) and Khorshid et al. (2007). In the former, the acceleration in the vicinity of three different speed humps was shown to vary between -2.5m/s^2 and +1.5m/s^2 with an average vehicle speed ranging from 28.74-36.61km/hr across the three sites (34.59km/hr in this study).

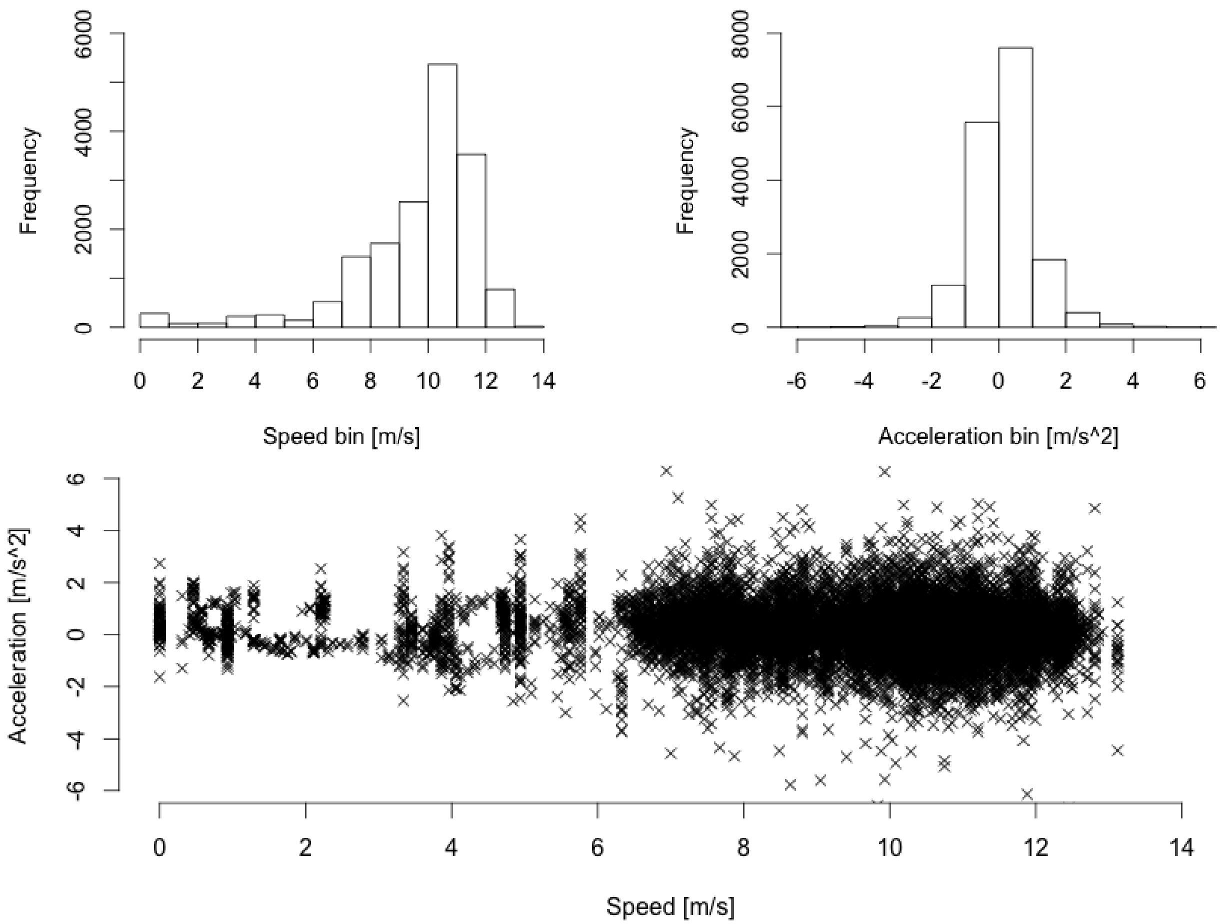


Figure 4.8 – speed and acceleration distributions, and vehicle activity at Obstacle A (speed cushion)

The engine-operating mode of a vehicle can be calculated at every time step using both the vehicle speed and acceleration. When there is a positive acceleration event (>0.1m/s^2) the vehicle is in the 'acceleration' mode. Similarly, when there is a negative acceleration event (<-0.1m/s^2), the vehicle is in the 'deceleration' mode. When the acceleration is in the range of -0.1-0.1m/s^2, the vehicle is in the 'idle' mode if the vehicle speed is ≤0.5m/s (1 mph) or in the 'cruise' mode if the vehicle speed is >0.5m/s.

Figure 4.9 shows the vehicle operation mode for all test runs of Obstacle A. The height of the bar is the total time taken to navigate the obstacle. As the data is collected at 20Hz, the time in seconds is 1/20th of the bar height. The time taken to navigate Obstacle A ranges from 3.6-19.8s, with the mean duration being 5.18s. The shading of the bars corresponds to the engine-operating mode. However, it is difficult to identify the relative time spent in each operating mode. In Figure 4.10, the height of each bar has been normalised to the time taken to navigate the obstacle, and the bars have been sorted by the proportion of time spent in the 'acceleration' mode. The proportion of time spent in the 'acceleration' mode ranges from 18.9%-70.1%, with the average being 41.4%. The average proportion of time spent in the deceleration, idle and cruise modes is 26.2%, 0.15% and 32.2% respectively. The very low proportion of time spent in the idle mode means that very few vehicles had to come to rest at the speed cushion due to the presence of a queue. This supports the finding that 86% of the data points fall into the 7-12m/s speed range.

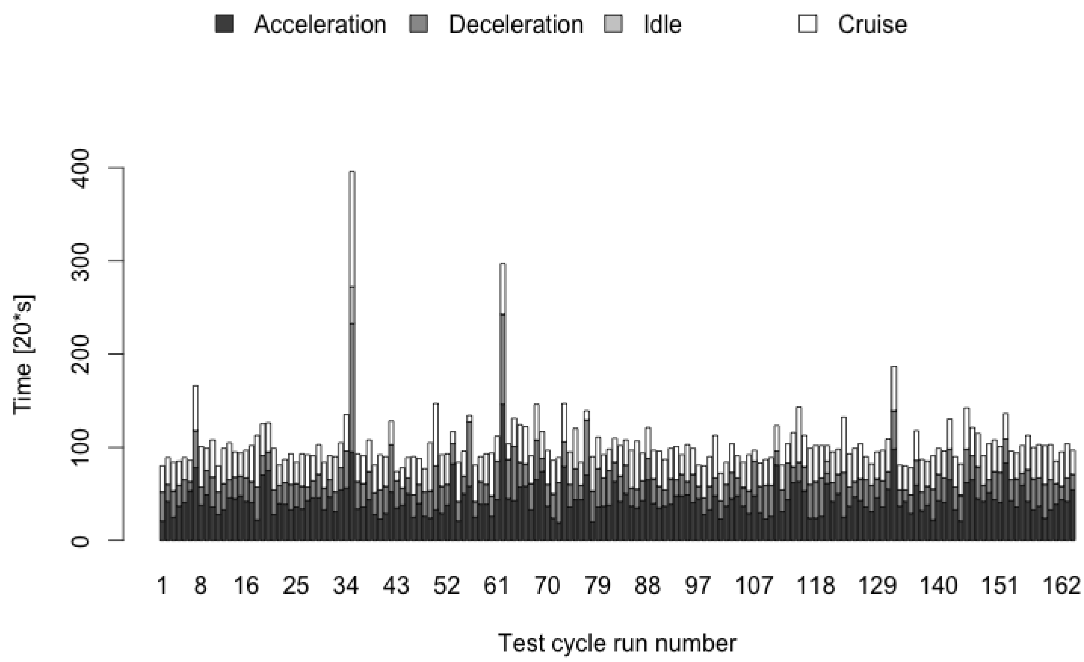


Figure 4.9 – vehicle operation mode for all test cycle runs for Obstacle A (speed cushion)

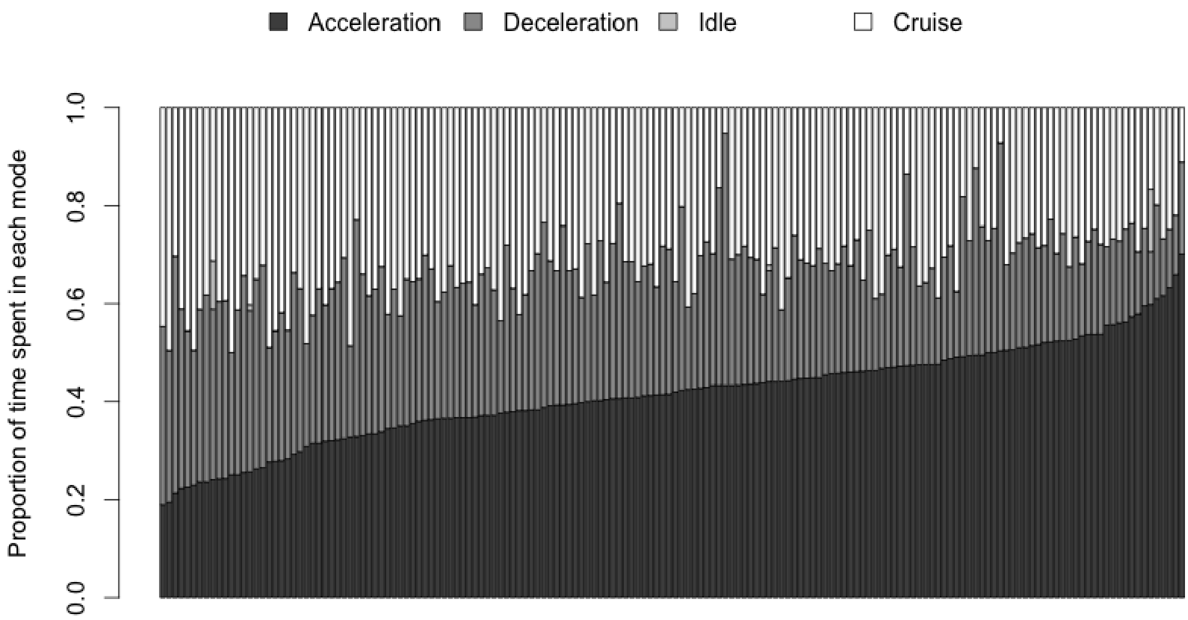


Figure 4.10 – vehicle operation mode sorted and normalised for Obstacle A (speed cushion)

4.3.2. Analysis of acceleration behaviour at Obstacle B (signalised junction)

Obstacle B is a signalised junction that lies at the intersection of a crossroads, where the movement followed by drivers on the test route is straight ahead. The signalised junction is required to manage the demand for road space from opposing traffic streams. The signalised junction also incorporates pedestrian crossing facilities, where an all-red pedestrian phase in the signal plan allows for pedestrian movements.

As shown in Table 4.1, the length of the impact zone is 80m with the first 24m being upstream of the stop line and the remaining 56m downstream of the obstacle.

Figures 4.11 and 4.12 show the distribution of speeds and accelerations that were extracted from the test cycle runs when vehicles were in the 80m impact zone in the vicinity of Obstacle B. Figure 4.11 shows the distributions over the full range of speeds and accelerations. However, it is evident that the dominant bins are the 0-0.25m/s speed bin and 0-0.25m/s^2 acceleration bin. This is due to vehicles waiting in the queue at the traffic signals. 52.8% of the data points are in the 0-0.25m/s speed bin and 43.4% of the data points are in the 0-0.25m/s^2 acceleration bin. Figure 4.12 shows a truncated version of the distribution plots. It can be seen that the remaining data points are spread across the speed bins up to about 10m/s. The lack of data points in the higher speed bins indicates that local traffic conditions prevented the vehicle from reaching its desired speed of 13.3m/s within the 56m downstream of the stop line. As seen with Obstacle A, the majority of the acceleration events (98.9%) fall between -2m/s^2 and +2m/s^2. Harsher accelerations would have been expected as 117 of the 164 runs involve the vehicle being stationary for at least one second. However, as the test vehicle is not always the lead vehicle in the queue, the acceleration of the test vehicle is constrained by the vehicle in front.

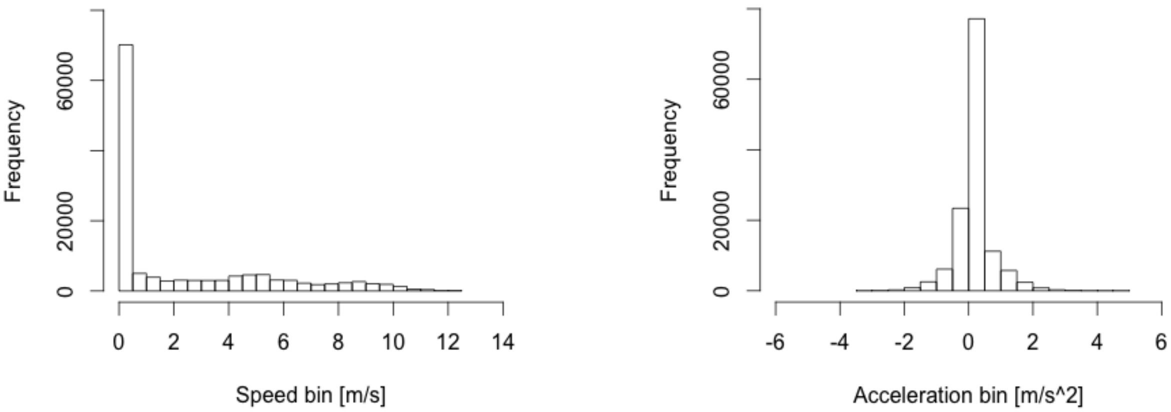


Figure 4.11 – full speed and acceleration distribution for Obstacle B (signalised junction)

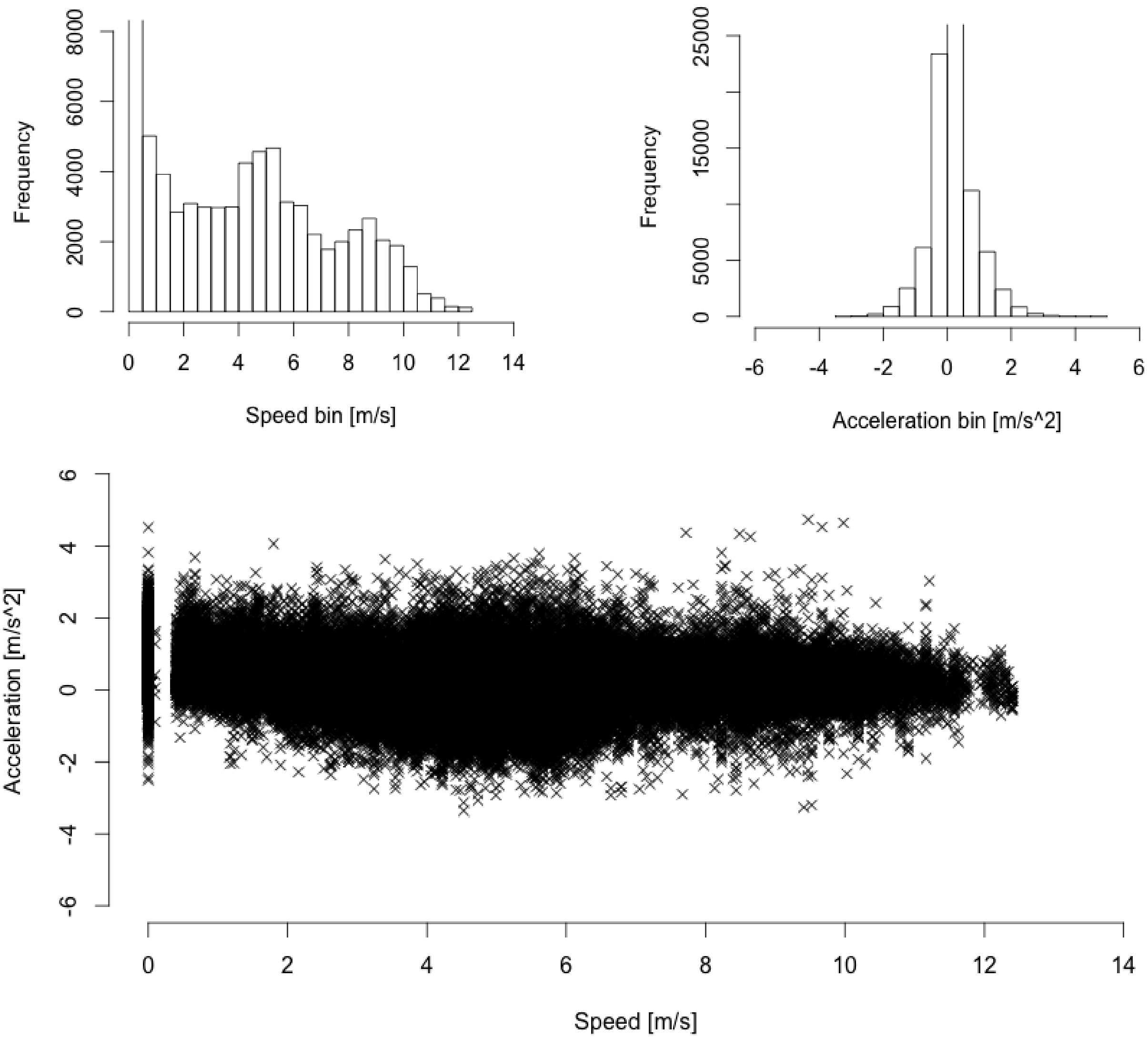


Figure 4.12 – speed and acceleration distributions, and vehicle activity at Obstacle B (signalised junction)

The vehicle activity plot is generated from the 130,100 data points that fall into the zone of influence of Obstacle B. The main cloud of data points is between 0-12m/s and -2-2m/s^2 as seen in the speed and acceleration distribution plots. This is expected as vehicles accelerate from rest towards their desired speed as they pass the signalised crossing. The lack of data points just above 0m/s is due to an inbuilt algorithm on the GPS module that corrects speeds below 0.3m/s to 0m/s (SkyTraq Technology, 2011). This is due to the reliability of the GPS speed data in this speed range being poor.

The accelerations at Obstacle B are inline with those of Akçelik and Besley (2001) who found average stop line accelerations of 1.53m/s^2. However, the average deceleration was -3.09m/s^2. This is considerably higher than what was observed in the vicinity of Obstacle B and could be due to the higher average vehicle speed of 35.2km/h (9.78m/s). Another study by Hu et al. (2014) which only focused on positive accelerations, showed average stop line accelerations of about

$3m/s^2$. This is higher than those observed at Obstacle B and is again due to the higher average speed (>40km/h). Local traffic, queuing and the presence of hazards such as parked vehicles constrain vehicle speed, and thus explain why more gentle accelerations and decelerations are observed in the vicinity of Obstacle B.

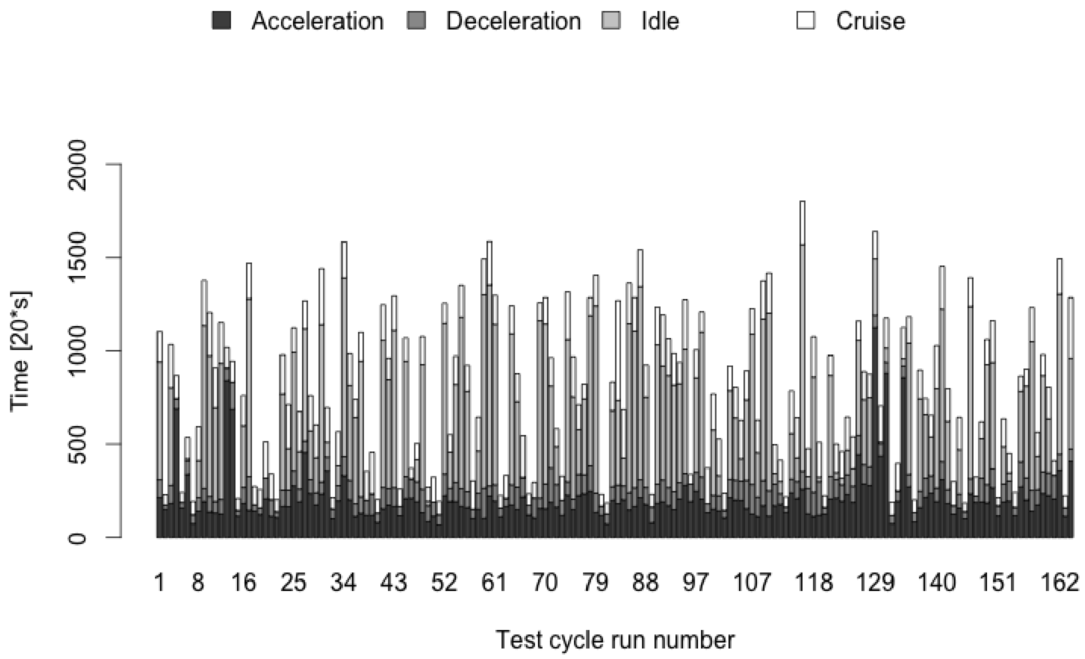


Figure 4.13 – vehicle operation mode for all test cycle runs for Obstacle B (signalised junction)

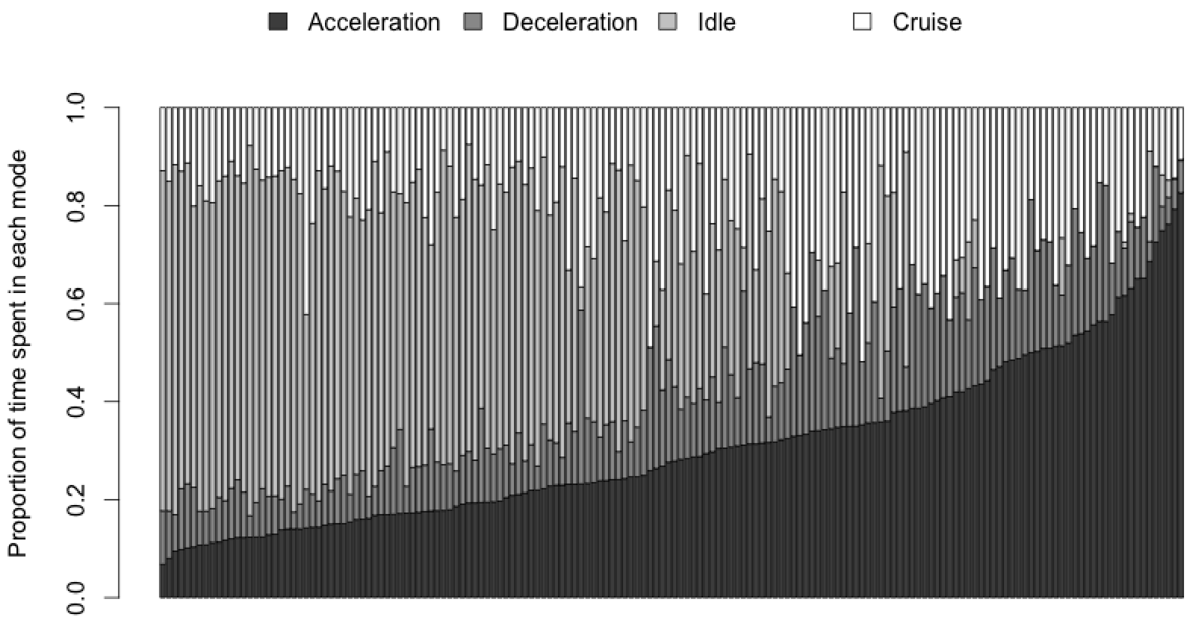


Figure 4.14 – vehicle operation mode sorted and normalised for Obstacle B (signalised junction)

Figure 4.13 shows the different vehicle operating modes for the duration of time that the vehicle is in the impact zone of Obstacle B. The height of the bars show that the time taken to navigate Obstacle B ranges from 9.2-90.1s, with the mean duration being 39.9s. The time taken to navigate Obstacle B depends on the vehicle's queue position and the point in the signal cycle that the vehicle arrives at the stop line. Figure 4.14 shows the proportion of time in each operation mode, with the time spent in the 'acceleration' mode ranging from 6.77%-82.6%, with the average being 30.7%. The average proportion of time spent in the deceleration, idle and cruise modes is 13.8%, 32.9% and 22.7% respectively.

At the signalised junction, vehicles on average spend the greatest proportion of time in the idle operating mode. This is in contrast to Obstacle A, the speed cushion, where vehicles spent the least amount of time on average in this operating mode. The key difference between the two obstacles is the mechanism by which they affect the vehicle. At the speed cushion, the vehicles used in this thesis will always encounter a delay due to the vertical deflection. However, they do not need to stop, unless there is a queue of vehicles. At the signalised junction, when the light is green and there is no queue, there is no delay caused by the traffic signals. However, when there is a red light or queue, the vehicle always encounters a delay, explaining the difference in the proportion of time spent in different vehicle operating modes.

4.3.3. Analysis of acceleration behaviour at Obstacle C (mini roundabout)

Obstacle C is a mini roundabout that lies at the centre of a three-armed junction. All three arms of the junction act as entry and exit points for the roundabout. Vehicles on the test route take the 2nd exit on the roundabout to continue straight ahead. Vehicles must give-way to those already on the roundabout or waiting to enter the roundabout from the right.

As shown in Table 4.1, the length of the impact zone is 60m with the first 13m being upstream of the roundabout stop line, next 18m being the roundabout and the remaining 29m downstream of the roundabout.

Figures 4.15 and 4.16 show the distribution of speeds and accelerations that were extracted from the 164 test cycle runs when vehicles were within the 60m impact zone in the vicinity of the mini roundabout. Figure 4.15 shows that the dominant speed bin is 0-0.25m/s with 30.6% of the data points. The dominant acceleration bin is -0.25-0m/s^2 with 25.7% of the data points. As with Obstacle B, this is due to vehicles waiting in a queue upstream of the obstacle. Figure 4.16 shows a truncated version of the distribution plots. It can be seen that the remaining data points are spread across the speed bins up to about 8m/s, before the number of data points in the higher speed bins tails off. The lack of any data points above 10m/s is because vehicles are not able to accelerate to their desired speed having passed the stop line of the roundabout, as they need to navigate the lateral deflection caused by the presence of the roundabout. As seen with Obstacles A and B, the majority of the acceleration events (96.5%) fall between -2m/s^2 and +2m/s^2. There is a negative skew in the distribution of acceleration events. This is expected to be due to the presence of a pedestrian crossing 26m upstream of roundabout and good visibility. This means vehicles may already decelerating as they enter the roundabout zone of influence.

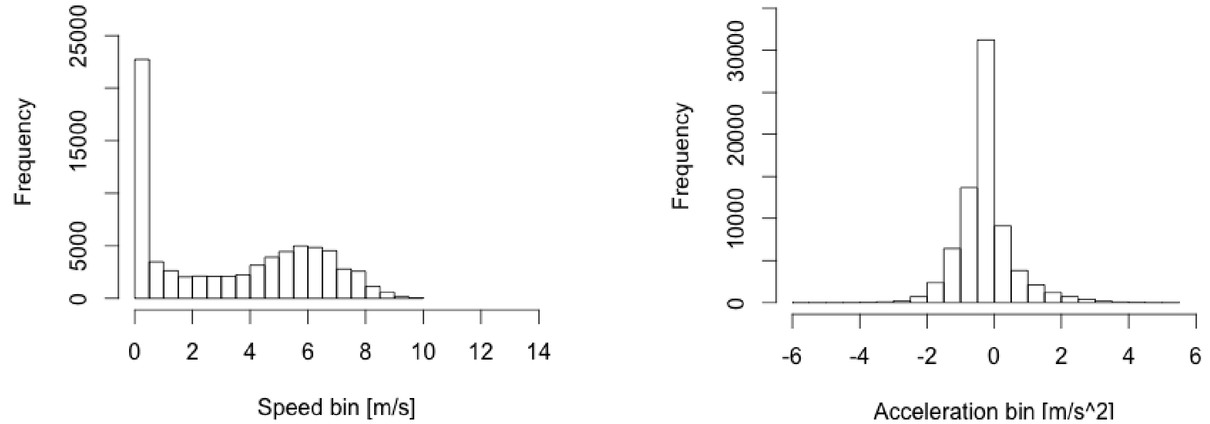


Figure 4.15 – full speed and acceleration distribution for Obstacle C (mini roundabout)

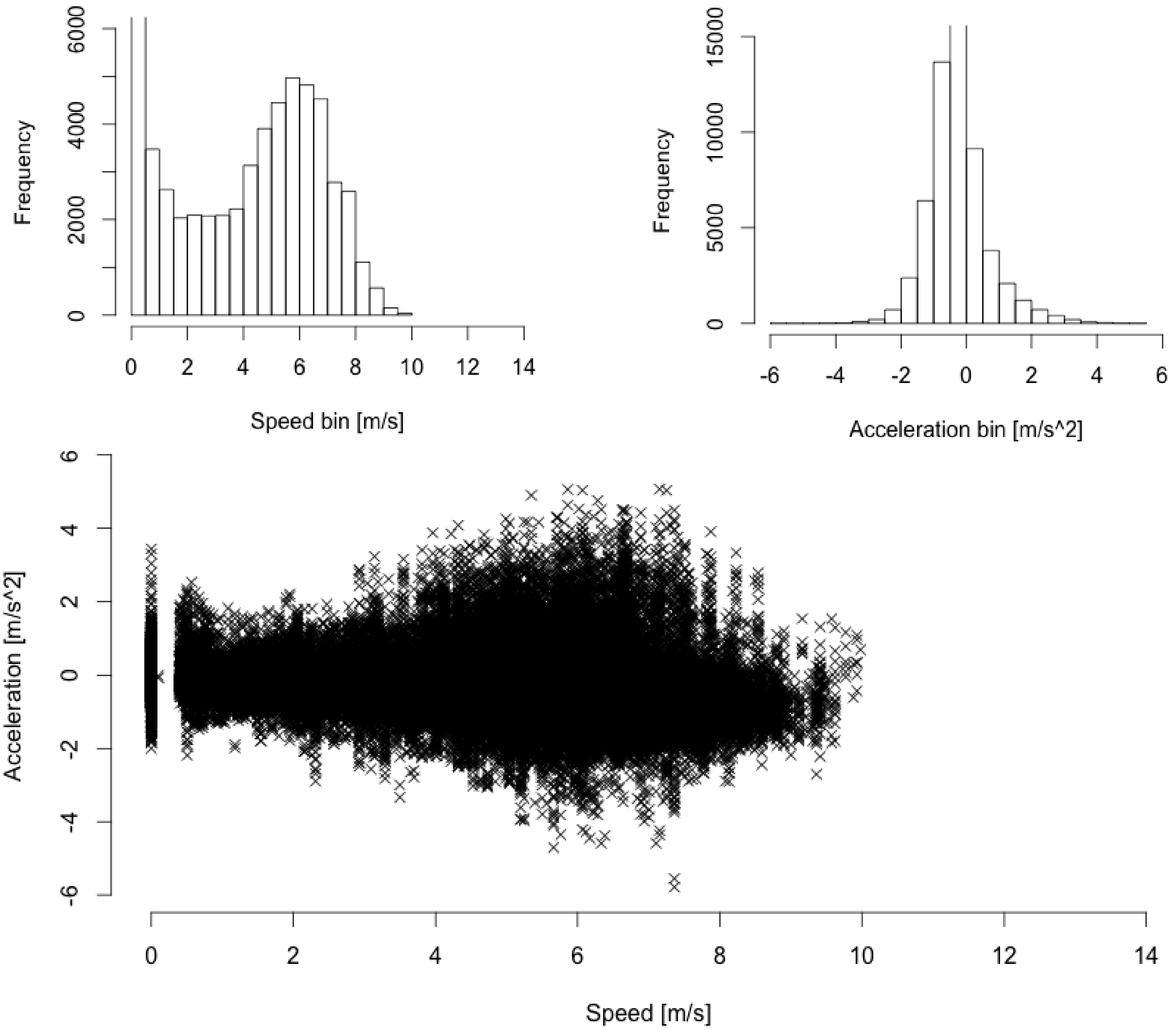


Figure 4.16 – speed and acceleration distributions, and vehicle activity at Obstacle C (mini roundabout)

The vehicle activity plot is generated from the 72,400 data points that fall into the zone of influence of Obstacle C. The main cloud of data points is between 0-10m/s and -2-2m/s^2 as seen in the speed and acceleration distribution plots. However, there are a few events between 5-7m/s where the acceleration and deceleration events reach ±4m/s^2. These harsher acceleration events are expected to be due to the vehicle accelerating to make a gap in the traffic to enter the roundabout. Similarly, the harsher deceleration events are probably due to the vehicle just missing a gap in the traffic to enter the roundabout. Without additional data such as video data or data from other vehicles in the vicinity, it is not possible to confirm whether these assumptions are true. However, there is a relationship between higher vehicle speeds and accelerations with a higher magnitude.

A study conducted by Várhelyi (2002) showed that the accelerations in the vicinity of 21 roundabouts in Sweden were typically in the range of +/- 1.5m/s^2. This is lower than what was measured in the vicinity of Obstacle C. However, in the study it was shown that the majority of the residential streets in the Sweden had an average speed of just 4.72m/s. It is therefore important that the vehicle speed is also considered when modelling acceleration in the subsequent modelling chapter. The use of vehicle activity as shown in Figure 4.16 is an effective way of representing the relationship between vehicle speed and acceleration.

Figure 4.17 shows the operating modes of the vehicles as they are in vicinity of Obstacle C, where the time taken to navigate the obstacle ranges from 6.8-105.5s with the mean being 22.1s. The time taken to navigate the roundabout is a function of the local congestion on the approach to the roundabout, but also on the approach to the right where vehicles have priority. For runs which took over 30 seconds, the 'idle' operation mode can clearly been seen in Figure 4.17. Figure 4.18 shows the proportion of time in each operation mode. The time spent in the 'acceleration' mode ranges from 1.8%-62.9%, with the average being 19.7%. The average proportion of time spent in the deceleration, idle and cruise modes is 53.4%, 7.9% and 19% respectively. The proportion of time in the idle operating mode is low. This implies the roundabout is more effective than the signalised junction at managing the competing demands for road space, assuming similar levels of congestion.

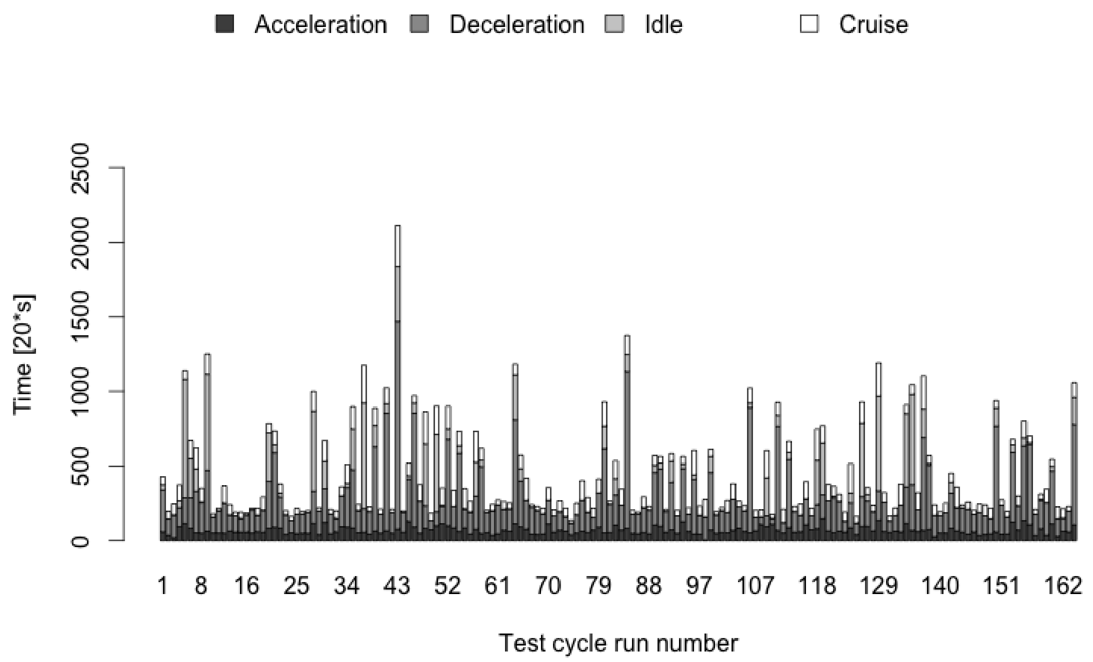


Figure 4.17 – vehicle operation mode for all test cycle runs for Obstacle C (mini roundabout)

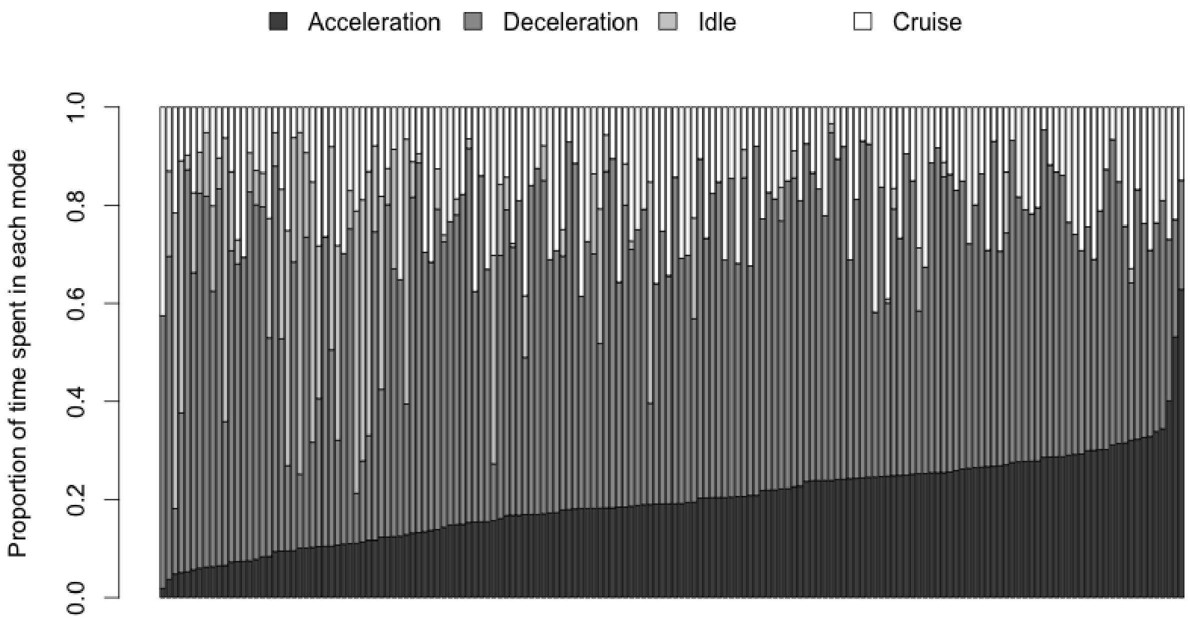


Figure 4.18 – vehicle operation mode sorted and normalised for Obstacle C (mini roundabout)

4.3.4. Analysis of acceleration behaviour at Obstacle D ("keep clear" zone)

Obstacle D is a 40m "keep clear" zone in the carriageway that vehicles are advised not to enter unless their exit from the zone is clear. The presence of the zone is to facilitate access to the off-street businesses and a fire station.

As shown in Table 4.1, the length of the impact zone is 15m. However, from reviewing the site the first 6m are upstream of the "keep clear" zone and the remaining 9m are within the zone. In order to assess the acceleration behaviour for the whole obstacle, the impact zone was extended to 52m. The first 6m is upstream of the "keep clear" zone, the following 40m is the "keep clear" zone and the remaining 6m the downstream of the zone. The extension of the impact zone allows for analysis of the deceleration events associated with the "keep clear" zone.

Figure 4.19 shows the distribution of speeds and acceleration events that were extracted from the vehicle trajectories in the impact zone of Obstacle D. There is a spike in the speed distribution in the 0-0.5m/s bin from vehicles waiting to enter the "keep clear" zone. There are a similar series of spikes in the higher speed bins as vehicles are able to approach their desired speed within the 40m "keep clear" zone. Only 11.3% of the data points lie between 1m/s and 8m/s as vehicles are generally accelerating across these speed bins. As with the previous obstacles, the majority (88%) of the data points fall between 2m/s^2 and +2m/s^2. As with Obstacle C, there is a negative skew in the distribution of acceleration events. This is due to vehicles decelerating as they come around a sharp bend upstream of the "keep clear" zone and also because are decelerating at the end of the "keep clear" zone. The vehicle activity plot shows that the 35,500 data points lie across the range of speeds up to the desired speed of 13.3m/s, with harsher acceleration and deceleration events between 8-13m/s. These harsher acceleration events are from vehicles that enter the "keep clear" zone with a non-zero speed and accelerate. The harsher deceleration events are typically found towards the end of the "keep clear" zone where vehicles join the back of another queue.

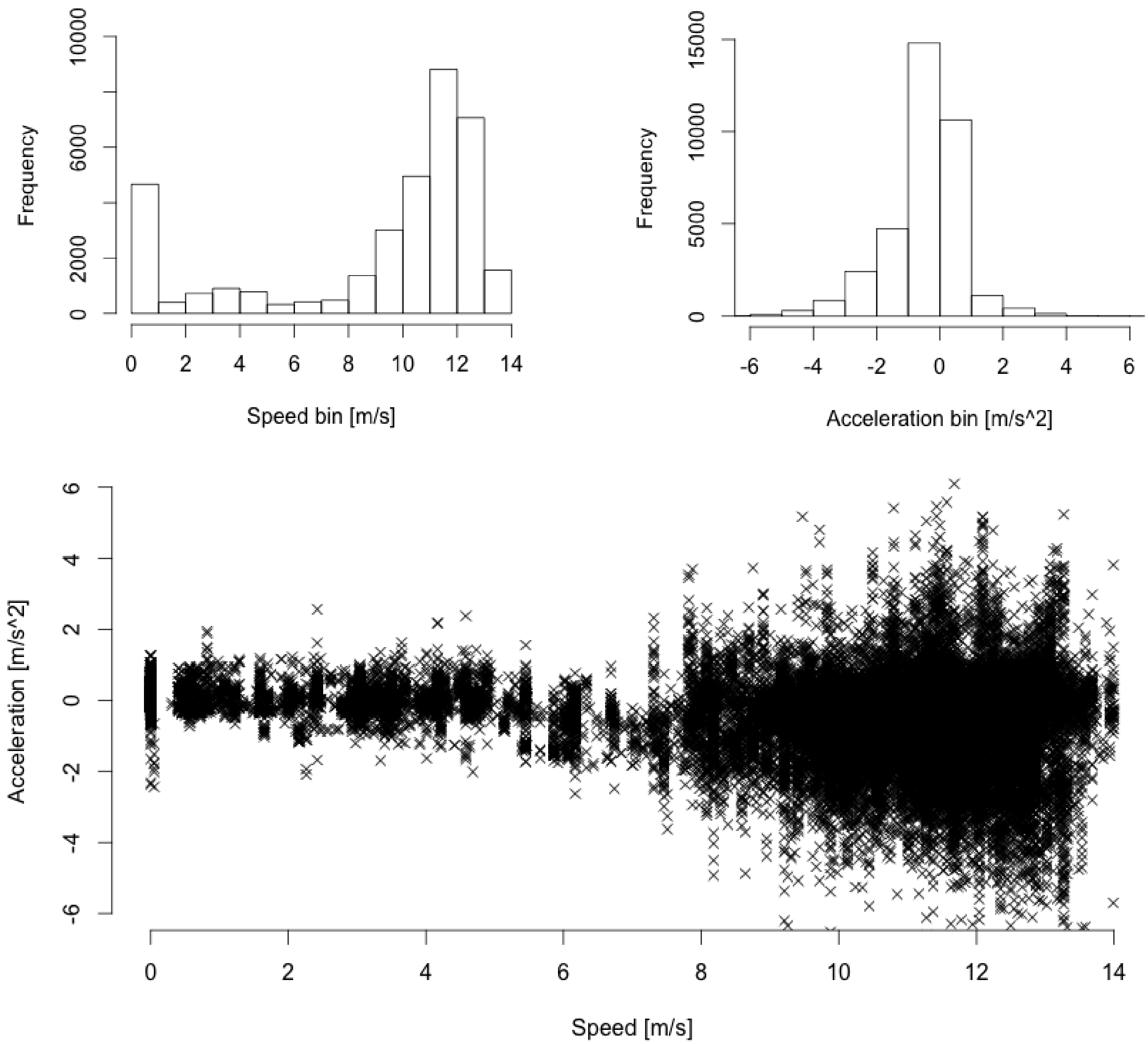


Figure 4.19 – speed and acceleration distributions and vehicle activity at Obstacle D ("keep clear" zone)

Figure 4.20 shows the total amount of time each vehicle spent in the different operating modes as they navigated Obstacle D. The time taken to navigate the obstacle ranges from 7-77.3s, with the mean being 10.8s. There are 10 runs where it took longer than 15 seconds to pass Obstacle D; this is either due to local congestion or due to vehicles occupying the "keep clear" zone to enter/exit the off-street premises. Figure 4.21 shows the proportion of time in each operation mode, with the time spent in the 'acceleration' mode ranging from 0.5%-71.5%, with the average being 19.8%. The average proportion of time spent in the deceleration, idle and cruise modes is 49.1%, 1.8% and 29.2% respectively. This implies very few vehicles stop in the vicinity of the obstacle. They are able to either cruise through, or accelerate/decelerate to ensure they do not need to stop, as seen with Obstacle A, the speed cushion.

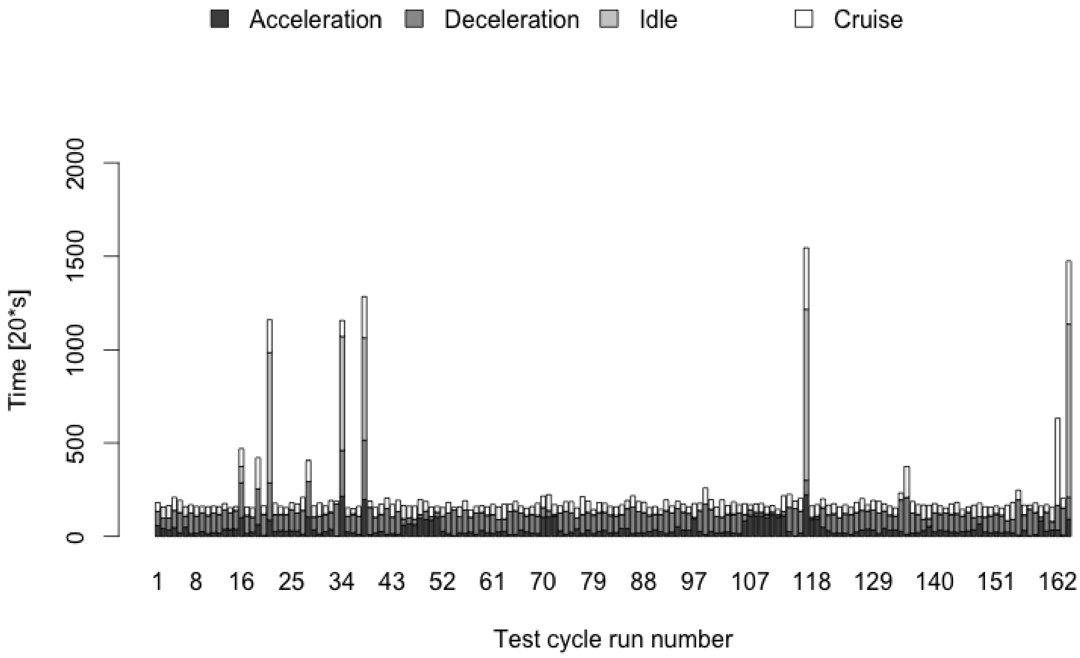


Figure 4.20 – vehicle operation mode for all test cycle runs for Obstacle D ("keep clear" zone)

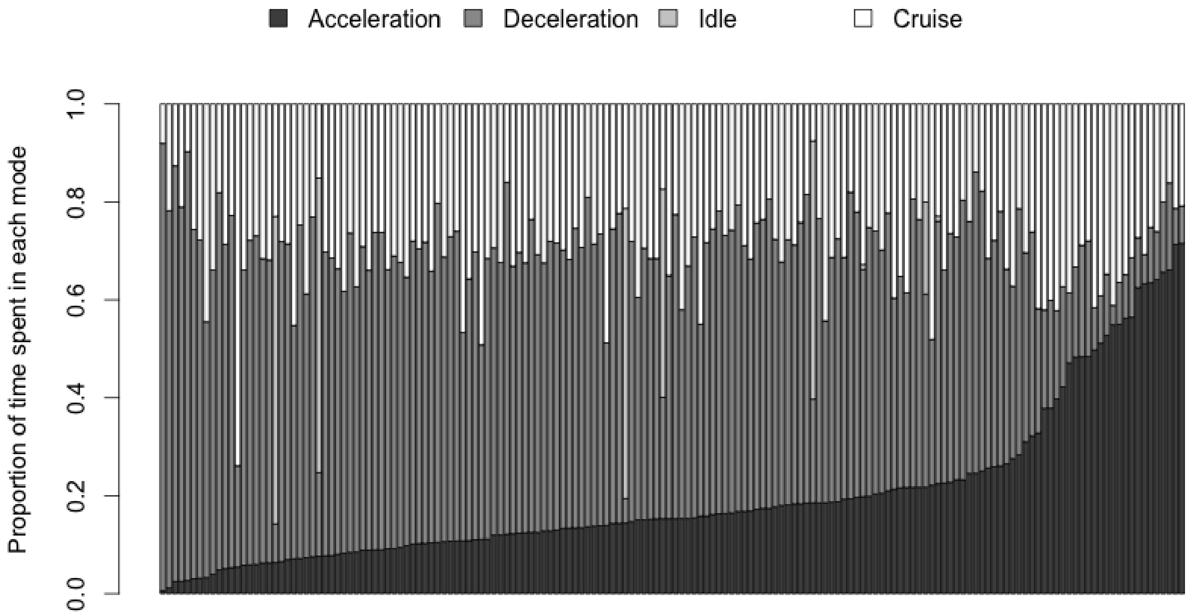


Figure 4.21 – vehicle operation mode sorted and normalised for Obstacle D ("keep clear" zone)

4.3.5. Inter-obstacle variability

Sections 4.31-4.3.4 presented the analysis of the acceleration behaviour in the vicinity of four different urban obstacles: a speed cushion; signalised junction; mini roundabout; and "keep clear" zone. Whilst the acceleration behaviour between the four obstacles could be compared using summary statistics such as the mean and range of accelerations observed, it would be more appropriate to use the vehicle activity plots. The vehicle activity plots show the relationship between speed and acceleration in the vicinity of the obstacle (e.g. Figure 4.19).

In order to conduct the comparison, the distribution of the data across the 2D surface that makes up the vehicle activity plot needs to be captured. This is achieved by using a two-dimensional binning routine where the data points are categorised into 1 m/s speed bins and a corresponding 1m/s^2 acceleration bin. The result is a 14x12 grid containing the number of data points falling into each bin with accelerations between +/- 6m/s^2 over the speed range of 0-14m/s. Whilst the 14x12 grid captures the distribution of the data points, the grid needs to be normalised to enable a fair comparison. This is due to the fact that the number of data points used to generate each activity plot varies between the obstacles due to the time taken to navigate each obstacle. After normalising the grid by the total number of data points, the grid represents the proportion of acceleration events in each 1m/s^2 acceleration bin over the range of speeds observed.

The acceleration behaviour between the four obstacles studied is compared using the Kolmogorov-Smirnov test (KS test). The KS test is a nonparametric test used to compare the probability distributions of two datasets, P and P_0.

$$H_0: P = P_0$$

$$H_1: P \neq P_0$$

If the p-value returned is lower than the significance level of 0.05, the null hypothesis can be rejected and it can be concluded that the two datasets are drawn from different distributions. The KS test also outputs a D-statistic, this is the maximum absolute difference between the cumulative distribution functions (CDFs) of the two datasets. Table 4.2 shows the results of the KS test when the acceleration behaviour in the vicinity of the four obstacles is compared.

Comparison	D-statistic	P-value	Comparison	D-statistic	P-value
Obstacle A - Obstacle B	0.2833	**0.0266**	Obstacle B - Obstacle C	0.2393	0.0763
Obstacle A - Obstacle C	0.2433	**0.0363**	Obstacle B - Obstacle D	0.1667	0.3752
Obstacle A - Obstacle D	0.2618	**0.0297**	Obstacle C - Obstacle D	0.1000	0.9251

Table 4.2 – results of the KS test on binned vehicle activity for each obstacle pair

In Table 4.2, when the acceleration behaviour at Obstacle A is compared to that of Obstacles B-D, a p-value of lower than the significance level of 0.05 is obtained. This means the null hypothesis that the two datasets compared in each case are drawn from the same distribution can be rejected. It is concluded that the acceleration behaviour at Obstacle A is different. At Obstacle A, the speed cushions, vehicles reduce their speed by decelerating upstream of the obstacle and then pass over the obstacle without coming to a complete stop. The typical proportion of time spent in the 'idle' mode was only 0.15%, and is largely due to two runs where the vehicle had to wait either for an on-coming vehicle or for a vehicle to complete a parking manoeuvre.

With Obstacle B, the signalised junction, there are times when there is no impact on the vehicle, such as when the traffic light is green and there is no queue. At other times, when there is a red signal or a queue, the vehicle is delayed and a corresponding acceleration event is expected. This behaviour is also expected at Obstacle D, the "keep clear" zone. When there are no vehicles at the entrance and exit to the "keep clear" zone, no delay is expected. However, when there is a queue upstream or downstream of the "keep clear" zone, a delay and resultant acceleration event is expected. The mechanisms by which the two obstacles impact a vehicle is similar and thus are expected to incite the same acceleration behaviour.

With Obstacle C, the mini roundabout, all vehicles will encounter at least a geometric delay when they navigate the mini roundabout. Some vehicles may face additional delays and acceleration events if the do not have priority on the roundabout or due to the presence of a queue.

Whilst the results of the statistical tests only show that there are two different acceleration distributions, given the mechanisms by which the obstacles affect vehicle acceleration, three are proposed. Further work where data for multiple examples of each obstacle is available could test this hypothesis. The grouping structures and acceleration values required to support the traffic modelling activity in Chapter 6 are presented in section 4.5.

4.4. Variability in acceleration behaviour between different vehicles

In section 4.3, all of the trajectory data collected in the vicinity of four different urban obstacles was aggregated and used to investigate differences in acceleration behaviour. Whilst this allowed for conclusions about the variations in the behaviour at the four obstacles to be drawn, it did not consider variations in behaviour between the vehicles at a particular obstacle. This is addressed in this section.

For each test, Emissions Analytics collect metadata about each vehicle and this contains specific details about the body style and mass, to details about the weather and test conditions. As the technician conducting the test collects these data, it is prone to errors and in many cases is incomplete.

In the following subsections, these data are used to develop a model to represent the acceleration behaviour observed at each obstacle. A response variable is proposed before the potential explanatory variables are considered. A suitable model is chosen and finally the results are presented.

4.4.1. Selection of response variable

A component of the second research objective of this study is to assess how acceleration behaviour varies between different vehicles at each obstacle. The response variable in a model is the variable in which differences or changes are observed as independent variables are changed. The response variable should therefore, be a metric that represents the acceleration behaviour of a vehicle whilst it is in the vicinity of an obstacle.

There are several potential metrics that could be used to represent the acceleration behaviour of a vehicle whilst it is in the vicinity of an obstacle. For example, the acceleration noise, the standard deviation of acceleration, as first as first proposed by Herman et al. (1959) could be used. However, considering the explanatory variables, and intended use of the model, the mean is more appropriate. Furthermore, as demonstrated in Chapter 6, the mean acceleration is input into acceleration behaviour model in the traffic modelling tool.

In Figure 4.22, a histogram of the mean acceleration at Obstacle A, the speed cushion is shown. Due to the positive and negative accelerations observed in the vicinity of an obstacle, the mean acceleration is generally less than 1m/s^2.

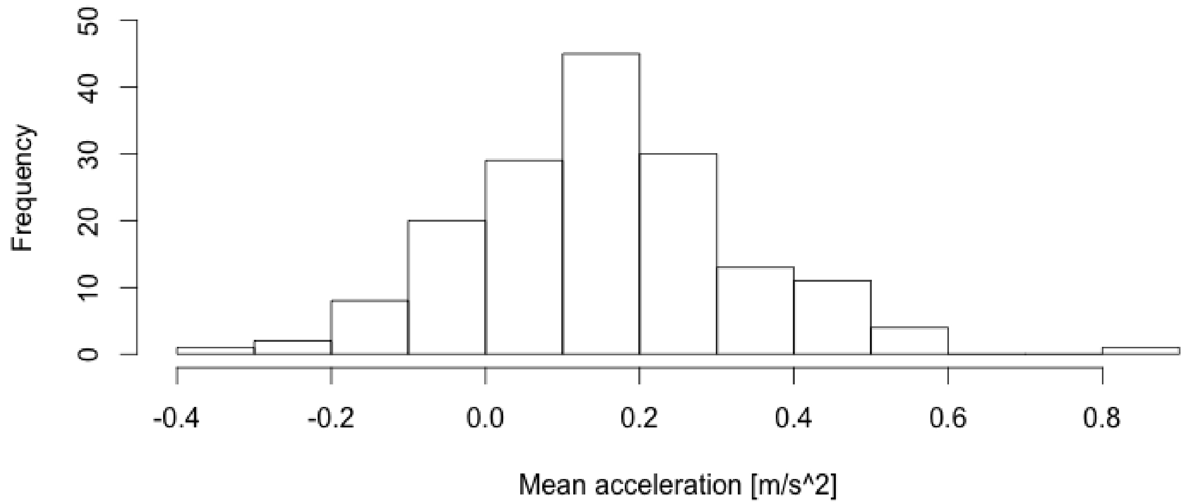


Figure 4.22 – a histogram of mean acceleration at Obstacle A, the speed cushion

An alternative response variable and as proposed in this thesis, is to use the mean positive acceleration. When vehicles have a positive acceleration, the power demands are higher and thus the rate at which pollutants are emitted is also higher. Given that the focus of this research is vehicle emissions, it is justified that the mean positive acceleration is used as the response variable as it is when emission rates are higher.

4.4.2. Selection of explanatory variables

The explanatory variable explains changes in the response variable; mean positive acceleration. All vehicles encounter the same obstacles. However, the variation in the response variable may be explained by the use of different vehicles, some of which may be able to accelerate more quickly than others. Emissions Analytics collect metadata for each vehicle test, however complete data was only available for the vehicle characteristics shown in Table 4.3.

Characteristic	Description
Engine size	The engine size is the volume of the engine cylinders in which fuel can be combusted. The engine size is measured in litres and is recorded to an accuracy of 0.1L based on the marketing information supplied with each vehicle.
Euro standard	The Euro standard is the European emissions standard that the vehicle conforms to. All vehicles used in this thesis conform to either the Euro 5 or

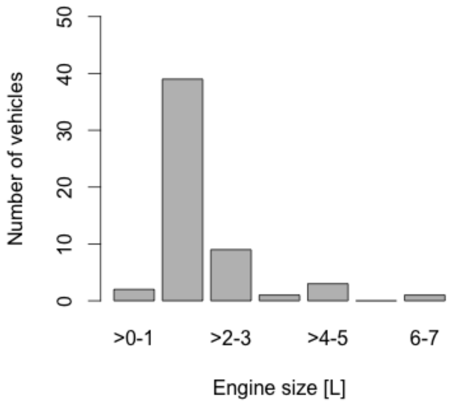
	Euro 6 emissions standard.
Fuel type	The fuel type is the energy source that is used to propel the vehicle; this is typically either petrol or diesel.
Number of doors	The number of doors is the number of openings on the vehicle that can be used by occupants to access the vehicle. The rear tailgate is also considered as a door, thus vehicles are reported to have either 3 or 5 doors.
Vehicle mass	The vehicle mass is the 'as tested' mass of the vehicle and includes the mass of vehicle occupants and monitoring equipment. The mass is recorded in kilograms to the nearest kilogram.
Vehicle power	Vehicle power is the maximum amount of energy the engine is able to produce per unit time. The vehicle power, which is obtained from the marketing material supplied by the vehicle manufacturer, is recorded in brake horsepower to the nearest 1 brake horsepower.

Table 4.3 – vehicle characteristics collected by Emissions Analytics in the metadata

Of the six vehicle characteristics presented in Table 4.3, there are four characteristics that could be used to explain changes in the response variable, mean acceleration. The fuel type and Euro standard are excluded because it is not envisaged that they will influence the mean acceleration of a vehicle. Whilst there may be differences in engine technology due to the fuel type or Euro standard, these are captured in other variables such as engine size and vehicle mass.

Engine size, number of doors, vehicle mass and vehicle power are vehicle characteristics where the influence on vehicle acceleration can be explained. The engine size is related to the amount of fuel that can be combusted on each engine stroke. Therefore, assuming similar levels of efficiency, a vehicle with a larger engine can combust more fuel and thus has more energy to propel the vehicle. The number of doors on the vehicle is a proxy for the aerodynamic properties of the vehicle. Vehicles with a larger frontal area will experience higher resistive forces at high vehicle speeds. Whilst the vehicle speeds in the vicinity of the obstacles investigated is less than 14m/s, there may still be an impact on vehicle acceleration. The vehicle mass will influence acceleration as the heavier the vehicle, the more power that is required to maintain the same rate of acceleration. Finally, the vehicle power is the maximum amount of energy the vehicle can produce per unit time, with a higher power output, a vehicle can accelerate more quickly.

Before the four characteristics can be used as explanatory variables, the composition of each variable needs to be explored to understand the distribution of the data. Table 4.4 shows whether each characteristic is continuous or categorical, summary statistics and the data distribution.

<table>
<tr><th>Characteristic</th><th>Data description</th><th>Distribution of data</th></tr>
<tr><td>Engine size</td><td>Type: continuous
Range: 1.0-6.2L
Mean: 2.1L
Median: 2.0L
Unique values: 15</td><td>
</td></tr>
<tr><td>Number of doors</td><td>Type: categorical
Range: 3 or 5 doors
Unique values: 2

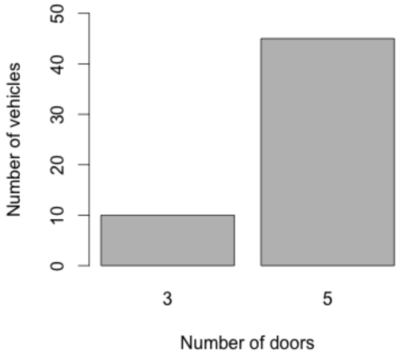
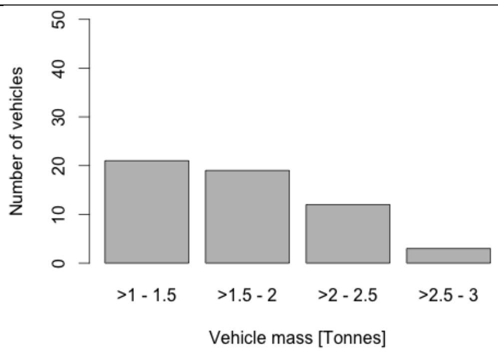
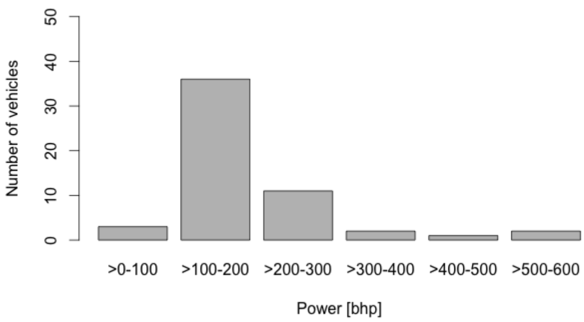
10 vehicles with 3 doors and 45 vehicles with 5 doors</td><td>
</td></tr>
<tr><td>Vehicle mass</td><td>Type: continuous
Range: 1100-2900kg
Mean: 1719kg
Median: 1540kg
Unique values: 55</td><td>
</td></tr>
<tr><td>Vehicle power</td><td>Type: continuous
Range: 70-580bhp
Mean: 187bhp
Median: 172bhp
Unique vales: 28</td><td>
</td></tr>
</table>

Table 4.4 – composition of the vehicle characteristics that are expected to influence vehicle acceleration

From Table 4.4 it can be seen that the data for each characteristic are not evenly distributed across the ranges observed, this is expected to introduce bias in the model results. However, given the limited number of explanatory variables, it is still proposed that the four characteristics are considered as potential explanatory variables.

Collinearity is the phenomenon where two or more explanatory variables are highly correlated. Multiple correlated variables in a subsequent statistical model may make interpretation more difficult. The collinearity between two variables can be measured by calculating the correlation coefficient, using either the Pearson product moment or Spearman rank-order. The Pearson product moment is used in this thesis as it relies on the raw data rather than the ranked values for each variable. Table 4.5 shows the collinearity for the four variables: engine size, number of doors, vehicle mass and vehicle power.

	Engine size	Number of doors	Vehicle mass	Vehicle power
Engine size		0.145	0.699	0.883
Number of doors			0.312	-0.030
Vehicle mass				0.558
Vehicle power				

Table 4.5 – collinearity between the four characteristics expected to influence vehicle acceleration

From Table 4.5 it can be seen that correlation is evident between vehicle mass, vehicle power and engine size. This can be explained by the fact that with a larger engine size, more fuel can be combusted on each engine stroke and thus more energy is produced to propel the heavier vehicle. Also, the larger the physical size of the engine, the heavier it is assuming material choices and engine configuration remain the same. The high correlation between engine size and vehicle power is expected, as a vehicle with a larger volumetric capacity for combusting fuel is able to produce more energy or power assuming similar levels of efficiency.

Considering the results of the collinearity testing, engine size is excluded from the subsequent analysis and the number of doors, vehicle mass and vehicle power are used as the explanatory variables.

4.4.3. Choice of model

In section 2.1.1, based on the fundamentals of how an engine works, it was shown that there is a largely linear relationship between the resistive forces on a vehicle, kinetic energy and tractive power (Heywood, 1988). Therefore, a multivariate linear regression model is used to explore the relationship between the explanatory and response variables. The ordinary least squares (OLS) method will be implemented for parsimony, but also because the data in this study meets the primary assumption that there is zero or negligible errors in the independent variable. Whilst a weighted least squares (WLS) method could be used with the standard deviation of the acceleration, the weighting will have limited effect due to the low standard deviation. The regression will be used to predict how much of the variation in the response variable is described by the explanatory variables[3].

In order to implement the regression model a dummy variable for number of doors has been created, as it is a categorical variable. The general form of the model implemented at each obstacle is shown below:

$$\begin{aligned} &Mean\ positive\ acceleration \\ &\qquad = \beta_0 + \beta_1 Doors\ dummy + \beta_2 Vehicle\ mass + \beta_3 Vehicle\ Power + \varepsilon \end{aligned}$$

$$where\ the\ parameters\ \beta_0, \beta_1, \beta_2, \beta_3\ and\ \varepsilon\ will\ be\ estimated\ by\ the\ model$$

4.4.4. Model estimation results and conclusions

The linear regression model explained above was implemented at the four obstacles and the results are shown below in Table 4.6. For each obstacle, the estimates of the beta parameters of each variable are shown as well as the standard error and whether the variable is significant at the

[3] Prior to implementing the regression model as explained in this section, the data from all four obstacles was aggregated. An additional explanatory variable for obstacle type was defined and implemented in the model using three dummy variables. The only beta parameters that were statistically significant at the 5% level were the three dummy variables for the obstacle type. This confirms the findings presented in section 4.3.5 based on the KS test and obstacle mechanism of impact. The lack of significance of the other explanatory variables led to the conclusion that they may not be statistically significant when the data from all obstacles is aggregated. However, they may be statistically significant when each obstacle is modelled individually – as presented in this section.

5% level (measured as whether the estimate is significantly different from zero). The adjusted R^2, which takes into consideration the number of variables is also reported.

The R^2 value for the model of mean positive acceleration at each obstacle shows the proportion of the variation that is accounted for using the three explanatory variables: number of doors, vehicle mass and vehicle power. The R^2 value for all four models is very small and ranges between 1-5%. The three beta parameters are also not significantly different from zero in all cases apart from Obstacle D, where vehicle power is significant at the 5% level. The model for Obstacle D was re-estimated by removing the non-significant variables and the R^2 increased marginally to 0.06, still low.

It is concluded that the poor performance of the model is due to the accelerations observed in the vicinity of each obstacle not being sufficiently aggressive that any of the three chosen explanatory variables are able to account for the variability observed. The number of doors was used as a proxy variable to account for the physical size of the vehicle and the drag forces that the vehicle may experience. However, the speeds observed in the vicinity of the obstacles are <13.3m/s in all cases, meaning drag would not be dominant in the resistive forces that the vehicle encounters (Jiménez-Palacios, 1999). The vehicle mass was shown to have a correlation coefficient of 0.699 with engine size in Table 4.5. This implies that heavier vehicles have larger engines to account for the additional mass. Therefore, the mass does not influence the acceleration in the vicinity of urban obstacles. The vehicle power explanatory variable used in this thesis is the maximum power the vehicle can output. Given the presence of the 30mph speed limit and other vehicles on the road, it is very unlikely that any vehicle is operating at its maximum output.

A component of the second research objective of this study was to assess how acceleration behaviour varies between different vehicles at a particular obstacle. Based on the models developed, it can be concluded that the explanatory variables used in models do not explain the variability in acceleration behaviour observed. Whilst further work could explore how other explanatory variables that describe the physical characteristics of the vehicle influence vehicle acceleration, this is not recommended. Explanatory variables such as the vehicle's queue position, traffic density or vehicle headway may be better suited to explaining the variability in acceleration at each obstacle. Due to the limited metadata available in this thesis, it is not possible to explore this further.

Obstacle A – speed cushion – n=164

Parameter	Variable	Estimate	Standard error of estimation	Significance at 5% level
β_0		1.78 x 10^{-1}	5.57 x 10^{-2}	Yes
β_1	No. of doors [5]	-3.80 x 10^{-2}	3.98 x 10^{-2}	No
β_2	Vehicle mass	1.18 x 10^{-6}	3.94 x 10^{-5}	No
β_3	Vehicle power	4.35 x 10^{-5}	1.86 x 10^{-4}	No

Adjusted R^2 for model at Obstacle A = 0.01

Obstacle B – signalised junction – n=164

Parameter	Variable	Estimate	Standard error of estimation	Significance at 5% level
β_0		2.11 x 10^{-1}	4.12 x 10^{-2}	Yes
β_1	No. of doors [5]	1.82 x 10^{-2}	2.95 x 10^{-2}	No
β_2	Vehicle mass	2.50 x 10^{-5}	2.92 x 10^{-5}	No
β_3	Vehicle power	7.40 x 10^{-5}	1.38 x 10^{-5}	No

Adjusted R^2 for model at Obstacle B = 0.03

Obstacle C – mini roundabout – n=164

Parameter	Variable	Estimate	Standard error of estimation	Significance at 5% level
β_0		2.94 x 10^{-1}	5.99 x 10^{-2}	Yes
β_1	No. of doors [5]	-9.78 x 10^{-3}	4.29 x 10^{-2}	No
β_2	Vehicle mass	1.26 x 10^{-5}	4.25 x 10^{-5}	No
β_3	Vehicle power	1.60 x 10^{-4}	2.00 x 10^{-4}	No

Adjusted R^2 for model at Obstacle C = 0.01

Obstacle D – "keep clear" zone – n=164

Parameter	Variable	Estimate	Standard error of estimation	Significance at 5% level
β_0		5.30 x 10^{-1}	1.75 x 10^{-1}	Yes
β_1	No. of doors [5]	2.02 x 10^{-1}	1.25 x 10^{-1}	No
β_2	Vehicle mass	5.73 x 10^{-5}	1.24 x 10^{-5}	No
β_3	Vehicle power	-1.41 x 10^{-3}	5.86 x 10^{-5}	Yes

Adjusted R^2 for model at Obstacle D = 0.05

Table 4.6 – results from the regression modelling for all four obstacles

4.5. Proposed grouping structures for vehicle acceleration

In section 4.3 and 4.4, the acceleration behaviour of vehicles in the vicinity of urban obstacles was analysed. First, the acceleration data from all vehicles in the vicinity of a particular obstacle were aggregated and comparisons made. Second, a regression model was developed for each obstacle to ascertain whether certain vehicle parameters affect vehicle acceleration in the vicinity of the obstacle. Using the findings from the analysis on acceleration behaviour, ways of grouping vehicles and obstacles are proposed to support the modelling exercise in Chapter 6.

4.5.1. Grouping structures based on obstacle type

Using 164 runs of a London based urban test cycle, the acceleration behaviour in the vicinity of four urban obstacles was analysed. The speed-acceleration relationship, vehicle activity, was used to determine differences. This was supported by summary statistics as well as observations from being present during the testing, as presented in section 4.3.5. Whilst the statistical test showed two distributions for vehicle acceleration, three were proposed based on an understanding of the mechanisms by which a vehicle is impacted. For the purpose of modelling acceleration behaviour, three groups of obstacles are defined as shown below:

1. Obstacles which will always result in an obstructed trajectory due to a vertical deflection e.g. a speed cushion
2. Obstacles which may result in an obstructed trajectory due to the vehicle being forced to stop on occasion e.g. a signalised junction/"keep clear" zone
3. Obstacles which will always result in an obstructed trajectory due to a lateral deflection e.g. a mini roundabout

Based on the proposed grouping structure, Table 4.7 shows the acceleration values as a function of vehicle speed. In order to generate the data in Table 4.7, the acceleration data for the obstacle(s) that fall into each group was binned into 1m/s speed bins. For each speed bin the mean, minimum and maximum acceleration has been calculated. The minimum and maximum values are based on the 5th and 95th percentile values to ensure the envelope around the mean is not based on a single data point. These data will be used to support the calibration of the acceleration behaviour model in the traffic modelling activity presented in Chapter 6.

	Speed bin (m/s)	0-1	1-2	2-3	3-4	4-5	5-6	6-7	7-8	8-9	9-10	10-11	11-12	12-13
A	Min	0.04	0.05	0.58	0.03	0.13	0.16	0.05	0.08	0.06	0.05	0.05	0.06	0.06
	Mean	0.62	1.05	1.06	0.90	0.90	1.00	0.69	0.88	0.78	0.72	0.65	0.70	0.66
	Max	1.76	1.68	1.75	2.95	2.05	2.47	1.66	2.31	2.13	2.05	1.84	2.04	1.96
B & D	Min	0.04	0.04	0.04	0.04	0.04	0.05	0.05	0.04	0.05	0.05	0.05	0.03	0.04
	Mean	0.26	0.52	0.59	0.67	0.74	0.74	0.70	0.91	0.74	0.55	0.62	0.64	0.59
	Max	0.89	1.67	1.75	1.78	1.91	1.97	1.81	2.33	1.84	1.70	2.08	2.43	2.06
C	Min	0.01	0.03	0.03	0.04	0.04	0.05	0.05	0.05	0.03	0.02	NA	NA	NA
	Mean	0.34	0.36	0.49	0.66	0.88	1.00	1.10	1.06	0.69	0.52	NA	NA	NA
	Max	1.08	1.00	1.31	2.02	2.36	2.68	3.02	2.91	2.35	1.34	NA	NA	NA

Table 4.7 – acceleration values in m/s^2 as a function of vehicle speed for the proposed obstacle groups

4.5.2. Grouping structures based on vehicle parameters

In section 4.4, the variability in acceleration behaviour between different vehicles at each obstacle was analysed using a regression model with three vehicle characteristics as explanatory variables. It was shown that none of the explanatory variables were statistically significant across all four obstacles. The explanatory power of the model was also very low, <5% for all four obstacles.

Therefore, it is concluded that from the number of doors on a vehicle, vehicle mass and vehicle power, vehicles can be considered equivalent when acceleration is the response variable. Based on the vehicles investigated in this thesis, a single mathematical formulation of vehicle acceleration should be used for modern light duty passenger cars in the vicinity of urban obstacles. However, it is recommended that further work should be conducted where access to data from more vehicles, a greater variety of obstacles and more complete metadata is available to confirm these findings.

4.6. Conclusions

In this chapter a methodology for identifying roadway obstacles in trajectory data from an urban test cycle was presented. The speed based obstacle identification method was used to identify four obstacles and the acceleration behaviour at each obstacle was analysed.

The data from each vehicle in the vicinity of a particular obstacle was aggregated and the variability in acceleration behaviour was assessed initially using summary statistics and vehicle operating mode. In order to determine whether the acceleration at each obstacle was drawn from a different population, the KS test was applied to the vehicle activity data. It was shown that the acceleration at a speed hump is different to that observed at a signalised junction, mini roundabout and "keep clear" zone. Considering the mechanism of impact, three groups of obstacles were defined and it was proposed that a different mathematical formulation of vehicle acceleration should be used at each.

The data from each vehicle at a particular obstacle was also considered separately. A regression model was developed to determine whether certain vehicle parameters could be used to explain the variability in the accelerations observed. It was found that that the number of doors on a vehicle, vehicle mass and vehicle power were only able to explain <5% of the variation in mean positive acceleration. Therefore, it is concluded that the vehicles used in this thesis are equivalent when vehicle acceleration in the vicinity of urban obstacles is concerned. When modelling vehicle acceleration, a single mathematical formulation is proposed for modern light duty passenger cars in the vicinity of urban obstacles.

With the analysis presented in this chapter, the second research objective 'identify urban obstacles and then assess how the acceleration behaviour varies at different obstacles and between different vehicles' has been addressed. The proposed groupings of urban obstacles and modern light duty passenger cars are used to support the modelling exercise in Chapter 6.

5. Understanding the variability in tailpipe emissions at urban obstacles

In this chapter the tailpipe emissions data collected in London are analysed in the vicinity of urban obstacles. As explained in Chapter 3, the data were collected using a portable emissions measurement system (PEMS) in partnership with Emissions Analytics. The data are used to address the third research objective:

Understand how tailpipe emissions vary at different obstacles and between different vehicles to support emissions modelling

The chapter begins with a discussion of the data used including the associated errors. The procedure for calculating the emissions associated with each obstacle is explained and the variation in emission rates between the four obstacles identified in Chapter 4 is analysed. The differences in emission rates at each obstacle are analysed using vehicle characteristics such as fuel type and engine size. Finally, ways of grouping obstacles and vehicles are proposed to better represent the observed emissions in the vicinity of urban obstacles.

5.1. Overview

In Chapter 2 it was explained that in order to move a vehicle, the vehicle requires power to overcome resistive forces. This power is generated through the combustion of hydrocarbons, a by-product of which is various pollutant emissions. Frey et al. (2003) assign the operating mode of a vehicle to one of four mutually exclusive modes: acceleration, deceleration, cruise and idle. In the former, it was demonstrated that when a vehicle is in an operating mode requiring more power, such as acceleration, fuel is consumed at a higher rate and thus pollutant emission rates are higher. These pollutant emissions are of interest due to the negative impact on both human health and the environment.

As demonstrated in Chapter 4, obstacles in the road network can cause a vehicle to deviate from its desired speed. This results in higher emission rates due to the increased power demand associated with additional acceleration events. There is a negative impact on human health and the environment associated with higher pollutant emissions rates. Therefore, there is a requirement to quantify the real-world tailpipe emissions associated with obstacles on the road network.

In Chapter 3 it was explained that Emissions Analytics have a robust testing procedure for collecting tailpipe emissions data from vehicles on a London-based test route. This dataset is used to extract the emissions associated with the urban obstacles identified in Chapter 4.

The analysis of the emissions should result in a better understanding of the variation between different obstacles, and between different vehicles at a particular obstacle. This will allow for an improved assignment of vehicles to emissions classes in emissions modelling tools and ultimately improved estimates of tailpipe emissions in the vicinity of urban obstacle, as shown in Chapter 6.

The following section explains how the Emissions Analytics data are used to carry out the subsequent analysis on tailpipe emissions in the vicinity of urban obstacles.

5.2. Data used for analysing vehicle emissions

In section 3.4, a suitable PEMS dataset was identified and the testing procedure was explained, along with the data structures and outputs. To date, Emissions Analytics have conducted over 1000 vehicle tests with more than 600 of these in the UK (Emissions Analytics, 2015a).

Due to changes in the testing procedure, such as the test route and the way metadata is stored, only vehicles tested after 1 January 2014 are included in the subsequent analysis to ensure experimental control. Between 1 January 2014 and 31 March 2015, there were 245 vehicle tests conducted by Emissions Analytics for which data are available. All of these tests were conducted in the UK on the same London based test route and aggregated forms of the data have been published (section 3.4.1).

Emissions Analytics collect a range of information about every vehicle tested. This includes vehicle weight, engine power output, engine size and conformance to European emissions standards. However, complete data were not available for about 30% of the vehicles tested. The missing information was retrieved from vehicle manufacturer websites and other vehicle information databases such as car leasing websites. For 19 vehicles it was not possible to retrieve some of the vehicle specific details required for the subsequent analysis. The vehicle registration mark can normally be used to acquire most of the data required for this research. However, due to vehicles generally being marketing vehicles, the vehicle registration mark is often recycled between different vehicles. Therefore, it is not possible to look up the vehicle information using the vehicle registration mark if it has been assigned to another vehicle.

For the 226 vehicles where complete data were available, the PEMS data files were processed using an R script to extract the same urban test cycle that was presented in Section 4.2. This resulted in a total of 475 observations of the urban test cycle (with 226 individual vehicles used), as shown in Figure 5.1.

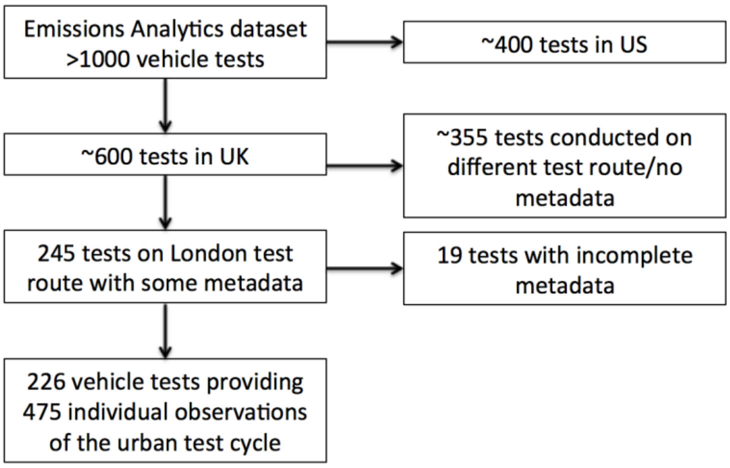


Figure 5.1 – the Emissions Analytics dataset used

5.2.1. Matching of PEMS and Hermes data

There are two distinct datasets available for this research:

- 20Hz Hermes data, relating to vehicle positioning and acceleration;
- 1Hz PEMS data, relating primarily to emissions, but also vehicle positioning and acceleration.

For investigations into vehicle dynamics (Chapter 4), the 1Hz positioning data provided by the PEMS dataset was previously deemed inadequate, as shown in section 3.2.2.1. Investigations into vehicle emissions as described in this chapter also require information on positioning and acceleration. Therefore, it is potentially desirable to augment the 1Hz PEMS data with 20Hz Hermes data in order to provide more accurate information on vehicle position and acceleration.

However, there is minimal benefit in doing this, for two main reasons:

1. High resolution Hermes data is only available for 55 of the 226 vehicles for which PEMS data are available. The Hermes data could be merged with the PEMS data using UTC time, which is available in both datasets. However, when conducting the subsequent analysis to assess the variability in tailpipe emissions, there is the potential to introduce additional errors depending on how the parameters that describe the dynamic behaviour of the vehicle are derived. For example, in the PEMS data, acceleration would be calculated using the speed measured from a 1Hz GPS module, whereas with the Hermes data, the acceleration is measured directly at 20Hz.
2. In the PEMS dataset, the parameters that describe the dynamic behaviour of the vehicle such as speed and change in altitude are acquired using the GPS module. They are

averages over a one second measurement period. Similarly for the emissions data, the mass flow rate for a particular pollutant is based on the average flow rate over a 1 second period (measured at up to 2.5kHz), multiplied by the concentration of the pollutant as measured by the gas analysers over 1 second. Therefore, every record in the PEMS data file presents the average behaviour of the vehicle over the previous second.

If the PEMS data were merged with the high resolution Hermes data, for each measurement in the PEMS dataset, there would be potentially 20 unique measurements of speed, acceleration and position in the Hermes data. Due to the resolution mismatch, interpolation would be required.

For each record in the resulting dataset, the speed, acceleration and positioning information would be an average over 0.05s. Whereas the emissions data would be averaged over 1s. In situations where the operation mode of the vehicle changes more frequently than 1Hz (e.g. in the vicinity of an urban obstacle), the resultant emissions would be incorrect. For example, the emission rate over a second would be constant despite the fact that the vehicle could be accelerating for a fraction of that second and decelerating for the remaining fraction of the second. As the dynamic behaviour of the vehicle will be used in parallel with the emissions data, it is suggested that the Hermes and PEMS data are not merged due to the potential errors it would introduce.

The Hermes data is available for less than 25% of the vehicles for which emissions data is also available. There are errors that may be introduced if the two datasets of differing frequencies are merged. Therefore, the analyses presented in this chapter are restricted to the PEMS dataset.

5.2.2. Calculation of total and distance based emissions

As highlighted in section 5.2.1, the PEMS dataset was collected at 1Hz. A vehicle travelling at the typical urban speed limit (30mph) covers a distance of 13.3 metres per second. In section 4.2.5 it was identified that the zone of influence of the speed cushion, Obstacle A, was 35m. This means there would be 2-3 emissions measurements for every vehicle whilst it is in the vicinity of the obstacle if the vehicle travels at the speed limit. Furthermore, due to the way the emissions are measured, it cannot be guaranteed that all of the emissions associated with navigating the obstacle are captured.

In order to estimate the total emissions associated with an obstacle, the data points that fall into the zone of influence of an obstacle are averaged to produce a median speed and median emission rate. This is done by pollutant and for each run of the test cycle. With the length of the zone of influence known, the total mass of pollutant (grams) as well as emissions rates as a function of time (grams/second) and distance (grams/kilometre) are calculated.

This method of estimating the emissions in the vicinity of urban obstacles makes the assumption that the emission rate is constant. Whilst this is a limitation of this research, improvements in measurement technology should allow for further work to address the data resolution limitations.

5.2.3. Improving confidence in PEMS positioning and speed data

The positioning and speed data in the PEMS dataset is obtained using a Garmin GPS-16 GPS receiver. The GPS module is able to output various accuracy parameters with each measurement that can be used to assess the precision of the measurement. Positional Dilution Of Precision (PDOP) is one of these accuracy parameters that indicates the combined error associated with horizontal and vertical position, as previously highlighted in section 3.5.5.

PDOP values of less than 4 are considered to be excellent and sufficiently accurate for all applications apart from those the are safety critical when the measurement error is ~1m (Zogg, 2002). Therefore, the PEMS data has been filtered to remove periods where the PDOP exceeds 4. The average PDOP for a typical run of the urban test cycle is 3.2 and the filtering removes less than 1% of the data.

The following subsections of this chapter present the analysis conducted to assess the variability in tailpipe emission rates between different urban roadway obstacles and between different vehicles at a particular obstacle.

5.3. Variability in tailpipe emissions at different urban obstacles

In order to navigate an urban obstacle, a vehicle may be forced to change its speed or trajectory. This changes the power demand the engine is required to meet, and thus the rate at which hydrocarbons are burnt and pollutants are emitted. It is hypothesised that the emission rate of pollutants will vary between different obstacles due to the power demand at each of these obstacles being different.

In order to assess the variability in tailpipe emissions, four metrics are presented:

- The total mass of pollutant (grams)
- Pollutant emission rate as a function of time (grams/second)
- Pollutant emission rate as a function of distance (grams/kilometre)
- Pollutant emission rate as a function of vehicle specific power (kilowatts/tonne)

The obstacles for consideration were previously identified and described in section 4.2.5. They are summarised below in Table 5.2.

Obstacle	Description
A – speed cushion	A vertical deflection on a bi-directional road that forces vehicles to reduce their speed.
B – signalised junction	This traffic management is located at the intersection of a crossroads. Vehicles encounter a delay if the signal is red or due to the presence of a queue.
C – mini roundabout	Located at the centre of a three-armed junction, the mini roundabout always results in a geometric delay and potentially additional delay due to queuing or lack of priority
D – “keep clear” zone	This obstacles causes a delay to vehicles if there is a queue upstream or downstream of the “keep clear” zone

Table 5.1 – summary of the obstacles investigated in this study

As explained in section 3.4, Emissions Analytics have two PEMS devices that they use for their vehicle tests. Both devices are capable of measuring carbon dioxide emission rates. However, only one of the devices is able to measure oxides of nitrogen. This means that CO_2 as a mass per unit time (g/s) is available for 475 runs of the test cycle and NO_x as a mass per unit time (g/s) is available for 315 runs of the test cycle. As explained in section 5.2.2, the total mass emitted and distance based emission rates are calculated. Sections 5.3.1-5.3.4 present the vehicle emission rates and total emissions at each obstacle before they are compared in section 5.3.5.

5.3.1. Analysis of tailpipe emissions at Obstacle A (speed cushion)

Obstacle A is a traffic calming measure located on a two-lane road that leads onto several residential streets and private roads. The purpose of the vertical deflection created by the speed cushion is to force vehicles to reduce their speed due to the potential hazard of vehicles trying to merge onto the road from the adjoining streets.

Figure 5.2 shows the distribution of tailpipe CO_2 emissions associated with vehicles navigating the speed cushion, Obstacle A. The mass of CO_2 emitted per unit time, as recorded by the PEMS instrumentation varies between 0.122 g/s and 6.1g/s, with a median of 2.169 g/s. The mass per unit distance for Obstacle A varies between 9.938 g/km and 794.8 g/km with a median of 220.1 g/km.

For comparison, a small passenger car such as a Vauxhall Corsa has a CO_2 emission rate of 127 g/km for the urban portion of the New European Drive Cycle (NEDC). A large passenger car such as a Land Rover Range Rover has a CO_2 emission rate of 376 g/km for the same urban portion of the NEDC (EU BCN, 2015). The NEDC figures are based on a full test cycle so include longer periods of idle and cruise, and are therefore expected to underestimate the emissions observed. In the vicinity of urban obstacles, vehicles spend a larger proportion of time accelerating and decelerating. That said, Figure 5.2 highlights why a NEDC emission rate cannot be used to estimate emissions in the vicinity of urban obstacles. Especially given several vehicles have emission rates over 500 g/km which is beyond the typical emission rates observed on the NEDC (EU BCN, 2015).

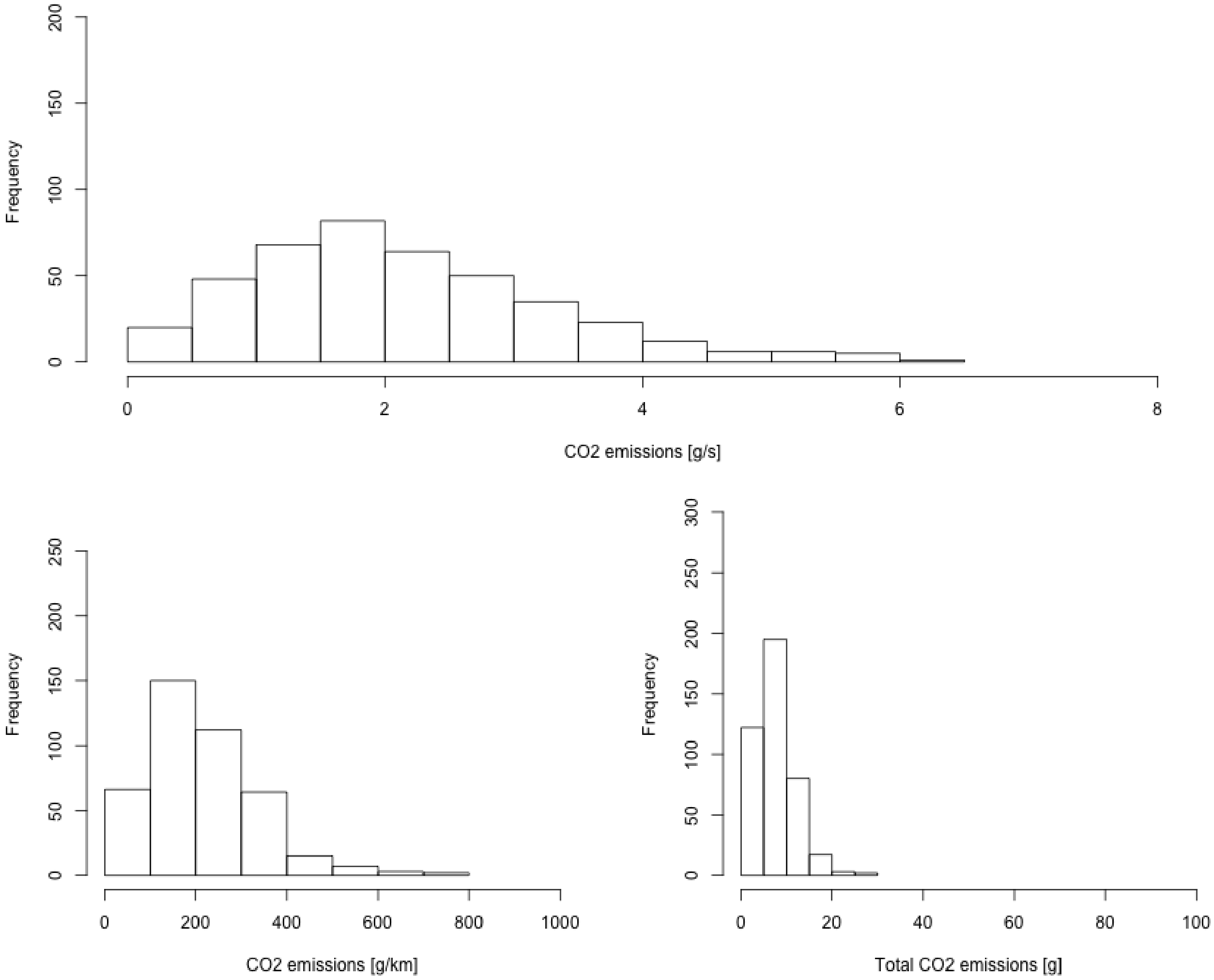


Figure 5.2 – distribution of CO_2 emissions associated with Obstacle A, the speed cushion

Figure 5.3 shows the tailpipe NO_X emissions associated with vehicles navigating Obstacle A. The mass of NO_x emitted per unit time varies between 0 g/s and 0.055 g/s with a median of $5x10^{-4}$ g/s. The NO_x emission rate can also be presented as a function of distance and varies between 0 g/km and 4.533 g/km with a median of 0.176 g/km. All the data used in this analysis comes from road-going passenger cars which conform to the European emissions standard, Euro 5 or Euro 6.

The limit value for NO_x emissions based on the NEDC is 0.060 g/km for a Euro 5 or Euro 6 petrol car and 0.180 g/km and 0.080 g/km for a Euro 5 and Euro 6 diesel car respectively (European Commission, 2015b). If the vehicle with a NO_x emission rate of 4.533 g/km were a Euro 5 diesel vehicle, it would be over 25 times the limit. Whilst the NEDC limit value is based on a cycle, Figure 5.3 once again highlights why a NEDC emission rate cannot be used to estimate emissions in the vicinity of urban obstacles. The limitations of the NEDC emissions testing procedure in representing real-world driving emissions is widely accepted in the research community as demonstrated in Kousoulidou et al. (2013) and Franco et al. (2013).

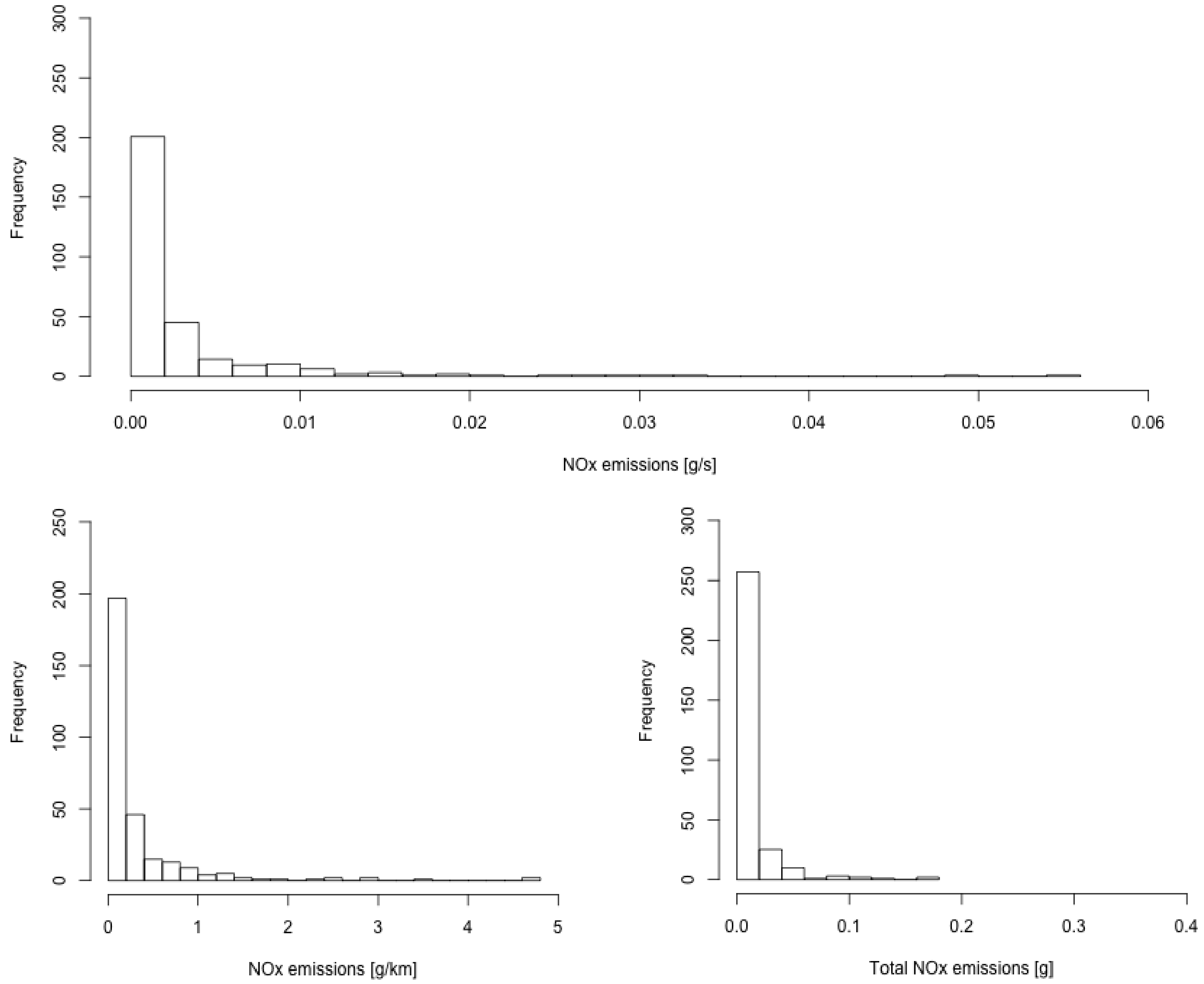


Figure 5.3 – distribution of NO_X emissions associated with Obstacle A, the speed cushion

The graphs presented in Figures 5.2 and 5.3 show the CO_2 and NO_x emissions emitted by vehicles when they are in the zone of influence of Obstacle A either as total mass of pollutant or as function of time or distance. Whilst these plots are useful for understanding the general variation in emissions in the vicinity of the speed cushion, they do not relate to what the vehicle was doing whilst the pollutants were emitted. The speed and positioning data collected using the GPS receiver connected to the PEMS unit can be used to explain the emissions further.

A common method of presenting vehicle emissions is as a function of speed as demonstrated by Ntziachristos and Samaras (2000), Gramotnev et al. (2003) and Smit et al. (2008). Whilst it is expected that the faster a vehicle is travelling, the harder the engine has to work to maintain that speed and therefore, the higher the emission rate; vehicle speed does not fully describe the pollutant emission rate. For example, a speed-based emission factor does not take into consideration whether the vehicle is accelerating or decelerating, or whether the vehicle is on a gradient or not. An alternative method of describing how hard the engine is working and thus the power demand is to use the metric 'Vehicle Specific Power' (VSP), which has the units kilowatts/tonne (kW/T).

The VSP metric was first introduced by Jiménez (2000) and built upon by Zhai (2007). The VSP metric is a proxy for the instantaneous power demand on the engine as a function of vehicle speed, vehicle acceleration, road gradient, rolling resistance and aerodynamic drag, as shown below.

$$VSP = v \times (a + \sin \Phi + \Psi) + \zeta \times v^3$$

Equation 5.1

v = vehicle speed (m/s)

a = vehicle acceleration (m/s^2)

g = acceleration due to gravity (m/s^2) – taken as 9.81m/s^2

Φ = road grade (degrees)

Ψ = rolling resistance (m/s^2) – taken as 0.132 m/s^2 and assumed constant for all vehicles

ζ = drag coefficient – taken as 3.02×10^{-4} and assumed constant for all vehicles

Vehicle speed is obtained from the GPS module and vehicle acceleration can be calculated by differentiating the vehicle speed with respect to time. The road grade is calculated using the change in altitude and distance travelled over a 1 second period. As the vehicle specific rolling resistance and drag coefficient values were not available, those recommended by Jiménez-Palacios (1999) were used. Whilst this is a limitation of using the VSP metric, both the rolling resistance and drag contributions to VSP are expected to be small given the speed observed within the vicinity of urban obstacles are less than 14 m/s.

Figure 5.4 shows the CO_2 emissions as a function of both speed and VSP for a typical vehicle on the 10km urban cycle used in this study. The top graph shows a cloud of data points when the emission rate of CO_2 is plotted against speed, with no clear trend. There is a vertical structure at 0 m/s that shows the emissions caused by vehicles accelerating from rest. There is also a horizontal structure around 0 g/s where vehicles travelling at speed begin to decelerate and the load on the engine reduces to near zero. The bottom graph shows CO_2 emissions plotted against VSP and there is a much clearer relationship. For positive VSP values, there is a positive correlation between VSP and CO_2 emission rate. The harder the engine is working to over come resistive forces, the higher the emissions. For negative VSP values, either when the vehicle is decelerating or on a negative gradient, there is a weaker relationship between VSP and CO_2 emission rate. If the engine has to work less to overcome resistive forces, less fuel is required and thus the resultant pollutant emission rates are lower. However, the emission rate does not reach zero if the engine is still switched on due to the load from auxiliary devices such as the ventilation system. A vertical structure when VSP is equal to 0 kW/T is also observed, this is due to emissions associated with the engine being switched on and when moving-off from rest.

VSP is a useful metric for analysing vehicle emissions, as shown in Figure 5.4 and work done by Coelho et al. (2005), Carslaw et al. (2013) and Huang et al. (2013). In the literature, VSP is normally binned due to inaccuracies and uncertainty in the measurement data. The emissions data for all runs of Obstacle A have been binned by VSP (Table 5.2) and plotted as shown in Figure 5.5. There is generally a weak relationship between emission rate and VSP bin when the data from all the vehicles are aggregated. This is expected to be due to differences in vehicle technology, fuel type and European emissions standard conformance and is further investigated in section 5.4.

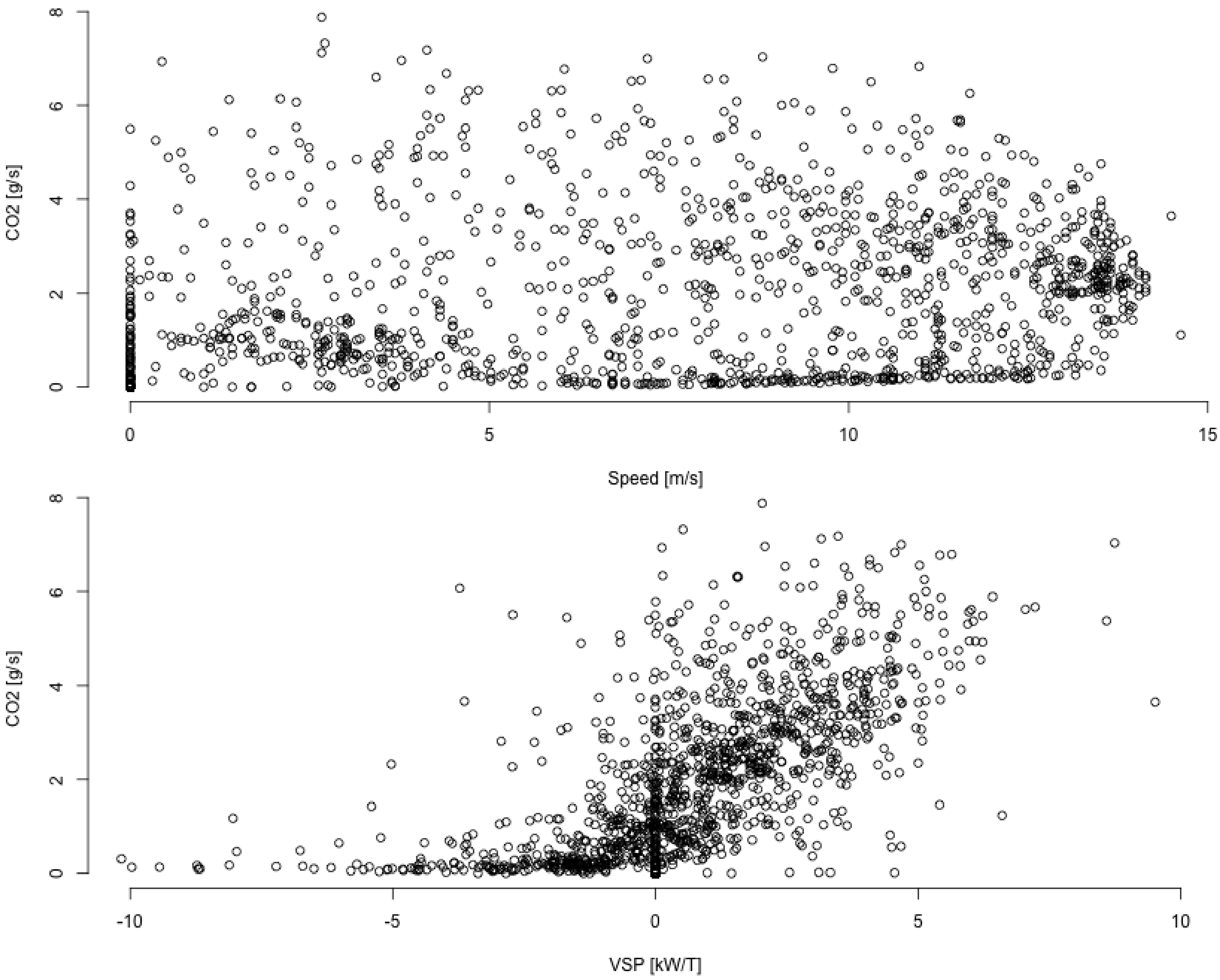


Figure 5.4 – tailpipe CO_2 emissions as function of speed and VSP

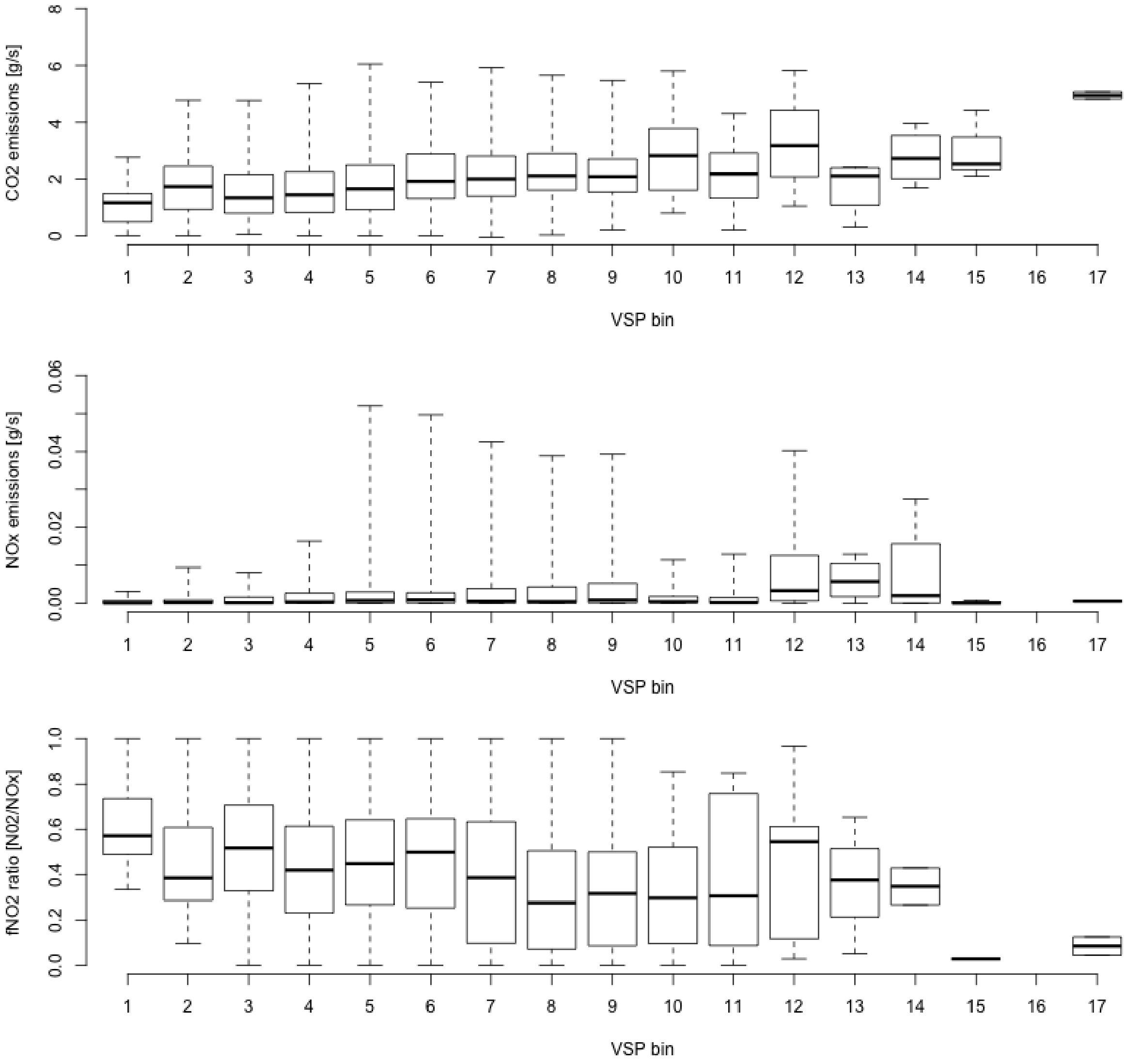


Figure 5.5 – CO_2, NO_x and fNO_2 as a function of VSP bin for Obstacle A, the speed cushion

VSP bin	VSP range [kW/T]	VSP bin	VSP range [kW/T]
1	-8 - < -6	10	10 - < 12
2	-6 - < -4	11	12 - < 14
3	-4 - < -2	12	14 - < 16
4	-2 - < 0	13	16 - < 18
5	0 - < 2	14	18 - < 20
6	2 - < 4	15	20 - < 22
7	4 - < 6	16	22 - < 24
8	6 - < 8	17	24 - < 26
9	8 - < 10		

Table 5.2 – Vehicle Specific Power (VSP) ranges used in the VSP binning process

5.3.2. Analysis of tailpipe emissions at Obstacle B (signalised junction)

Obstacle B is a signalised junction used to manage the competing demands for road space in time. The junction has four arms and the signal plan is formed of two stages. This allows for movement in the north-south direction and then the east-west direction, right turn manoeuvres are accommodated using late release. Vehicles on the urban test route used for this thesis continue straight ahead at the junction and obey the traffic signals rules as presented in the Highway Code. In some instances the vehicle is able to pass through the junction unhindered by the presence of the traffic signals (green light). On other instances, the vehicle may be forced to wait due to a red light or due to the presence of a queue.

Figure 5.6 shows the distribution of CO_2 emission rates whilst vehicles are in the zone of influence of the traffic signal. The mass of CO_2 per unit time, as output directly from the PEMS instrumentation varies between 0.028 g/s and 6.130 g/s, with a median of 1.452 g/s. The mass of CO_2 per unit distance varies between 1.211 g/km and 967.0 g/km with a median of 305.5 g/km. Figure 5.7 shows the distribution of NO_x emission rates for Obstacle B, the mass of NO_x emitted per unit time varies between 0.002 g/s and 0.048 g/s with a median of 6.4×10^{-4} g/s. The mass of NO_x per unit distance varies between 0.001 g/km and 3.904 g/km with a median of 0.271 g/km.

The CO_2 emissions associated with Obstacle B are lower than those of Obstacle A when considering the emission rate as a function of time. This is expected because a proportion of the vehicles passing Obstacle B will have to come to a complete stop where the CO_2 emission rate will reduce, as the engine is idle. Furthermore, many modern vehicles including those used in this thesis are fitted with 'Stop-start technology'. The eco-technology switches off the engine when the vehicle is stationary and taken out of gear on a manual vehicle, or when the vehicle is stationary and the break is depressed on an automatic vehicle. The engine restarts when the clutch is depressed on a manual vehicle or if the accelerator is pressed on an automatic vehicle. The engine may also restart if additional power is required for an auxiliary system such as air conditioning. During the period where stop-start is engaged and the engine is off, the CO_2 emissions will be zero. Figure 5.8 shows the speed and CO_2 emissions profile for a vehicle whilst it is in the zone of influence of Obstacle B. Once the vehicle is stationary and taken out of gear (t=8s), the emission rate drops to zero. As soon as the clutch is depressed before moving off (t=34s), there is a sharp increase in the emission rate.

The vehicle being idle and the use of 'stop-start' technology explains why the CO_2 emission rates as a function of time are lower for Obstacle B compared to Obstacle A. The same would be expected for NO_x emissions, however this is not the case. Vehicle manufacturers use a range of techniques to reduce NO_x emissions. A common approach is the use of a Selective Catalytic Reduction (SCR) system. The effectiveness of the SCR system in mitigating NO_x emissions is temperature dependent. Thus the reduction in NO_x emissions is lower at lower exhaust temperatures (Clean Air Technology Center, 1999). When the engine is switched on after being off for a short period, the SCR system is no longer at its optimum temperature, resulting in more NO_x being emitted as the system is not at its maximum efficiency for NO_x reduction. This is compounded by the fact that there is usually an acceleration event as soon as the engine is switched on, resulting in even more NO_x being emitted.

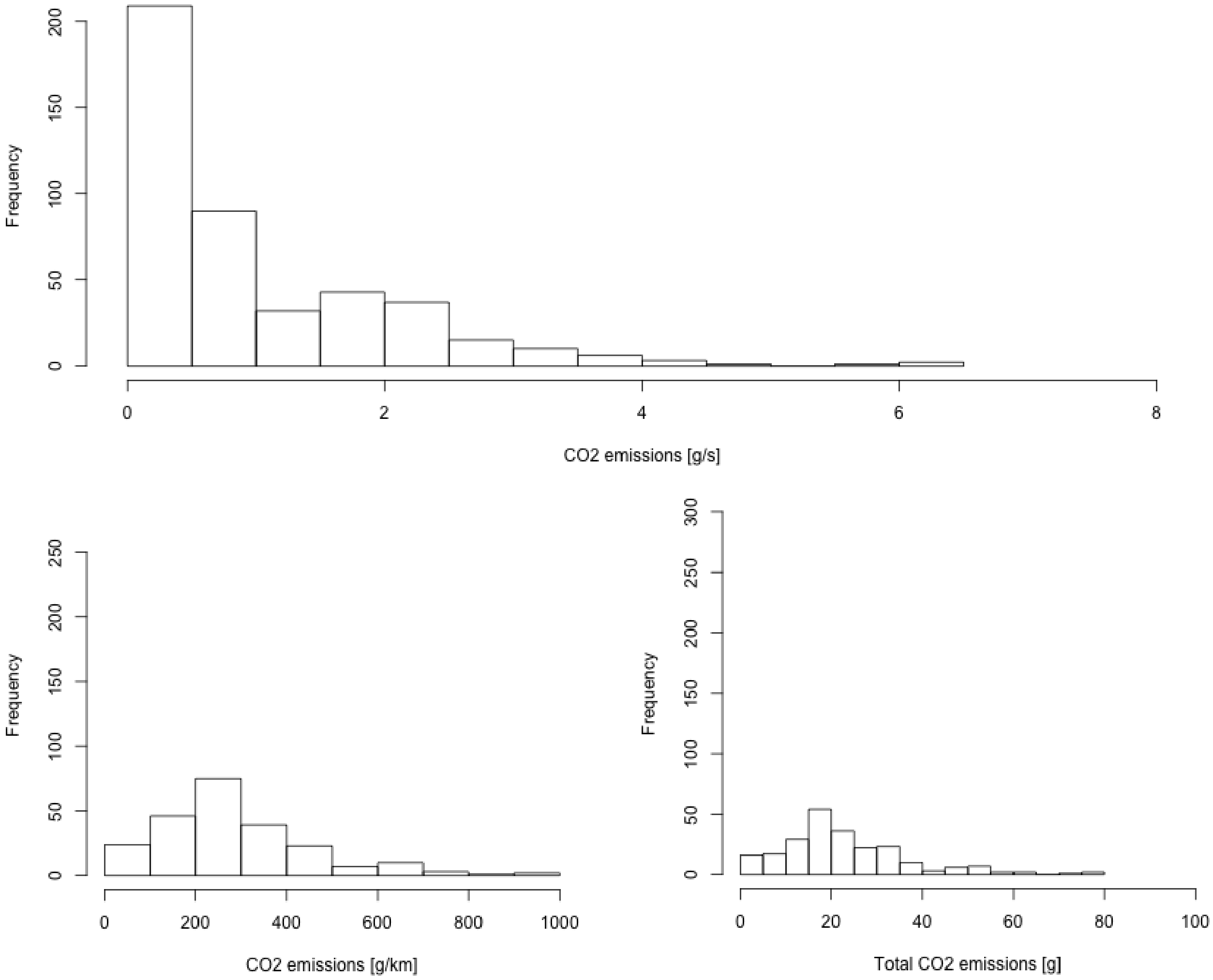


Figure 5.6 – distribution of CO_2 emissions associated with Obstacle B, the signalised junction

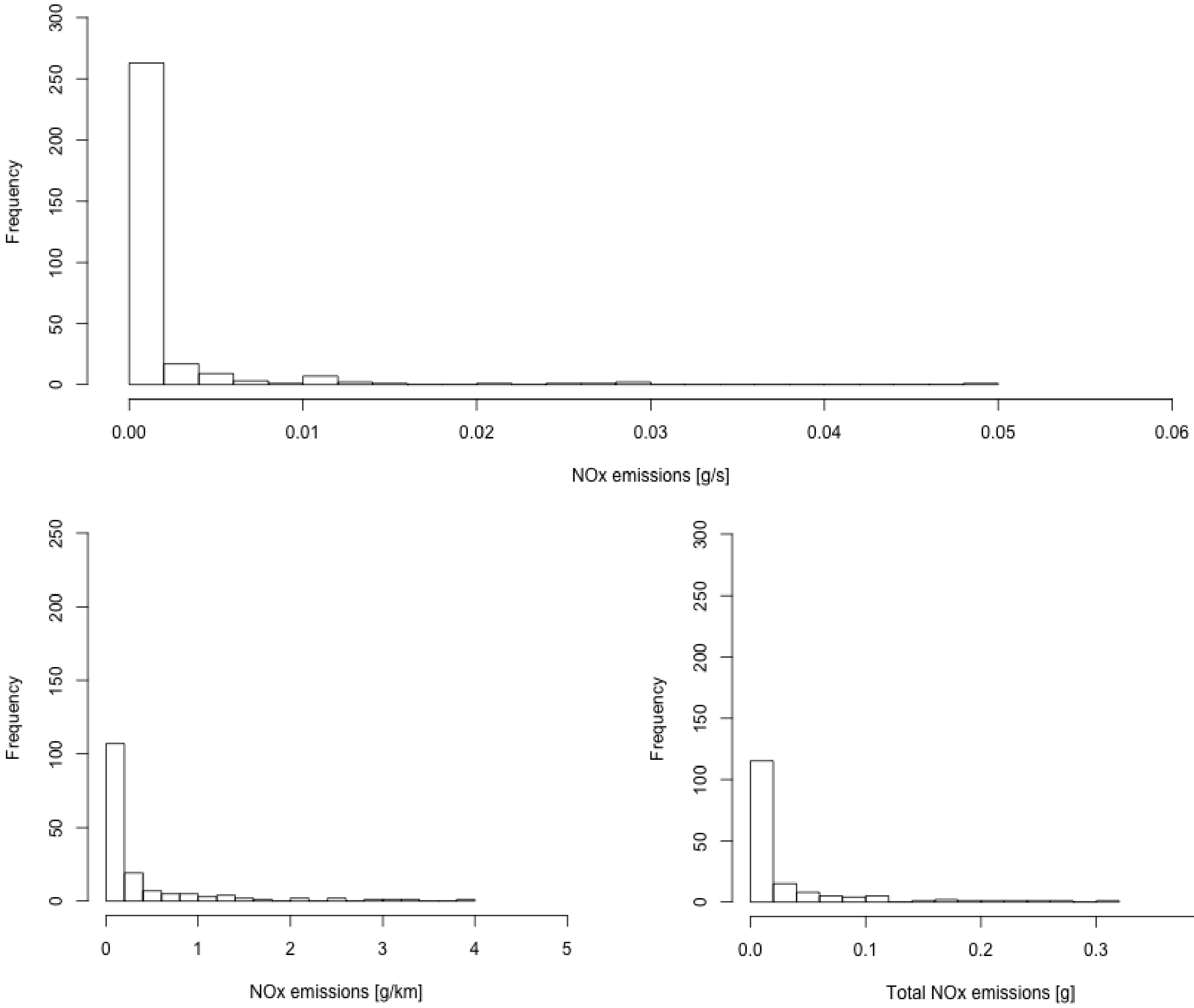


Figure 5.7 – distribution of NO_X emissions associated with Obstacle B, the signalised junction

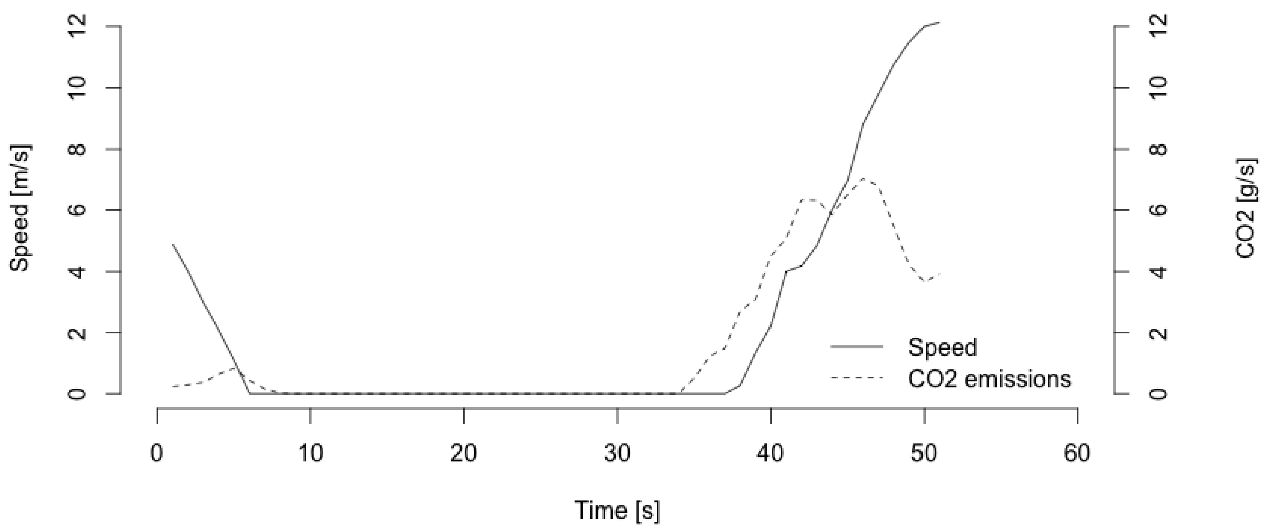


Figure 5.8 – the effect of 'stop-start technology' on tailpipe emissions, time series of speed and CO_2 emission rate

Figure 5.9 shows the CO_2 and NO_x emission rates as a function of VSP. As shown in Table 5.2, the VSP is negative in bins 1-4 and positive in bins 5-17. In both the plots for CO_2 and NO_x a step change in emission rates is observed between bin 4 and bin 5 due to the positive power demand and thus higher rate of fuel combustion. Section 5.4 presents a more detailed analysis of emissions where vehicles are categorised by fuel type, engine size and European emissions standard conformance.

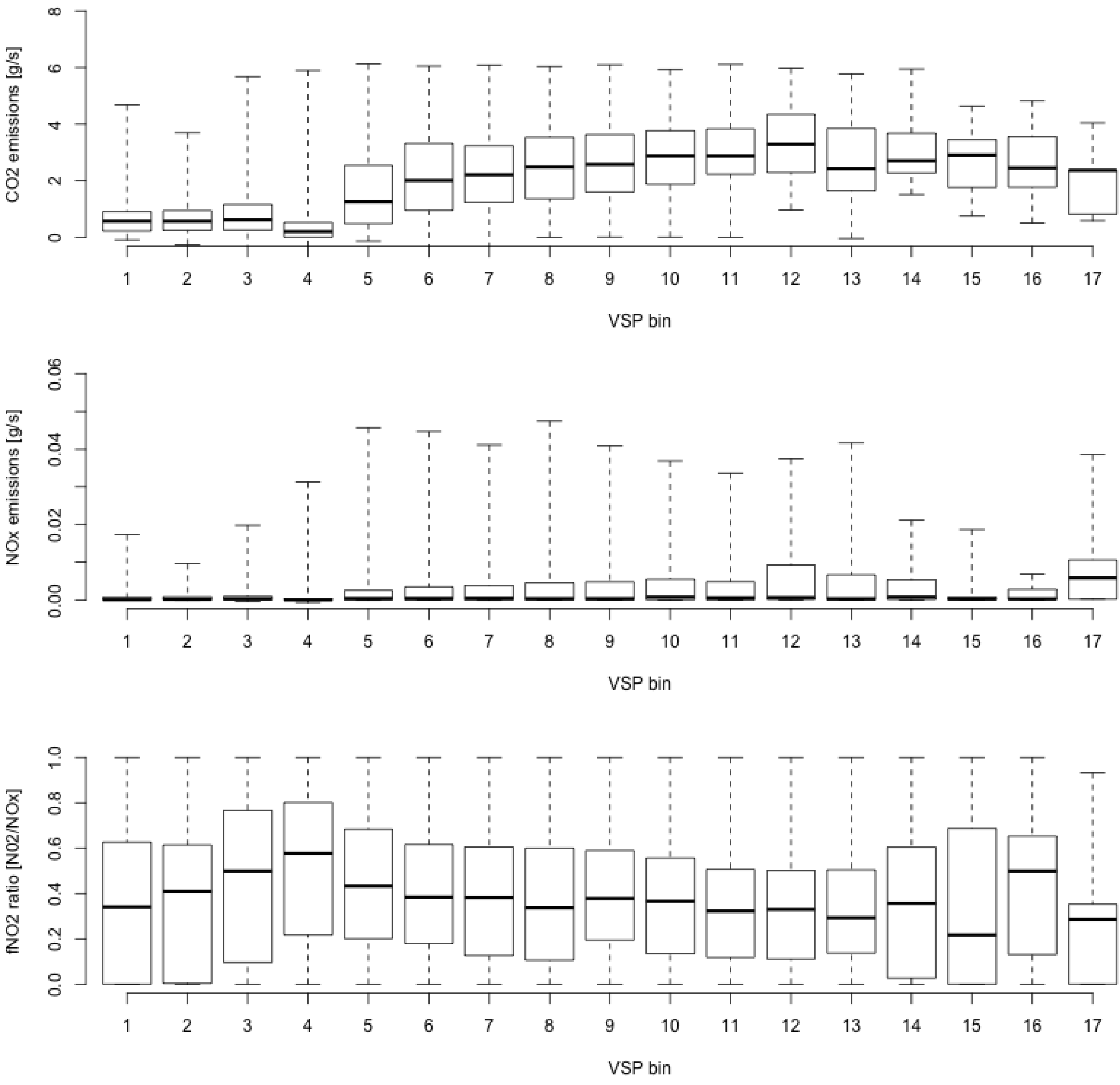


Figure 5.9 – CO_2, NO_x and fNO_2 as a function of VSP bin for Obstacle B, the signalised junction

5.3.3. Analysis of tailpipe emissions at Obstacle C (mini roundabout)

Obstacle C is a mini roundabout located at the centre of a three-armed junction, with each arm being an entry and exit from the roundabout. All vehicles following the urban test cycle take the 2nd exit from the roundabout (straight ahead).

Figure 5.10 shows the distribution of CO_2 emission rates whilst vehicles are in the zone of influence of the mini roundabout. The mass of CO_2 per unit time, as output directly from the PEMS instrumentation varies between 0.017 g/s and 3.311 g/s, with a median of 0.745 g/s. The mass of CO_2 per unit distance varies between 8.893 g/km and 1493.0 g/km with a median of 196.4 g/km. Figure 5.11 shows the distribution of NO_x emission rates for each run of Obstacle C. The mass of NO_x emitted per unit time varies between 0.001 g/s and 0.018 g/s with a median of 5.8×10^{-4} g/s. The mass of NO_x per unit distance varies between 0.001 g/km and 3.549 g/km with a median of 0.198 g/km.

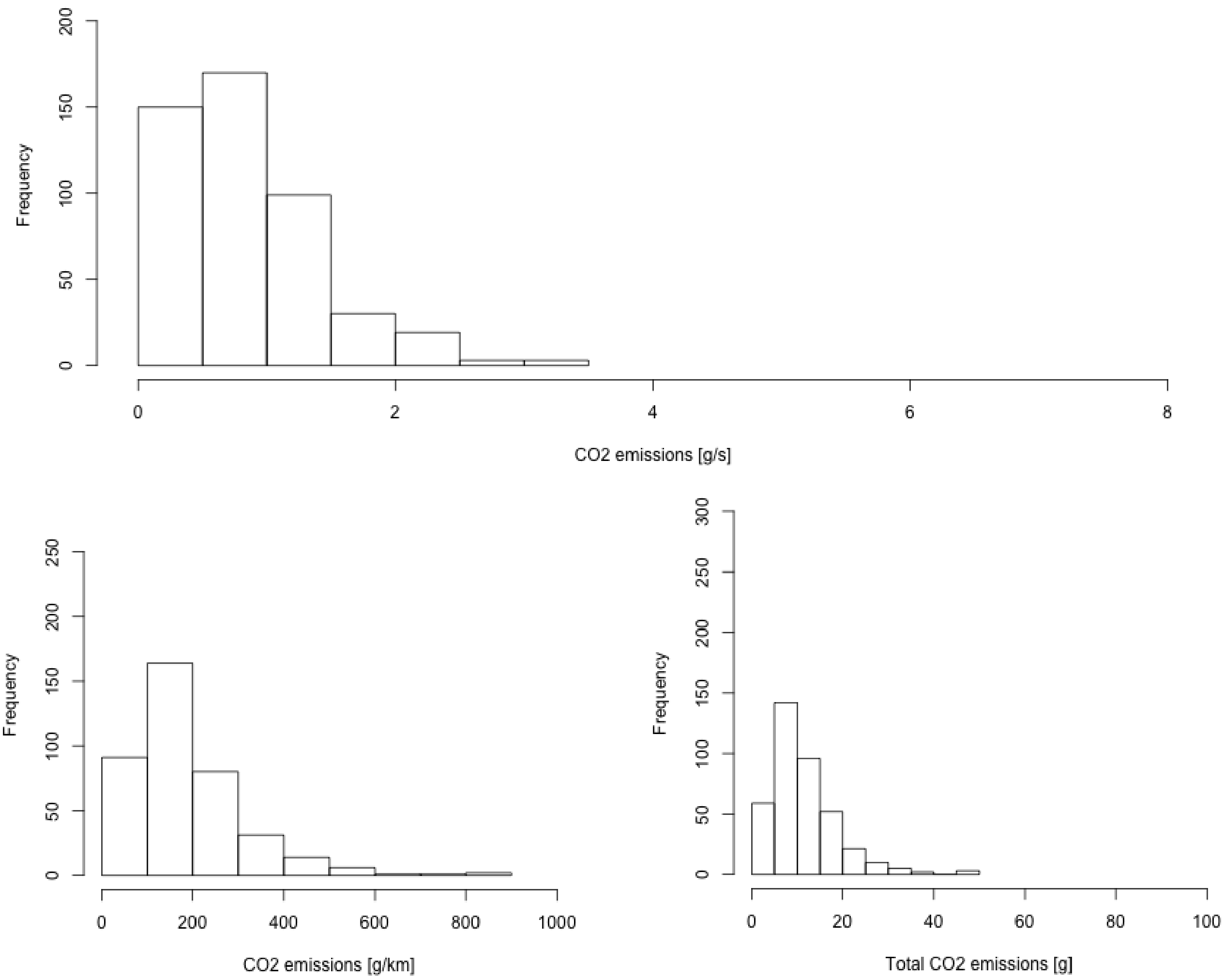


Figure 5.10 – distribution of CO_2 emissions associated with Obstacle C, the mini roundabout

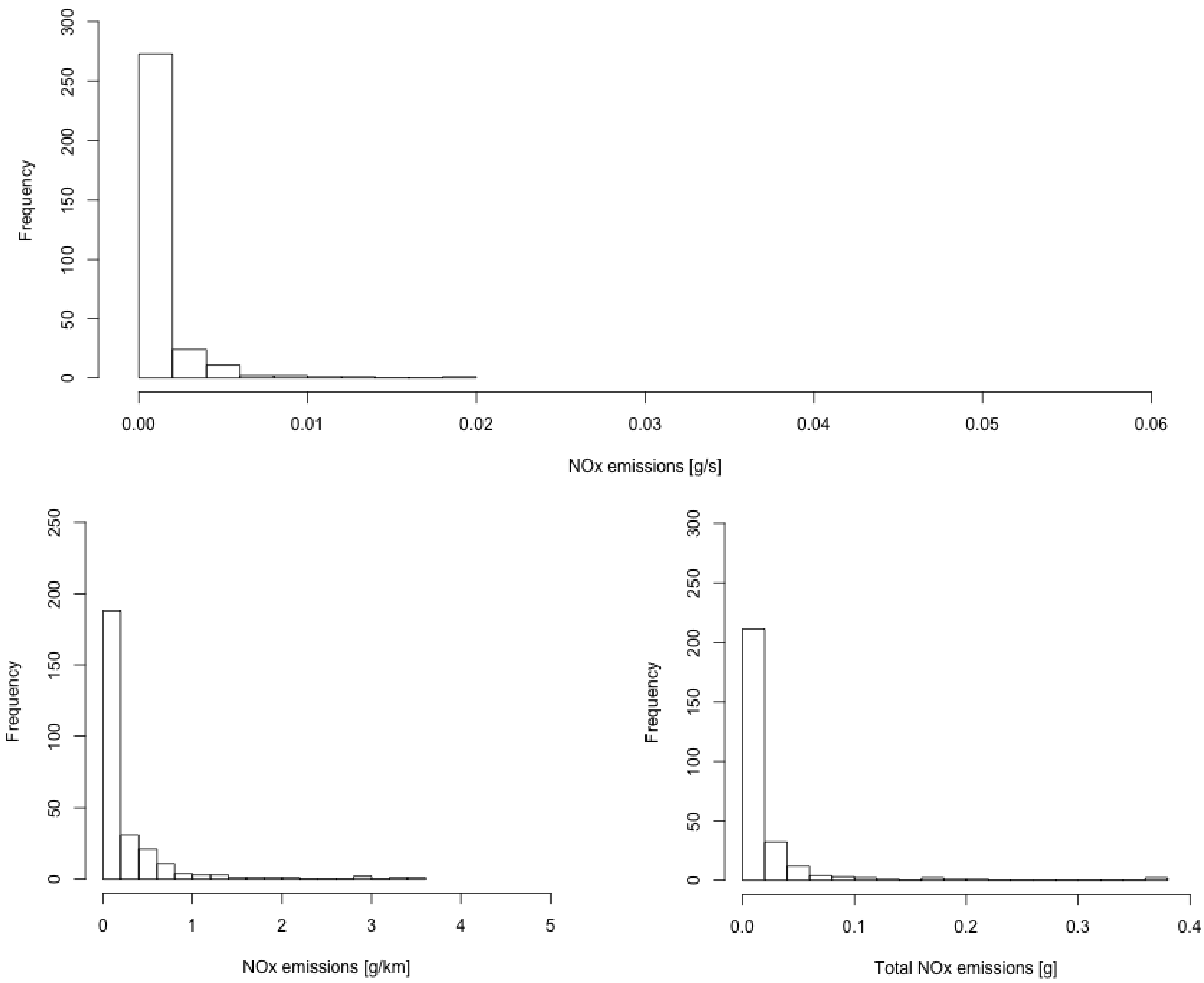


Figure 5.11 – distribution of NO_X emissions associated with Obstacle C, the mini roundabout

The CO_2 and NO_x emissions at Obstacle C are lower than those at Obstacle B when considered as both a function of time and a function of distance. This can be explained by the vehicle operation mode analysis presented in section 4.3.3. It was shown that vehicles spend on average 53.4% of the time they were navigating the mini roundabout in the 'deceleration' mode. This means that the power demand is lower when navigating the mini roundabout compared to the traffic signal where vehicles have to accelerate from rest if the vehicle encounters a red traffic signal or a queue. Such a large proportion of time in the deceleration operation mode is not expected for all roundabouts and is something that further work could address. In this particular scenario, vehicles are not obstructed upstream of the roundabout and thus can travel close to their desired speed. At the mini roundabout, there is good visibility so vehicles can pass without having to come to rest. At a roundabout there is no legal requirement to stop, only to give way to vehicles that have priority. Therefore meaning the only guaranteed delay is geometric delay.

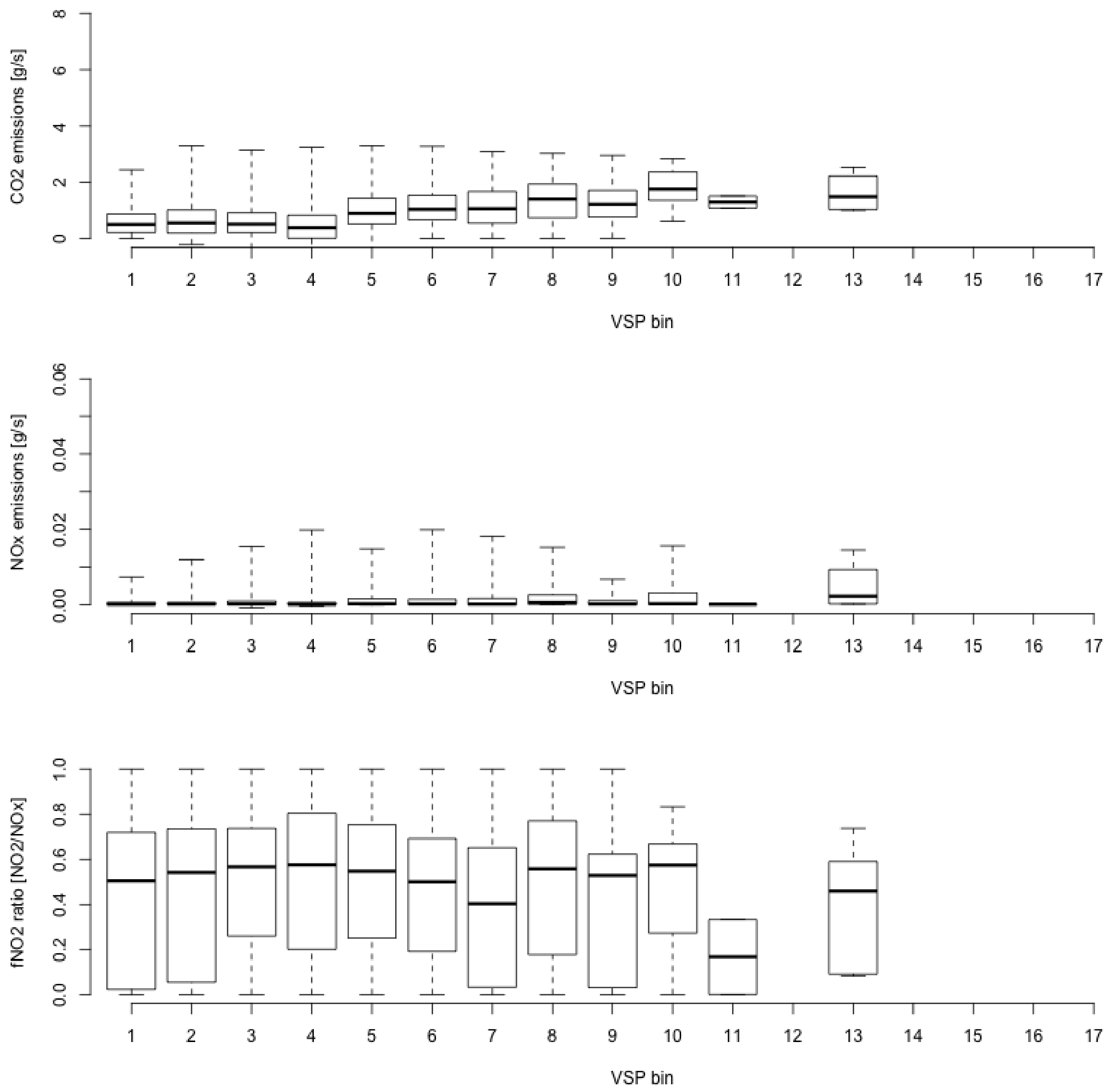


Figure 5.12 – CO_2, NO_x and fNO_2 as a function of VSP bin for Obstacle C, the mini roundabout

Figure 5.12 shows the CO_2 and NO_x emission rate as a function of VSP bin. As with Obstacle B, there is an increase in median emission rates with increasing VSP bin, as the engine has to work harder to meet the instantaneous power demand. The third plot in Figure 5.12 shows the proportion of NO_2 to NO_x emitted for the VSP ranges observed at Obstacle C, the fraction of NO_x emissions that are primary NO_2. COPERT, a well established emissions model estimates based on forecasts that the fNO_2 ratio should be between 0.2 and 0.4 for the Euro 5-6 petrol and diesel vehicles used in this study (Emisia, 2011). For Obstacle C, the median fNO_2 ratio is 0.497 and this includes a mixture of petrol and diesel vehicles conforming to either Euro 5 or Euro 6. Whilst this figure is obtained from a segment of an urban cycle, rather than the whole cycle, it again highlights why in-use vehicle emissions are required to accurately evaluate tailpipe emissions in the vicinity of urban obstacles.

5.3.4. Analysis of tailpipe emissions at Obstacle D (“keep clear” zone)

Obstacle D is a 40m “keep clear” zone with an intended purpose of creating space in the carriageway. This is to ensure that private and emergency vehicles can join and leave the carriageway without having to wait for a gap in the traffic. Vehicles are advised to not enter the zone unless their exit is clear.

Figure 5.13 shows the distribution of CO_2 emission as measured by the PEMS instrumentation whilst vehicles are in the vicinity of Obstacle D. The mass of CO_2 per unit time varies between 0.022 g/s and 5.165 g/s with a median of 1.299 g/s. The mass of CO_2 per unit distance varies between 6.485 g/km and 769.30 g/km with a median of 120.70 g/km. Figure 5.14 shows the distribution of NO_x emission rates for each run of Obstacle D. The mass of NO_x emitted per unit time varies between 0.001 g/s and 0.046 g/s with a median of $6.1x10^{-4}$ g/s. The mass of NO_x per unit distance varies between 0.001 g/km and 2.943 g/km with a median of 0.183 g/km.

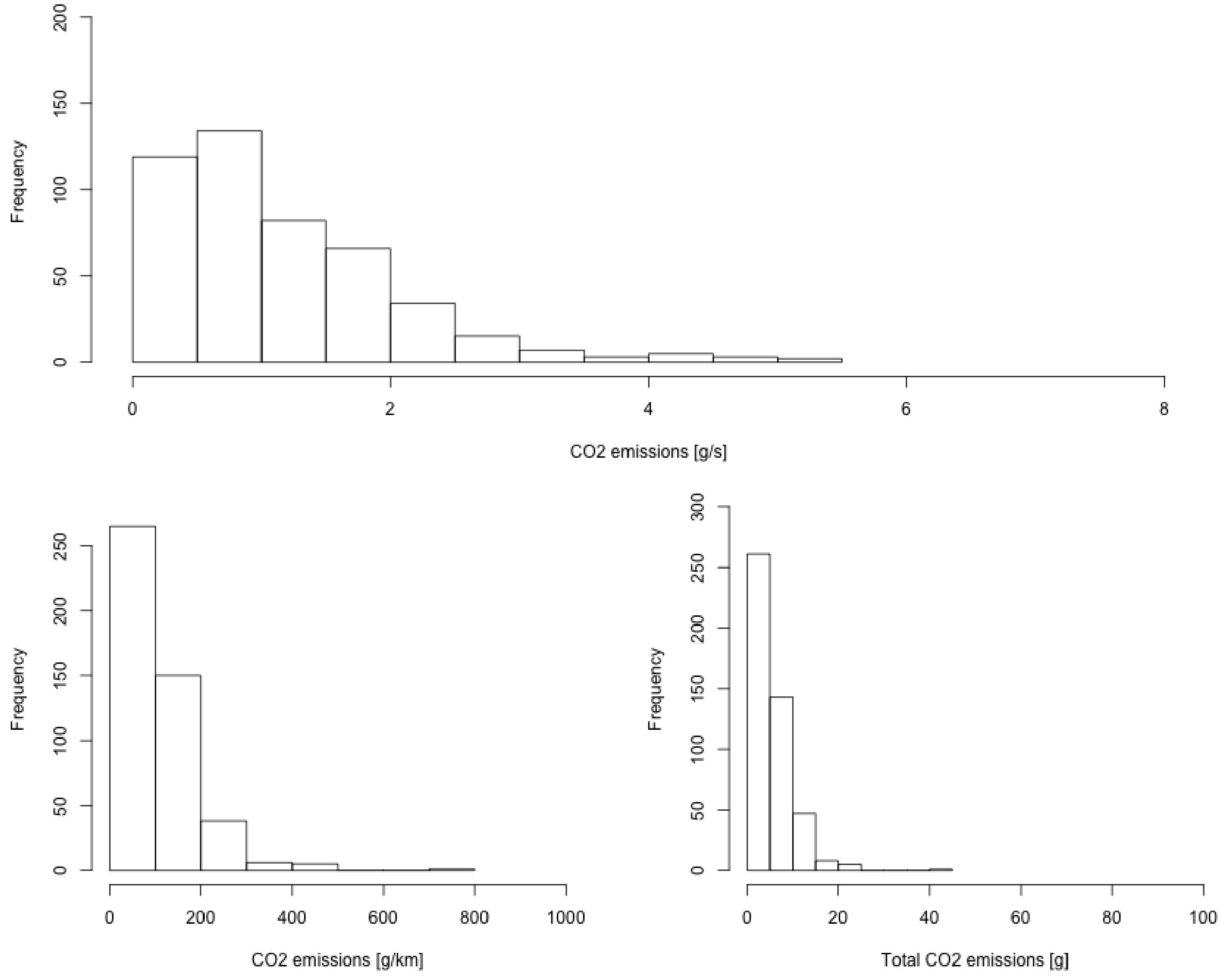


Figure 5.13 – distribution of CO_2 emissions associated with Obstacle D, the “keep clear” zone

Comparing the emission rates of CO_2 and NO_x to those observed at the other obstacles, the emission rates are most similar to those observed at Obstacle B, the signalised junction. This result was expected considering the mechanism of action at both obstacles is comparable. Vehicles are not guaranteed to encounter a delay as is found at the speed cushion and mini roundabout. Vehicles only encounter a delay if there is a queue or a red traffic signal (Obstacle B); otherwise they are able to navigate the obstacle unhindered. The statistical significance of the variation in tailpipe emissions between the obstacles investigated is discussed further in section 5.3.5.

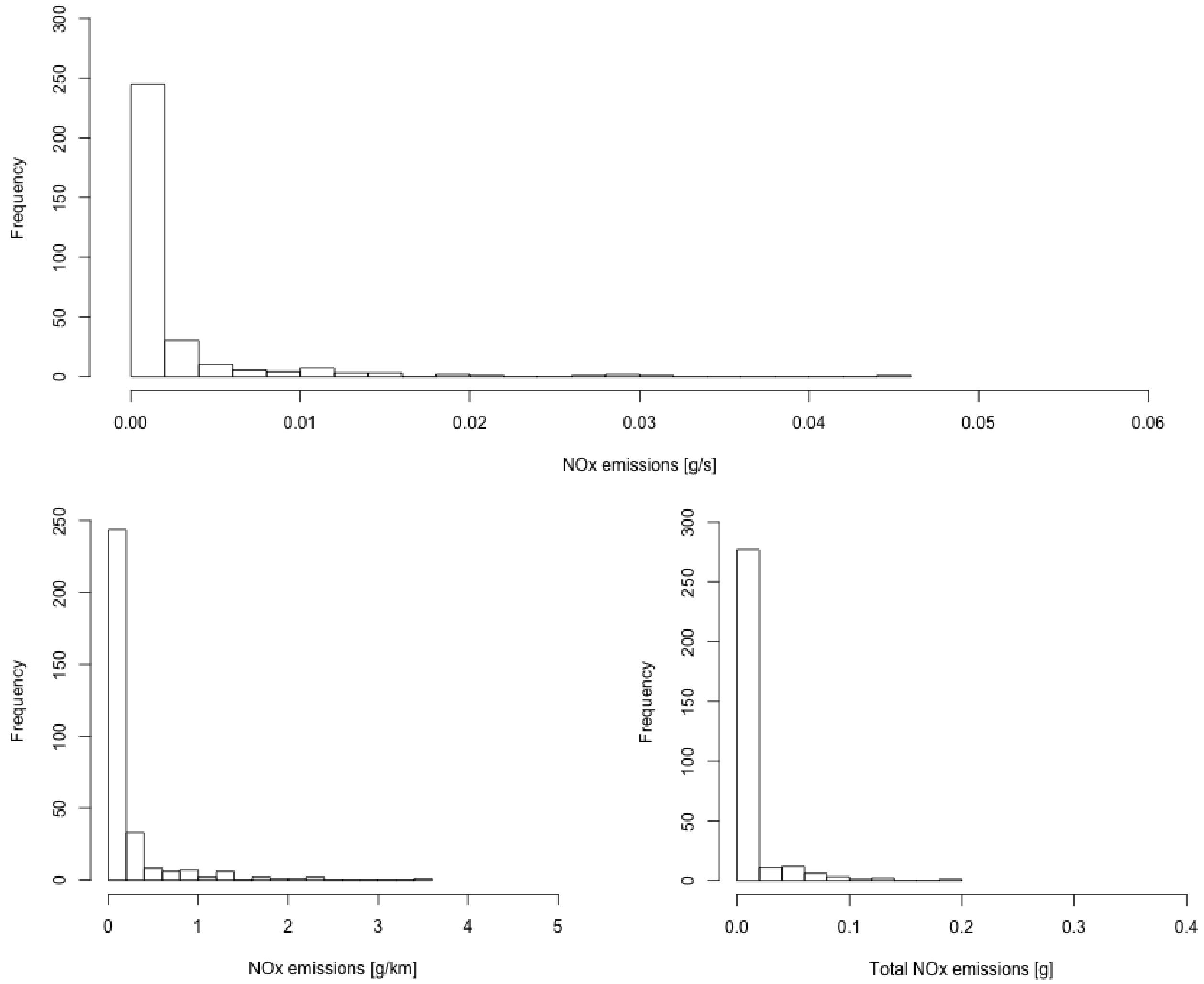


Figure 5.14 – distribution of NO_X emissions associated with Obstacle D, the "keep clear" zone

Figure 5.15 shows the CO_2 and NO_x emissions rates for vehicles in the zone of influence of Obstacle D by VSP bin. The median emission rates generally increase with VSP bin because the higher the power demands, the more fuel that is combusted. The median fNO_2 ratio is 0.438, which like the median fNO_2 ratio for Obstacle C, is outside the range predicted by widely used emissions modelling tools such as COPERT. The higher than expected fNO_2 ratio is cause for concern as NO_2 is a gas that is toxic for humans.

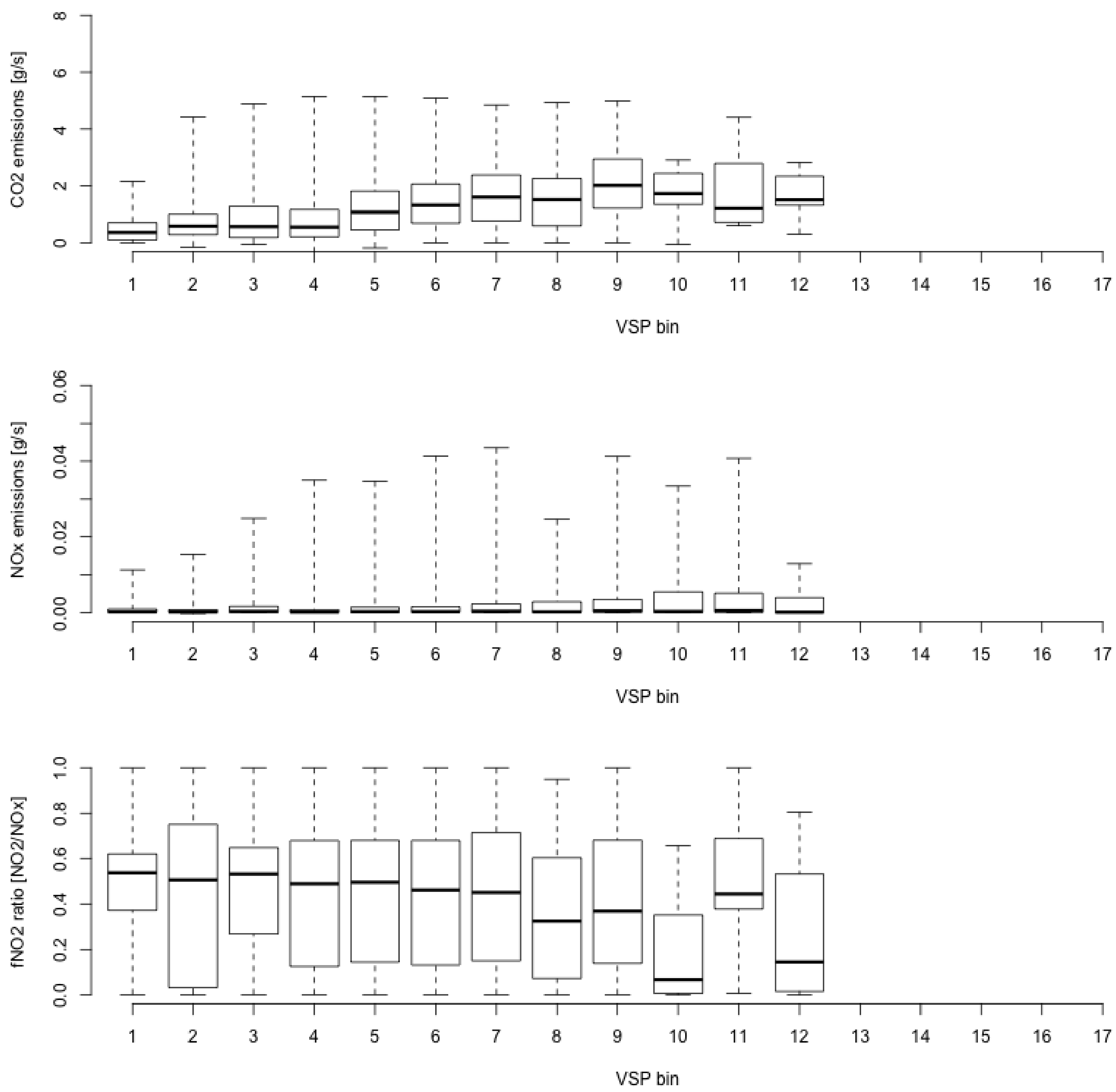


Figure 5.15 – CO_2, NO_x and fNO_2 as a function of VSP bin for Obstacle D, the "keep clear" zone

5.3.5. Summary of inter-obstacle variability

Sections 5.3.1-5.3.4 present the tailpipe emissions observed from 475 runs of the four obstacles identified in Chapter 4. For each obstacle, the tailpipe CO_2 and NO_x emissions data collected using PEMS monitoring equipment have been presented and comparisons are made to existing values, such as those derived from the regulatory testing.

Table 5.3 shows the median CO_2 and NO_x emission rates based on all the vehicles in the zone of influence of each obstacle. A higher emission rate as a function of time (g/s) does not necessarily correspond to a higher emission rate as a function of distance (g/km) as vehicle speeds in the vicinity of each obstacle varies as shown in section 4.3.

	Median CO_2		**Median NO_x**	
	g/s	**g/km**	**g/s**	**g/km**
Obstacle A (speed cushion)	2.169	220.1	5.0×10^{-4}	0.176
Obstacle B (signalised junction)	1.542	305.5	6.4×10^{-4}	0.271
Obstacle C (mini roundabout)	0.745	196.4	5.8×10^{-4}	0.198
Obstacle D (“keep clear” zone)	1.299	120.7	6.1×10^{-4}	0.183

Table 5.3 – table to show median CO_2 and NO_x emission for all obstacles studied

Whilst the median emission rates for each obstacle gives an indication of the variation, in order to determine whether the emission rates at each obstacle are indeed different, the Kolmogorov-Smirnov (KS) test can be employed. The KS test is a nonparametric test where two samples can be compared based on the probability distribution, P and P_0. In this application, the emission rates (g/km) from all 475 runs of each obstacle will be compared for both CO_2 and NO_x.

$$H_0: P = P_0$$

$$H_1: P \neq P_o$$

The null hypothesis that the two samples are drawn from the same population can be rejected if the p-value returned is less than the 0.05 significance level.

Tables 5.4 and 5.5 show the results of the KS test for all potential combinations of obstacles based on the emission rates as a function of distance (g/km). The D statistic is a measure of the absolute maximum difference between the two cumulative distribution functions. For all cases, the p-value was less than 0.05 and therefore, the null hypothesis can be rejected and thus the emission rates are not drawn from the same population. Therefore, the tailpipe emission rates at the four obstacles investigated are different for both CO_2 and NO_x.

There are several reasons why the emission rates of CO_2 and NO_x would be different at the four obstacles studied. Referring to the analysis presented in Chapter 4, the vehicles spend differing proportions of time in each of the mutually exclusive vehicle operating modes, namely acceleration, deceleration, idle and cruise. This means that the power demands will vary and thus differences are expected in the rate of combustion of fuel and the resultant tailpipe emissions. For example, at Obstacle A, the speed cushions, vehicles spent on average 0.15% of the time they were in the zone of influence, in the idle mode, compared to 32.9% for Obstacle B, the signalised junction. At Obstacle C, the mini roundabout, vehicles spent 53.4% of their time in the deceleration mode, one of the least polluting engine operation modes, compared to just 13.8% for Obstacle B. At Obstacle D, the "keep clear" zone, vehicles were in the acceleration mode for 19.8% of time, compared to 41.4% for Obstacle A.

Whilst this result was generally expected, it demonstrates that the tailpipe emission rates in the vicinity of urban obstacles vary. This means that the tools used to model the emissions at urban obstacles should consider the differences in power demand. Furthermore, if obstacle specific emissions factors are to be used in a modelling exercise, caution should be employed to ensure the factors are representative.

Vehicle specific properties such as whether the vehicle is fitted with 'stop-start technology' or other emissions control strategies that require the vehicle to be in a particular state can affect the resulting tailpipe emissions. The engine size, type of fuel used and conformance to European emissions standards can also affect pollutant emission rates, and this is discussed further in section 5.4.

Comparison	D statistic	p-value
Obstacle A – Obstacle B	0.4583	**2.2×10^{-16}**
Obstacle A – Obstacle C	0.4911	**2.2×10^{-16}**
Obstacle A – Obstacle D	0.3148	**2.2×10^{-16}**
Obstacle B – Obstacle C	0.1432	**2.2×10^{-16}**
Obstacle B – Obstacle D	0.2496	**2.2×10^{-16}**
Obstacle C – Obstacle D	0.1800	**2.2×10^{-16}**

Table 5.4 – results of KS test for CO_2 emission rates between all obstacles

Comparison	D statistic	p-value
Obstacle A – Obstacle B	0.2215	**2.2×10^{-16}**
Obstacle A – Obstacle C	0.2154	**2.2×10^{-16}**
Obstacle A – Obstacle D	0.1471	**2.2×10^{-16}**
Obstacle B – Obstacle C	0.0782	**2.2×10^{-16}**
Obstacle B – Obstacle D	0.1372	**2.2×10^{-16}**
Obstacle C – Obstacle D	0.0870	**2.0×10^{-15}**

Table 5.5 – results of KS test for NO_x emission rates between all obstacles

5.4. Variability in tailpipe emissions between different vehicles

In section 5.3, the tailpipe emissions data collected at each urban obstacle was aggregated and used to investigate differences in emission rates. Whilst this allowed for an understanding of the variation in emission rates between the four obstacles, it did not consider the variation between vehicles at a particular obstacle. Variations in emissions rates are expected between different vehicles due to differences in the vehicle characteristics such as the fuel used or engine size, as discussed in section 2.1.3. This is addressed in this section through the development of a model that takes into consideration vehicle specific characteristics.

In the following subsections, vehicle specific characteristics are used to develop a model that represents the tailpipe emission rates observed at each obstacle. A response variable is proposed and the potential explanatory variables are considered. A suitable model is then chosen and the model results are discussed.

5.4.1. Selection of response variable

As explained in section 4.4.1, the response variable in a model is the variable in which differences or changes are observed as independent variables are changed. A component of the third research objective of this study is to understand how tailpipe emissions vary between different vehicles at urban obstacles to support emissions modelling. The response variable should therefore, be a metric that represents the tailpipe emissions whilst in the vicinity of an obstacle.

The median emission rate of CO_2 and NO_x for each run of an obstacle has been chosen as the metric that represents the tailpipe emissions of vehicles in the vicinity of an urban obstacle. The emission rate as the mass of pollutant emitted per unit distance (g/km) has been chosen over the mass of pollutant emitted per unit time (g/s), as it is a takes into consideration differences in speed between the vehicles. An alternative would be to use the total mass of pollutant emitted (g) whilst navigating the obstacle. However, as demonstrated in Chapter 6, emissions estimates from modelling tools are commonly output as a mass per unit distance (g/km).

5.4.2. Selection of explanatory variables

As explained in section 4.4.2, the explanatory variable is the variable that is used to explain changes in the response variable, the median emission rate in the vicinity of an obstacle. All vehicles navigate the same urban obstacles, however the variation in the response variable may be explained by the use of different vehicles, some may have higher pollutant emission rates than others. As shown in Table 4.3, Emissions Analytics collect metadata for each vehicle test that includes the engine size, Euro standard, fuel type, number of doors, vehicle mass and vehicle power.

Of the six vehicle characteristics, five are expected to influence the tailpipe emission rates in the vicinity of urban obstacles. The number of doors on the vehicle is excluded from the model despite it potentially being a proxy for the physical size of the vehicle and aerodynamics drag. Given that the vehicle speeds observed in the vicinity of the obstacles are typical less than 13.3m/s, drag is not expected to be a dominant term (Jiménez, 2000).

Engine size, Euro standard, fuel type, vehicle mass and vehicle power are vehicle characteristics that influence tailpipe emission rates. The engine size is the volume of the engine cylinders in which fuel is combusted. As pollutant emissions are a by-product of the combustion process, engine size is expected to affect pollutant emission rates. The Euro standard the vehicles conform to places limits on the tailpipe emission rates of harmful pollutants, such as NO_x, and therefore influences tailpipe emission rates. The fuel used is another factor that affects tailpipe emissions due to differences in the chemical composition and thus the pollutants that are emitted, as reflected in the European emissions standards (European Commission, 2015b). Finally, the vehicle mass and vehicle power will be combined to create a power/weight ratio (PWRT) metric. The higher the PWRT, the more energy the vehicle can produce per unit mass and thus the higher the tailpipe emission rates assuming similar levels of efficiency.

Prior to using the four vehicle characteristics as explanatory variables, each variable needs to explored to understand the distribution of the data. Table 5.6 shows whether each characteristic is continuous or categorical, summary statistics and the distribution of the data.

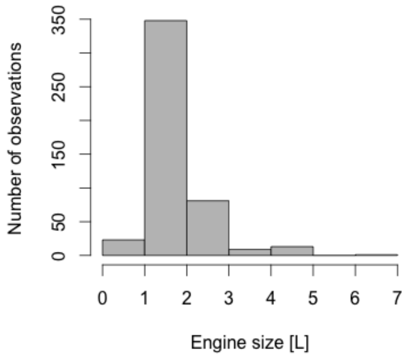
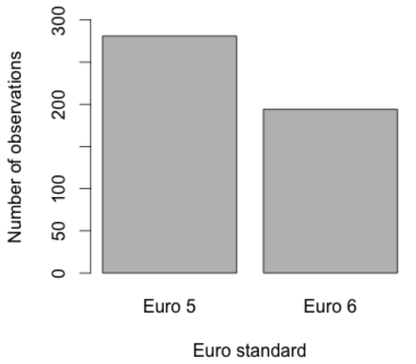
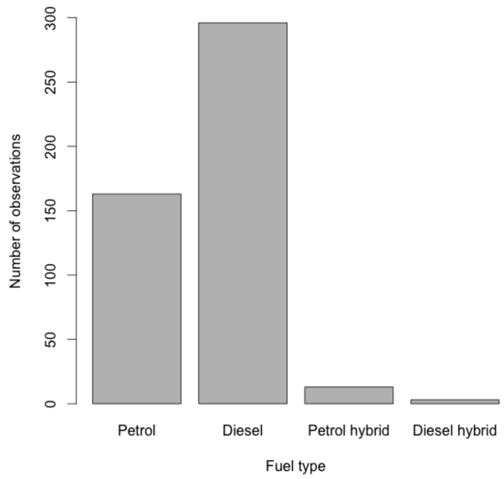
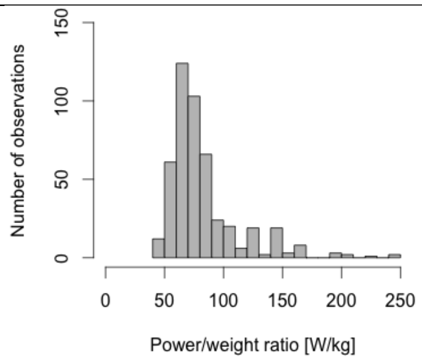
Characteristic	Data description	Distribution of data
Engine size	Type: continuous Range: 0.9-6.2L Mean: 2.0L Median: 2.0L Unique values: 27	
Euro standard	Type: categorical Range: Euro 5 or 6 Unique values: 2 281 Euro 5 and 194 Euro 6 observations	
Fuel type	Type: categorical Range: Petrol, diesel, petrol hybrid, diesel hybrid Unique values: 4 163 petrol, 296 diesel, 13 petrol hybrid and 3 diesel hybrid observations	
Power/weight ratio (PWRT)	Type: continuous Range: 43-249W/kg Mean: 83W/kg Median: 74W/kg Unique values: 226	

Table 5.6 – vehicle characteristics that influence tailpipe pollutant emission rates

From Table 5.6 it can be seen that the data for each vehicle characteristic is not evenly distributed, in particular for the fuel type. Therefore, it is proposed that the data for petrol hybrid and diesel hybrid vehicles are removed. With the removal of 16 of the 475 observations, it is proposed that all four characteristics are considered as potential explanatory variables of tailpipe pollutant emission rates in the vicinity of urban obstacles.

As explained in section 4.4.2, collinearity is the phenomenon where two or more explanatory variables are highly correlated. The collinearity between two variables can be measured using the Pearson product moment as shown in Table 5.7.

	Engine size	**Euro standard**	**Fuel type**	**PWRT**
Engine size		-0.05	0.186	0.651
Euro standard			0.068	-0.038
Fuel type				0.324
PWRT				

Table 5.7 – collinearity between the four variables expected to influence tailpipe emission rates

From Table 5.7 it can be seen that correlation is evident between engine size and PWRT. This can be explained by the fact that vehicles with a larger engine size are able to combust more fuel on each engine stroke. Therefore, they are able to produce more power per unit mass to propel the vehicle, assuming similar levels of efficiency. Considering the results of the collinearity testing, it is suggested that the PWRT is excluded from the subsequent analysis and the engine size, Euro standard and fuel types are used as the explanatory variables.

5.4.3. Choice of model

In section 2.1.1, considering vehicles as a rigid body, it was explained that there is a largely linear relationship between the resistive forces on a vehicle, kinetic energy and tractive power (Heywood, 1988). Given that the tractive power is generated through the combustion of fuel, of which pollutant emissions are a by-product, a multivariate linear regression model is proposed. The model is used to explore the relationship between the explanatory variables and the response variable, pollutant emission rate. The regression is used to predict how much of the variation in pollutant emission rate can be described by the explanatory variables. The ordinary least squares (OLS) method is implemented for parsimony, but also because the data in this thesis meets the primary assumption that there is zero or negligible errors in the independent variable.

In order to implement the regression model, dummy variables for euro standard (euro dummy) and fuel type (fuel dummy) have been created, as they are categorical variables. The general form of the two models that is implemented, one for each pollutant, at each obstacle are shown below[4]:

$$\begin{aligned} &Median\ emission\ rate\ of\ CO_2 \\ &\qquad = \beta_0 + \beta_1 Engine\ size + \beta_1 Euro\ dummy + \beta_2 Fuel\ dummy + \varepsilon \end{aligned}$$

$$where\ the\ parameters\ \beta_0, \beta_1, \beta_2\ and\ \ \varepsilon\ will\ be\ estimated\ by\ the\ model$$

$$\begin{aligned} &Median\ emission\ rate\ of\ NO_x \\ &\qquad = \gamma_0 + \gamma_1 Engine\ size + \gamma_1 Euro\ dummy + \gamma_2 Fuel\ dummy + \varepsilon \end{aligned}$$

$$where\ the\ parameters\ \gamma_0, \gamma_1, \gamma_2\ and\ \varepsilon\ will\ be\ estimated\ by\ the\ model$$

5.4.4. Model estimation results

The linear regression models as explained above were implemented for the four urban obstacles: a speed cushion, signalised junction, mini roundabout and "keep clear" zone. Tables 5.8 and 5.9 show the estimates of the beta parameters of each variable as well as the standard error and whether the variable is significant or not at the 5% level (measured as whether the estimate is significantly different from zero). The adjusted R^2, which takes into consideration the number of variables is also reported. The results of the models developed for estimating CO_2 and NO_x emission rates are discussed in turn below.

<u>Model for CO_2 emission rate</u>

The R^2 value for the model of median CO_2 emission rate at each obstacle shows the proportion of the variation that is accounted for by the three explanatory variables: engine size; Euro standard; and fuel type. The R^2 value for the four obstacles ranges between 13.6-25.5%. Whilst low, is

---

[4] As with the acceleration models, prior to implementing the regression model as explained in this section, the data from all four obstacles was aggregated. An additional explanatory variable for obstacle type was defined and implemented in the model using three dummy variables. The only beta parameters that were statistically significant at the 5% level were the three dummy variables for the obstacle type. This confirms the findings presented in section 5.3.5 based on the KS test. The lack of significance of the other explanatory variables led to the conclusion that they may not be statistically significant when the data from all obstacles is aggregated. However, they may be statistically significant when each obstacle is modelled individually – as presented in this section.

considerably higher than the R^2 values obtained when modelling vehicle acceleration, which was less than 5%. Across the four obstacles, the only explanatory variable that is significant in all four models is the Euro standard.

The engine size was shown to be statistically significant only at Obstacle B, the signalised junction where a large proportion of vehicles accelerate from rest. Whilst engine size is related to the amount of fuel that can be combusted on each engine stroke, there are other factors involved. For example, the ratio of air/fuel used in the combustion process will affect the tailpipe emission rates of CO_2. Furthermore, as explained in section 3.4, all of the vehicles used in this research are modern vehicles that are less than 18 months old. As explained by Zammit et al. (2015), many modern vehicles use cylinder disablement technologies to improve fuel economy and reduce tailpipe emissions. It is not known which vehicles are fitted with these technologies and whether they were active whilst in the vicinity of urban obstacles. However, given the lower power demand in an urban environment compared to a motorway environment, it is more than likely that some vehicles had cylinder disablement technologies active. This partially explains why engine size is not statistically significant in estimating tailpipe emission rates.

The fuel type was also shown to be statistically significant only at one obstacle, the "keep clear" zone. In the literature, it has been shown that diesel fuelled vehicles produce less CO_2 per unit distance than equivalent petrol fuelled vehicles due to the higher efficiency of diesel engines (Kousoulidou et al., 2013). Therefore, it was expected that fuel type would be a statistically significant explanatory variable of tailpipe emission rate of CO_2. However, vehicle manufacturers have been developing various engine technologies such as gasoline direct injection (GDI) to improve the efficiency of petrol vehicles (Wang et al., 2014). Due to the use of new engine technologies such as GDI, the differences in CO_2 emission rates between petrol and diesel vehicles has been reduced. Future work where more detailed information about each test vehicle is available could investigate the impact of engine technology and tailpipe emission rates of CO_2.

The Euro standard that the vehicles conform to was the only explanatory variable that is statistically significant across the models developed for each urban obstacle. Tailpipe CO_2 emissions are currently not covered by the European emissions standards. However, there is a mandatory manufacturer limit of an average emission rate of 130g/km of CO_2 for all passenger cars registered in the EU in 2015 (European Commission, 2015a). Whilst CO_2 emissions are not covered by the European emissions standards, it is expected that the improvements in vehicle and emissions abatement technologies that are used to meet the more stringent Euro 6 emissions standard, also impact CO_2 emission rates.

Considering that the Euro standard was the only statistically significant explanatory variable, the model was re-estimated with just the Euro standard as an explanatory variable. In all cases, the R^2 value increased to 18.7%, 26.2%, 15.4% and 23.1% for Obstacles A, B, C and D respectively. The models developed are able to explain between 18.7-26.2% of the variation in tailpipe CO_2 emission rates in the vicinity of urban obstacles using the Euro standard the vehicle conforms to. The use of additional explanatory variables such as engine type, CO_2 abatement technology and air/fuel ratio may be able to explain more of the variation in tailpipe CO_2 emission rates.

<u>Model for NO_X emission rate</u>

R^2 values for the models of NO_x emission rates in the vicinity of each urban obstacle are shown in Table 5.9. Using the explanatory variables: engine size; Euro standard; and fuel type, the R^2 values for the models range between 16.7-27.3%. This again is relatively low, although is higher than the models of CO_2 emission rate and vehicle acceleration at each urban obstacle. Across the four obstacles, both fuel type and Euro standard are statistically significant at the 5% level as explanatory variables.

The engine size as an explanatory variable was only statistically significant at Obstacle B, the signalised junction. The same arguments about vehicle technology that were presented when discussing the models of CO_2 emissions are relevant to the models of NO_x emissions. Furthermore, some vehicles use technologies such as exhaust gas recirculation (EGR) as a NO_x abatement technology. NO_x is produced under conditions of high heat and pressure. Therefore, recirculating exhaust gases that are inert to combustion reduces the oxygen in the cylinder and lowers peak in-cylinder temperatures and NO_x emission rates. The use of technologies such as EGR and cylinder disablement will have distorted the relationship with engine size and NO_x emission rates, partly explaining why it is not a statistically significant explanatory variable.

The fuel type as an explanatory variable was statistically significant in all four models of NO_x emissions rates. It has been demonstrated in the literature that diesel fuelled vehicles produce more NO_x per unit distance than petrol fuelled vehicles, as found in Mock et al. (2012). Despite the use of NO_x abatement technologies such as EGR and catalysts to reduce NO_x, the fuel type is an explanatory variable of the emission rate. This is reflected in the European emissions standard where there are different limits for petrol and diesel fuelled vehicles (European Commission, 2015b).

Tailpipe NO_x emissions are covered by the European emissions standards and it was a focus of the new Euro 6 standard for diesel vehicles. The emission threshold for Euro 5 diesel vehicles is 0.180g/km and for Euro 6 diesel vehicles is 0.080g/km, a 56% reduction (European Commission, 2015b). With this in mind, it is no surprise that the Euro standard as an explanatory variable is statistically significant at the 5% level for all obstacles when NO_x is an explanatory variable.

Considering that the engine size was not statistically significant, the models were re-estimated using just the fuel type and Euro standard. In all cases, the adjusted R^2 value increased to 19.1%, 28.2%, 20.6% and 28.1% for Obstacles A, B, C and D respectively. The models developed are able to explain between 19.1-28.1% of the variation in tailpipe NO_x emission rates in the vicinity of urban obstacles using the Euro standard the vehicle conforms to and fuel type. The use of additional explanatory variables such as NO_x abatement technologies employed and exhaust cylinder temperature, may explain more of the variation in NO_x tailpipe emission rates.

5.4.5. Model estimation conclusions

A component of the third research objective of this thesis was to understand how tailpipe emission rates of CO_2 and NO_x vary between different vehicles at urban obstacles. The median tailpipe emission rate of CO_2 and NO_x for each observation at the four obstacles was defined as the response variable. Of the six potential explanatory variables, three were used in a regression model after considering the mechanism of impact and collinearity. It was shown that the Euro standard vehicles conform to was the only statistically significant explanatory variable for estimating tailpipe CO_2 emissions at all four obstacles. When developing a model for NO_x emission rates, the fuel type and Euro standard were both statistically significant at the 5% level for all the obstacles studied. The models are able to represent just under 30% of the variability in tailpipe emission rates. The appropriateness of using a linear regression model was investigated by plotting the residuals for each model. The residuals are randomly distributed which confirms the suitability of a linear model. With this in mind, it is proposed that fuel type and Euro standard are considered in the subsequent modelling activity, as discussed further in section 5.5.1.

Obstacle A – speed cushion – n=459

Parameter	Variable	Estimate	Standard error of estimation	Significance at 5% level
β_0		1.41E+00	1.93E-01	Yes
β_1	Engine size	3.27E-01	8.27E-02	No
β_2	Euro standard [6]	-5.23E-02	1.19E-01	Yes
β_3	Fuel type [Petrol]	2.62E-01	1.21E-01	No

Adjusted R^2 for model at Obstacle A = 0.136

Obstacle B – signalised junction – n=459

Parameter	Variable	Estimate	Standard error of estimation	Significance at 5% level
β_0		6.80E-01	1.67E-01	Yes
β_1	Engine size	1.50E-01	7.07E-02	Yes
β_2	Euro standard [6]	-8.88E-02	1.03E-01	Yes
β_3	Fuel type [Petrol]	7.69E-03	1.06E-01	No

Adjusted R^2 for model at Obstacle B = 0.255

Obstacle C – mini roundabout – n=459

Parameter	Variable	Estimate	Standard error of estimation	Significance at 5% level
β_0		1.86E-01	8.43E-02	Yes
β_1	Engine size	2.71E-01	3.61E-02	No
β_2	Euro standard [6]	-6.76E-02	5.14E-02	Yes
β_3	Fuel type [Petrol]	3.77E-01	5.29E-02	No

Adjusted R^2 for model at Obstacle C = 0.148

Obstacle D – "keep clear" zone – n=459

Parameter	Variable	Estimate	Standard error of estimation	Significance at 5% level
β_0		3.68E-01	1.35E-01	Yes
β_1	Engine size	3.51E-01	5.77E-02	No
β_2	Euro standard [6]	-1.20E-01	8.26E-02	Yes
β_3	Fuel type [Petrol]	3.97E-01	8.50E-02	Yes

Adjusted R^2 for model at Obstacle D = 0.228

Table 5.8 – results from the regression modelling at all four obstacles using 3 explanatory variables for CO_2 emission rate

Obstacle A – speed cushion – n=309

Parameter	Variable	Estimate	Standard error of estimation	Significance at 5% level
γ_0		6.39E-03	1.21E-03	Yes
γ_1	Engine size	-7.75E-04	5.51E-04	No
γ_2	Euro standard [6]	-9.35E-04	7.45E-04	Yes
γ_3	Fuel type [Petrol]	-4.18E-03	7.28E-04	Yes

Adjusted R^2 for model at Obstacle A = 0.167

Obstacle B – signalised junction – n=309

Parameter	Variable	Estimate	Standard error of estimation	Significance at 5% level
γ_0		4.27E-03	9.15E-04	Yes
γ_1	Engine size	-6.98E-04	4.14E-04	Yes
γ_2	Euro standard [6]	-1.10E-03	5.57E-04	Yes
γ_3	Fuel type [Petrol]	-2.53E-03	5.51E-04	Yes

Adjusted R^2 for model at Obstacle B = 0.273

Obstacle C – mini roundabout – n=309

Parameter	Variable	Estimate	Standard error of estimation	Significance at 5% level
γ_0		1.34E-03	3.55E-04	Yes
γ_1	Engine size	1.06E-04	1.61E-04	No
γ_2	Euro standard [6]	-4.03E-04	2.18E-04	Yes
γ_3	Fuel type [Petrol]	-1.27E-03	2.15E-04	Yes

Adjusted R^2 for model at Obstacle C = 0.181

Obstacle D – "keep clear" zone – n=309

Parameter t	Variable	Estimate	Standard error of estimation	Significance at 5% level
γ_0		3.77E-03	9.74E-04	Yes
γ_1	Engine size	-1.60E-04	4.42E-04	No
γ_2	Euro standard [6]	-1.37E-03	5.97E-04	Yes
γ_3	Fuel type [Petrol]	-2.15E-03	5.90E-04	Yes

Adjusted R^2 for model at Obstacle D = 0.243

Table 5.9 – results from the regression modelling at all four obstacles using 3 explanatory variables for NO_x emission rate

5.5. Proposed grouping structures for tailpipe emissions

In sections 5.3 and 5.4, the tailpipe emission rates of CO_2 and NO_x in the vicinity of urban obstacles were investigated. A more thorough understanding of how tailpipe emission rates vary between different obstacles and between different vehicles at a particular obstacle can aid the modelling and estimation of tailpipe emissions. For example, if the emission rate of CO_2 observed in the vicinity of two obstacles is not statistically different, they can be modelled using the same emissions factors. Using the same emissions factors can reduce the complexity and resources required to model the emissions at an obstacle. However, assuming the emission rates at all obstacles are the same may result in inaccurate emissions estimates. Sections 5.5.1 and 5.5.2 discuss how different obstacles and vehicles may be group or classified as the same when modelling tailpipe emissions of CO_2 and NO_x.

5.5.1. Grouping structures based on obstacle type

Using data collected from 475 runs of a London based urban test cycle, the tailpipe emission rates of CO_2 and NO_x were analysed. The emission rates were studied as a function of time and space, as well as the total mass of pollutant associated with navigating each obstacle. Through examining the median and range of the emission rates, and also through the application of the KS test, it was determined that the tailpipe emission rates are statistically different at the four obstacles studied. This is due to the difference in power demand at each obstacle. Whilst only one example of each obstacle is studied in this thesis, further work could investigate the emission rates at multiple examples of the same obstacle to further validate these findings. However, given the data available for this thesis, the four obstacles should be considered independently when modelling tailpipe emissions of CO_2 and NO_x. Therefore, all four obstacles studied should have their own groups and associated obstacle emissions factors as shown below:

1. Speed cushion
2. Signalised junction
3. Mini roundabout
4. “keep clear” zone

5.5.2. Grouping structures based on vehicle characteristics

In section 5.4, the variation in tailpipe emission rates of CO_2 and NO_x between different vehicles at each obstacle were analysed using a regression model. With emission rate as the dependent variable, three explanatory variables were defined: engine size, Euro standard and fuel type. It was found that the estimated coefficients for Euro standard were statistically significant in predicting CO_2 and NO_x emission rates. The fuel type was statistically significant in predicting NO_x emission rates. Therefore, it is proposed that vehicles should not be aggregated into a single group for all Euro standards or fuel types when modelling tailpipe emission rates of CO_2 and NO_x in the vicinity of urban obstacles. Based on the data available for this thesis, the only grouping that could be defined is engine size, which was not shown to be statistically significant at all four obstacles when estimating both CO_2 and NO_x emission rate. As discussed in section 5.4, further work where additional metadata is available could explore how other vehicle characteristic influence tailpipe emission rates in the vicinity of urban obstacles and thus support the modelling of vehicle emissions.

5.6. Conclusions

In this chapter the tailpipe emission rates of 226 vehicles in the vicinity of four urban obstacles were analysed in terms of CO_2 and NO_x emissions. The data was presented using four key metrics:

- The total mass of pollutant (grams)
- Pollutant emission rate as a function of time (grams/second)
- Pollutant emission rate as a function of distance (grams/kilometre)
- Pollutant emission rate as function of vehicle specific power (kilowatts/tonne)

Initially the data for each obstacle were aggregated and using the pollutant emission rate as a function of distance, a statistical test was employed to determine whether the emission rates were drawn from different distributions. It was found that the emission rates at all four obstacles were statistically different and therefore, when using a modelling technique that has obstacle related emissions factors, each obstacle should be modelled using different factors.

The data collected at each obstacle was also considered independently to assess the variation between different vehicles. A regression model was developed to determine whether certain vehicle specific characteristic such as engine size, Euro standard and fuel type were statistically significant in estimating emission rates of CO_2 and NO_x. It was shown that the Euro standard vehicles conform to is statistically significant in predicting both CO_2 and NO_x emission rates, whilst the fuel type was only statistically significant in predicting NO_x emission rates. Therefore, it is proposed that vehicles should not be grouped into a single Euro standard or fuel type. Both parameters should be considered in the emission modelling process when modelling tailpipe emissions of CO_2 and NO_x in the vicinity of urban obstacles.

The analysis presented in this chapter meets the third research objection of this work 'understand how tailpipe emissions vary at different obstacles and between different vehicles to support emissions modelling'. The proposed groupings of urban obstacles and vehicle characteristics important for emission modelling are used to support the modelling exercise in Chapter 6.

6. Modelling the variability in vehicle dynamics and emissions at urban obstacles

In Chapter 2, the importance of being able to accurately estimate the tailpipe emissions of vehicles in the vicinity of urban obstacles was explained. Traffic models can be used to predict the behaviour of individual vehicles in the vicinity of urban obstacles, and emissions models can be used to estimate the resultant emissions. However, in order to assess the suitability of these tools in representing real-world behaviours, a methodology for collecting real-world vehicle trajectory and tailpipe emissions was developed in Chapter 3. In Chapter 4 the acceleration behaviour in the vicinity of four obstacles was investigated by comparing the behaviour at different obstacles and between different vehicles at a particular obstacle. In Chapter 5 the tailpipe emission rates were investigated and a similar comparison between different obstacles and between different vehicles at a particular obstacle was conducted.

Using the findings from the analysis in Chapters 4 and 5, recommendations were made on how best to group obstacles and vehicles based on the data collected. In this chapter, these recommendations are used to address the fourth research objective:

Propose a methodology for adapting traffic and emissions modelling tools to better represent the observed behaviours in the vicinity of urban obstacles

This chapter is formed of three components which when combined meet the requirements of the research objective outlined above. The first is the re-estimation of the underlying mathematical formulation of the acceleration behaviour model in a traffic microsimulation tool using the empirical data presented in Chapter 4. The second is the modification of the emissions classes in an emission modelling tool using the PEMS data analysed in Chapter 5. The third component is the use of more representative traffic and emission models when estimating emission associated with an urban roadwork case study.

6.1. Background

Computer based models are used in a variety of fields to predict or reproduce the behaviour of a system. Traffic models are commonly used to predict how a particular road network may behave under a certain scenario. For example, how increasing the capacity of a link affects network performance characteristics such as travel times and flow rate. The model has a series of assumptions or rules that are used to control how it behaves, for example, how vehicles are assigned to particular routes. Emissions models work in a similar fashion where the input is vehicle activity data and the output is estimated vehicle emissions. A typical use of an emissions model is to answer questions such as how changing a traffic signal plan affects total emissions. They are also used to simply evaluate traffic flows and emissions across networks to feed into air pollution dispersion models.

These traffic and emissions models are based on a complex series of underlying physical and behaviour models. In some models, certain parameters can be modified or adapted by the end user to best represent the behaviour of a complex system of interest. For example, there might be a compliance factor that influences the number of vehicles that pass a traffic signal on an amber light or obey Variable Message Signs (VMS). Whilst it may be possible to change these parameters, the difficulty lies in being able to choose an appropriate value. Furthermore, due to the complex interactions within models, changing one parameter may have an unexpected impact on other model outputs, as the relationship is not always explicit.

6.1.1. Modelling of roadworks

Accurate modelling of roadworks allows investigation into how they could be configured and coordinated to minimise the impact on network performance and vehicle emissions. Typical measures of network performance include travel time, average speed and flow rate. An example of a roadwork modelling exercise is to assess whether it would be less disruptive to road users to phase a roadwork over several weeks by partially closing the carriageway, or whether the carriageway should be closed completely for a few days. Similarly, when multiple planned roadworks are due to take place on the same part of the network, it may be possible to coordinate the roadworks to minimise the overall impact on road users.

As outlined in the introductory chapter of this thesis, before using existing modelling tools to model roadworks, the tools must be appropriate for the scenario to be modelled. Walker and Calvert (2015) explained that the presence of roadworks and the associated traffic management may cause drivers and vehicles to behave differently to when there is no disruption, for example, differences in vehicle dynamics. The existing suite of traffic modelling tools were designed to represent vehicle behaviour under 'normal' operating conditions and were calibrated and validated accordingly (Transport Research Laboratory, 2007). When a disruption or an obstacle is introduced into a model of the road network, the model may operate outside of its design parameters due to the congestion caused and thus unrealistic behaviour may be observed. For example, a vehicle may be unable to make its desired lane-changing manoeuvre due to an insufficient gap in the traffic as a result of congestion. In reality, a vehicle would either creep forward and force a gap or decide not to make the manoeuvre. However, in some modelling tools the vehicle is just removed from the network after a predefined waiting time (PTV AG, 2011).

There are several parameters that could be investigated to improve the modelling of vehicles in the vicinity of urban obstacles, for example, the 'waiting time' before diffusion. However, the focus in this thesis is the acceleration behaviour and emissions class assignment in the vicinity of urban obstacles due to the negative impact of tailpipe pollutant emissions on human health and the environment.

The accuracy of the acceleration behaviour affects the individual vehicle trajectories as they navigate the urban obstacles. Section 6.2 explains the calibration procedure for a traffic microsimulation model. The emissions class assignment is equally important as an incorrect assignment will mean the wrong emissions factors are used, thus resulting in inaccurate emissions estimates. Section 6.3 explains the procedure for choosing or creating appropriate emissions classes. In section 6.4 a London based roadworks case study is presented and the effect of using a more representative acceleration behaviour model and emissions class assignment, is discussed. Finally, section 6.5 explains how accurate modelling of the behaviour of vehicles in the vicinity of roadworks influences existing roadwork management techniques described in section 2.3.

6.2. Traffic microsimulation modelling

When modelling road traffic there are several modelling tools and techniques that can be used which are typically categorised by their simulation resolution. Traffic simulation packages are generally categorised into the following classes: macroscopic, mesoscopic, microscopic and nanoscopic. Macroscopic models have the lowest resolution and therefore, have the least detail; whereas nanoscopic models have the highest resolution and the most detail. A macroscopic model does not simulate the behaviour of individual vehicles; meaning the outputs are based on the fundamental speed-flow relationships. On the other end of the spectrum, nanoscopic models simulate the behaviours of individual drivers, such as the uncertainty in decision making and vehicle movements on a two-dimensional planar surface (i.e. travelling on a curve) (Dia and Panwai, 2009).

To support this research, there is a requirement that vehicles are modelled individually so that individual vehicle trajectories can be obtained to support the subsequent emissions modelling. This means that only microscopic and nanoscopic modelling packages are suitable given that they are capable of modelling individual vehicle trajectories. In a nanoscopic modelling tool, the individual behaviours of each vehicle such as the throttle and brake pedal position would be modelled at a resolution of >100ms (Ratrout and Rahman, 2009). Whilst this resolution may be required for modelling the interaction between vehicles and pedestrians, for example, it is not required for emissions modelling tools which typically operate at 1Hz or lower (Smit et al., 2010). Furthermore, nanoscopic models have significant data and computation requirements that are not justified if the output trajectory data will be aggregated for use with an emission model (Dia and Panwai, 2009).

For this research, a microscopic model is the most appropriate as it allows for an urban network to be modelled whilst individual vehicle behaviours can be captured. The use of microsimulation models for scheme design and modelling roadway obstacles such as junctions is not uncommon. It is recommended by Transport Research Laboratory (2007), Transport for London (2010), Mitran et al. (2012) and many others, particularly when coupling with an emissions model.

There are several traffic micro-simulation models that could be used, including CORSIM, SimTraffic, AIMSUN, Vissim, Paramics, MITSIMlab, SUMO and SATURN. The most popular packages amongst the traffic modelling community are Vissim and Paramics (Fontes et al., 2015), with Vissim previously having been the model of choice within Transport for London (2010). However, Vissim is now being used in parallel with AIMSUN in Transport for London (AIMSUN, 2015). Both Vissim and Paramics allow for the individual vehicle trajectories to be output, either as a 'car positions' file in Paramics or as a 'vehicle record' file in Vissim. Widespread use of both of these modelling packages demonstrates their effectiveness and applicability in representing the UK road network.

For this research, it is essential that the underlying acceleration behaviour of vehicles can be modified to represent the behaviour observed in the vicinity of urban obstacles. In Paramics, whilst a maximum acceleration can be defined for each vehicle, this represents the physical properties of the vehicle rather than a 'desired acceleration' (SIAS Limited, 2009). The 'desired acceleration' of a vehicle is controlled using an 'aggressiveness' parameter which also influences the car following model, gap acceptance model and lane changing model (Hidas, 2005). The 'aggressiveness' parameter is a scalar value that is not based on a measurable quantity such as acceleration noise or minimum headway. With this in mind, the use of Paramics would not be suitable in this modelling exercise as the key input is observed vehicle acceleration.

In Vissim, the end user is able to modify the acceleration behaviour model and therefore it has been selected for the subsequent modelling activity. Whilst the remainder of this chapter focuses on Vissim, the techniques are still valid for any microsimulation tool where the end user is able to modify the acceleration behaviour model. Section 6.2.1 details how the acceleration behaviour of vehicles is modelled in Vissim 5.40.

6.2.1. Modelling acceleration behaviour in Vissim

In Vissim, there are several underlying models that affect the dynamic behaviour of vehicles; these include the car following model, gap acceptance model, lane changing model and acceleration behaviour model as detailed by Lownes and Machemehl (2006). A full description of the underlying models and their interaction is described in Fellendorf and Vortisch (2010). Whilst several of these models can influence when an acceleration or deceleration event takes place, only the car following model and acceleration behaviour model define the rate at which a vehicle accelerates or decelerates (Hidas, 2005).

In the acceleration behaviour model, the acceleration behaviour of individual vehicles is modelled using a speed-acceleration function that is applied globally in the traffic model. The speed-acceleration function is defined for each vehicle type. By default, it is specified for the following vehicle types: car, HGV, bus, tram, pedestrian and bike. For each vehicle type, there are four speed-acceleration functions that define the following behaviours: desired acceleration, maximum acceleration, desired deceleration and maximum deceleration.

In the car following model, a deceleration rate is defined, however the software manufacturers do not explicitly disclose when the car following model governs a vehicle's deceleration behaviour and when it is governed by the acceleration behaviour model. Therefore, it is proposed that the focus is on calibrating the acceleration functions in the acceleration behaviour model, as it is explicit when these functions are used to influence the dynamic behaviour of the vehicle. Furthermore, given that the focus is on tailpipe emissions, it is justified that the emphasis is on the positive accelerations as this is when the power demand and emission rates are highest, as shown in Chapter 5.

The desired and maximum acceleration functions by default have the same speed-acceleration relationships for the car vehicle type. The desired acceleration function is used to model the positive acceleration of individual vehicles. The maximum acceleration function is the maximum technically feasible acceleration and is only used when the vehicle is required to maintain a particular speed on a slope (PTV AG, 2012). The empirical data presented in this thesis were collected whilst the vehicle was operating under normal conditions, not whilst on a steep gradient trying to maintain a particular speed. Therefore, the focus in this thesis is on the desired acceleration function.

As mentioned above, a desired acceleration function is defined for every vehicle type in the model. By default in Vissim 5.40, the same function is used for cars, buses, pedestrians and bikes. These default values are present in all the example models bundled with the software, and also when a new model is created[5].

---

[5] The acceleration function can be viewed by accessing the menu options Base Data-> Functions-> Desired Acceleration. A dialog box will then appear prompting the user to select the vehicle type and the desired acceleration will be visible as shown in Figure 6.1.

Figure 6.1 shows the desired acceleration and maximum acceleration curves for the 'car' vehicle type. The plots show the vehicle speed (km/h) against vehicle acceleration (m/s^2) that were derived from Wiedemann's work as explained in section 6.2.2. Both plots are identical by default as Vissim uses the same values for desired and maximum acceleration. On each plot there are three lines that represent the minimum, mean and maximum acceleration value for a particular speed. Given that there is essentially an envelope of acceleration values for a particular speed, Vissim makes use of a random seed. The random seed is used to represent the heterogeneity in traffic and each random seed assigns particular speed-acceleration values for a given vehicle.

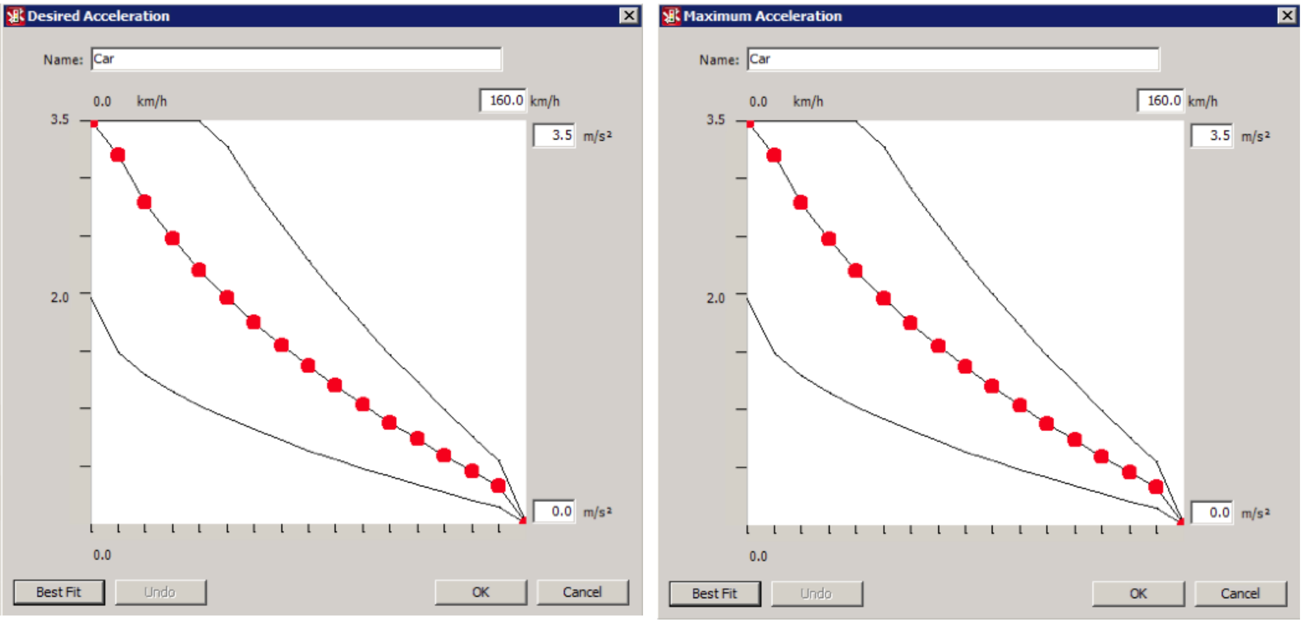


Figure 6.1 – the default desired and maximum acceleration curves for the 'car' vehicle type

6.2.2. Calibration of acceleration behaviour model in Vissim

The end user can modify the acceleration functions in the acceleration behaviour model using either the graphical user interface (GUI) or by modifying the model input file. In the GUI (as shown in Figure 6.1), the curves that form the speed-acceleration relationship can be adjusted by manually dragging the curves. This method is not very accurate as it is difficult to define a precise acceleration value for a particular speed. The alternative is to edit the model input file (.inp) using a standard text editor. The structure of the file is shown in Figure 6.2 where the acceleration function is defined along with the vehicle type number, vehicle type name and the limits for the axes on the graph (line 822). On line 823 the values that are used to define the curves that form the acceleration function can be seen. The acceleration function is coded in blocks of four values that correspond to the speed, mean acceleration, minimum acceleration and maximum acceleration. By modifying the model input file, precise acceleration values can be defined for each speed.

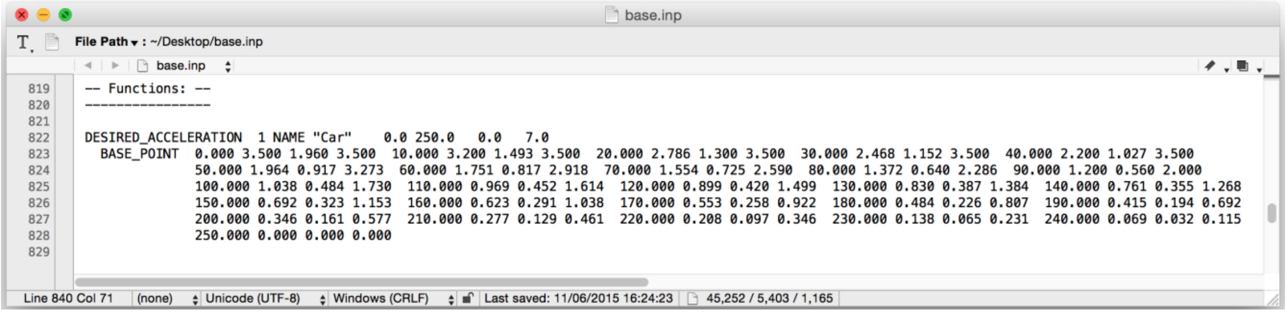


Figure 6.2 – the desired acceleration function in the Vissim input file

The default values defined for the 'car' vehicle type are based on the original values provided in the Wiedemann 74 model (PTV AG, 2011). The Wiedemann model is founded on experiments carried out in Germany prior to 1974. Since 1974 there have been significant changes in vehicle technology, for example, advances in engine and tyre performance, which are expected to have an impact on the acceleration behaviour of vehicles.

As mentioned above, by editing the Vissim input file, the end user can change the default values for the desired acceleration function. The desired acceleration of a vehicle is the acceleration the vehicle would want to achieve if it were unimpeded by vehicles or other obstructions on the road network. When collecting acceleration data to model the behaviour in the vicinity of urban obstacles, it is very difficult to collect desired accelerations in a real-world environment. Whilst a driving simulator or a closed track could be used to collect the data, these may not result in realistic desired accelerations because the driver would be aware that there are no other vehicles or obstructions on the road.

In this research, the observed accelerations are used in the desired acceleration function. This is the most realistic representation of desired acceleration that could be obtained given the requirement that data in the vicinity of urban obstacles is required. Furthermore, the default values in Vissim are based on observed data (PTV AG, 2011). The use of observed accelerations in the desired acceleration function is common place in the literature, for example Gomes et al. (2004) and Manjunatha et al. (2013).

In Chapter 4, a large repository of speed and acceleration data collected using the Hermes monitoring platform was presented. In section 4.5 it was explained that based on the mechanism of impact, the acceleration behaviour at certain urban obstacles can be considered to be equivalent and therefore, the same mathematical model of acceleration behaviour can be used. For each group of urban obstacles, the speed and acceleration data were used to re-estimate the acceleration curve as shown in Table 4.7. The acceleration envelope was defined in 1m/s speed increments over the speed ranges observed in the vicinity of the obstacles studied (0-13m/s). The re-estimated acceleration curves are used to modify the acceleration behaviour model so that it is more representative of the situations modelled in sections 6.2.3 and 6.4.

6.2.3. Comparison of default and calibrated acceleration behaviour

Vissim comes pre-packaged with several example models, one of which is designed and calibrated for the UK, a mini roundabout model. Obstacle C is an example of a mini roundabout, the data from which were presented in section 4.3.3 and can be used to re-estimate the speed-acceleration curve. The example model is a generic one for a roundabout where the flow of vehicles is controlled using priority rules, and therefore, expected to incite the same behaviour in vehicles. In order to understand the impact of using a re-estimated acceleration behaviour model, the proportion of time spent in different vehicle operating modes and network performance statistics are output from the model.

Figure 6.3 shows the default acceleration curve and the calibrated acceleration curve based on the data collected in the vicinity of Obstacle C, as explained in section 4.5.1. The calibrated acceleration curve was defined by modifying values in the Vissim input file as explained in section 6.2.2. Only values between 0-10m/s (0-36km/h) were modified, as this was the range of speeds for which acceleration measurements were obtained.

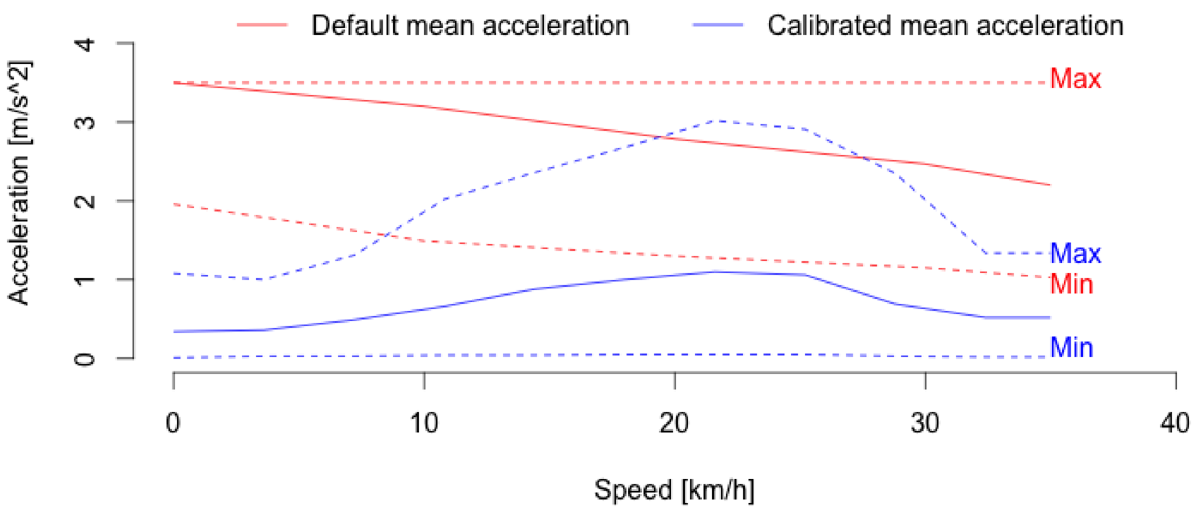


Figure 6.3 – the default and calibrated speed-acceleration curve used in the modelling

The roundabout model was initially run[6] with the default values for all parameters and then again with the only change being the desired acceleration curve for the car vehicle type. For each model run the individual vehicle trajectories were output, along with more general metrics that are used to evaluate network performance. Note, the vehicle trajectories and network performance statistics were filtered for just the roundabout; vehicles on input links and the wider network were ignored.

By extracting the speed and acceleration data from the individual vehicle trajectories, the vehicle activity between the two scenarios can be compared as shown in Figure 6.4. The vehicle activity is directly related to the desired acceleration curves that were defined in the model (Figure 6.3). The vehicle activity plots for the uncalibrated and calibrated acceleration model have similar characteristic shapes to the input acceleration model. The shape of the calibrated model differs considerably from the default model. However, it is similar to other empirical studies on vehicle acceleration such as Snare (2002). The default model has higher acceleration rates compared to the calibrated model across the full speed range that the model was calibrated for, as was found in another calibration study by Song et al. (2012). This means that the default acceleration behaviour is overly aggressive for modelling vehicles in the vicinity of urban obstacles. This aggressive acceleration will impact many other traditional measures of network performance as shown in Table 6.1.

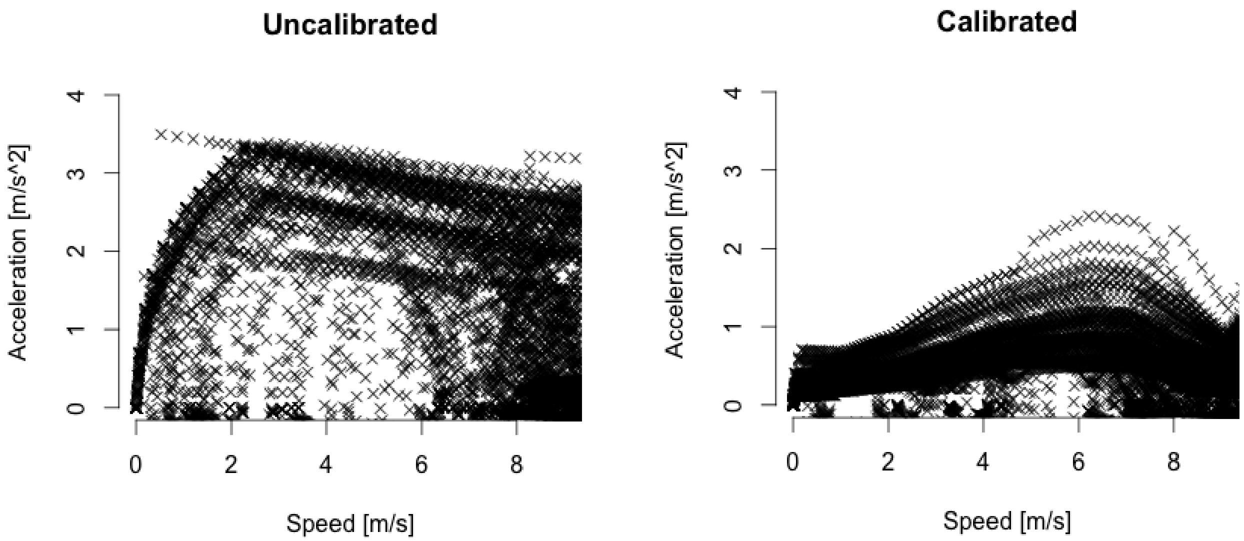


Figure 6.4 – vehicle activity for the uncalibrated (default) and calibrated acceleration behaviour

[6] The model was run 10 times to account for the stochastic nature of traffic – 10 runs is the default for a multi-run simulation in Vissim. For the roundabout model, over the 10 runs the maximum difference in flow rate is 42 vehicles, <1%.

The proportion of time spent in the different vehicle operating modes also differs between the two models. The proportion of time vehicles in the default model were in the acceleration vehicle operating mode was 8.7%. However, in the calibrated mode this was 22.3% and this compares to 19.7% found at Obstacle C, the mini roundabout. This is explained by the fact that the accelerations in the uncalibrated model are more aggressive. Therefore, vehicles are able to reach their desired speed more quickly, and thus spend a lower proportion of time in the acceleration mode. With the calibrated model, vehicles take longer to reach their desired speed due to the less aggressive acceleration, and thus spend a larger proportion of time in the acceleration mode.

Also output from the model, were the following network performance statistics: average vehicle delay, average speed, average travel time and number of completed trips. The average vehicle delay is the time in seconds spent stationary in a queue averaged across all vehicles. The average speed is the mean speed in m/s for all vehicles whilst in the network. The average travel time is the time taken for a vehicle to complete its journey, measured from the time the vehicle joins the entry link onto the roundabout and leaves the exit link off the roundabout. The number of completed trips is the total number of vehicles that leave their desired exit link off the roundabout. The network performance statistics were averaged across the 10 model runs for each scenario and are presented in Table 6.1. The significance of the results was tested using a paired t-test, a test that compares the population means of two related samples, μ_1 and μ_2, to assess whether they are drawn from the population.

$$H_0: \mu_1 = \mu_2$$

$$H_1: \mu_1 \neq \mu_2$$

For all four network performance metrics, the p-values returned were <0.05 and thus the null hypothesis that there is no significant difference in the population means can be rejected.

Metric	Default acceleration model	Calibrated acceleration model	Percentage change
Average delay [s]	18.94	51.27	170.65%
Average speed [m/s]	8.33	4.47	-46.36%
Average travel time [s]	53.24	149.18	180.22%
Completed trips [veh]	4112	2918	-29.04%

Table 6.1 – percentage change in network performance metrics between the calibrated and default models

As shown in Table 6.1, calibrating the acceleration behaviour model has a negative impact on all four network performance metrics considered in this analysis. The average delay increased by over 170%, the average speed reduced by almost 50% and as a result the travel time increased by over

180%. This result was expected, as vehicles are unable to accelerate from rest as aggressively in the calibrated model compared to the uncalibrated model. This means that it takes longer for vehicles to reach their desired speed and negatively impacts the travel time. Furthermore, as vehicles take longer to navigate the roundabout, the capacity of the roundabout is reduced and thus fewer vehicles are able to complete their trips.

When developing a traffic model, there is a requirement to calibrate the model so that the underlying physical and behavioural models are representative for the network being modelled. Traditionally, this includes parameters such as the fleet mix or the minimum gap vehicles are willing to accept when merging or changing lane. Once the model has been developed, it is then validated using metrics that describe the network performance as shown in Table 6.1 (Transport for London, 2010). Calibration of the acceleration behaviour model is not a part of the typical modelling process. However, it is important for accurately representing the dynamic behaviour of vehicles. This raises the question about the suitability of existing model validation procedures. The calibration of the acceleration behaviour model influences several network performance metrics, however it is generally not calibrated. In section 6.4, a roadwork case study is used to further demonstrate the effect of model calibration or adaptation where measured data for network performance is available.

6.3. Instantaneous emissions modelling

When modelling vehicle emissions there are several types of models that could be used depending on the data available. The main types of models used as categorised by Smit et al. (2010) are average speed, cycle variable and modal emissions models. Average speed models use the mean speed of the vehicle over a predefined segment of the drive cycle to estimate the vehicle emissions. The key issue with the average speed based emissions models is whether the mean speed is representative of the vehicle's speed over the drive cycle being studied. Figure 6.5 shows the speed-time trace of two vehicles that both have an average speed of 30mph. The power demands for Vehicle 1 are expected to be higher than Vehicle 2, due to the multiple acceleration events. The resultant tailpipe emissions are therefore expected to be very different, however an average speed model would estimate the emissions to be the same. The limitations of average speed based models are widely discussed in the literature as presented in Barlow and Boulter (2009), Rakha and Ahn (2004) and Holmén and Niemeier (1998).

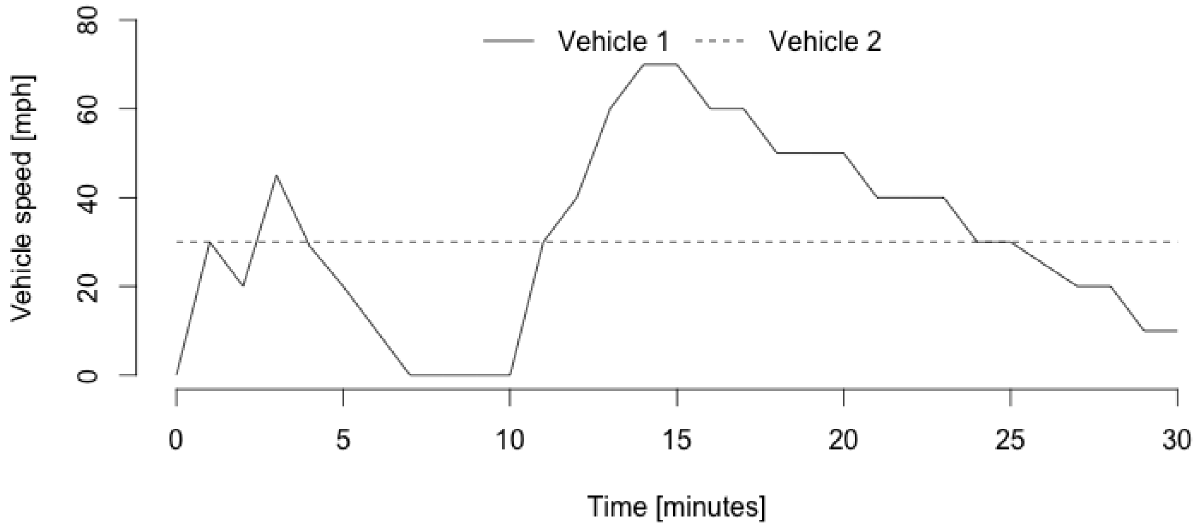


Figure 6.5 – speed time trace of two vehicles with an average speed of 30mph

The key limitation of average speed models is addressed in the cycle variable and modal emissions models. Cycle variable models use emissions factors that are a function of the drive cycle, for example time spent idle. Modal models use emissions factors that are function of engine or vehicle operation, for example high acceleration in a low gear. Both types of model require instantaneous data on vehicle speed, acceleration and road grade. The pollutant emission rates are calculated using instantaneous data. Therefore, the models are able to use emissions factors that correspond to what the vehicle is doing at that instant, rather than what the vehicle is doing over the cycle or a particular segment. The limitation of using these models is that more detailed vehicle trajectory data are needed. These data are typically obtained from a microscopic traffic model or GPS trajectory data – both of which are available in this thesis.

For this research, a model that uses instantaneous vehicle data is required due to the significant variation in speed as vehicles pass urban obstacles, as shown in Chapter 4. Both cycle variable and modal emission models would be suitable. However, given the lack of precise information about gear position and engine data, there would be limited opportunity to calibrate the gearshift and engine maps. Therefore, a cycle variable model is used in the subsequent analysis in this chapter.

There are several cycle variable models, also referred to as instantaneous emissions models, which could be used to model tailpipe emissions. For this particular application, a key requirement of the modelling tool is that it is able to estimate emissions for Euro 5 and Euro 6 passenger cars. This therefore means emissions models such as AIRE (Analysis of Instantaneous Road Emissions) are not suitable. AIRE was developed by the Transport Research Laboratory (TRL) and is maintained by SIAS Limited (2011). However, it only contains emissions factors for vehicles conforming to Euro 1-4. The use of AIRE in this research would be inappropriate as it is likely to overestimate tailpipe emissions due to the later Euro standards being more stringent.

In section 6.2 it was explained that Vissim would be used to model traffic and generate trajectory data to support emissions modelling. EnViVer and PHEM (Passenger car and Heavy duty Emissions Model) are examples of instantaneous emission models that can be used directly with Vissim without having to use a conversion tool to generate the required model inputs. Whilst both models are suitable for the emissions modelling required in this research, EnViVer has been chosen due to availability of software licenses.

EnViVer is developed and maintained by TNO (Netherlands Organisation of Applied Scientific Research) and PTV (Planung Transport Verkehr). It has emissions factors for several vehicle types conforming to Euro 1-6, however Euro 6 emissions are based on a limited number of vehicles. EnViVer is based on a version of the Versit+ emission model and has been adapted for use with Vissim. The underlying emissions factors are from over 12,000 vehicle tests conducted in a laboratory using a dynamometer and on-road using PEMS (TNO, 2012). EnViVer is able to estimate tailpipe emission rates of CO_2, NO_x and PM_{10} as a function of time or as a total over a particular drive cycle.

EnViVer Enterprise 4.5.2 is an example of an emissions modelling tool that meets the requirements of this thesis. However, the general modelling procedure outlined in the following subsections is similar to other cycle variable/instantaneous emissions models. Note all EnViVer modelling presented in this thesis was conducted during March 2015.

6.3.1. Modelling tailpipe emissions in EnViVer

Modelling tailpipe emissions in EnViVer or any cycle variable model requires trajectory data and details about the vehicle's specification. For EnViVer, the trajectory data must have a minimum of a 1Hz resolution and include timing, speed and positioning information. The data also need to be stored in a particular format, details of which can be found in the user manual (TNO, 2012). The details about the vehicle's specification aid emissions class assignment. They include details such as the vehicle type, fuel type, vehicle age, Euro standard and whether it is an urban or motorway environment.

Once the required dataset has been assembled, the procedure for modelling tailpipe emissions is relatively straightforward. The trajectory data is imported into EnViVer and the software automatically groups vehicles by vehicle type as defined in the input file, for example car, bus and HGV. The model year is used to assign each vehicle type to particular emissions class. The model year influences the vehicle age distribution and thus the proportion of vehicles conforming to the different European emissions standards. The emissions class assignment matches a particular vehicle type to an appropriate set of emissions factors for that vehicle type. For example, a standard passenger car in an urban environment in 2009 would be assigned to the 'Light_Duty_City_2009' emissions class. Similarly, a HGV on a motorway in 2013 would be assigned to the 'HD_Heavy_Highway_2013' emissions class. Once all the vehicle types have been assigned to an emissions class, EnViVer can estimate the tailpipe emissions. The pollutant emissions for CO_2, NO_x and PM_{10} are output by the model as network totals and can be disaggregated by time and space.

6.3.2. Calibration of emissions class assignment

As explained in Section 6.3.1, emissions estimates depend on the emissions class that a vehicle type is assigned to. By default, EnViVer has several pre-defined emissions classes that cover both urban and motorway networks for various vehicle types. The difference between the urban and motorway emissions classes is that the urban emissions classes have additional emissions to account for ‘cold start’. Cold start is where the exhaust after-treatment systems are not working at their optimum due to catalysts and other systems not being sufficiently warm. The emission rates during cold start are expected to be higher than those during normal driving conditions as demonstrated by Weilenmann et al. (2013). The urban cycle used in this thesis is after a 40-minute motorway segment so it can be said with confidence that the data collected are for vehicles producing hot tailpipe emissions. Furthermore, whilst ‘cold start’ emissions could be investigated, it is challenging to reliably estimate the proportion of vehicles operating under ‘cold start’ conditions, therefore the majority of studies assume or focus on ‘hot-running’ operation.

In Chapter 5, the tailpipe emission rate of CO_2 and NO_x from 475 observations of vehicles navigating four urban obstacles was presented. As 1Hz trajectory data are also available for each observation, it is possible to estimate the tailpipe emission rates using EnViVer. The default emissions classes contained within the emissions model do not take into consideration the proportion of vehicles using each fuel type, the vehicle age distribution and the relative number of vehicles confirming to different Euro standards (Vialis, 2011). The default values provided within the emissions classes are based on the Dutch vehicle fleet. However, it is not common place to calibrate the model due to a lack of vehicle information as found in Csikós and Varga (2012) and Margreiter et al. (2014).

In this thesis, using the metadata for each vehicle test as presented in section 5.4, EnViVer will be calibrated to ensure the emissions class is more representative of the vehicles for which emissions estimates are sought. In section 5.5.2, it was explained that the fuel type and Euro standard vehicles conform to were statistically significant in estimating tailpipe pollutant emission rates. It is therefore proposed that four parameters will be modified in the calibration of the emissions class assignment as detailed below:

1. Fuel type – percentage of vehicles that are fuelled by petrol, diesel, LPG (liquefied petroleum gas), CNG (compressed natural gas) and electric
2. Vehicle age distribution – percentage of vehicles newer than 1 year, average vehicle age, average vehicle exit age and maximum vehicle age
3. Emissions legislation – year of introduction of Euro 1-6 emissions standards

4. Average regional CO_2 emissions – petrol and diesel emission rates as a mass per unit distance (g/km)

A component of the fourth research objective is to propose a methodology for adapting emissions modelling tools to better represent the observed behaviours in the vicinity of urban obstacles. This is demonstrated in section 6.3.3, where the emissions estimates using the default emissions class and calibrated emissions class are compared to the measured emissions. This allows for the potential improvement in emissions estimates to be quantified and reported.

6.3.3. Comparison of default and improved emissions class assignment

The predefined emissions class that would be best suited to modelling the tailpipe emissions from the vehicles used in this thesis would is 'Light_Duty_Highway_2013'. This is due to the fact that all the vehicles in this thesis are passenger cars and there are no cold start emissions. The default values for the four parameters that will be modified in this exercise are outlined below:

1. Fuel type – 67% petrol, 30.5% diesel, 2.3% LPG, 0.1% CNG and 0.1% electric
2. Vehicle age distribution – 7.5% vehicles <1 year old, average vehicle age 7.7 years, average vehicle exit age 19.0 years and maximum vehicle age 40 years
3. Emissions legislation – Euro 1 1992, Euro 2 1996, Euro 3 2000, Euro 4 2005, Euro 5 2009 and Euro 6 2014
4. Average regional CO_2 emissions – 166g/km for petrol fuelled vehicles and 158g/km for diesel fuelled vehicles

In the subsequent analysis, the measured emissions from 475 runs of Obstacle B, the signalised junction, are compared to the modelled emissions as the four parameters outlined above are modified for the vehicle fleet used in this thesis. The values used, such as the proportion of vehicles with a particular fuel type or Euro class is shown in section 5.4. The signalised junction was selected for this analysis as the trajectory files are longer and thus the comparison is based on more data points. As EnViVer uses distributions for many of the parameters that are calibrated, multiple runs of the model are required to account for the stochasticity. In order to determine the number of runs, the model was run 100 times and the standard deviation of CO_2 as a function of number of runs was calculated, as also demonstrated in Thiyagarajah (2011) and Chu et al. (2003).

It was found that after 16 runs, the standard deviation of modelled CO_2 converges to a single value with an error of less than 5%. Therefore, 20 model runs was selected.

Table 6.2 shows the 13 comparisons that have been made as each parameter is calibrated in turn and the results are shown in Table 6.3. As before, statistical significance was confirmed used a paired t-test. The difference between the modelled and measured emissions is calculated as follows:

$$Percentage\ difference = 100 * \frac{modelled\ emissions - measured\ emissions}{measured\ emissions}$$

Comparison A shows the difference between measured and modelled emissions when the predefined emissions class is used, and there is a difference of about 30% in emissions of both CO_2 and NO_x. For comparison B, the fuel type is defined and there is a marginal improvement in the estimate of CO_2 emissions from petrol vehicles. However, the estimate of NO_x emissions gets considerably worse and the same is true for the emissions estimates of the diesel vehicles. In comparison C, the vehicle age distribution is defined and this also in turn affects the European emissions classes as they are related to the vehicle's age. The modelled CO_2 emissions are within 20% of the measured values for both petrol and diesel vehicles and the NO_x estimates are also closer to the measured values. In comparison D, the conformance to European emissions standards is explicitly defined and all pollutant estimates across the four comparisons improve. However, it should be noted that the emissions factors for the Euro 6 vehicles are based on limited empirical data. With the NO_x estimates for three of the four comparisons, the model underestimates emissions. This underestimation of NO_x emissions and over estimation of CO_2 emissions is likely to be related to the use of stop-start technology and its negative impact on NO_x abatement strategies as discussed in Chapter 5. Finally, in comparison E, the average regional CO_2 emissions are defined. This has no impact on the NO_x emission estimates. However, the CO_2 estimate for all four groups is reduced. This is expected as original values are based on Dutch measurements pre-2013, and vehicle technology has improved since.

As predicted, it can be seen that calibrating an emissions model using parameters such as fuel type, vehicle age, conformance to European emissions standards and average regional CO_2 emissions can have a positive impact on the model's performance. Whilst this result is expected, the magnitude of the error has not previously been reported on this scale due to the lack of PEMS data, for example Vreeswijk et al. (2010) and Mahmod et al. (2013). Whilst real-world data may not be available in all modelling scenarios, this analysis highlights the potential errors in emissions estimates that are then often used by decision makers. There is a clear trade-off between using additional resources to collect the data required to calibrate an emissions model versus a more representative emissions estimate. Section 6.4 emphasises this trade-off even further with the use of a roadworks case study example.

Comparison reference	Parameter calibrated	Description
A	None	Default emissions class used for all vehicles in one group
B	Fuel type	Fuel type is defined in the model vehicles are modelled in two separate groups B-1 – Petrol vehicles only B-2 – Diesel vehicles only
C	Vehicle age distribution	Vehicle age is defined for the two fuel groups C-1 – Petrol vehicles only with vehicle age defined C-2 – Diesel vehicles only with vehicle age defined
D	Emissions legislations	Conformance to European emissions standard is defined for petrol and diesel vehicles separately, thus vehicle are modelled in four groups D-1 – Petrol Euro 5 vehicles D-2 – Petrol Euro 6 vehicles D-3 – Diesel Euro 5 vehicles D-4 – Diesel Euro 6 vehicles
E	Average regional CO_2 emissions	Average CO_2 emissions are defined based on the full urban test cycle and vehicles are modelled in the four groups as in comparison D E-1 – Petrol Euro 5 vehicles E-2 – Petrol Euro 6 vehicles E-3 – Diesel Euro 5 vehicles E-4 – Diesel Euro 6 vehicles

Table 6.2 – the different comparisons between the measured and modelled tailpipe emissions using EnViVer Enterprise 4.5.2 during March 2015

Comparison reference	Measured emissions		Modelled emissions		Difference	
	CO_2 (g)	NO_x (g)	CO_2 (g)	NO_x (g)	CO_2 (%)	NO_x (%)
A	42.872	0.076	55.984	0.097	30.58%	28.47%
B-1	47.845	0.015	58.409	0.037	22.08%	141.91%
B-2	40.191	0.111	53.761	0.205	33.76%	84.07%
C-1	47.845	0.015	56.719	0.027	18.55%	72.63%
C-2	40.191	0.111	48.061	0.178	19.58%	60.46%
D-1	51.052	0.018	54.528	0.009	6.81%	-47.98%
D-2	42.025	0.010	49.475	0.009	17.73%	-8.18%
D-3	41.875	0.121	41.904	0.181	0.07%	49.56%
D-4	37.758	0.093	42.141	0.041	11.61%	-56.65%
E-1	51.052	0.018	47.327	0.009	-7.30%	-47.98%
E-2	42.025	0.010	42.942	0.009	2.18%	-8.18%
E-3	41.875	0.121	36.729	0.181	-12.29%	49.56%
E-4	37.758	0.093	36.938	0.041	-2.17%	-56.65%

Table 6.3 – the estimated tailpipe emissions compared to the measured emissions for all comparison scenarios investigated

6.4. Case study example

In this section, a case study example is used to demonstrate the impact of adapting both the acceleration behaviour model in a traffic microsimulation tool and the emissions class assignment in an emissions modelling tool. This meets the requirements of the fourth research objective, which is to propose a methodology for adapting modelling tools to better represent the observed behaviours in the vicinity of urban obstacles. The chosen case study is a planned roadwork on Old Brompton Road in South Kensington, UK (Thiyagarajah and North, 2013). Figure 6.6 shows the modelling workflow employed to estimate the change in vehicle emissions due to model calibration, adapted from North et al. (2009).

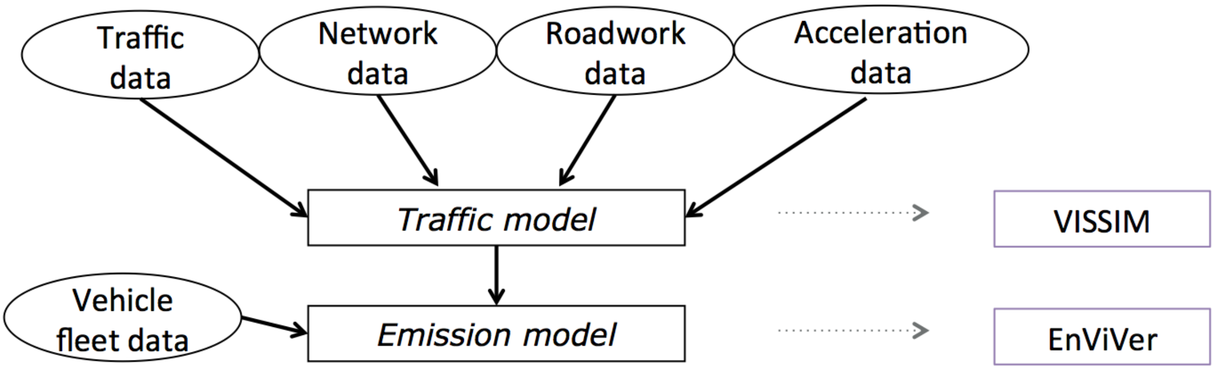


Figure 6.6 – the modelling workflow that will be employed to assess the impact of model calibration on vehicle emissions

Old Brompton Road (OBR) is a busy shopping street that allows for two-way traffic and also has on-street parking on both sides of the road. The segment of OBR considered in this research has a signalised junction on both ends with the eastern end of the road connecting to South Kensington underground station. During summer 2013, there were a series of roadworks on the carriageway to allow Thames Water to carry out maintenance on their buried assets. Due to the roadworks on the westbound lane, temporary traffic signals were introduced to ensure that a two-way traffic flow was maintained, as shown in Figure 6.7. As part of an unpublished project[7], simplified traffic microsimulation models of OBR were built by the author to investigate the impact of a typical roadwork and were calibrated using measurements on OBR. These validated models are used in the subsequent analysis.

---

[7] Project titled 'The impact of roadworks on network performance and the environment' completed in collaboration with the Royal Borough of Kensington and Chelsea (RBKC), and the Department for Environment, Food and Rural Affairs (DEFRA).

A full description of the traffic model development can be found in the consultancy report titled 'The impact of roadworks on network performance and the environment' (Project Reference 345b2012) submitted to the Department for Environment, Food and Rural Affairs (DEFRA). To summarise, the network layout was drawn using a 2D CAD model supplied by the Royal Borough of Kensington and Chelsea (RBKC). The inputs into the model such as the vehicular flows and fleet mix were based on manual traffic counts conducted as part of the project. Data for bus routes and frequencies were obtained from the Transport for London bus schedule. The model was validated using the GEH statistic that considers the modelled and measured traffic flows. The model was further validated using data obtained from an instrumented vehicle. GPS data was used to validate travel times, average speed and stopped delay. Additional details about the model validation results can be found in the aforementioned consultancy project or in the summary presentation by Thiyagarajah and North (2013).

Figure 6.7 – the location of temporary traffic signal on OBR (image from OpenStreetMap)

In order to assess the impact of calibrating the traffic and emissions model on tailpipe emissions, a four-way comparison is conducted. In section 6.4.1 the effect of using a calibrated acceleration behaviour model is assessed. Section 6.4.2 highlights how the emissions model can be adapted to represent the fleet being modelled. Section 6.4.3 presents the impact of using the calibrated models on tailpipe emissions.

6.4.1. OBR traffic model calibration

As explained in section 6.2.2 and demonstrated in section 6.2.3, the desired acceleration behaviour for the car vehicle type was calibrated using the measured data presented in Chapter 4. For modelling the roadwork and in particular the temporary traffic signals, the data from Obstacle B, the signalised junction is used. The temporary traffic signal and the signalised junction both have two signal phases and cycle times of 80 and 90 seconds respectively. The traffic signals are expected to incite the same behaviour, as vehicles will encounter a delay if there is a queue or red traffic light.

The base model was built using the measured data and network features such as reduced speed areas were introduced to ensure the model is a fair representation of the actual roadworks. The full model description and setup can be found in Thiyagarajah and North (2013), Figure 6.8 shows the simplified model of Old Brompton Road whilst the roadworks were present.

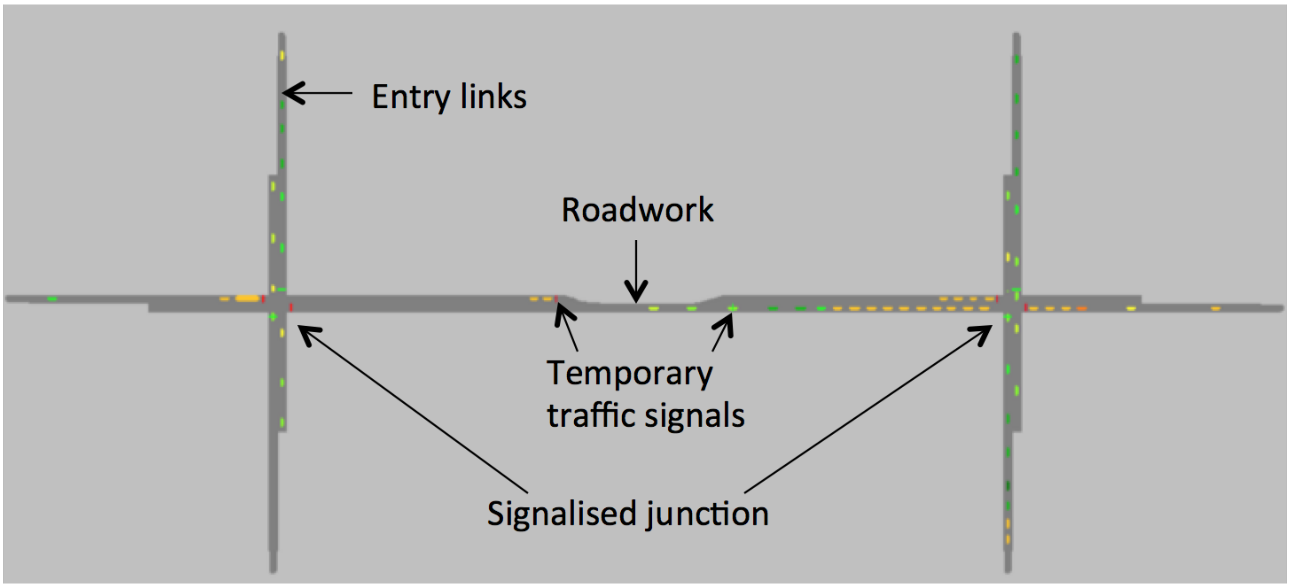


Figure 6.8 – the simplified traffic model created to model the roadworks on OBR

Table 6.4 shows the how measures that describe the network performance change between the two models and the measured data. It is clear that the use of a calibrated acceleration behaviour model results in traditional measures of network performance deviating further from the observed data. The statistical significance of four network performance metrics was confirmed using the t-test as explained in section 6.3.3. With vehicles accelerating more smoothly at lower speeds in the calibrated model, it takes longer for vehicles to reach their desired speed. This negatively impacts the average speed and travel time. Due to vehicles taking longer to navigate the roadwork, the capacity is reduced resulting in slightly fewer completed trips.

Metric	Measured data	Base model	Calibrated model	Difference (measured-base)	Difference (measured-calibrated)
Average delay [s]	27.23	25.88	42.65	-4.96%	56.63%
Average speed [m/s]	7.87	8.33	5.76	5.84%	-26.81%
Average travel time [s]	87.19	82.57	117.21	-5.30%	34.43%
Completed trips [veh]	324	352	298	8.64%	-8.02%

Table 6.4 – difference in network performance metrics for the base and calibrated model compared to the measured data

For all runs of the base model and calibrated model, the speed and acceleration data was extracted from the individual vehicle trajectory files. Using the same methodology as presented in section 4.3, the proportion of time spent in each vehicle operating mode is calculated for the two models, as shown in Table 6.5.

With the harsher default acceleration behaviour in the base model, vehicles are able to reach their desired speed more quickly and can cruise for a greater proportion of time, more than double what was observed at Obstacle B. With the calibrated model, the proportion of time in each vehicle operation mode is more evenly split, as was observed at Obstacle B, the signalised junction. Vehicles spend the greatest proportion of time in the acceleration mode as the more gentle acceleration mean it takes longer for them to reach their desired speed. The proportion of time in the idle vehicle operation mode is higher for the calibrated model than the base model. This is due to a greater proportion of vehicles waiting in queues at the temporary traffic signals and is further supported by the higher average delay.

Operation mode	Acceleration	Deceleration	Cruise	Idle
Observed	30.7%	13.8%	22.7%	32.9%
Base model	18.94%	24.27%	50.79%	14.56%
Calibrated model	35.38%	17.60%	16.59%	21.86%

Table 6.5 – table to show difference in vehicle operation mode between the base and calibrated model

In this section, the acceleration behaviour model was calibrated so that it was more representative of the accelerations observed in the vicinity of a traffic signal. When the metrics traditionally used to validate a traffic model were assessed, it was found that the error was greater with the calibrated model. However, by considering the proportion of time spent in the different vehicle operating modes, the calibrated model had the lower error.

This raises the question about how traffic models should be validated and whether the traditional network performance metrics are suitable. By using empirical data to re-estimate the speed-acceleration curves, it would be expected that the model is more representative of the situation being modelled. For the purpose of modelling vehicle emissions in an emissions modelling tool such as EnViVer, it is important that vehicle acceleration is modelled accurately. Zhao et al. (2013) showed that the vehicle acceleration is the key parameter in EnViVer for estimating vehicle emissions. However, it is noted that there are situations where the acceleration is not considered at all, for example when investigating the impact of a change in traffic management on average delay.

Through the findings presented in this section, it is proposed that the proportion of time in different vehicle operating modes is used as validation metric, especially when the intended use of the model is estimating emissions. In section 6.4.3, the traffic model outputs are used with EnViVer to compare the emissions estimates when uncalibrated and calibrated acceleration behaviour models are used.

6.4.2. OBR emissions model calibration

As described in section 6.3.2 and demonstrated in section 6.3.3, the emissions classes and the assignment can be calibrated in an emissions model to better represent the vehicle fleet being modelled. During the OBR project, information on the fleet composition was collected. However, data on the fuel type used or conformance to European emissions standards were not collected. In order to collect such data, vehicles would need to be individually surveyed or collected number plate data would need to be linked with a vehicle information database.

An alternative source of vehicle fleet information is the survey data collected in London by the Department for Transport. The survey data include information on the fleet composition in terms of fuel type, vehicle age and conformance to European emission standards, as required for the calibration of the emissions class. Whilst these data were not collected on OBR during the roadworks, this is the best data available for calibration of the emissions class and expected to be more representative than the default Dutch fleet. Furthermore, these data are used as an input into the London Atmospheric Emissions Inventory (LAEI) for emission estimation across London (Greater London Authority, 2013). Section 6.4.3 presents the emissions estimates obtained when the default (section 6.3.3) and calibrated (Table 6.6) emissions classes are used with the outputs from the traffic microsimulation models.

Parameter	Values used
Fuel type	44% petrol and 56% diesel (Department for Transport, 2013) The 0.07% electric vehicles were not defined in the model as this is below the minimum threshold for the fuel type definition
Vehicle age distribution	7.8% vehicles <1 year old, average vehicle age 7.9 years, average vehicle exit age 19.0 years and maximum vehicle age 40 years (Department for Transport, 2015b)
Emissions legislation	For petrol vehicles – 3% Euro 2, 20% Euro 3, 29% Euro 4, 39% Euro 5 and 9% Euro 6 (Department for Transport, 2013) For diesel vehicles - 1% Euro 2, 11% Euro 3, 27% Euro 4, 50% Euro 5 and 11% Euro 6 (Department for Transport, 2013)
Average regional CO_2 emissions	153.8g/km – emissions split by fuel type not available (Department for Transport, 2015d)

Table 6.6 – data used to calibrate the emissions class passenger vehicles are assigned to

6.4.3. Impact of model calibration on emissions

In order to assess the impact of model calibration on estimated tailpipe emissions, a four-way comparison is conducted. The individual vehicle trajectories from the base and calibrated traffic model are input into EnViVer with the default emissions class and the calibrated emissions class. Table 6.7 shows the four setups that will be used for the comparison.

Table 6.8 shows the estimated tailpipe emissions from just the 'car' vehicle type during one hour of the roadworks being in operation on OBR. Comparing setup A and B, the use of the calibrated emissions class results in an increase in both CO_2 and NO_x emissions. This is due to differences in the London and Dutch fleet, the London fleet has a much higher proportion of Euro 3 and 4 vehicles but a lower proportion of Euro 5 vehicles. As a greater proportion of the vehicles meet the less stringent European emissions standards in the calibrated emission model, the overall mass of pollutant emitted is higher.

Focusing on setup A and C, there is a reduction in estimated emissions when the calibrated traffic model is used. Despite the calibrated model resulting in vehicles spending a greater proportion of time in the acceleration operating mode as shown in Table 6.5, the total emissions are lower as the magnitude of the acceleration is also smaller. Furthermore, the period of time spent in the idle mode is also marginally higher in the calibrated model as vehicles take longer to depart from queues.

In setup D, the calibrated acceleration behaviour model is combined with the calibrated emissions model. The estimated total emissions of both CO_2 and NO_x are lower than those estimated in setup A, with a difference of about -20%. Considering the two previous comparisons, this result is expected, as the magnitude of the accelerations is lower. However, there are more vehicles that conform to the less stringent European emissions standards.

From the last column in Table 6.8, it is clear that using models that are calibrated using on road data can result in substantial differences in modelled emission from the uncalibrated case. In section 6.2 and 6.3, it was demonstrated that the use of empirical data to calibrate the acceleration behaviour model and emissions class resulted in models that were more representative of the real-world behaviours. It was not possible to collect PEMS data from multiple vehicles navigating the OBR roadworks. However, it is expected that the calibrated models (setup D), resulted in the most realistic emissions estimates. Further work should model a roadwork where PEMS and acceleration data is available to confirm this.

The emissions modelling process is vastly simplified if the default emissions classes are used. However, in this calibration exercise a difference of about 20% was found for both CO_2 and NO_x emissions. Studies such as Csikós and Varga (2012) and Margreiter et al. (2014) that use EnViVer to estimate vehicle emissions, fail to calibrate the emissions classes. Based on the findings of this research, this is not recommended. The outputs from emissions models are normally used to support decision making, such as whether the flow on a particular road should be reduced or whether traffic management infrastructure should be changed. With unrepresentative emissions classes, the emissions estimates are potentially wrong and thus there is limited confidence in the decisions that are made based on the results.

The fourth research objective of this thesis was to propose a methodology for adapting modelling tools to better represent the observed behaviours in the vicinity of urban obstacles. Through the calibration of the acceleration behaviour model and modifying emissions classes, the fourth research objective has been achieved. Section 6.5 explains how the findings from the calibration exercises and the OBR case study could be of benefit to the wider transport modelling community and potentially those that make policy recommendations.

Setup reference	Modelling	Description
A	Base traffic model and default emissions class	Outputs from the base traffic model with the uncalibrated acceleration behaviour model are input into EnViVer with the default emissions class assignment
B	Base traffic model and calibrated emissions class	Outputs from the base traffic model with the uncalibrated acceleration behaviour model are input into EnViVer with the calibrated emissions class assignment based on the Central London fleet composition
C	Calibrated traffic model and default emissions class	Outputs from the calibrated traffic model with the updated acceleration behaviour model are input into EnViVer with the default emissions class assignment
D	Calibrated traffic model and calibrated emissions class	Outputs from the calibrated traffic model with the updated acceleration behaviour model are input into EnViVer with the calibrated emissions class assignment based on the Central London fleet composition

Table 6.7 – model setups that will be made to assess the impact of model calibration on emissions

Setup reference	Modelled CO_2 [Kg]	Modelled NO_x [g]	CO_2 difference from A	NO_x difference from A
A	88.297	149.970	-	-
B	93.773	173.001	6.20%	15.36%
C	56.617	102.229	-35.88%	-31.83%
D	69.981	120.987	-20.74%	-19.33%

Table 6.8 – estimated tailpipe emissions from four different model setups of OBR

6.5. Guidance and recommendations

In this chapter, the acceleration and emissions data collected using the procedure outlined in Chapter 3 were used to calibrate both a traffic and emissions model. The understanding of the variability in vehicle acceleration and tailpipe emissions from Chapters 4 and 5 was used to inform how vehicles and obstacles were represented in the modelling. Based on the findings presented in this chapter, guidance and recommendations are made for traffic modellers, modelling tool developers and policy makers, as discussed below.

Guidance for traffic modellers

In the traffic model, the speed-acceleration curve in the acceleration behaviour model was re-estimated using data related to the obstacle being modelled. It was found that the calibration resulted in large deviations in the measures traditionally used to assess network performance and validate traffic models, such as average vehicle speed. When the proportion of time in different vehicle operating modes was evaluated, it was found that the calibrated model was more representative of the real-world scenario. It was expected that using empirical data to calibrate a model would make the model more representative of the situation being modelled, especially when using traditional validation metrics. This raises questions about the suitability of traditional validation metrics and whether additional measures should also be used.

Based on the findings of the acceleration behaviour model calibrations, it is recommended that the proportion of time spent in different vehicle operating modes be another measure used in the validation process. In order to carry out this validation, vehicle trajectory data would be required which could be collected using a standalone GNSS receiver as described in section 3.2.2.1. This data could be collected using any modern mobile phone or tablet device that contains a GPS receiver. The results of the validation of this measure would be particularly important when using the traffic model outputs to estimate vehicle emissions.

In the emissions modelling, new emissions classes were created to represent the fleet of vehicles being modelled. Based on the results of the regression analysis in section 5.4, the fuel type and conformance to European emissions standards were adjusted to reflect the fleet of vehicles being modelled. As expected, it was found that using more representative emissions classes resulted in emission estimates that were closer to those measured using PEMS.

Based on these findings, it is recommended that the emissions class should always be adapted so that it is representative of the vehicles being modelled. Whilst this is a typical recommendation whenever using a model to represent a system, it is not routine procedure to calibrate the emission class, for example Csikós and Varga (2012) and Margreiter et al. (2014). This research presented a unique opportunity to quantify the error between modelled and measured emissions from 475 observations. An error of about 30% was observed when comparing the measured and modelled CO_2 and NO_x emissions using the default emissions class. This error reduced to a maximum of 12% for CO_2 emissions when the calibrated emissions class was used. There are several practical and financial limitations when collecting real-world emissions data or detailed fleet information. Therefore, it is recommended that where it is not possible to collect exact vehicle information, at least country or city specific data should be used, as demonstrated in section 6.4.2.

<u>Guidance for modelling tool developers</u>

As shown in this thesis, the default acceleration behaviour used in a modelling tool does not necessarily correspond to the observed behaviours. In the modelling tool used in this research, Vissim, it was possible to calibrate the acceleration behaviour model resulting in a better representation of the scenario being modelled. Therefore, it is recommended that all traffic modelling tools should support the calibration of the underlying acceleration behaviour model, especially when the behaviour of individual vehicles is being represented. Furthermore, the acceleration behaviour model is a global parameter that applies to the full network being modelled. Additional functionality that allows multiple acceleration behaviour models to be implemented should be introduced. For example, the vehicle accelerations will be less aggressive in an urban area where there are obstacles compared to a motorway environment where there are on-ramps and high-speed lane changes. In existing modelling tools such as Vissim, this functionality does not exist.

In section 6.3.3, tailpipe emissions data measured using PEMS were compared to emissions estimates obtained by using the real-world trajectory data as an input into EnViVer. Whilst the calibration of the emissions class improved the estimates of CO_2 emissions, the NO_x estimates only improved in certain circumstances and were overall quite poor. It was explained that the discrepancy between the modelled and measured NO_x emissions is expected to be due to the use of vehicle 'eco technologies' and NO_x abatement technologies. It was concluded that whilst 'stop-start' technologies are active, the exhaust system cools down due to flow of hot exhaust gases being stopped. This causes the catalysts used in the NO_x abatement systems to also cool down, reducing their efficiency in NO_x abatement. Therefore, it is recommended that emissions models take into consideration the emissions reduction technologies that vehicles are fitted with. For example, if the trajectory data shows an extended portion of time where the vehicle is idle at a signalised junction, the model could assume the engine is switched off and not running for certain vehicles. The inclusion of emissions reduction technologies in emissions modelling tools is expected to reduce the differences observed between measured and modelled emissions.

Guidance for policy makers

In section 2.3, the key roadwork management techniques used in London, UK were presented. Under the London Permit Scheme (LoPS) and the Lane Rental Scheme, the works promoter is required to pay a fee to gain access to the carriageway. This fee depends on the class of the roadworks, their duration and the physical footprint of the works. The fees do not take into consideration the environmental impact of the roadworks due to the additional congestion caused.

Through the use of calibrated traffic and emission models, it would be possible to estimate the impact on vehicle emissions due to the presence of a roadwork. This could then be reflected in the fees that works promoters are required to pay. For example, if the roadwork resulted in additional CO_2 being released in the vicinity of the roadwork, this could be quantified and a cost calculated using figures from the European Union Emissions Trading Schemes (EU ETS). Where works promoters use innovating technologies or working practices that reduce the environment impact of the works, these fees could be waived. Therefore, it is recommended that appropriately calibrated models be used to support the fee structure in schemes such as LoPS and the Lane Rental Scheme. By including the environmental impact cost component in the fee structure, it is hoped that the additional vehicle emissions due to the presence of a roadwork will be reduced. This will have a positive impact on air quality and the wider natural environment.

In this subsection, recommendations to the traffic modelling community and roadwork policy makers were presented. Adopting these recommendations is expected to improve how roadworks are modelled. This will allow for methods of reducing their impact to be investigated through policy changes, but also using alternative roadwork configuration and coordination plans.

6.6. Conclusions

The fourth research objective of this thesis is to 'propose a methodology for adapting traffic and emissions modelling tools to better represent the observed behaviours in the vicinity of urban obstacles'. In this chapter, this research objective was addressed in three parts. The first was the demonstration of how the acceleration behaviour model could be calibrated, the second was the calibration of the emissions class assignment in an emission model, and the final part was the use of a roadworks case study. Based on the findings presented in this chapter, guidance for the traffic modelling community and policy makers was provided through a series of recommendations.

In this chapter it was demonstrated how the acceleration behaviour model, particularly the desired acceleration, could be modified to be more reflective of the real-world observations. Whilst using a calibrated acceleration behaviour model resulted in more realistic vehicle dynamics, it negatively impacted network performance metrics traditionally used to validate a model, such as travel time and average speed. This raises questions about the suitability of measures traditionally used to validate a traffic model. It was recommended that the proportion of time spent in different vehicle operating modes should be another measure used to validate a model. This metric is especially important when using the outputs from the traffic model with an emission modelling tool.

The calibration of an instantaneous emission model was also explored in this chapter. The emissions class was modified using the fuel type, vehicle age and compliance to European emissions standards. It was shown that the estimated emissions were more representative of those obtained from PEMS when the calibrated emissions class was used over the default class. Whilst this is obvious, the data collected in this research presented an opportunity to quantify the magnitude of the error, about 30% for both CO_2 and NO_x when the default emissions class was used. This error reduced to 6% on average for CO_2 emissions with the calibrated emissions class. The error for NO_x emissions increased to about 40% on average with the calibrated emission class, this is thought to be due to eco-technologies and NO_x abatement strategies not being represented in the emission model. It was recommended that emissions modellers should always calibrate the emissions class, and functionality to represent pollution mitigation technologies should be included in the modelling tools.

In section 6.4, roadworks on Old Brompton Road were used as a case study to investigate the effect of model calibration on estimated tailpipe emissions. It was found that calibrating both the acceleration behaviour in the traffic model, and the vehicle assignment in the emission model resulted in differences in the order of 20% for both CO_2 and NO_x. This difference in CO_2 estimates was 18.3kg/hr of roadworks. For context, this is approximately the equivalent energy use of an average household for 12 hours[8].

The transport community routinely uses traffic and emissions models to understand the impact of a particular scheme or scenario. Decision makers then often use the model outputs as the basis for new policy and guidance. The work presented in this chapter highlights the need for appropriate model calibration. The use of inappropriately calibrated models can result in misleading results and ultimately policies that cause unexpected results.

[8] Figures obtained from www.youstain.com, where an average household has four occupants and three bedrooms

7. Conclusions and further work

In the introductory chapter to this thesis, it was explained that roadworks are a feature of the road network that impact vehicle tailpipe emissions. Given that vehicle emissions have a negative impact on human health and the environment, methods to minimise them are of interest. It was highlighted that adopting a different roadwork configuration or coordination plan could minimise the impact of roadworks. In order to carryout this investigation, existing modelling tools could be used, however it is important that they are suitable for modelling roadworks.

In order to assess the suitability of existing modelling tools, a requirement of this research is that emissions data in the vicinity of urban obstacles such as roadworks be collected. Furthermore, it was explained that emissions modelling tools require vehicle dynamics data to estimate emissions. In the literature, accurate representation of vehicle acceleration has been shown to be critical for the estimation of vehicle emissions. It was therefore proposed that vehicle acceleration data also be collected. In order to address the research problem, four research objectives were defined:

1. Develop and validate a robust device for capturing vehicle dynamics that complements existing methods of measuring vehicle tailpipe emissions
2. Identify urban obstacles and then assess how the acceleration behaviour varies at different obstacles and between different vehicles
3. Understand how tailpipe emission vary at different obstacles and between different vehicles to support emissions modelling
4. Propose a methodology for adapting traffic and emissions modelling tools to better represent the observed behaviour in the vicinity of urban obstacles

Section 7.1 details how the research objectives have been addressed in this thesis. In section 7.2, opportunities for further work are discussed with reference to areas of this research that could be developed upon.

7.1. Research objectives and conclusion

Four research objectives were defined, how they have been met is discussed in the following subsections with the relevant research findings.

7.1.1. Objective 1: Measurement of vehicle dynamics and emissions

To assess the suitability of existing tools used to model roadworks and their impact, there is a requirement to obtain real-world acceleration and emissions data. In order to obtain the required data:

- The mechanism by which a roadwork impacts vehicle dynamics and the resultant emissions was assessed. It was found that it is the traffic management that causes a vehicle to deviate from its desired speed or direction, not the roadwork itself. Roadworks are temporary and not always located where they are planned. To aid the data collection, it was proposed that all urban obstacles be considered. It was argued that other objects, events and traffic management on the road network would incite similar behaviours in vehicles.
- With a requirement to collect vehicle dynamics and emissions data in the vicinity of urban obstacles, the different measurement options were evaluated. It was found that in both cases, a vehicle based solution was the most appropriate to collect the data required for this research.
- For the measurement of tailpipe emissions, the use of a Portable Emissions Monitoring Systems (PEMS) was proposed. A PEMS dataset was identified and assessed. It was found that the Emissions Analytics data collection procedure met the requirements of this research.
- The trajectory data collected by the PEMS unit was deemed to not have sufficient resolution for the analysis of vehicle acceleration. A trajectory monitoring platform, Hermes, was developed to meet the needs of this research. The Hermes unit was calibrated and validated with a reference measurement system.
- The data collection procedure for this research was presented. The data processing steps required to output real-world vehicle trajectory and emissions data were also explained.

7.1.2. Objective 2: Variability in vehicle dynamics at urban obstacles

To support the modelling of vehicle acceleration in the vicinity of urban obstacles, it is important to understand the how acceleration behaviour varies between different obstacles and vehicles. In order to understand the variability:

- Methods of identifying obstacles in trajectory data were presented. A speed based obstacle identification method was selected. The method does not make any prior assumptions about the location of obstacles, or whether they resulted in an obstructed trajectory.
- The speed based obstacle identification method was used to identify four urban obstacles. They correspond to segments of the test cycle that have the highest number of acceleration events across the population of vehicles for which trajectory data was available.
- By considering the distribution of vehicle speeds and accelerations, the variability in acceleration behaviour at the four urban obstacles was assessed. Differences in the proportion of time spent in the four mutually exclusive vehicle operating modes were highlighted.
- Through application of the KS test to the vehicle activity data (speed against acceleration), it was determined that the vehicle dynamics at the speed cushion was different to that observed at the other three urban obstacles.
- Reflecting on the mechanism of impact for each urban obstacle, two additional types of obstacle groups were proposed. These were those that cause a delay due to a lateral deflection (roundabout) and those that may intermittently result in a vehicle being forced to stop (signalised junction/”keep clear” zone).
- The variability in vehicle acceleration between different vehicles at each obstacle was also investigated. Regression models were developed for the obstacles using vehicle characteristics as explanatory variables. The regression modelling showed that vehicle characteristics such as vehicle mass and vehicle power were not statistically significant in estimating vehicle acceleration.
- Based on the understanding of variability in vehicle acceleration, grouping structures to aid the modelling of vehicle dynamics were proposed. Three groups for obstacle type were recommended based on the mechanism of impact. Based on the data available for this

thesis, it was suggested that vehicles with different vehicle characteristics are equivalent when modelling vehicle acceleration in the vicinity of urban obstacles.

7.1.3. Objective 3: Variability in tailpipe emissions at urban obstacles

To accurately model vehicle tailpipe emission rates in the vicinity of urban obstacles, an understanding of the variation is required. Emissions rates will differ depending on the power demands required to navigate an obstacle, but also due to individual vehicle characteristics. In order to understand the variability:

- A PEMS dataset was processed to extract the same urban obstacles that were identified when assessing vehicle acceleration.
- The variability in tailpipe emissions between the four obstacles was assessed using the total mass of pollutant emitted, the emission rate as a function of time, the emission rate as a function of distance and the emission rate as a function of vehicle specific power.
- The emissions rates in the vicinity of urban obstacles were several magnitudes higher than those obtained from regulatory emissions testing. Whilst the regulatory emissions testing is based on a cycle rather than an isolated event, NO_x emission rates 25 times the regulatory values in the vicinity of speed cushions were not expected.
- In order to understand whether the emission rates at the four obstacles were different, the KS test was applied to the data. The test showed that the emission rates at each obstacle were drawn from different distributions.
- The difference in emission rates at each urban obstacle was discussed as being due to the differing proportion of time spent in each of the four mutually exclusive vehicle operating modes. This changes the power demands placed upon the engine at each obstacle, and thus the rate at which fuel is combusted and pollutants are emitted.
- The variability in tailpipe emission rates between different vehicles was also assessed. Regression models for CO_2 and NO_x emission rate were developed using vehicle characteristics as explanatory variables. The regression modelling showed that the fuel type and European emissions standard conformance, were statistically significant in estimating emission rate.
- Based on the understanding of the variability in tailpipe emission rates, grouping structures to aid the modelling of vehicle emissions were proposed. It was recommended that if obstacle specific emissions factors are used, the power demands are each obstacle should

be considered. For the four obstacles investigated in this thesis, individual emissions factors should be used. Based on the regression modelling, it is important that fuel type and conformance to European emissions standards are considered in emissions modelling. Passenger cars should not be considered as one group either by fuel type or Euro standard.

7.1.4. Objective 4: Modelling vehicle dynamics and emissions

To assess the suitability of existing modelling tools, a method of adapting the tools to be more representative of the observed behaviours is required. To meet this requirement:

- The different traffic modelling tools were assessed based on the measurement resolution. Given the need to model the behaviour of individual vehicles, a microscopic model was identified as the most suitable. By considering the most widely used tools and those that support the modification of the acceleration behaviour model, Vissim was selected.
- The procedure for using empirical acceleration data to re-estimate the mathematical formulation of the acceleration behaviour model was explained.
- The data for a mini roundabout was used to calibrate the acceleration behaviour in an example model. Vissim was run with the default acceleration behaviour model and with the calibrated model. It was found that the calibrated model negatively impacted measures used to traditionally assess network performance. Average delay increased by over 170% and the number of completed trips reduced by about 30%. However, when the proportion of time spent in different vehicle operating modes was assessed, the calibrated model was more representative of the measured data. This raises questions about the metrics used to validate traffic models.
- The different emissions modelling tools were also reviewed. It was determined that a cycle variable or instantaneous emissions model would suit the requirements of this research. EnViVer was selected due to its compatibility with Vissim and as it supports the modification of the emissions classes.
- The trajectory data from 475 observations of the signalised junction were used as an input into EnViVer. The vehicle fleet information was progressively defined in the model and the difference between the measured and modelled emissions was quantified. With the vehicle fleet information defined in EnViVer, the difference between the measured and modelled emissions reduced from about 30% to less than 12% for CO_2 emissions. Whilst

defining the vehicle fleet was expected to improve the model performance, quantification of the error is not normally possible due to data limitations.

- The calibration of the acceleration behaviour model and emission class was combined in a roadworks case study. The difference in the emissions estimates between the default and calibrated models was about 20%. This is a significant difference that highlights why models should be calibrated and that they are not suitable when default values are used.
- Based on the findings from the traffic and emissions modelling, a series of recommendation were made to policy makers and the traffic modelling community. They as summarised below:
    1. The proportion of time spent in different vehicle operating modes should be used a validation metric.
    2. The emissions classes in an emissions model should always be calibrated. Where exact fleet information is not available, city or country specific fleet information should be used.
    3. Traffic modelling tools should support the modification of the acceleration behaviour model. Especially, when the intended purpose of the model is to estimate vehicle emissions. The acceleration behaviour model should also not be a global parameter. Functionality should be introduced to support multiple acceleration models for different parts of the network where behaviours may change.
    4. Emissions modelling tools should allow the end user to define whether more popular eco-technologies are present in the fleet being modelled. For example, the proportion of vehicles fitted with stop-start technology.
    5. Finally, policy makers should consider the use of traffic and emission modelling tools when deciding the charging structure for schemes such as the London Permit Scheme and Lane Rental Scheme. The fees should incorporate the environmental impact of the roadworks due to the negative impact on human health and the environment. Furthermore, the roadwork modelling may present opportunities to minimise the impact of roadworks though changes in their configuration and coordination.

7.2. Further work

By meeting the specified research objectives, this thesis has improved the understanding of the variability in vehicle dynamics and emissions at urban obstacles. This section details three broad areas of potential future research that could further advance our understanding. This will ultimately improve the modelling of urban obstacles to ensure the models are more representative of the observed behaviours.

7.2.1. Vehicle acceleration data

In this thesis, vehicle dynamics data was collected from 55 vehicles and resulted in 164 observations of a London-based urban test cycle. A methodology for identifying obstacles in trajectory data was demonstrated and four urban obstacles were analysed in detail. The 164 observations of each obstacle allowed for the variability in acceleration behaviour to be investigated. However, additional data from a more diverse range of vehicles on different test routes would allow for a deeper understanding of the variability in vehicle acceleration.

With data from multiple vehicles on different test routes, the variability in acceleration behaviour at different examples of the same obstacle type could be examined. This would allow for greater confidence in the data that are used to re-estimate the underlying mathematical formulation of the acceleration behaviour model.

In addition, future measurement campaigns should support the collection of information about local traffic characteristics. For example, whether there is a queue at a particular urban obstacle and whether the vehicle's ability to accelerate is constrained by a lead vehicle. This would allow for additional explanatory variables to be used when developing models of acceleration behaviour. During the data collection for this research, opportunities to install a forward-facing camera were sought. However, this was not permitted due to concerns about the disclosure of the test route.

7.2.2. Vehicle emissions data

In Chapter 5, tailpipe emissions data from 226 vehicles was collected and resulted in 475 observations of an urban test cycle. The data allowed for a detailed understanding of how tailpipe emission rates vary between different obstacles and vehicles. However, this analysis was constrained to four urban obstacles and only Euro 5/6 vehicles. Collecting data from a wider range of vehicles at a variety of obstacles would support a more comprehensive assessment of existing emission modelling tools. The data could also potentially be used to develop obstacle specific emissions factors.

In this thesis, a Portable Emission Measurement System (PEMS) is used to collect the required real-world emissions data. A limitation of the device used and PEMS in general, is that the measurement resolution is typically up to 1Hz. With advancements in technology, PEMS devices that are able to operate at higher measurement resolutions would allow for the emission rates in the vicinity of urban obstacles to be investigated with greater granularity.

In conjunction with the emissions measurement in this thesis, metadata about each vehicle and each test was collected. However, this data was limited to a few vehicle characteristics and incomplete for many of the vehicles tested. Future measurement campaigns should record additional details about the vehicle, such as the presence of eco-technologies and whether or not they are active. Opportunities should also be sought to obtain data from the vehicle's on-board computer about the air/fuel ratio and other factors that influence tailpipe emission rates. This additional data will aid the explanation of the differences observed in tailpipe emission rates, and potentially influence the inputs into emissions modelling tools.

7.2.3. Modelling roadworks

In this research, Vissim and EnViVer were used as examples of traffic and emissions modelling tools. The models were selected as they support the modification of underlying parameters such as the acceleration behaviour model in Vissim and the emission class in EnViVer. Future work should investigate the errors associated with other modelling tools using the same procedures outlined in this thesis. With an assessment of the errors associated with multiple modelling tools, additional guidance could be given to the modelling community who use the tools to model roadworks and other urban obstacles.

The motivation of this research was to be able to use existing modelling tools to investigate opportunities to minimise the environmental impact of roadworks. Using the findings of this research, scope for configuring roadworks differently or coordinating multiple roadworks should be explored. Future work could also look at existing traffic models of proposed schemes or changes to the road network, and assess whether the decisions based on the modelling differ when the models are calibrated as in this thesis.

References

ABBOTT, E. & POWELL, D. An examination of the relative merits of various sensors for vehicle navigation. ION GPS-95, 1995. 1269-1284.

ABDEL-HAFEZ, M. F. 2012. On the GPS/IMU sensors' noise estimation for enhanced navigation integrity. *Mathematics and Computers in Simulation,* 86**,** 101-117.

ABDULHAI, B. & TABIB, S. M. 2003. Spatio-temporal inductance-pattern recognition for vehicle re-identification. *Transportation Research Part C: Emerging Technologies,* 11**,** 223-239.

AHMED, K. I. 1999. *Modeling drivers' acceleration and lane changing behavior.* Massachusetts Institute of Technology.

AIMSUN. 2015. *Aimsun helps TfL retain detail in traffic modelling* [Online]. Available: https://www.aimsun.com/wp/?p=8548 [Accessed January 31st 2016].

AKÇELIK, R. Operating cost, fuel consumption and pollutant emission savings at a roundabout with metering signals. ARRB 22nd Conference, 2006.

AKÇELIK, R. & BESLEY, M. Acceleration and deceleration models. 23rd Conference of Australian Institutes of Trasnport Research (CIATR 2001), 2001 Melbourne, Australia.

ALMEIDA, L. Q. D., SALES, L. C. M. & SODRÉ, J. R. 2015. Fuel consumption and emissions from a vehicle operating with ethanol, gasoline and hydrogen produced on-board. *International Journal of Hydrogen Energy,* 40**,** 6988-6994.

ARDUINO. 2015. *Frequently Asked Questions* [Online]. Available: https://www.arduino.cc/en/Main/FAQ [Accessed 5th June 2014].

AXER, S., ROHDE, J. & FRIEDRICH, B. 2012. Level of Service Estimation at Traffic Signals Based on Innovative Traffic Data Services and Collection Techniques. *Procedia - Social and Behavioral Sciences,* 54**,** 159-168.

BACHMAN, W., SARASUA, W., HALLMARK, S. & GUENSLER, R. 2000. Modeling regional mobile source emissions in a geographic information system framework. *Transportation Research Part C: Emerging Technologies,* 8**,** 205-229.

BARBOSA, H. M., TIGHT, M. R. & MAY, A. D. 2000. A model of speed profiles for traffic calmed roads. *Transportation Research Part A: Policy and Practice,* 34**,** 103-123.

BARCELLOS, P., BOUVIÉ, C., ESCOUTO, F. L. & SCHARCANSKI, J. 2015. A novel video based system for detecting and counting vehicles at user-defined virtual loops. *Expert Systems with Applications,* 42**,** 1845-1856.

BARLOW, T. J. & BOULTER, P. 2009. *Emission factors 2009: Report 2-a review of the average-speed approach for estimating hot exhaust emissions*.

BAUER, D., BELBACHIR, A. N., DONATH, N., GRITSCH, G., KOHN, B., LITZENBERGER, M., POSCH, C., SCHÖN, P. & SCHRAML, S. 2007. Embedded vehicle speed estimation system using an asynchronous temporal contrast vision sensor. *EURASIP Journal on Embedded Systems,* 2007**,** 34-34.

BELLA, F. & SILVESTRI, M. 2015. Effects of safety measures on driver's speed behavior at pedestrian crossings. *Accident Analysis & Prevention,* 83**,** 111-124.

BELZ, N. & AULTMAN-HALL, L. 2011. Analyzing the Effect of Driver Age on Operating Speed and Acceleration Noise: On-Board Second-by-Second Driving Data. *Transportation Research Record: Journal of the Transportation Research Board***,** 184-191.

BENSON, P. Data requirements for micro-scale modeling of mobile sources. Transportation Modeling Tips and Trip-Ups Proceedings, an Air and Waste Managements Association Specialty Conference, Pittsburgh, 1992.

BERGMANN, M., KIRCHNER, U., VOGT, R. & BENTER, T. 2009. On-road and laboratory investigation of low-level PM emissions of a modern diesel particulate filter equipped diesel passenger car. *Atmospheric Environment,* 43**,** 1908-1916.

BIGAZZI, A. Y. & FIGLIOZZI, M. A. 2012. Congestion and emissions mitigation: A comparison of capacity, demand, and vehicle based strategies. *Transportation Research Part D: Transport and Environment,* 17**,** 538-547.

BOLLEN, J. & BRINK, C. 2014. Air pollution policy in Europe: Quantifying the interaction with greenhouse gases and climate change policies. *Energy Economics,* 46**,** 202-215.

BOTERO, V., HERNÁNDEZ, W. & FERNÁNDEZ, E. 2014. ORIENTATION OF A TRIAXIAL ACCELEROMETER USING A HOMOGENEOUS TRANSFORMATION MATRIX AND KALMAN FILTERS. *International Journal on Smart Sensing & Intelligent Systems,* 7.

BURGARD, D. A., BISHOP, G. A. & STEDMAN, D. H. 2006. Remote Sensing of Ammonia and Sulfur Dioxide from On-Road Light Duty Vehicles. *Environmental Science & Technology,* 40**,** 7018-7022.

CARSLAW, D. C. & RHYS-TYLER, G. 2013. New insights from comprehensive on-road measurements of NOx, NO2 and NH3 from vehicle emission remote sensing in London, UK. *Atmospheric Environment,* 81**,** 339-347.

CARSLAW, D. C., WILLIAMS, M. L., TATE, J. E. & BEEVERS, S. D. 2013. The importance of high vehicle power for passenger car emissions. *Atmospheric Environment,* 68**,** 8-16.

CHALKO, T. 2009. Estimating Accuracy of GPS Doppler Speed Measurement using Speed Dilution of Precision (SDOP) parameter. *NU Journal of Discovery*.

CHAMBERLIN, R., SWANSON, B., TALBOT, E., DUMONT, J. & PESCI, S. Analysis of MOVES and CMEM for evaluating the emissions impact of an intersection control change. Transportation Research Board 90th Annual Meeting, 2011.

CHEN, C., HUANG, C., JING, Q., WANG, H., PAN, H., LI, L., ZHAO, J., DAI, Y., HUANG, H., SCHIPPER, L. & STREETS, D. G. 2007. On-road emission characteristics of heavy-duty diesel vehicles in Shanghai. *Atmospheric Environment,* 41**,** 5334-5344.

CHU, L., LIU, H. X., OH, J.-S. & RECKER, W. A calibration procedure for microscopic traffic simulation. Intelligent Transportation Systems, 2003. Proceedings. 2003 IEEE, 2003. IEEE, 1574-1579.

CHUNG, Y. 2011. Assessment of non-recurrent traffic congestion caused by freeway work zones and its statistical analysis with unobserved heterogeneity. *Transport Policy,* 18**,** 587-594.

CLEAN AIR TECHNOLOGY CENTER 1999. Nitrogen oxides (NOx) : why and how they are controlled. Research Triangle Park, N.C: Office of Air Quality Planning and Standards, U.S.: Environmental Protection Agency.

COELHO, M. C., FARIAS, T. L. & ROUPHAIL, N. M. 2005. Impact of speed control traffic signals on pollutant emissions. *Transportation Research Part D: Transport and Environment,* 10**,** 323-340.

COLIN BUCHANAN. 2010. *Road Works Count!* [Online]. Available: http://www.scribd.com/doc/38384520/Economic-Impact-of-Road-Works [Accessed 5th May 2012].

CSIKÓS, A. & VARGA, I. 2012. Real-time Modeling and Control Objective Analysis of Motorway Emissions. *Procedia - Social and Behavioral Sciences,* 54**,** 1027-1036.

DAHAM, B., ANDREWS, G. E., LI, H., PARTRIDGE, M., BELL, M. C. & TATE, J. 2005. Quantifying the effects of traffic calming on emissions using on-road measurements. *SAE Technical Papers*.

DARLINGTON, T. L., KORSOG, P. E. & STRASSBURGER, R. Real world and engine operation: results of the MVMA/AIAM instrumented vehicle pilot study. Proceedings of the 85th Annual Meeting of the Air and Waste Management Association, 1992.

DECC. 2012. *Emissions and Climate Change Statistics* [Online]. Available: http://www.decc.gov.uk/en/content/cms/statistics/climate_stats/climate_stats.aspx [Accessed 1st February 2012].

DEFRA. 2014. *Defra National Statistics Release: Emissions of air pollutants in the UK, 1970 to 2013* [Online]. Available: https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/388195/Emissions_of_air_pollutants_statistical_release_2014.pdf [Accessed 10th October 2015].

DEMUYNCK, J., BOSTEELS, D., DE PAEPE, M., FAVRE, C., MAY, J. & VERHELST, S. 2012. Recommendations for the new WLTP cycle based on an analysis of vehicle emission measurements on NEDC and CADC. *Energy Policy,* 49**,** 234-242.

DEPARTMENT FOR TRANSPORT 1995. The Design of Pedestrian Crossings - Local Transportation Note 2/95.

DEPARTMENT FOR TRANSPORT. 2008. *An Introduction to the Use of Portable Vehicular Signals* [Online]. Available: http://assets.dft.gov.uk/publications/portable-vehicular-signals/portable-vehicular-signals-booklet.pdf [Accessed 14th March 2013].

DEPARTMENT FOR TRANSPORT. 2009. *Traffic Signs Manual - Chapter 8* [Online]. Available: https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/128759/traffic-signs-manual-chapter-08-part-01.pdf [Accessed 14th March 2013].

DEPARTMENT FOR TRANSPORT. 2012a. *Design Manual for Roads and Bridges* [Online]. Available: http://www.dft.gov.uk/ha/standards/dmrb/ [Accessed 6th January 2012].

DEPARTMENT FOR TRANSPORT. 2012b. *Manual of Contract Documents for Highway Works* [Online]. Available: http://www.dft.gov.uk/ha/standards/mchw/index.htm [Accessed 3rd January 2012].

DEPARTMENT FOR TRANSPORT. 2012c. *Street works guidance documentation* [Online]. Available: http://www.dft.gov.uk/topics/road-management/street-works/ [Accessed 3rd April 2012].

DEPARTMENT FOR TRANSPORT. 2013. *Vehicle fleet composition projections* [Online]. Available: http://naei.defra.gov.uk/resources/rtp_fleet_projection_Base2013_v3.0_final.xlsx [Accessed 12th March 2015].

DEPARTMENT FOR TRANSPORT. 2015a. *Licensed cars by CO2 emission band, Great Britain, annually from 2000* [Online]. Available: https://www.gov.uk/government/statistical-data-sets/veh02-licensed-cars [Accessed 5th August 2015].

DEPARTMENT FOR TRANSPORT. 2015b. *Licensed cars by years since first registration, Great Britain, annually from 2000* [Online]. Available: https://www.gov.uk/government/statistical-data-sets/veh02-licensed-cars [Accessed 7th August 2015].

DEPARTMENT FOR TRANSPORT. 2015c. *Road Investment Strategy: for the 2015/16-2019/20 Road Period* [Online]. Available: https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/408514/ris-for-2015-16-road-period-web-version.pdf [Accessed 10th October 2015].

DEPARTMENT FOR TRANSPORT. 2015d. *Vehicle Licensing Statistics: Quarter 1(Jan-Mar) 2015* [Online]. Available: https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/433994/vls-2015-q1-release.pdf [Accessed 8th August 2015].

DIA, H. & PANWAI, S. 2009. *Models of Driver Behaviour for Supporting Vehicle Telematics and ITS Simulations* [Online]. Available: http://asiacongress.com/AsiaCongressNewsletter/ITS/pdf_pres//july9/Dr._Hussein_Dia_Models.pdf [Accessed 8th May 2012].

DYTRAN. 2007. *Accelerometer Mounting Considerations* [Online]. Available: http://www.dytran.com/assets/PDF/Accelerometer_Mounting_Considerations.pdf [Accessed 3rd June 2014].

EL-NAGGAR, A. M. 2011. Enhancing the accuracy of GPS point positioning by converting the single frequency data to dual frequency data. *Alexandria Engineering Journal,* 50**,** 237-243.

EMISIA. 2011. *COPERT 4 v9.0 - Primary NO2 factors* [Online]. Available: http://naei.defra.gov.uk/resources/PrimaryNO2_factors_NAEIBase_2013_v1.xls [Accessed 02 February 2015].
EMISSIONS ANALYTICS. 2015a. *Emissions Analytics - About Us* [Online]. Available: http://emissionsanalytics.com [Accessed 12th February 2015].
EMISSIONS ANALYTICS. 2015b. *Emissions Analytics - What we do* [Online]. Available: http://emissionsanalytics.com/what-emissions-analytics-does/ [Accessed 17th September 2015].
EMISSIONS ANALYTICS. 2015c. *Snapshot #5 - We are celebrating our 1000th emissions test* [Online]. Available: http://us5.campaign-archive2.com/?u=4eafc5b25c733af31e4195e46&id=df60e8e20b&e=6833e1d242 [Accessed 21st September 2015].
ENVIRONMENTAL PROTECTION AGENCY. 2015. *Nitrogen Dioxide - Health* [Online]. Available: http://www3.epa.gov/airquality/nitrogenoxides/health.html [Accessed 17 August 2015].
ESSP. 2015. *Egnos performance explained* [Online]. Available: http://www.essp-sas.eu/egnos_performance_explained [Accessed 3/1 2015].
EU BCN. 2015. *Carbon Dioxide Emissions of Cars in Europe* [Online]. Available: https://www.energy.eu/car-co2-emissions/ [Accessed 12th February 2015].
EUROPEAN COMMISSION. 2015a. *Reducing CO2 emissions from passenger cars* [Online]. Available: http://ec.europa.eu/clima/policies/transport/vehicles/cars/index_en.htm [Accessed 20th May 2015].
EUROPEAN COMMISSION. 2015b. *Transport & Environment - Road Vehicles* [Online]. Available: http://ec.europa.eu/environment/air/transport/road.htm [Accessed 20th May 2015].
FELLENDORF, M. & VORTISCH, P. 2010. Microscopic Traffic Flow Simulator VISSIM. *In:* BARCELÓ, J. (ed.) *Fundamentals of Traffic Simulation.* Springer New York.
FERNANDES, P., SALAMATI, K., ROUPHAIL, N. M. & COELHO, M. C. 2015. Identification of emission hotspots in roundabouts corridors. *Transportation Research Part D: Transport and Environment,* 37**,** 48-64.
FONTES, T., PEREIRA, S. R., FERNANDES, P., BANDEIRA, J. M. & COELHO, M. C. 2015. How to combine different microsimulation tools to assess the environmental impacts of road traffic? Lessons and directions. *Transportation Research Part D: Transport and Environment,* 34**,** 293-306.
FRANCO, V., KOUSOULIDOU, M., MUNTEAN, M., NTZIACHRISTOS, L., HAUSBERGER, S. & DILARA, P. 2013. Road vehicle emission factors development: A review. *Atmospheric Environment,* 70**,** 84-97.
FREY, H. C., UNAL, A., ROUPHAIL, N. M. & COLYAR, J. D. 2003. On-Road Measurement of Vehicle Tailpipe Emissions Using a Portable Instrument. *Journal of the Air & Waste Management Association,* 53**,** 992-1002.
GOKHALE, S. 2012. Impacts of traffic-flows on vehicular-exhaust emissions at traffic junctions. *Transportation Research Part D: Transport and Environment,* 17**,** 21-27.
GOMES, G., MAY, A. & HOROWITZ, R. 2004. Calibration of VISSIM for a Congested Freeway. *California Partners for Advanced Transit and Highways (PATH)*.
GONZÁLEZ, V. & ECHAVEGUREN, T. 2012. Exploring the environmental modeling of road construction operations using discrete-event simulation. *Automation in Construction,* 24**,** 100-110.
GOODALL, C., CARMICHAEL, S. & SCANNELL, B. 2013. The Battle Between MEMS and FOGs for Precision Guidance. *Analog Devices Technical Article MS,* 2432.

GRAMOTNEV, G., BROWN, R., RISTOVSKI, Z., HITCHINS, J. & MORAWSKA, L. 2003. Determination of average emission factors for vehicles on a busy road. *Atmospheric Environment,* 37**,** 465-474.

GREAT BRITAIN 2004. *Traffic Management Act 2004*, Stationery Office.

GREATER LONDON AUTHORITY. 2009. *Mayor's Code of Conduct for Roadworks* [Online]. Available: http://www.tfl.gov.uk/roadusers/reportastreetfault/934.aspx [Accessed 3rd May 2012].

GREATER LONDON AUTHORITY. 2012. *Mayor's Code of Conduct for Road Works 2012* [Online]. Available: http://content.tfl.gov.uk/2012-13-mayor-code-of-conduct-roadworks.pdf [Accessed 12th June 2015].

GREATER LONDON AUTHORITY. 2013. *London Atmospheric Emission Inventory 2010* [Online]. Available: http://data.london.gov.uk/dataset/london-atmospheric-emissions-inventory-2010 [Accessed 12th August 2014].

GROVES, P. D. 2013. *Principles of GNSS, inertial, and multisensor integrated navigation systems*, Artech house.

GUENSLER, R., WASHINGTON, S. & BACHMAN, W. Overview of the MEASURE modeling framework. Proc Conf Transport Plan Air Quality, 1998. 51-70.

GUO, R. & ZHANG, Y. 2014. Exploration of correlation between environmental factors and mobility at signalized intersections. *Transportation Research Part D: Transport and Environment,* 32**,** 24-34.

GUOCHANG, X. 2007. *GPS: Theory, Algorithms and Applications*, Springer Berlin Heidelberg.

HARVEY, T. 1992. *A Review of Current Traffic Calming Techniques* [Online]. Institute of Transport Studies, University of Leeds, UK. Available: http://www.its.leeds.ac.uk/projects/primavera/p_calming.html.

HAWTHORN, I. 2011. *London Permit Scheme, First Year Evaluation Report* [Online]. Available: http://www.njug.org.uk/uploads/1106_Oneroadnetwork_lops_review.pdf. [Accessed 15th June 2011].

HERMAN, R., MONTROLL, E. W., POTTS, R. B. & ROTHERY, R. W. 1959. Traffic dynamics: analysis of stability in car following. *Operations research,* 7**,** 86-106.

HEYWOOD, J. B. 1988. *Internal combustion engine fundamentals*, Mcgraw-hill New York.

HIDAS, P. Modelling individual behaviour in microsimulation models. Australasian Transport Research Forum, Sydney, 2005.

HOFMANN-WELLENHOF, B., LICHTENEGGER, H. & WASLE, E. 2007. *GNSS – Global Navigation Satellite Systems: GPS, GLONASS, Galileo, and more*, Springer Vienna.

HÖGLUND, P. G. 1994. Alternative intersection design — a possible way of reducing air pollutant emissions from road and street traffic? *Science of The Total Environment,* 146–147**,** 35-44.

HOLMÉN, B. A. & NIEMEIER, D. A. 1998. Characterizing the effects of driver variability on real-world vehicle emissions. *Transportation Research Part D: Transport and Environment,* 3**,** 117-128.

HU, J., MASCIA, M., LITZENBERGER, M., THIYAGARAJAH, A., NORTH, R. & HAN, K. 2014. Field Investigation of Vehicle Acceleration at the Stop Line with a Dynamic Vision Sensor. *Journal of Traffic and Transportation Engineering***,** 116.

HUANG, C., LOU, D., HU, Z., FENG, Q., CHEN, Y., CHEN, C., TAN, P. & YAO, D. 2013. A PEMS study of the emissions of gaseous pollutants and ultrafine particles from gasoline- and diesel-fueled vehicles. *Atmospheric Environment,* 77**,** 703-710.

HUANG, Y., BIRD, R. & BELL, M. 2009. A comparative study of the emissions by road maintenance works and the disrupted traffic using life cycle assessment and micro-simulation. *Transportation Research Part D: Transport and Environment,* 14**,** 197-204.

HUNT, J. G. & YOUSIF, S. Y. 1994. Traffic Capacity at Motorway Roadworks - Effects of Layout, Incidents and Driver Behaviour. *Proceedings of the 2nd International Symposium on Highway Capacity*.

HUO, H., YAO, Z., ZHANG, Y., SHEN, X., ZHANG, Q., DING, Y. & HE, K. 2012. On-board measurements of emissions from light-duty gasoline vehicles in three mega-cities of China. *Atmospheric Environment,* 49**,** 371-377.

IMAR NAVIGATION. 2012. *iTraceRT: Systems for precise Motion and Dyamics Surveying of Vehicles and for Automated Driving Control* [Online]. Available: http://www.imar-navigation.de/index.php/en/products/by-product-names/item/itracert-f200-itracert-f400-itracert-mvt [Accessed 14th March 2015].

INTERNATIONAL COUNCIL ON CLEAN TRANSPORT. 2015a. *EPA's notice of violation of the Clean Air Act to Volkswagen* [Online]. Available: http://www.theicct.org/news/epas-notice-violation-clean-air-act-volkswagen-press-statement [Accessed 12th October 2015].

INTERNATIONAL COUNCIL ON CLEAN TRANSPORT. 2015b. *In-use emissions testing of light-duty diesel vehicles in the U.S.* [Online]. Available: http://www.theicct.org/use-emissions-testing-light-duty-diesel-vehicles-us [Accessed 31st January 2016].

JIE, L., VAN ZUYLEN, H., CHUNHUA, L. & SHOUFENG, L. 2011. Monitoring travel times in an urban network using video, GPS and Bluetooth. *Procedia - Social and Behavioral Sciences,* 20**,** 630-637.

JIMÉNEZ, J. L. 2000. *Modeling Mobile-source Emissions,* Washington, D.C., National Academy Press.

JIMÉNEZ-PALACIOS, J. L. 1999. *Understanding and Quantifying Motor Vehicle Emissions with Vehicle Specific Power and TILDAS Remote Sensing.* Doctor of Philosophy, Massachusetts Institute of Technology.

JOHNSON, K. C., DURBIN, T. D., COCKER III, D. R., MILLER, W. J., BISHNU, D. K., MALDONADO, H., MOYNAHAN, N., ENSFIELD, C. & LAROO, C. A. 2009. On-road comparison of a portable emission measurement system with a mobile reference laboratory for a heavy-duty diesel vehicle. *Atmospheric Environment,* 43**,** 2877-2883.

KARIM, M. & DEHGHANI, A. 2010. Vehicle speed detection in video image sequences using CVS method. *International Journal of the Physical Sciences,* 5**,** 2555-2563.

KAWAHARA, N. 2008. 3.12 - Automotive Applications. *In:* ZAPPE, Y. B. G. T. (ed.) *Comprehensive Microsystems.* Oxford: Elsevier.

KHORSHID, E., ALKALBY, F. & KAMAL, H. 2007. Measurement of whole-body vibration exposure from speed control humps. *Journal of Sound and Vibration,* 304**,** 640-659.

KIM, J., SONG, H., JUNG, E., KIM, J. & KIM, S. 2012. Minimization of Accumulated Angular Error using Kalman Filter and Two Gyroscopes. *SCIS-ISIS.* Kobe, Japan.

KOUSOULIDOU, M., FONTARAS, G., NTZIACHRISTOS, L., BONNEL, P., SAMARAS, Z. & DILARA, P. 2013. Use of portable emissions measurement system (PEMS) for the development and validation of passenger car emission factors. *Atmospheric Environment,* 64**,** 329-338.

LANGLEY, R. B. 1997. The GPS error budget. *GPS world,* 8**,** 51-56.

LANGLEY, R. B. 1999. Dilution of Precision. *GPS World*.

LEE, S. J. 2013. 6 - MEMS for passenger comfort in vehicles. *In:* KRAFT, M. & WHITE, N. M. (eds.) *Mems for Automotive and Aerospace Applications.* Woodhead Publishing.

LEICA GEOSYTEMS. 2015. *Leica Viva GS10 & GS25* [Online]. Available: http://leica-geosystems.com/en/Leica-Viva-GS10-GS25_105545.htm [Accessed 14th March 2015].

LEPERT, P. & BRILLET, F. 2009. The overall effects of road works on global warming gas emissions. *Transportation Research Part D: Transport and Environment,* 14**,** 576-584.

LI, H., ANDREWS, G. E., DAHAM, B., BELL, M., TATE, J. & ROPKINS, K. 2007. Impact of traffic conditions and road geometry on real world urban emissions using a SI car. *SAE Technical Papers*.

LONDON BOROUGH OF ISLINGTON. 2015. *London Permit Scheme Order 2015* [Online]. Available: https://www.islington.gov.uk/publicrecords/library/Transport-and-infrastructure/Information/Advice-and-information/2015-2016/(2015-09-03)-London-Permit-Scheme-2015.pdf [Accessed 12th October 2015].

LONDON FIRST. 2010. *Road Sense - Balancing the cost and benefit of roadworks* [Online]. Available: http://www.londonfirst.co.uk/documents/Road_Sense_WEB_FINAL.pdf [Accessed 3rd February 2012].

LOWNES, N. E. & MACHEMEHL, R. B. Vissim: A Multi-Parameter Sensitivity Analysis. Simulation Conference, 2006. WSC 06. Proceedings of the Winter, 3-6 Dec. 2006 2006. 1406-1413.

MAHMOD, M., AREM, B. V., PUEBOOBPAPHAN, R. & LANGE, R. D. 2013. Reducing local traffic emissions at urban intersection using ITS countermeasures. *IET Intelligent Transport Systems* [Online], 7. Available: http://digital-library.theiet.org/content/journals/10.1049/iet-its.2011.0222.

MANDAVILLI, S., RYS, M. J. & RUSSELL, E. R. 2008. Environmental impact of modern roundabouts. *International Journal of Industrial Ergonomics,* 38**,** 135-142.

MANJUNATHA, P., VORTISCH, P. & MATHEW, T. V. Methodology for the Calibration of VISSIM in Mixed Traffic. Transportation Research Board 92nd Annual Meeting. Washington, DC, 2013.

MARGREITER, M., KRAUSE, S., TWADDLE, H. & LÜSSMAN, J. 2014. Evaluation of Environmental Impacts of Adaptive Network Signal Controls Based on Real Vehicle Trajectories. *Transportation Research Procedia,* 4**,** 421-430.

MELLIOS, G., HAUSBERGER, S., KELLER, M., SAMARAS, Z. & NTZIACHRISTOS, L. 2011. Parameterisation of Fuel Consumption and CO2 Emissions of Passenger Cars and Light Commercial Vehicles for Modelling Purposes. . *European Commission Joint Research Centre Technical Report EUR 24927 EN,* Publications Office of the European Union.

MILLO, F., DEBNATH, B. K., VLACHOS, T., CIARAVINO, C., POSTRIOTI, L. & BUITONI, G. 2015. Effects of different biofuels blends on performance and emissions of an automotive diesel engine. *Fuel,* 159**,** 614-627.

MITRAN, G., ILIE, S., TABACU, I., IVAN, F. & NICOLAE, V. 2012. The Estimation of Air Pollution from Road Traffic by Transport Modelling. *MECH-ING*.

MOCK, P., GERMAN, J., BANDIVADEKAR, A. & RIEMERSMA, I. 2012. Discrepancies between type-approval and real-world fuel consumption and CO2 values in 2001-2011 European passenger cars. The International Council on Clean Transportation.

MORAWSKA, L., RISTOVSKI, JOHNSON, JAYARATNE & MENGERSEN, K. 2006. Novel Method for On-Road Emission Factor Measurements Using a Plume Capture Trailer. *Environmental Science & Technology,* 41**,** 574-579.

MUDGAL, A., HALLMARK, S., CARRIQUIRY, A. & GKRITZA, K. 2014. Driving behavior at a roundabout: A hierarchical Bayesian regression analysis. *Transportation Research Part D: Transport and Environment,* 26**,** 20-26.

MYUNG, C.-L., KO, A., LIM, Y., KIM, S., LEE, J., CHOI, K. & PARK, S. 2014. Mobile source air toxic emissions from direct injection spark ignition gasoline and LPG passenger car under various in-use vehicle driving modes in Korea. *Fuel Processing Technology,* 119**,** 19-31.

NOLAND, R. B. & QUDDUS, M. A. 2006. Flow improvements and vehicle emissions: effects of trip generation and emission control technology. *Transportation Research Part D: Transport and Environment,* 11**,** 1-14.

NORTH, R. J., HOOSE, N., POLAK, J. W., VAN BAALEN, J. & COHEN, J. 2009. On-Demand Evaluation of Alternative Strategies for Environmental Traffic Management. *ITS World Congress 2009*.

NORTH, R. J., THIYAGARAJAH, A. & WILLIAMS, D. I. 2012. Measuring real-world energy consumption and vehicle emissions: innovative solutions for the RAC Future Car Challenge. *Centre for Transport Studies (CTS) Seminar.* London, UK.

NTZIACHRISTOS, L. & SAMARAS, Z. 2000. Speed-dependent representative emission factors for catalyst passenger cars and influencing parameters. *Atmospheric Environment,* 34**,** 4611-4619.

OBER-SUNDERMEIER, A. & ZACKOR, H. Prediction of congestion due to road works on freeways. Intelligent Transportation Systems, 2001. Proceedings. 2001 IEEE, 2001 2001. 240-244.

OCHIENG, W. Y. & SAUER, K. 2002. Urban road transport navigation: performance of the global positioning system after selective availability. *Transportation Research Part C: Emerging Technologies,* 10**,** 171-187.

PELKMANS, L. & DEBAL, P. 2006. Comparison of on-road emissions with emissions measured on chassis dynamometer test cycles. *Transportation Research Part D: Transport and Environment,* 11**,** 233-241.

PETRACOVICI, L. & ROSENBLATT, J. M. 1999. *Introduction to Sampling* [Online]. University of Illinois at Urbana-Champaign. Available: http://www.math.uiuc.edu/SPHAA/98FA/sampling.pdf.

PTV AG. 2011. *Vissim 5.40 User Manual* [Online]. [Accessed 10th February 2015].

PTV AG. 2012. *VISSIM - Multi-Modal Traffic Flow Modelling* [Online]. Available: http://www.ptvag.com/software/transportation-planning-traffic-engineering/software-system-solutions/vissim/ [Accessed 10th May 2012].

PU, Y. & YANG, C. 2014. Estimating urban roadside emissions with an atmospheric dispersion model based on in-field measurements. *Environmental Pollution,* 192**,** 300-307.

RACELOGIC. 2015a. *VBOX 3i Dual Antenna* [Online]. Available: http://www.racelogic.co.uk/_downloads/vbox/Datasheets/Data_Loggers/RLVB3iSL_Data.pdf [Accessed 14th March 2015].

RACELOGIC. 2015b. *Video VBOX Pro* [Online]. Available: https://www.vboxmotorsport.co.uk/index.php/en/products/video-loggers/video-vbox-pro [Accessed January 31st 2016].

RAKHA, H. & AHN, K. 2004. Integration modeling framework for estimating mobile source emissions. *Journal of transportation engineering*.

RAKHA, H., SNARE, M. & DION, F. 2004. Vehicle dynamics model for estimating maximum light-duty vehicle acceleration levels. *Transportation Research Record: Journal of the Transportation Research Board***,** 40-49.

RATROUT, N. T. & RAHMAN, S. M. 2009. A Comparative analysis of currently used microscopic and macroscopic traffic simulation software. *The Arabian Journal for Science and Engineering,* Volume 34.

REZE, M. & OSAJDA, M. 2013. 2 - MEMS sensors for automotive vehicle stability control applications. *In:* KRAFT, M. & WHITE, N. M. (eds.) *Mems for Automotive and Aerospace Applications.* Woodhead Publishing.

RHYS-TYLER, G. A. & BELL, M. C. 2012. Toward Reconciling Instantaneous Roadside Measurements of Light Duty Vehicle Exhaust Emissions with Type Approval Driving Cycles. *Environmental Science & Technology,* 46**,** 10532-10538.

ROUPHAIL, N. M., FREY, H. C., COLYAR, J. D. & UNAL, A. Vehicle emissions and traffic measures: exploratory analysis of field observations at signalized arterials. 80th Annual Meeting of the Transportation Research Board, Washington, DC, 2001.

RYU, J. & GERDES, J. C. Estimation of vehicle roll and road bank angle. American Control Conference, 2004. Proceedings of the 2004, 2004. IEEE, 2110-2115.

SAE STANDARD 2002. E/E Diagnostic Test Modes. *SAE J1979, Apr*.

SAMUEL, S., AUSTIN, L. & MORREY, D. 2002. Automotive test drive cycles for emission measurement and real-world emission levels-a review. *Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering,* 216**,** 555-564.

SENSORS INC. 2010. *On Board Vehicle Emissions Analyzer User Manual* [Online]. Available: http://www.sensors-inc.com/support.html [Accessed 23rd August 2014].

SENTOFF, K. M., AULTMAN-HALL, L. & HOLMÉN, B. A. 2015. Implications of driving style and road grade for accurate vehicle activity data and emissions estimates. *Transportation Research Part D: Transport and Environment,* 35**,** 175-188.

SIAS LIMITED. 2009. *S-Paramics Principles* [Online]. Available: http://www.iltp.ie/Downloads/S-Paramics Principles.pdf [Accessed 1st March 2014].

SIAS LIMITED. 2011. *AIRE* [Online]. Available: http://www.sias.com/ng/AIRE/AIRE.htm [Accessed 10th May 2012].

SILEGHEM, L., BOSTEELS, D., MAY, J., FAVRE, C. & VERHELST, S. 2014. Analysis of vehicle emission measurements on the new WLTC, the NEDC and the CADC. *Transportation Research Part D: Transport and Environment,* 32**,** 70-85.

SKYTRAQ TECHNOLOGY. 2011. *Venus638FLPx GPS Receiver Data Sheet* [Online]. Available: http://dlnmh9ip6v2uc.cloudfront.net/datasheets/Sensors/GPS/Venus/638/doc/Venus638FLPx_DS_v07.pdf [Accessed 02 February 2015].

SMIT, R., NTZIACHRISTOS, L. & BOULTER, P. 2010. Validation of road vehicle and traffic emission models – A review and meta-analysis. *Atmospheric Environment,* 44**,** 2943-2953.

SMIT, R., POELMAN, M. & SCHRIJVER, J. 2008. Improved road traffic emission inventories by adding mean speed distributions. *Atmospheric Environment,* 42**,** 916-926.

SNARE, M. C. 2002. *Dynamics model for predicting maximum and typical acceleration rates of passenger vehicles.* Virginia Polytechnic Institute and State University.

SONG, G., YU, L. & ZHANG, Y. 2012. Applicability of traffic microsimulation models in vehicle emissions estimates: case study of VISSIM. *Transportation Research Record: Journal of the Transportation Research Board***,** 132-141.

SPARKFUN. 2014. *SparkFun 9 Degrees of Freedom IMU Breakout - LSM9DS0* [Online]. Available: https://www.sparkfun.com/products/12636 [Accessed 7th June 2014].

SPELTA, C., SAVARESI, S. M. & FABBRI, L. 2010. Experimental analysis of a motorcycle semi-active rear suspension. *Control Engineering Practice,* 18**,** 1239-1250.

ST MICROELECTRONICS. 2013. *LSM9DS0 - iNEMO intertial module* [Online]. Available: http://www.st.com/st-web-ui/static/active/en/resource/technical/document/datasheet/DM00087365.pdf [Accessed 8th July 2014].

STRATFORD, H. 2010. *The Effect of Traffic Emissions* [Online]. Available: http://www.pollutionissues.co.uk/effect-traffic-emissions.html. [Accessed 18th March 2012].

SUN, W., WANG, D., XU, L. & XU, L. 2013. MEMS-based rotary strapdown inertial navigation system. *Measurement,* 46**,** 2585-2596.

THIYAGARAJAH, A. 2011. *An Investigation of the impact of Roadway Disruptions on Road Traffic Pollutant Emissions.* Master of Engineering, Imperial College London.

THIYAGARAJAH, A. & NORTH, R. J. 2013. *The impact of roadworks on network performance and the environment* [Online]. Available: http://www.april-network.org/transport_and_noise/documents/Impact_of_roadworks_25th_Mar_14.pdf [Accessed 25th April 2015].

THIYAGARAJAH, A., WILLIAMS, D. I. & NORTH, R. J. 2013. Measuring real-world energy consumption and vehicle emissions. *European Network on New Sensing Technologies for Air-Pollution Control and Environmental Sustainability (EuNetAir) Conference.* Cambridge, UK.

TNO. 2012. *EnViVer: model traffic flow and emissions* [Online]. Available: http://www.tno.nl/content.cfm?context=thema&content=prop_case&laag1=894&laag2=914&laag3=105&item_id=853&Taal=2 [Accessed 18th November 2012].

TRANSPORT FOR LONDON 2009. London Permit Scheme. *Traffic Management Act 2004.* Transport for London.

TRANSPORT FOR LONDON. 2010. *Traffic Modelling Guidelines* [Online]. Available: http://www.tfl.gov.uk/assets/downloads/businessandpartners/traffic-modelling-guidelines.pdf [Accessed 10th May 2012].

TRANSPORT FOR LONDON. 2011a. *Locations where charging applies* [Online]. Available: http://consultations.tfl.gov.uk/streets/lane-rental/supporting_documents/Appendix locations where charging applies.pdf [Accessed 11th May 2012].

TRANSPORT FOR LONDON 2011b. London Permit Scheme Evaluation Report. Transport for London.

TRANSPORT FOR LONDON. 2011c. *Network Operating Strategy* [Online]. Available: http://consultations.tfl.gov.uk/streets/nos/supporting_documents/Network Operating Strategy NOS issue 5 Public Consultation 12th May 2011.pdf [Accessed 12th May 2012].

TRANSPORT FOR LONDON. 2011d. *Transport for London Lane Rental Scheme - Cost Benefit Analysis* [Online]. Available: http://consultations.tfl.gov.uk/streets/lane-rental/supporting_documents/coba v1.1.pdf [Accessed 25th Novemeber 2011].

TRANSPORT FOR LONDON. 2011e. *Travel in London Report 4* [Online]. Available: http://www.tfl.gov.uk/assets/downloads/corporate/travel-in-london-report-4.pdf [Accessed 1st February 2012].

TRANSPORT FOR LONDON. 2012. *Transport for London Lane Rental Scheme (TLRS)* [Online]. Available: http://consultations.tfl.gov.uk/streets/lane-rental/results/tfl-lane-rental-scheme-submission.pdf [Accessed 11th May 2012].

TRANSPORT FOR LONDON. 2014. *Lane Rental Scheme 2014 Refresh* [Online]. Available: https://consultations.tfl.gov.uk/streets/lane-rental-scheme [Accessed 12th October 2015].

TRANSPORT RESEARCH LABORATORY. 2007. *The Links Between Micro-scale Traffic, Emission and Air Pollution Models* [Online]. Available: http://www.highways.gov.uk/knowledge_compendium/assets/documents/Portfolio/The links between micro-scale traffic, emission and air pollution models - 936.pdf [Accessed 8th May 2012].

TRANSPORT RESEARCH LABORATORY 2009. A Charge Structure for trenching in the highway. Transport Research Laboratory.

TRANSPORTATION RESEARCH BOARD 2010. *HCM 2010: The Highway Capacity Manual*.

U-BLOX. 2015. *u-blox 7 precise point positioning GNSS module* [Online]. Available: https://www.u-blox.com/en/product/neo-7p [Accessed 14th March 2015].

UK GOVERNMENT. 1950. *Public Utilities and Street Works Act* [Online]. Available: http://www.legislation.gov.uk/ukpga/Geo6/14/39/contents [Accessed 3rd February 2012].

UK GOVERNMENT. 1991. *New Roads and Street Works Act* [Online]. Available: http://www.legislation.gov.uk/ukpga/1991/22/contents [Accessed 3rd February 2012].

UNECE. 2015. *World harmonized Light vehicles Test Procedure (WLTP)* [Online]. Available: https://www2.unece.org/wiki/pages/viewpage.action?pageId=2523179 [Accessed 17th September 2015].

VÁRHELYI, A. 2002. The effects of small roundabouts on emissions and fuel consumption: a case study. *Transportation Research Part D: Transport and Environment,* 7**,** 65-71.
VIALIS. 2011. *EnViVer Online Help Function* [Online]. [Accessed 18th November 2010].
VREESWIJK, J. D., MAHMOD, M. K. M. & VAN AREM, B. Energy efficient traffic management and control - the eCoMove approach and expected benefits. Intelligent Transportation Systems (ITSC), 2010 13th International IEEE Conference on, 19-22 Sept. 2010 2010. 955-961.
WALKER, G. & CALVERT, M. 2015. Driver behaviour at roadworks. *Applied Ergonomics,* 51**,** 18-29.
WANG, C., XU, H., HERREROS, J. M., WANG, J. & CRACKNELL, R. 2014. Impact of fuel and injection system on particle emissions from a GDI engine. *Applied Energy,* 132**,** 178-191.
WATSON, H. C. 1995. Effects of a wide range of drive cycles on the emissions from vehicles of three levels of technology. SAE Technical Paper.
WEILENMANN, M. F., SOLTIC, P. & HAUSBERGER, S. 2013. The cold start emissions of light-duty-vehicle fleets: A simplified physics-based model for the estimation of CO2 and pollutants. *Science of The Total Environment,* 444**,** 161-176.
WEISS, M., BONNEL, P., KÜHLWEIN, J., PROVENZA, A., LAMBRECHT, U., ALESSANDRINI, S., CARRIERO, M., COLOMBO, R., FORNI, F., LANAPPE, G., LE LIJOUR, P., MANFREDI, U., MONTIGNY, F. & SCULATI, M. 2012. Will Euro 6 reduce the NOx emissions of new diesel cars? – Insights from on-road tests with Portable Emissions Measurement Systems (PEMS). *Atmospheric Environment,* 62**,** 657-665.
WITTE, T. H. & WILSON, A. M. 2004. Accuracy of non-differential GPS for the determination of speed over ground. *Journal of Biomechanics,* 37**,** 1891-1898.
WORLD HEALTH ORGANISATION. 2011. *Air Quality: Facts and figures* [Online]. Available: http://www.euro.who.int/en/what-we-do/health-topics/environment-and-health/air-quality/facts-and-figures [Accessed 7th May 2012].
ZAMMIT, J. P., MCGHEE, M. J., SHAYLER, P. J., LAW, T. & PEGG, I. 2015. The effects of early inlet valve closing and cylinder disablement on fuel economy and emissions of a direct injection diesel engine. *Energy,* 79**,** 100-110.
ZHAI, H. 2007. *Regional On-road Mobile Source Emissions Characterization for Conventional and Alternative Vehicle Technologies*, North Carolina State University.
ZHANG, K., BATTERMAN, S. & DION, F. 2011. Vehicle emissions in congestion: Comparison of work zone, rush hour and free-flow conditions. *Atmospheric Environment,* 45**,** 1929-1939.
ZHANG, K., YAO, L. & LI, G. 2013. Factors Affecting Vehicular Emissions and Emission Models. *ICTE 2013.*
ZHAO, Q., YU, L. & SONG, G. Comparison of Micro-scale Fuel Consumption Models Based on VSP and Ln (TAD) for Light-Duty Vehicles on Urban Roads. Transportation Research Board 92nd Annual Meeting, 2013.
ZOGG, J.-M. 2002. GPS Basics Introduction to the system Aplication overview.

Appendix A: Publications and presentations

This appendix contains the dissemination activities associated with this research. The publications are separated into journal and conference papers. Invited presentations about research in this thesis are also shown below.

Journal

J1	Hu, S., Mascia, M., Litzenberger, M., **Thiyagarajah, A.**, North, RJ., 2015. Field Investigation of Vehicle Acceleration at the Stop Line with a Dynamic Vision Sensor. Journal of Traffic and Transportation Engineering.
J2	O'Driscoll, R., **Thiyagarajah, A.**, Oxley, T., ApSimon, H., Molden, N. 2015. Portable Emissions Measurement System (PEMS) data for Euro 6 diesel cars and comparison with emissions modeling. *Accepted to Environmental Science and Technology (ES&T) – awaiting approval of corrections

Conference

C1	Williams, DI., **Thiyagarajah, A.**, North, RJ., 2012. Assessment of temporal variation in vehicle emissions at an urban intersection. 44th Annual UTSG conference, Aberdeen, UK.
C2	**Thiyagarajah, A.**, North, RJ., Polak, JW., 2013. An assessment framework for the effect of capacity reduction on urban road traffic vehicle emissions and delay. 45th Annual UTSG conference, Oxford, UK.
C3	**Thiyagarajah, A.**, North, RJ., 2013. An investigation of the environmental impact of urban road capacity reductions. Transportation Research Board 92nd Annual Meeting, Washington D.C., USA.
C4	**Thiyagarajah, A.**, Williams, DI., North, RJ. 2013. Measuring real-world energy consumption and vehicle emissions. European Network on New Sensing Technologies for Air-Pollution Control and Environmental Sustainability (EuNetAir) Conference, Cambridge, UK.
C5	Mascia, M., Hu, J., Han, K., North, RJ., **Thiyagarajah, A.**, Van Poppel, M., Beckx, C., Kolbl, R., Litzenberger, M., 2014. Environmental impact of combined ITS traffic management strategies. 20th International Transport and Air Pollution Conference, Graz, Austria.
C6	North, RJ., **Thiyagarajah, A.**, Ruxton, J., Roocroft, A., Molden, N., 2014. On-road nitrogen

	oxide emissions for modern diesel vehicles and the effects of DPF regeneration. 20th International Transport and Air Pollution Conference, Graz, Austria.
C7	North, RJ., **Thiyagarajah, A.**, Molden N., 2014. Portable Emissions Monitoring System (PEMS) on-vehicle emission testing and its role in Euro 6. Investigation of Air Pollution Standing Conference (IAPSC), Birmingham, UK.
C8	Hu, J., Mascia, M., Han, K., **Thiyagarajah, A.**, North, RJ., 2015. Assessment of different urban traffic control strategy impacts on vehicle emissions. 47th Annual UTSG conference, London, UK, 2015.
C9	**Thiyagarajah, A.**, Hu, J., Molden, N., North, RJ. 2015. The use of PEMS for validation of emissions modeling tools. 18th IEEE International Conference on Intelligent Transportation Systems – WS6 Data-Enabled Advancements in Transportation Theory and Application, Las Palmas de Gran Canaria, Spain.
C10	Hu, J., Mascia, M., **Thiyagarajah, A.** 2015. Methodology for Estimation and Validation of Black Carbon Emissions for Traffic Model. 18th IEEE International Conference on Intelligent Transportation Systems – WS6 Data-Enabled Advancements in Transportation Theory and Application, Las Palmas de Gran Canaria, Spain.
C11	**Thiyagarajah, A.**, Hu, J., Molden, N., Han, K., Mascia, M., North, RJ., Polak, JW. 2015. Validation of vehicle emission modeling tools using real-world measurement data. 14th World Conference on Transport Research, Shanghai, China. *Accepted and will be presented in July 2016

Invited presentations

P1	North, RJ., **Thiyagarajah, A.**, Williams, DI. 2012. Measuring real-world energy consumption and vehicle emissions: innovative solutions for the RAC Future Car Challenge. CTS Seminar, Imperial College London, UK.
P2	**Thiyagarajah, A.** 2014. The impact of roadworks on network performance and the environment. Air Pollution Research in London (APRIL) Committee Presentation, London, UK.
P3	**Thiyagarajah, A.** 2014. Evaluation of the Exhibition Road Project using Vissim and EnViVer. PTV Innovation Day, London, UK.
P4	O'Driscoll, R., **Thiyagarajah, A.**, Oxley, T., ApSimon, H., Molden, N. 2015. PEMS measurements of Euro 6 diesel car exhaust emissions and comparisons with COPERT. Air Pollution Research in London (APRIL) Committee Presentation, London, UK.

Appendix B: Stakeholder interviews conducted

This appendix details that 19 stakeholder interviews that were conducted with representatives from Transport for London, Royal Borough of Kensington and Chelsea, London Borough of Hounslow and Vinci-Ringway.

Date	Organisation	Name
12th December 2011	Network Performance, Transport for London	Andy Emmonds, Chief Transport Analyst Alexandre Santacreu, Senior Analyst
5th January 2012	Special Projects, Royal Borough of Kensington and Chelsea	Bill Mount, Lead Officer
20th March 2012	Special Projects, Royal Borough of Kensington and Chelsea	Bill Mount, Lead Officer Chris Hamshar, Site Manager Exhibition Road Project
1st April 2012 (email)	Planned Interventions, Transport for London	Helena Kakouratos, Works Coordination and Permitting Manager
3rd April 2012	Planned Interventions, Transport for London	Gerard O'Toole, Operational Analysis Manager
4th April 2012 (email)	Planned Interventions, Transport for London	Lisa Tansley, Works Coordination Team
18th April 2012 (email)	Planned Interventions, Transport for London	James Booth, Works Coordination Team
19th April 2012 (email)	Planned Interventions, Transport for London	Melanie Grindrod, Works Coordination Team
24th April 2012	Traffic Team, Royal Borough of Kensington and Chelsea	Tony Pegrum, Traffic Manager
25th April 2012	PFI Project, London Borough of Hounslow	Suresh Kamath, Project Lead Krishnan Radhakrishnan, Deputy PFI Project Director
2nd May 2012	Planned Interventions, Transport for London	Roger Pye, Forward Planning Manager

15th May 2012	PFI Project, London Borough of Hounslow	Krishnan Radhakrishnan, Deputy PFI Project Director
15th May 2012	Highways, London Borough of Hounslow	Rob Gibson, Strategic Pollution Officer
17th May 2012	Highways, London Borough of Hounslow	Nick Woods, Head of Traffic Christopher Deakins, Senior Traffic Engineer
17th May 2012	Vinci-Ringway	Rob Gillespie, Mobilisation Director Simon Aggus, Works Coordination
18th May 2012	Highways, London Borough of Hounslow	Satbir Gill, Highways Asset Manager Godfrey Osakue, Network Operations and Streetworks Manager
18th May 2012	Highways, London Borough of Hounslow	John Reynolds, Environmental Projects/Infrastructure Manager
18th May 2012	PFI Project, London Borough of Hounslow	Trevor Wallis, Project Director
21st May 2012	Environment Team, Royal Borough of Kensington and Chelsea	Kyri Eleftherious-Vaus, Environmental Officer Ashley Smith, Environmental Team

Appendix C: Hermes processor code

This appendix contains the processing code that was used on the Hermes monitoring platform to acquire, process and output the required data.

```
//Hermes IMU code
//Code written by Aravinth Thiyagarajah, Imperial College London - a.thiyagarajah@imperial.ac.uk
//This code will run on the Arudino Due with the LSM9DS0, standard GPS, a bluetooth module and
SD card module
//Revisions
  //v1.00 - code runs at 10Hz with data being output only to the SD card
  //v1.01 - added 8 digit lat/lon and now running at 16Hz
  //v1.02 - code now running at 20Hz only to SD card
  //v1.03 - updated to Venus 20Hz GPS and modified acc/gyro parameters
  //v1.04 - added delay in void setup to initialise acc/gyro



//----------------Library setup----------------
#include <TinyGPS++.h> //for GPS module
#include <SPI.h> //for IMU breakout board
#include <Wire.h> //for IMU breakout board
#include <SFE_LSM9DS0.h> //for IMU breakout board - note library was modified by Aravinth
Thiyagarajah to be compatible with the Due
#include <SD.h> //for SD module

TinyGPSPlus gps; //define gps for Tiny GPS library
LSM9DS0 dof(MODE_I2C, 0x6B, 0x1D); //define mode and input

//----------------Variable/string definition----------------
long int t0=0,t1=0; //interger for loop timing
String printer; //string for storing GPS data prior to output6
String gprinter; //string for storing IMU data prior to output
char name[]="data00.txt"; //string for filename format
```

```
//----------------void setup----------------

void setup()
{
 Serial.begin(9600); //for USB
 Serial1.begin(38400); //for GPS
 //Serial2.begin(9600); //for BT

 t0=micros(); //for loop timing t0

 uint16_t status = dof.begin(); //start LSM9DSO
 delay (1000);
 dof.setAccelODR(dof.A_ODR_25); //set acc to 25Hz
 delay (1000);
 dof.setAccelScale(dof.A_SCALE_2G); //set acc scale to 2G
 delay (1000);
 dof.setGyroODR(dof.G_ODR_95_BW_25); //set gyro to 25Hz
 delay (1000);
 dof.setGyroScale(dof.G_SCALE_245DPS); // set gyro to 245DPS
 delay (10000); //wait 10 seconds for LSM9DS0 to initialise

 if (!SD.begin(52)) {
 return;
 } //initialise SD card
 for (uint8_t i = 0; i < 100; i++) { //creating and naming the data file
  name[4] = i/10 + '0';
  name[5] = i%10 + '0';
  if (File dataFile=SD.open(name, O_CREAT | O_EXCL | O_WRITE))break;
 }

}
```

```
//----------------void loop----------------

void loop()
{
  t1=micros(); //loop counter t1
  if(t1-t0>49990) //time difference for loop (100,000 micro seconds = 0.1 seconds = 10Hz)
//49990=0.049990s=20.004Hz
  {
    gprinter = ""; //clear gps printer string and store data
    gprinter +=t1; gprinter +=',';
    gprinter +=gps.date.value(); gprinter +=','; gprinter +=gps.time.value(); gprinter +=',';
    gprinter +=String(gps.location.lat(),6); gprinter +=','; gprinter +=String(gps.location.lng(),6);
gprinter +=',';
    gprinter +=gps.course.deg(); gprinter +=','; gprinter +=gps.speed.mps(); gprinter +=','; gprinter
+=gps.altitude.meters(); gprinter+=',';
    printer=""; //clear printer string and acquire & store data
    dof.readAccel();
    printer +=dof.calcAccel(dof.ax);printer +=',';printer +=dof.calcAccel(dof.ay);printer +=',';printer
+=dof.calcAccel(dof.az);printer +=',';
    dof.readGyro();
    printer +=dof.calcGyro(dof.gx);printer +=',';printer +=dof.calcGyro(dof.gy);printer +=',';printer
+=dof.calcGyro(dof.gz);

    File dataFile = SD.open(name, O_WRITE | O_CREAT);
    if (dataFile) { // if the file is available, write to it:
      dataFile.print(gprinter);
      dataFile.println(printer);
      dataFile.close();
    }
   else { //do nothing
    }
    //print to the serial USB too:
    //Serial.print(gprinter);
```

```
    //Serial.println(printer);

    // print to the serial bluetooth too:
    //Serial2.print(gprinter);
    //Serial2.println(printer);

    t0=t1; //reset loop timer
  }

  while (Serial1.available() >0) //check GPS module is streaming data
  {
    gps.encode(Serial1.read()); //read GPS data

  }

}
```