Emissions Abatement Technology, Fuels and Low Emissions Vehicles: Win-Win for Air Quality and Climate Change?

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Abstract

The impact of a change in emissions abatement technology, fuel or vehicle on carbon dioxide (CO_2) and toxic air pollutant emissions derived from road transport was investigated.

Road transport emissions were calculated and non-mobile source emissions rates were compiled for the base year 2005 for the City of Leicester, which was the case study for the research.

Factor and cluster analysis were applied so that roads could be classified into groups, allowing diurnal traffic profiles to be assigned to roads with similar attributes prior to air quality modelling and to enable the characteristics of typical roads in Leicester to be identified. Five road classifications were developed.

The emissions inventory compiled along with meteorological data, background pollutant concentration values and the five diurnal traffic profiles were input into an air quality model. The BOOT evaluation framework (Chang and Hanna 2005) was used to statistically evaluate the performance of the air quality model through comparisons of predicted and observed pollutant concentrations. The model was found to significantly over-predict and under-predict concentrations of nitrogen dioxide (NO_2) and particles with a diameter of less than ten microns (PM_{10}) at seven and five monitoring locations across Leicester. A discussion of the sources of error in prediction was presented.

The base-case was edited to reflect a change in emissions abatement technology, fuel or vehicle and emissions were recalculated. In addition, a vehicle kilometres travelled (VKT) restriction was imposed on the vehicle fleet that did not allow any increase in VKT from the base year. The changes to the base-case were made in increments of 5% until 100% was reached. Regression analysis was used to create 13 models that allowed the impact of the road transport strategies on CO_2 and pollutant emissions to be explored.

A reduction in both CO_2 and toxic air pollutant emissions (‘win-win’) was found when the penetration of zero emissions vehicles (ZEVs) and plug-in hybrid electric vehicles (PHEVs) to the car fleet was modelled. Overall, the highest reduction in toxic pollutant and CO_2 emissions were found for ZEVs, which represent electric vehicles (EVs) under current legislation. A 53% (or greater) penetration of ZEVs to the car fleet was the only strategy for which a 50% reduction in CO_2 for a 1990 base was found. Therefore, this indicates that substantial and arguably radical changes are required if air quality and climate change limit values and targets to be achieved.

A win-win for air quality and climate change was found when new emissions abatement technology was introduced into the car fleet. However, greater pollutant emissions reductions were observed with the introduction of new emissions abatement technology to light goods vehicle (LGV) and heavy goods vehicle (HGV) stocks. These strategies were found to have a negligible impact on CO_2 emissions. Consequently a trade-off was found where a 'win-win' was achieved through changes to the car fleet but at the cost of higher pollutant emissions reductions from other strategies.

The introduction of new emissions abatement technology to the bus fleet on roads predominantly on key traffic corridors within Leicester's air quality management area (AQMA) resulted in substantial air quality benefits. The same strategy did not result in a reduction in CO_2 emissions. However, in the context of an overall sustainable transport strategy the benefits of increasing bus patronage, which in turn may reduce the number of single occupancy vehicles on the road, is likely to have a more than compensatory effect.

Substantial pollutant emissions reductions were found as a result of the introduction of new emissions abatement technology into the HGV and LGV fleets. However, these strategies were found to have negligible CO_2 emissions reductions and therefore did not provide a win-win for air quality and climate change. Similarly, a win-win from the introduction of LPG to the car fleet was not found. Therefore, the uptake of LPG or investment in the introduction of new emissions abatement technology to the LGV or HGV fleets should only be considered as a part of a sustainable policy package that comprises other measures, such as logistics optimisation or a reduction in VKT.

The findings of this research were used to inform a set of policy actions for Leicester City Council.

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CHAPTER 1

1. Introduction

Improved road networks, increased car production, cheaper vehicles and increased road construction have made on road travel more accessible to the worlds ever growing population (SMMT, 2010; OICA, 2010; OECD, 2010a; DfT, 2009a; Schafer, 1998). Higher average salaries have meant more and more people are using the passenger car as their first choice of convenient transport (Grupta *et al.*, 2006). Urbanisation has increased and with it the number of people living in cities (Fenger, 2009). The increase in global demand for road transport has resulted in the deterioration of air quality in nearly every city in the world (Mayer, 1999). Road traffic is now acknowledged as the dominant source of air pollution in urban areas (DEFRA, 2010a; Cameron *et al.,* 2004). Similarly, the impact of anthropogenic Greenhouse Gas (GHG) emissions on the Earth's climate is also of major concern (IPCC, 2010). The 2007 fourth assessment report from the Intergovernmental Panel on Climate Change (IPCC) concluded that 'it is very likely (90%) that man-made GHG emissions caused most of the observed increase in global average temperatures since the mid-20th century.' According to the Climate Change Committee (CCC) (2009) global GHG emissions need to peak in 2016 and fall by at least 50% below 1990 levels by 2050 if a 2°C temperature limit is to be maintained. Failure to reach this target could have severe consequences on Earth's climate system, including melting of polar ice caps (Lindsay and Zhang, 2005; Winten, 2006), the collapse of the global carbon cycle (Kondratyev *et al.*, 2003) and an increase in the number of extreme weather events (Hansen, 2006). The road transport sector is one of the only sectors which has seen a continued increase in GHG emissions (CCC, 2010). Consequently governing bodies across the globe are, through legislation, obligated to develop and implement strategies to reduce air pollution and GHG emissions from all sources including road transport.

1.1 Motivation for Study

At present, air quality and climate change targets and the associated policies and strategies lack synergy and a recent government document entitled 'Air Pollution: action in a changing climate' revealed that future air quality targets need to be aligned with climate change measures (DEFRA, 2010a). This document highlighted that in order to achieve this alignment 'further work is needed to facilitate comparison of air quality and climate change impacts.' Greater insight into the impacts of road transport measures on air quality and climate change issues will allow those strategies that reduced both toxic air pollution and GHGs (termed 'win-win' in this thesis), those that result in a trade off and those that have little impact on these environmental issues to be identified. In turn this will enable trade-offs (where a win-win is achieved but at the cost of greater reductions in either toxic air pollution or CO_2 as a result of another strategy) to be examined and the most effective measures to be identified and implemented simultaneously, thereby aligning toxic air pollution or CO_2 reduction measures.

Therefore, the research presented here aims to investigate the impact of road transport strategies on air quality and carbon dioxide (CO_2; a primary GHG) emissions. The two fundamental research questions that this thesis aims to address are:

1) Can current and potential future technology, fuels or vehicles result in a win-win for air quality and climate change and do these strategies result in trade-offs?

2) Which strategies, if any, can result in a 50% reduction in CO_2 emissions over the base case (a common target for local authorities in the UK) and what impact do these strategies have on air pollution?

1.2 Aim and Objectives of Research

The aim of this research is to assess the impact of a vehicle kilometres travelled (VKT) restraint and a change in emissions abatement technology, fuel or vehicle on CO_2 emissions and toxic air pollutants derived from road transport.

1.2.1 Objectives

- The first objective was to develop a base-case of traffic and emissions data for the Leicester city local authority area, which was the case study of this research.

- The second objective was to identify and develop a suitable method for classifying roads into groups so that characteristics of roads with similar attributes can be shared and to enable the characteristics of typical roads in Leicester to be identified.

- The third objective was to carry out a quality check on the emissions inventory compiled to allow it's representativeness to be assessed.

- The fourth objective was to, in a flexible way, assess the impact of a VKT restraint and a change in technology, fuel or vehicle within the Leicester fleet on CO_2 and toxic air pollutant emissions.

- The fifth objective was to identify strategies that can achieve a 50% reduction in CO_2 emissions in Leicester and to assess the associated changes in toxic air pollutant emissions resulting from these policy options.

- The sixth and final objective was to develop a list of policy actions for Leicester council that were win-win for air quality and climate change.

1.2.2 Thesis Contents

As an introduction to the key concepts of road transport emissions, Chapter 2 begins with a brief overview of the release of air pollution from road transport. In the remainder of Chapter 2 and in Chapter 3 an extensive literature review is presented in two parts. In the first part, the different methodologies for modelling emissions from road transport are described. Emissions factor development, emissions models and the methods by which emissions inventories can be validated are documented. The role of air quality models as tools for pollutant forecasting is briefly reviewed and common Gaussian air quality models and their limitations are described. The methods by which an air quality model's performance can be evaluated are highlighted. In the second part of the literature review, the different strategy options that aim to reduce emissions from road transport are discussed. New emissions abatement technology, fuels, low emissions vehicles and a reduction in VKT are reviewed.

Having provided the reader with the background information on the important areas of emissions and dispersion modelling, and on the methods by which emissions can be reduced from road transport; Chapter 4 describes the methodological approach used in this research. The scene is set by describing the study area on which this research focuses. Leicester's air quality problems and CO_2 emissions targets are described. The method used in this investigation is then documented and a flow diagram guiding the reader through the modelling approaches adopted is presented. The key data and software used are described.

The use of factor and cluster analysis to classify roads is presented in Chapter 5 that enables diurnal traffic profiles to be assigned to roads with similar attributes. The characteristics of the roads in

Leicester were identified. The use of simulated traffic data in the approach described and its influence on the outputs is discussed.

Chapter 6 documents the development of an emissions inventory and it's representativeness of real-world emissions is evaluated through the use of an air quality model. Comparison between the air quality model performance and the performance of models documented in the literature is made. A discussion of the impacts of meteorological data, background pollutant data, simulated traffic data, chemical reaction schemes and emissions factors on air quality model performance is presented.

With a quality check on the emissions inventory provided previously, Chapter 7 presents the strategy modelling approach used in this research to edit the base-case emissions inventory to reflect a change in technology, fuel or vehicle. The impacts of these strategies on CO_2 and toxic air pollutant emissions are explored and discussed and a set of policy options for Leicester are documented.

CHAPTER 2

2. Background: Emissions and Dispersion Modelling

In this Chapter the different methods used to estimate emissions from road traffic are described. In addition, the role of air quality models as tools for emissions inventory validation and for pollutant forecasting is reviewed. However, in order to provide the reader with information on the key concepts of this thesis, a brief overview of the release of air pollution from road transport is first presented. Should the reader require a broader introduction to the impacts of road transport on the environment, Appendix A documents a review of road transport's contribution to global and regional air pollution.

2.1 Release of Air Pollution from Road Transport

To date nearly 3000 anthropogenic gaseous species have been identified (Fenger, 1999) of which in excess of 700 are emitted from motor vehicles (EPA, 2006). Furthermore, it has been identified that a significantly large portion of these chemicals are harmful to human health (see Appendix B). On a similar note a large number of GHGs and GHG precursors are emitted in vehicle exhausts fumes, which have the potential to induce climate forcing (USEPA, 2012a). The ability to monitor the emissions of such a large number of environmentally damaging gases and pollutants is neither physically or financially feasible. 'Indicators' which are identified as being the most common gases emitted, are representative of the total mix of pollutants or GHGs in the atmosphere. The major pollutants measured and GHGs monitored are commonly defined as indicators. For example oxides of nitrogen or NO_x is the collective name for nitrogen dioxide (NO_2) and nitric oxide (NO) (Ojelede *et al.,* 2008) and is used as being representative of these species. Hydrocarbon (HC) is the name given to a large number of chemical species including volatile organic carbons (VOCs), which in turn is the name given to a large number of chemicals such as methane (CH_4), benzene (C_6H_6), 1,3-butadiene (C_4H_6), toluene (C_7H_8), formaldehyde (CH_2O) and polycyclic aromatic hyrodcarbons (PAHs) (Environment Agency, 2010; USEAP, 2010). Particulates is the name given to particulate matter (PM) which can comprise an array of chemicals including sodium chloride, black carbon, mineral dust, trace metals, water (taken up by a number of secondary particles), VOCs and secondary particles (Hueglin *et al.,* 2005; Vallero, 2008; Jacobson, 2002). PM is usually characterised by size with particles with a diameter of less than ten microns (PM_{10}) and particles with a diameter of less than 2.5 microns ($PM_{2.5}$) used as being representative of all the particles that fall within their associated size range.

In Kyoto (Japan) in 1997 the UK and many other nations worldwide signed a legally binding document confirming their agreement to reduce emissions of six GHGs to or below fixed targets by 2012 (see section 3.1.2). Known as the Kyoto Protocol, it resulted (in Europe and the UK) in the definition of GHG environmental indicators. The legislation covered six of the most common GHGs; CO_2, methane (CH_4), nitrous oxide (N_2O), sulphur hexafluoride (SF_6), hydrofluorocarbons (HFCs), and perfluorocarbons (PFCs) (UNFCCC 1998). These are referred to as the 'basket six.' However, out of these six, CO_2 is emitted from anthropogenic sources in the largest volume and is the dominant GHG emitted from road transport (UNFCCC, 2008). When other GHGs are reported in the literature they are often converted to CO_2 equivalents (via the use of their global warming potential see AEA, 2011) allowing for comparison between their emissions to be made. Therefore, it can be said that CO_2 is the primary GHG environmental indicator for the transport sector.

It should be noted that in this research chemicals are referred to through the use of environmental indicators and CO_2 is of primary focus with regards to GHGs. However, it is acknowledge that CO_2 and the other indicators mentioned are often broadly representative of a myriad of other chemical species.

Although the majority of emissions from road transport are from a vehicle tail pipe (Boulter *et al.,* 2009b) toxic air pollutants are also released into the atmosphere due to vehicle brake and tyre wear (Omstedt *et al.,* 2005), evaporative processes (Koutidis *et al.,* 1999) and leaks in engine casings and tubing (Boulter *et al.,* 2009a). In addition, some species emitted from vehicles undergo chemical transformations in the atmosphere and are converted to environmentally damaging gases or particles (Vallero, 2008). Such emissions are commonly defined as 'indirect emissions.'

2.1.1 Exhaust Emissions

The incomplete combustion of fuel within a vehicles engine results in a complex mix of chemicals being released in the exhaust fumes (Heck and Farrauto, 2001). The composition of exhaust gases is dependent on engine type (e.g. diesel, four-stroke spark ignition) and the vehicle operating conditions (Kaspar *et al.,* 2003). In general, exhaust gases comprise primarily un-burnt fuel, HCs, carbon monoxide (CO), NO_x, PM, lead (Pb) and sulphur (S) (Van der Westhuisen *et al.,* 2004). In modern vehicles the latter two species have been controlled by their removal from diesel and petrol fuel (e.g. Hm-Treasury, 2008a, 2008b) and NO_x, CO and HC exhaust emissions are controlled by a catalytic converter (Boulter *et al.,* 2009a). Catalytic converters were introduced in the USA in the 1970s and into Europe in the 1980s (Moidovan *et al.,* 2002). The reactions that occur on a modern exhaust catalyst involve oxidation and reduction processes and a simplified set of these reactions are shown in Table 1 (Kaspar *et al.,* 2003). The control of CO and HC emissions results primarily in CO_2 being emitted in vehicle exhaust fumes. In contrast, reduction reactions convert NO_x species to water vapour (H_2O), nitrogen (N_2) and nitrogen containing species as well as CO_2. The nitrogen containing species emitted in a vehicle exhaust after catalytic reduction include N_2O which is also a GHG (Cant *et al.,* 1998; Odaka *et al.,* 2000; Graham *et al.,* 2008).

Numerous vehicle technologies have been developed to reduce emissions of toxic air pollutants from road transport (Uherek *et al.,* 2010). Diesel particulate filters are ceramic devices that collect PM in the exhaust stream (DEQ, 2012; Boulter *et al.*, 2009a). The high temperature of the exhaust heats the ceramic structure and allows the particles inside to oxidize into less harmful components (USEPA, 2003). Typically a DPF lowers exhaust PM emissions to 0.5mg/km (this value is used in the UK 2009 emissions factors for Euro 5 and Euro 6 vehicles; Boulter *et al.,* 2009a). Exhaust gas recirculation (EGR) systems lower emissions of NO_x from the exhaust stream but (like DPFs) increase fuel consumption (USEPA, 2003; Dong *et al.,* 2008). In contrast, selective catalytic reduction (SCR) systems lower NO_x emissions by reduction of NO_x to Nitrogen (N_2) using ammonia or urea without incurring a fuel penalty (Sojvall *et al.*, 2006).

Table 1 Oxidation and reduction reactions occurring on a vehicle catalyst (Kaspar *et al.*, 2003)

Reaction Type	Equation
Oxidation	$2CO + O_2 \rightarrow 2CO_2$
	$HC + O_2 \rightarrow CO_2 + H_2O$ [a]
Reduction	$2CO + 2NO \rightarrow 2CO_2 + N_2$
	$HC + NO \rightarrow CO_2 + H_2O + N_2$ [a]
	$2H_2 + 2NO \rightarrow 2H_2O + N_2$

[a] unbalanced equation

2.1.2 Indirect Emissions

Indirect emissions from road transport occur due to chemical reaction and condensation processes in the atmosphere transforming vehicle derived emissions into environmentally harmful species. Secondary particulates and aerosols form in the atmosphere from the condensation of tailpipe gases such as SO_2, NO_x and VOCs into tiny droplets (Quah and Boon, 2003). In addition, NO_x along with CO and HC species are involved in a complex set of photochemical reactions in the atmosphere that result in the formation of ozone (O_3) (Barry and Chorley, 2003) which is a potent GHG and toxic to humans (Bree *et al.,* 1995; Inoue *et al.,* 2008; Jorge *et al.,* 2002; Cheng *et al.,* 2003). The production of O_3 in the troposphere involves hydroxyl radical oxidation of CO, CH_4, and other HCs in the presence of NO_x. A coupled reaction between NO_x and O_3 leads to the establishment of a photostationary state between NO_2, NO and O_3, which has about a 100 second time scale (Brasseur *et* *al.,* 2003). Due to increased emissions of anthropogenic NO_x and VOCs, primarily sourced from road traffic, background levels of O_3 in the UK increased from 42μg/m^3 to 57μg/m^3 between 1993 and 2007 (DEFRA, 2008).

2.1.3 Evaporative Emissions

It is primarily VOCs that are vented into the air under evaporative processes from both parked and moving vehicles (Boulter *et al.,* 2009a; Van der, Westhuisen *et al.*, 2004). VOCs can evaporate from a vehicle due to faulty fuel caps, during refuelling and due to cracks in engine casings and tubing (Latham and Boulter, 2009). Evaporative VOCs emissions from diesel vehicles are negligible due to the presence of heavier HCs and extremely low volatility of diesel fuel (Boulter *et al.,* 2009b). In contrast, evaporative emissions from petrol vehicles have been shown to significantly contribute to ambient VOC concentrations. For example, Koutidis *et al.* (1999) documented around 25% of total VOC emissions in Athens were attributed to evaporative emissions in 1999. Batteman *et al.* (2005) highlighted that in the extreme case up to 62.7mg/h of non-methane hydrocarbons (NMVOCs) can be emitted from vehicles with loose or malfunctioning fuel caps during the summer season.

2.1.4 Emissions from Abrasive and Mechanical Friction

Non-exhaust derived vehicle pollution from brake and tyre wear is caused by abrasive and mechanical friction and primarily results in the emission of PM, which can range in size from a few hundred nanometers (nm) to a few tens of micrometers (μm) (Thorpe and Harrison 2008). Emissions from brake and tyre wear have been shown to contribute significantly to ambient pollution concentration levels. For example Omstedt *et al.* (2005) documented that non-tailpipe, mechanically generated emissions account for 90% of the total traffic contribution to PM_{10} in Stockholm and Querol *et al.* (2005) showed non-exhaust (abrasive) and exhaust emissions to contribute equally to ambient PM_{10} and $PM_{2.5}$ levels in European cities. However, the rate of brake wear is highly dependent on the composition of the linings used and the mode of driving to which the brakes are subjected (Thorpe and Harrison 2008).

2.2 Emissions Factor Development

The continuous monitoring of emissions from mobile sources is at present not practically or financially feasible (Smit *et al.,* 2010). Therefore, a method was needed to estimate emissions from road traffic that used readily available data. The internationally agreed procedures and guidelines for reporting emissions from road traffic involves the combination of traffic activity data (km travelled and speed) with vehicle fleet composition data (vehicle mix by engine size, vehicle size, age, engine and exhaust treatment technology, Euro emissions standard, fuel type, and vehicle use) and emissions factors (g/km) (Barlow and Boulter, 2009; Boulter *et al.,* 2009a, 2009b; Murrels, 2009). Emissions factors are defined by the United Nations Framework Convention on Climate Change (UNFCCC, 2012a) as 'a unique value for scaling emissions to activity data in terms of a standard rate of emissions per unit of activity.' For road traffic the National Atmospheric Emissions Inventory (NAEI) defines an emissions factor as the 'relationship between the amount of pollution produced and the number of vehicle miles travelled' (NAEI, 2012b) i.e. an emissions factor is a representative value of the typical rate at which a pollutant is released into the air from a vehicle.

Emissions factors can be grouped to make an emissions model that allows for the calculation of pollutant emissions from a number of different source types (e.g. passenger cars, buses, artic HGVs etc.). Emissions models are typically used to estimate total emissions from a given geographical area including a stretch of road or road network (e.g. Kassomenos *et al.,* 2006; Goncalves *et al.,* 2009; Kantor *et al.,* 2010; Theil *et al.,* 2010; Brady and O'Mahony, 2011; Che *et al,*. 2011; Ginnouli *et al.,* 2011; Kyle and Kim, 2011; Streimikiene and Sliogeiene, 2011; Thambiran and Diab, 2011; Collet *et al.,* 2012; Leighty *et al.,* 2012; Oxley *et al.,* 2012; Pasaoglu *et al.,* 2012; Takeshita, 2012). A list of emissions by source for a given geographical area and time period is known as an emissions inventory and can be compiled using an emissions model (NAEI, 2012b). A number of different emissions modelling approaches have been adopted such as, average-speed, corrected average-speed, traffic situation, multiple linear regression and instantaneous models (Barlow and Boulter, 2009). Smit *et al.* (2008a) give an excellent review of these models and they are only briefly described below. However, given that emissions models are more often than not represented by emissions factors and emission factors are in turn dependent on several other factors (such as type of fuel, type of engine, age of the vehicle, driving cycle etc.) (Kamble *et al.,* 2009), it is first necessary to document the methods by which emissions factors are developed.

There are a number of different ways in which emissions factors can be estimated from road vehicles. Typically laboratory dynamometer tests are used to determine emissions factors from road vehicles (Grieshop *et al.,* 2012). Some common alternatives to dynamometer experiments include on-board measurements (e.g. Huo *et al.,* 2012a, 2012b), remote sensing measurement campaigns (e.g. Guo *et al.,* 2007) and tunnel experiments (e.g. Colberg *et al.,* 2005). It is these four approaches that are the focus of the following sections. Other methods, such as inverse modelling (e.g. Zarate *et al.,* 2007) and mass balance (e.g. Klthoff *et al.,* 2002) are less commonly used to estimate emissions and are beyond the scope of this work.

It should be noted that CO_2 emissions are more easily estimated from road vehicles as their emission is directly related to fuel consumption (Thambiran and Diab, 2011). In contrast, the emissions of pollutants from road vehicles are dependent on many other parameters such as engine load, ambient temperature and therefore it is harder to accurately estimate their emissions rates (Boulter *et al.,* 2009b).

2.2.1 Dynamometer Tests

The dynamometer test is the most widely used method of estimating emissions from road vehicles (Joumard *et al.,* 2000). They involve a vehicle being run on a dynamometer under controlled conditions whilst simultaneously collecting the vehicle exhaust gases and subsequently quantifying them (Prati *et al.,* 2011). During these tests the vehicles are subjected to various driving cycles, which involve the changing of the dynamics (speed, engine load etc.) of the vehicle to reflect 'real world' driving conditions (Andre *et al.,* 2006; Kamble *et al.,* 2009). During these test (or drive) cycles various activity parameters can be measured, such as speed, engine load, acceleration, deceleration etc. (Boutlter *et al.,* 2009b). These parameters can be plotted against emissions and through the use of regression analysis continuous functions can be applied to the data in order to develop emissions factors (Barlow and Boulter, 2009).

The main advantage of the dynamometer tests over other emissions factor development approaches is that the tests can be carried out in a controlled environment (laboratory) under standard conditions, which allows for test procedures to be easily reproduced (de Vlieger, 1997; Boutlter *et al.,* 2009b). In turn this allows the emissions factors produced from different dynamometer tests to be compared and subsequently compiled into a single database, increasing the number of sampled vehicles. However, the standardisation of dynamometer test conditions can be an advantage on the one hand but a disadvantage on the other. Sample size, maintenance level, vehicle size and age of test cars, uniform measurement methods and test conditions and driving patterns are all sensitive parameters during dynamometer tests (Winther, 1998). A failure to take into account the sensitivity of these parameters whilst conducting emissions laboratory investigations can lead to un-representative emissions factors and ultimately under-prediction or over-prediction of emissions model estimates (Boutlter *et al.,* 2009a). However, it is the dynamometer (or driving) cycle that is widely accepted as a major limitation of laboratory based emissions testing (see Carslaw *et al.,* 2011, Carslaw and Beevers, 2005, Carslaw and Beevers, 2004; Latham *et al.,* 2001; Jenkin, 2004a; Jenkin, 2008; AQEG, 2007).

Driving cycles used in dynamometer tests provide a speed-time profile of driving behaviour in a specific area/region (Newman *et al.,* 1992). Current driving cycles are developed with on-road driving data (e.g. ARTEMIS; Assessment and Reliability of Transport Emissions Models and Inventory Systems, see Andre 2004) rather than simulation methods (such as the Japanese driving cycle, California-seven cycle and mode-cycle see Kamble *et al.,* 2009) and are normally stratified by route type (e.g. urban, rural, motorway), vehicle type (e.g. HGV, LGV), time period (e.g. peak, off-peak) and speed level (Hung *et al.*, 2012). Once a dynamometer test is complete it is necessary to apply correction factors to the emissions rates recorded to account for deviations between laboratory and on-road conditions such as temperature and average vehicle speed (Grieshop *et al.*, 2012). However, it is well documented in the literature that there are also deviations between the representivity of laboratory dynamometer driving cycles and on-road real world driving conditions (Joumard, 1999; Lau *et al.*, 2001; de Vlieger, 1997; Andre, 2006; Grieshop *et al.*, 2012; Boutlter *et al.*, 2009a; Smit and Bluett, 2011; Nutraman and Supachart, 2009; Andre, 2004). Much of the literature documenting these deviations concerns the application of emissions factors developed from generic, often national (e.g. Indian driving cycle) or international driving cycles (e.g. ECE 15, modem-hyzem cycles) known as 'standard' driving cycles (e.g. Joumard, 1999; Joumard, 2000; Lin and Niemeire, 2003; Kamble *et al.*, 2009; Durbin *et al.*, 2002; Lenaers, 1996). These cycles are typically the legislative cycles used for testing vehicles registered within a country or region (e.g. Europe). Given that the driving characteristics of each city are unique due to different vehicle fleet composition, driving behaviour and road network topography (Andre *et al.*, 2006; Tsai *et al.*, 2005), the use of emissions factors developed from these standard driving cycles have been shown to substantially underestimate emissions (e.g. Carslaw *et al.*, 2011; Joumard, 2000). For example, Rhys-Tyler and Bell (2012) compared results from an RSD campaign in London with emissions results over the New European Drive Cycle (NEDC) and found CO emissions from gasoline-powered cars less than three years old measured using remote sensing to be 1.3 times higher than the NEDC. This value was found to increase to 2.2 times for cars between four and eight years and to 6.4 for cars between nine and 12 years old. Similar results were found by Rhys-Tyler and Bell (2012) when NO_x, HC and PM emissions were compared. Discrepancies between dynamometer and 'real-world' estimates have been documented by Carslaw *et al.* (2011), Carslaw and Beevers (2005), Carslaw and Beevers (2004), Latham *et al.* (2001), Jenkin (2004a, 2008) and AQEG (2007). The discrepancies between emissions estimates developed from dynamometer test and those developed from RSD campaigns are discussed further in section 2.3.1.

In some cases dynamometer driving cycles have been developed using more local on-road driving data in an attempt to better represent real world conditions in emissions estimates. For example, Nutraman and Supachart (2009) compared the more local Bangkok driving cycle to that of the European driving cycle (the adopted legislative cycle for testing vehicles registered in Thailand) and found that HC and CO emissions from the Bangkok driving cycle were almost two and four times greater and NOx emissions 10% higher than those of the European driving cycle. Similarly, Durbin *et al.* (2002) observed substantially higher emissions estimates from tests using the New York City driving cycle compared to experiments with the Federal Test Procedure (FTP). They concluded that the discrepancies found were due to the inability of the standard FTP cycle to take into account the more aggressive acceleration behaviour that was present at a local level. Tsai *et al.* (2005) compared a local driving cycle (Karohsiung Driving cycle) to the standard legislative cycle used for testing vehicles in China (European driving cycle). They documented that the percentage of time spent in acceleration, and deceleration modes was substantially lower for the European driving cycle than for the Karohsiung Driving cycle, resulting in completely different emissions factors and fuel consumption. However, despite the development of such local cycles it is impractical to develop and regularly update driving cycles at every locality and so it is inevitable that the use of 'standard' driving cycles will continue in the future as common practice.

Other disadvantages of dynamometer tests include the use of set ambient temperatures and preconditioning routines and the absence of road gradients (Franco et *al.* 2013). In addition, emissions factors developed from dynamometers tests are typically not representative of the entire vehicle fleet as only a few vehicles of each technology type are usually tested (Boutlter *et al.,* 2009b). This shortfall can result in the failure of dynamometer tests to represent the local extremes (or gross emitters) of real-world driving (Liau and Dubarry, 2007). These gross emitters (often poorly maintained vehicles; see Muncaster *et al,.* 1996) are responsible for a high percentage of total pollutant gases but represent a small number of the vehicle fleet meaning that their emissions behaviour are often not captured in dynamometer tests (Huo *et al.,* 2012a; Grieshop *et al.,* 2012; Lau *et al.,* 2001; Cadle *et al.,* 1997). Similarly, the continuous functions commonly applied to dynamometer data in order to develop a set of emissions factors represent an average and as such extremes or gross emitters are removed from these datasets (Barlow and Boulter, 2009).

2.2.2 Instrumented Vehicles

Another method by which emissions factors from vehicles can be estimated is using the on-board measurement or instrumented vehicle approach (e.g. Lopez *et al.,* 2009; Chen *et al.,* 2007; Lenaers *et al.,* 1996; Hung *et al.,* 2007). This method involves the fitting of devices to a vehicle which directly measure the rate of emissions and other activity parameters (e.g. speed, engine load, gear change etc.) of the vehicle whilst it is operated in real world conditions (Lau *et al.,* 2001). The main advantage of this approach over dynamometer tests is that emissions are collected under real world conditions and as such the representivity of external variables, such as temperature, are accurately reflected in emissions estimates (Lau *et al.,* 2001). Furthermore, vehicle dynamics during on road experiments are documented as being more representative of real world driving (Lau *et al.,* 2001; Huo *et al.,* 2012a; Huo *et al.,* 2012b; De Vlieger, 1997) than dynamometer tests, although it is necessary to choose routes on the network that are 'typical' of the journeys they are trying to describe.

The main disadvantage of instrumented vehicle experiments is that they are restricted by sample size as these tests are often conducted using a limited number of vehicles of a specific type. For example, Dee Hann and Keller (2000) conducted extensive on-board measurements of Euro-I petrol passenger cars during real world driving to produce a set of emissions factors and subsequently an instantaneous emissions model. Although the model was shown to predict emissions more accurately than models developed using dynamometer tests over standard driving cycles, the instantaneous emissions model was restricted by its sample size and vehicle type i.e. it was developed based on a small number of Euro-I petrol cars. Therefore, the model cannot be applied to a wider vehicle fleet.

2.2.3 Remote Sensing

The use of remote sensing detectors (RSD) involves the use of ultraviolet and infrared beams of light which, when passed through a vehicle exhaust plume, are absorbed by its constituent gases and particles allowing volume concentrations of HC, CO, CO_2 and NO to be estimated simultaneously (Guo *et al.*, 2007; Guenther *et al.*, 1994). In contrast to the on-board measurement approach, the use of RSD has enabled emissions data to be gathered from large samples of vehicles driving in real world conditions. For example, a campaign carried out by Chan *et al.* (2004) involved a series of remote sensing exhaust emissions measurements in Hong Kong resulting in the collection of emissions data from a total of 10,781 petrol vehicles. Kuhns *et al.* (2004) compiled an emissions inventory of 61,207 gasoline and 1,180 diesel vehicles based on RSD studies in Las Vegas, US and Sjodin and Andreasson (2000) documented an RSD campaign involving the monitoring of 30,000 vehicles in Gothenburg, Sweden. Furthermore, an RSD measurement campaign in the UK by Carslaw *et al.* (2011) has not only resulted in the compilation of a large emissions factor database but also highlighted the discrepancies between dynamometer based emissions factors and real world conditions (see section 2.3.1 below). Other RSD studies, such as those by Guo *et al.* (2007), Smit and Bluett (2011) and Beevers *et al.* (2012) have similarly documented a lack of agreement between RSD data and dynamometer based emissions inventories. These discrepancies are due to the fact that RSD data better reflects real world driving dynamics compared to dynamometer studies (Sadler *et al.*, 1996). Rhys-Tyler *et al.* (2011) documented that RSD campaigns (and other real world driving measurement techniques such as instrumented vehicles) allow for ‘variability in driver behaviour, interactions with other road users and interactions with highway infrastructure.’ Laboratory experiments do not explicitly reflect these parameters which can result in unrepresentative emissions factors.

There are a number of limitations associated with RSD experiments, namely dependence on appropriate meteorological conditions (high winds cause rapid dispersion of exhaust plumes), inability to capture vehicle emissions emitted from exhausts at varying heights and the restriction of use to specific road types (i.e. single lane, urban roads that are on a gradient) (see Carslaw *et al.*, 2011a; Carslaw *et al.*, 2011b). In addition, in order to maintain a consistent and acceptable level of accuracy, RSD equipment requires daily multi-point calibration with real wet exhaust which in some experiments may not be common practice (Sjodin and Andreasson, 2000).

2.2.4 Tunnel Experiments

In a typical tunnel study, pollutant concentrations are sampled at the entrance and exit of a tunnel (Kuhns *et al.,* 2004). The difference in pollutant concentrations between the entrance and exit points is assumed to be directly related to the mass emitted from the vehicles travelling through the tunnel during the sample period (Mancilla and Mendoza, 2012). It is possible to calculate average emissions factors from this data that are representative of the total vehicle fleet passing through the tunnel (Colberg *et al.,* 2005). There are two types of tunnel study, those concerned with the development of emissions factors and those with the air quality levels within a tunnel and its compliance with legislation (El-Fadel and Hashisho, 2000). Both types of study can be considered beneficial over other emissions factor development methods because tunnel studies can determine the average emissions of large number of vehicles, reflect vehicle exhaust in real-world traffic, are cheaper than laboratory based tests (Hung- Lung and Yao-Sheng, 2009) and provide emissions estimates that are representative of tail pipe and non-tail pipe emissions (McGaughey *et al.,* 2000).

Although tunnel studies have been shown to provide accurate estimates of local emissions (Touaty and Bonsang, 2000; El-Fadel and Hashisho, 2000; Weingarter *et al.*, 1997; Ho *et al.*, 2007) they are subject to a number of limitations. They are limited in their application as they provide emissions factors that are specific to a tunnel and its particular driving conditions and road geometry and topography (Ning *et al.,* 2008). Furthermore, the vehicle mix passing through the tunnel may not be representative of the urban fleet in the surrounding area and as a result, the information they provide are often not broadly applicable to the wider road network (Hung- Lung and Yao-Sheng, 2009). In addition, tunnel studies do not explicitly measure emissions by vehicle class or type and as such provide a composite factor for all vehicles that have passed through the tunnel (Gentler and Pierson, 1996). It is possible to subsequently estimate emissions by vehicle type using various calculations and regression analysis (e.g. Kristensson *et al.,* 2004) but these are subject to assumptions and limitations of their own (Grieshop *et al.,* 2006).

2.2.5 Emission Factor Development: Summary

Dynamometer tests do not accurately represent real world driving conditions but have the advantage of reproducibility and real world driving studies allow variability in vehicle dynamics to be represented in emissions factors but can be restricted by their sample size (i.e. instrumented vehicles), their sensitivity to meteorological conditions (i.e. remote sensing), or by their lack of applicability to the wider road network (i.e. tunnel studies).

The fact dynamometer experiments are highly reproducible enables governing bodies to have a legislative driving cycle in place that ensures new vehicles meet required standards before going on general sale. Ultimately this means that dynamometer tests will remain key to emissions factor development. However, a combination of dynamometers test data with real world data can provide a more robust approach to estimating emissions from road vehicles (De Vlieger, 1997) and the application of multiple methods to estimate emissions factors on a national scale is important if air quality limit values are to be met in the UK.

2.3 Emissions Models

During emissions factor development different activity parameters can be recorded and subsequently used in conjunction with emissions rates, to develop emissions models. Given that there are many parameters that influence emissions rates, many different emissions models have been developed over the years some of which are described next. It should be noted that these models are greatly influenced by the emissions factors they comprise. Emissions factors are in turn governed by the method from which they were developed (see above). As a result emissions models often share the same advantages and disadvantages as the emissions factors they use as it is hard to incorporate the uncertainties associated with emissions factors into emissions models (Hung-Lung and Yao-Sheng 2009).

Average-speed models (e.g. MOBILE (EPA), EMFAC (California Air Resources Board), COPERT (Ahlvik *et al.,* 1997; Ntziachristos *et al.*, 2000), and Namdeo *et al.* (2002) are the most commonly used emissions models (Smit *et al.,* 2010). This is primarily due to the fact that their data requirements, traffic flow, vehicle type and vehicle average-speed, are more often than not readily available for use (Barlow and Boulter, 2009). The emissions factors used in these models are based upon the principle that the average emissions for a certain pollutant and a given type of vehicle varies according to the average-speed during a trip (Boulter *et al.*, 2009a). Consequently the model assigns an average emissions factor based on the user specified average-speed and vehicle type.

One major concern with average-speed models is that trips having very different vehicle dynamics and emissions can have the same average-speed (Balrow and Boulter, 2009). For example, an average-speed of 60km/h on an arterial road could represent uncongested free-flowing conditions, whereas the same speed on a motorway would represent much more congested conditions, involving stop and go dynamics (Smit *et al.,* 2008). This is especially relevant in the case of modern catalyst equipped vehicles, for which a large proportion of total emissions during a trip can be as a result of congested, stop-start conditions (Huo *et al.,* 2012a). Such conditions result in very short, sharp increases in emissions (Grieshop *et al.,* 2012; Lau *et al.,* 2001). Average-speed models fail to explicitly take into account these peaks in emissions and as such it is hard to determine their representativeness.

One approach used to overcome the inability of average-speed models to accurately represent the impact of changing vehicle dynamics is the corrected average-speed emissions modelling method. Corrected average-speed models (e.g. TEE model; Nagrentini, 1998) use average-speed, green time, percentage of traffic signals, link length and traffic density variables to estimate a congestion correction factor which is subsequently applied to an average-speed model (Smit *et al.,* 2010). Using these variables the model identifies vehicle time spent in different modes (e.g. idle, acceleration, cruise etc) and adjusts emissions profiles so that they better represent the short-sharp peaks in emissions that may have taken place during a trip (Smit *et al.,* 2008a). It should be noted that the term 'link' refers to a section of road. In this research 'link' and 'road' are used interchangeably.

Traffic situation models (e.g. that from ARTEMIS [Andre, 2004], HBEFA [Hand Book for Emissions Factors see HBEFA, 2012]) assign specific emissions factors to specific traffic 'situations' such as 'stop and go' or 'free flow' (Colberg *et al.,* 2005). The user is required to input a textual description for each road that directly relates to these textual descriptions. The model relies on the premise that users can relate to the traffic situations defined in the model (Boulter *et al.,* 2009a).

Multiple linear regression models (e.g. VERSIT +; Smit *et al.,* 2005) are based on the completion of a large number of dynamometer test cycles during which a number of descriptive parameters are recorded (Barlow and Boulter, 2009). Regression analysis is used to fit continuous functions to average emissions and each variable. This allows the variable that best describes the emissions to be identified (Smit *et al.,* 2008a). The user is required to input vehicle driving cycle data from which the model predicts the same range of variables and assigns the most appropriate emissions factors accordingly (Smit *et al.,* 2007).

Instantaneous emissions models (e.g. De Hann and Keller, 2000; MODEM; PHEM) relate emissions to vehicle operation over a small time period (e.g. seconds, minutes). An emissions rate is calculated for each time period and the sum of all the time period rates is used as the overall link emissions value (Balrow and Boulter, 2009a). Boulter *et al.* (2007) documented a comprehensive evaluation of instantaneous emissions models in which they conclude that, given the level of detail required, 'instantaneous models are not suitable for use on larger (e.g. national) scales.'

2.3.1 Estimating Road Transport Emissions in the UK

On a national scale, emissions from road traffic in the UK are estimated using the UK NAEI, which comprises a set of average-speed emissions factors specific to the general UK vehicle fleet along with national road traffic activity data (flow) from the Department for Transport (DfT) traffic census. The inventory comprises emissions factors for a large number of pollutants, including PM_{10} and NO_x which are of primary concern. The National Green House Gas Emissions Inventory (NGHGI) forms a part of the NAEI and similarly comprises emissions factors for a large number of GHGs, including CO_2. The emissions factors have been revised and updated over the years. In 2009 the Transport Research Laboratory (TRL) was commissioned by the DfT to review the NAEI methodology used to predict emissions factors. The work resulted in reports that reviewed NAEI methodologies for estimating hot exhaust emissions factors (Boutler *et al.,* 2009b), cold start emissions (Boutler and Latham, 2009a), fuel properties (Boutler and Latham, 2009b), exhaust emission factors for road vehicles in the UK (Boulter *et al.,* 2009a) and evaporative emissions (Latham and Boulter, 2009) for road vehicles. In addition, a report was produced documenting deterioration factors and other modelling assumptions of road vehicles (Boulter *et al.,* 2009c). Primary outputs from the work included a driving cycle reference book (as a result of extensive comparisons of a wide range of European test cycles), the subsequent revision of the average-speed approach for estimating hot exhaust emissions and the production of fuel and mileage scaling factors (Barlow and Boutler, 2009). It should be noted that an important change in the NAEI methodology was made for the estimation of CO_2 emissions from light duty vehicles (LDVs; cars and light goods vehicles). The revised CO_2 emissions factors take into account the forecast decline in new car CO_2 emissions in accordance with the 130gCO_2/km by 2015 legislation (see section 3.1.2; Boulter *et al.*, 2009a). This means that a progressive decline in CO_2 emissions factors occurs with change in Euro class despite CO_2 not being a regulated pollutant.

Despite the revision of the UK emissions factors, more recently a number of discrepancies between real world emissions and those in the NAEI have been documented. A substantial amount of research has focused on trends in NO_x emissions from road vehicles (Carslaw *et al.,* 2011; Carslaw and Beevers, 2005; Carslaw and Beevers, 2004; Latham *et al.,* 2001; Jenkin, 2004a; Jenkin, 2008; AQEG, 2007; Rhys-Tyler *et al.,* 2011). This has come about due to the fact that although emissions standards set in the UK have been shown to decrease, a synergistic decline in ambient NO_2 concentrations has not been observed (Carslaw *et al.,* 2011). Moreover, in some places (primarily at roadside locations) an increase in NO_2 concentrations has been shown (AQEG, 2007). The reason for this lack of synergy between emissions standards and NO_2 concentrations is due to an increase in the proportion of NO_x emitted as f-NO_2 in vehicle exhaust fumes (Carslaw and Beevers, 2004). In the UK f-NO_2 has increased from 5-7% in 1996 to 15-16% in 2009 and in London the increase has been greater (5-7%

1996 to 21-22% in 2009) (Carslaw *et al.*, 2011). Recent research based on UK data has shown that the increase in f-NO_2 has been due to increased penetration of diesel vehicles into the fleet and an increase in the number of vehicles (primarily buses) equipped with diesel particulate filters (DPF) and oxidation catalyst exhaust after treatment technologies (AQEG, 2007; Jenkin, 2008). Similar findings have been documented for road traffic in Europe and Asia with Hueglin *et al.* (2006), Hopfner and Lambrecht (2005), Grice *et al.* (2009) and Kousoulisdou *et al.* (2008) observing an increase in f-NO_2 due to diesel vehicle penetration and specific after treatment technology uptake in Switzerland, Germany, and several European cities. Shon *et al.* (2011) and Minour and Ito (2010) have documented similar trends in East Asia. A study by Mavroidis *et al.* (2010) concluded that in Athens, the fraction of f-NO_2 had not altered between 1998 and 2006 due to the fact that diesel cars were not allowed in the Athens area and after treatment technologies such as DPF and oxidation catalysts were not adopted in Greece during the 8 year period. The study provided an insight into the possible strategies to prevent the increase in f-NO_2 that has been observed elsewhere in Europe.

A comprehensive investigation by Carslaw *et al.* (2011) involved the analysis of emissions data from 72,000 vehicles which was captured based on field campaigns and the use of a RSD. The data was compared to current UK emissions factors and alternative emissions factor estimates from Swiss/German handbook of Emissions Factors (HBEFA) and COPERT 4 which enabled discrepancies between current UK factors to be highlighted. Table 2 shows a summary of the findings from the research carried out by Carslaw *et al.* (2011). The terms 'LGV' and 'HGV' refer to light goods vehicle and heavy goods vehicle respectively.

Table 2 Summary of findings from the remote sensing detector research carried out by Carslaw *et al.* (2011)

Data Set	Comparison With	Vehicle Type	Euro Class	Conclusion
UKEF	COPERT 4 and HBEFA	Diesel Cars, LGVs	Euro 3 onwards	UKEF Lower
RSD	UKEF and HBEFA	Petrol Cars	Euro 1 and Euro 2	RSD Higher
RSD	UKEF and HBEFA	Diesel LGVs	Euro 3 onwards	RSD Higher
RSD	UKEF and HBEFA	Diesel Cars	All Euros	RSD Higher
RSD	UKEF and HBEFA	Rigid HGV (Diesel)	Euro I to Euro IV	RSD Higher

Carslaw *et al.* (2011) attributed the discrepancies between the RSD data and other emissions factor data sets observed for petrol cars to be as a result of greater real world catalyst failure and emissions degradation rates. For those observed for HGVs it was concluded that selective catalyst reduction (SCR) was ineffective at urban driving speeds and as result emissions were substantially higher under these conditions and for discrepancies observed for diesel LDVs, particularly diesel cars, it was documented that the LDV test cycles used to develop the UKEFs were inadequate to accurately reflect real world conditions resulting in an underestimate of NO_x emissions (Carslaw *et al.*, 2011).

An equally robust study was completed by Rhys-Tyler *et al.* (2011) using data from an RSD campaign in London. The study found Euro 2 diesel cars to have NO emissions significantly higher than Euro 1 or Euro 3, Euro 4 diesel cars to have between 6 and 17 times higher NO emissions than the equivalent Euro 4 petrol car and median NO emissions from Euro IV diesel light commercial vehicles (<3.5t) were observed to be approximately 25% higher than emissions from Euro 4 diesel passenger cars. The results from the work of Rhys-Tyler *et al.* (2011) further support the findings of Carslaw *et al.* (2011) and suggest that the introduction of emissions abatement technology and the emissions testing of such technology in some cases has not been successful.

2.4 Evaluating the Impact of Road Transport Strategies on Air Pollution

It is necessary for governing bodies to develop strategies and policies in order to reduce the impact of vehicle emissions on human health and the environment. It is an advantage to have the ability to evaluate such strategies and policies prior to implementation, so to allow the best possible option (often for the least cost) to be identified. A key approach to strategy modelling is the editing of a base-case emissions inventory to reflect the proposed changes to the vehicle fleet. The strategies can be evaluated relative to the base-case and the cost in terms of emissions reductions calculated allowing the 'best' strategy to be identified. For example Kyle and Kim (2011) documented an assessment of the impact of technology advancement in the global LDV fleet on GHG emissions. They documented the greatest reductions in GHGs as a result of increased penetration of electric vehicles (EVs) into the fleet. Ginnouli *et al.* (2011) documented a study that involved the assessment of the impact of European emissions control strategies on urban and local air quality in 20 European cities. They found NO_2 and PM_{10} reductions to be greatest when the base-case was edited to reflect greater uptake of alternative technologies. Goncalves *et al.* (2009) edited a base-case inventory for the Barcelona and Madrid road networks in order to model the switching of conventional fuels to natural gas. The highest pollutant emissions reductions resulted from the switching of conventional fuelled cars to natural gas powered cars. Similar strategy modelling studies are documented by Takeshita (2012), Streimikiene and Sliogeiene (2011), Theil *et al.* (2010), Kantor *et al.* (2010), Che *et al.* (2011), Kassomenos *et al.* (2006), Leighty *et al.* (2012), Brady and O'Mahony (2011), Thambiran and Diab (2011) and Collet *et al.* (2012). However, these studies all differ in their approaches to strategy modelling. These differences are primarily due to assumptions made, such as those concerning new technology efficiency and penetration, emissions factors, number and type of vehicles, social behaviour and changes in fuel production processes (Oxley *et al.*, 2012). In addition, Pasaoglu *et al.* (2012) documents that in relation to strategy modelling studies 'there is significant amount of degrees of freedom in the presentation and aggregation of assumptions and findings.' As a result it often becomes hard to compare studies. Furthermore, given the level of assumptions made, their use is often not to provide absolute emissions results but rather to provide an indication of what a change in the vehicle fleet may have on vehicle emissions (or concentrations) (Ginnouli *et al.*, 2011). However, in order to estimate such emissions changes it is common practice to validate the base-case emissions inventory first.

2.5 Validation of Emissions Models

It has been stated above that a number of different models and approaches have been developed to estimate vehicle derived emissions. It is important that these models are validated so that their ability to predict emissions from road traffic can be estimated. However, it is not possible to validate an emissions model without simultaneously assessing the accuracy of the emissions inventory compiled and used in the model. As such validating an emissions model inherently results in the validation of the emissions inventory as well. From here on reference to emissions models and subsequent validation will include the validation of the emissions inventory, although it may not be explicitly mentioned.

Emissions models can be validated using data collected from tunnels (e.g. Robinson *et al.,* 1996; Hausberger *et al.,* 2003), instrumented vehicles (e.g. Joumard *et al.,* 1995) and remote sensing (Carslaw *et al.,* 2011; Chan *et al.,* 2004). The advantages and disadvantages of these techniques have been described above. An alternative approach to emissions inventory validation is the use of ambient concentration measurements. Emissions data can be input for use in an air quality model. Subsequent predicted pollutant concentrations can be compared with observed data which allows the accuracy of the emissions inventory compiled to be assessed (see section 2.6 below). Zarate *et al.* (2007) documented the use of ambient concentration data to validate emissions models as a useful approach in times of economic uncertainty. A comprehensive and extensive meta-analysis of road traffic emissions model validation studies was documented by Smit *et al.* (2010). They provide an excellent table of comparison between the different methods used for emissions model validation which can be found in Appendix C of this work. Smit *et al.* (2010) concluded that there was limited literature concerning emissions model validation. They importantly highlighted that testing the overall accuracy of road traffic emissions models is difficult, as 'true' emissions values are unknown and cannot practically be determined by measurement.

2.6 Atmospheric Dispersion Modelling

In a perfect world pollution concentrations would be continuously measured and monitored everywhere throughout a conurbation. In reality this is neither physically or financially feasible. Instead policy makers must rely on air quality models (atmospheric dispersion models) to predict the spatial and temporal distribution of pollutants over a given area. Righi *et al.* (2009) acknowledge pollution dispersion models to 'compliment measurement techniques as they allow the spatial distribution of measured values to be represented, providing concentration values in areas where monitoring equipment is absent.' In the UK air quality models are regularly used by local authorities for air quality review and assessment and for pollutant concentration forecasting (Namdeo, 1995). In addition, air quality models are commonly used to evaluate emissions inventories by comparing their outputs with monitored data. For example, Taghavi *et al.* (2005) used the Regional Atmospheric Modelling System (RAMS) to evaluate two emissions inventories compiled for O_3, CO, SO_2 and NO_x over southern France. Zhang *et al.* (2008) compared SO_2, NO_x and PM_{10} concentration outputs from AERMOD with monitored data to evaluate an emissions inventory for Hangzhou, China. Peace *et al.* (2004) used ADMS-Urban to evaluate three different emissions inventories compiled for NO_x and NO_2 over Greater Manchester, UK. Banerjee *et al.* (2011) used two dispersion models, the Gaussian Finite Line Source Model (GFLSM) and Industrial Source Complex Model (ISCT-3) to evaluate an emissions inventory complied for NO_2 over Pantnagar, India and Guttikunda and Calari (2013) evaluated a PM_{10} and $PM_{2.5}$ emissions inventory for Delhi, India using the Atmospheric Transport Modelling System (ATMoS).

Over the years there have been many different types of dispersion models developed, including statistical (e.g. Stedman *et al.,* 2001), numerical (HIWAY series; Zimmerman and Thompson,1975) receptor (e.g. COPREM; Wahlin, 2003), box (e.g. STREET BOX; Johnson *et al.,* 1973), street canyon (e.g. OSPM; Hertel and Berkowicz, 1989), microscale CFD (e.g. FLUENT; www.Fluent.com), urban scale (e.g. MEMO; see Moussiopoulous *et al.,* 1993), Gaussian (e.g. GFLSM; Luhar and Patil, 1989), Lagrangian (e.g. GEM-AG; see O'Neill *et al.,* 2003) and screening (e.g. UK DMRB; Highways Agency, 2009) models. There is no universally accepted way in which to classify these models. They can be grouped in terms of complexity, based on their physical principles, the mathematical techniques they employ, their ability to model chemical reactions or the coordinate system they use (see Namdeo, 1995). A comprehensive overview of the different approaches adopted by dispersion models was documented by Holmes and Morawska (2006) and Namdeo (1995). The following sections focus on the Gaussian approach to dispersion modelling and the statistical methods used to validate their performance.

2.6.1 Fundamental Gaussian Principles

In the UK the most widely used models for air quality modelling for regulatory purposes are those based on Gaussian dispersion theory (Gurjar *et al.,* 2010). On the one hand, the way in which modern

Gaussian air quality models calculate the dispersion of pollutants has become much more advanced, whereas on the other hand they still retain the fundamental Gaussian principles on which their more simple predecessors were developed. As a result, modern Gaussian models have inherited a number of assumptions and limitation.

Gaussian models assume that pollutant concentrations are normally distributed in the vertical and horizontal planes around a given wind direction (Vallero, 2008; Tiwary and Colls, 2010; Huber, 1991; Wagner *et al.,* 2006; Gurjar *et al.,* 2010). In addition, Gaussian plume formula assumes that wind speed and turbulence are vertically homogenous and that surface topography and meteorology are constant over time and distance between source and receptor ('steady state') (Yura *et al.,* 2007; Lazaridis, 2011). Furthermore, crosswind dispersion is assumed to be uniform over a given meteorological wind sector e.g. 30^{o} or 10^{o} (Lutman *et al.,* 2004). The Gaussian plume equation for estimating normalized ground-level concentrations is:

$$C = \frac{Q}{\pi\sigma_y\sigma_z U} \exp\left[-{}^{1}/_{2}\left({}^{y}/_{\sigma_y}\right)^2\right] \exp\left[-{}^{1}/_{2}\left({}^{z}/_{\sigma_z}\right)^2\right]$$

(Equation 1)

Where C is the pollutant concentration, U is the mean wind speed affecting the plume, Q is the emissions rate, h the effective emissions height above the ground, σ_y and σ_z are the values of horizontal (y) and vertical dispersion (z) coefficients. Equation 1 assumes that the plume spread has a Gaussian distribution, the wind affecting the plume is uniform and that the plume is perfectly reflected at ground level (Huber, 1991). In some models the values for horizontal (σ_y) and vertical (σ_z) dispersion coefficients are defined according to Pasquill stability classes (see Pasquill, 1978; Venkatram, 1996). Stability classes range from A (stable) to G (very unstable) with each different class specifying a different set of σ_y and σ_z depending on the level of turbulence (defined by wind speed, daytime solar radiation and night time cloud cover) in the atmosphere they describe (Tiwary and Colls, 2010). In other models (e.g. ADMS-Urban) atmospheric stability is defined based on two different variables namely boundary layer height (h) as a function of height above ground level (z/h) and the Monin-Obukhov Length (L_{MO}) as a function of height above ground level (z/L_{MO}):

$$L_{MO} = \frac{-u.^3}{kgF_{\theta_0}/(pc_pT_0)}$$

(Equation 2)

Where u_{*} is the friction velocity at the Earth's surface, k is the von Karman constant (0.4), g is the acceleration due to gravity, F_{θ_0} is the surface heat flux, p is the density of air, c_p is the specific heat capacity of air and T_0 is the surface temperature. Unlike the Pasquill-Gifford estimation this approach allows the variation in dispersion parameters with height to be modelled as the parameters in Equation 2 will change depending on h (Tiwary and Colls, 2010; CERC, 2006).

2.6.2 Modern Gaussian Air Quality Models

Early Gaussian models, such as APRAC (Johnson *et al.*, 1973), Highway series (Zimmerman and Thompson, 1975) and CALINE series (Benson *et al.*, 1972; Ward *et al.*, 1975; Benson, 1979, 1980); Benson, 1984) were simple in their approach to dispersion modelling. They failed to take into account physical removal, chemical reactions in the atmosphere and the influence of surface roughness on pollutant dispersion (EPA, 1982; EPA, 1989). As a result these models have become almost redundant in the modern world. However, in their place, more complex models, such as ADMS-series (see CERC, 2006) and AERMOD (see USEPA, 2004a) have been developed that incorporate an array of algorithms that compute a multitude of dispersion parameters and processes. For example, ADMS-Urban has algorithms for dry deposition, wet deposition, particle settling, chemical reaction schemes (simplified generic reaction sets), meteorological pre-processing (for calculating boundary layer parameters) and for modelling the effect of buildings and street canyons (see Hertel and Berkowicz, 1989 and in Hertel *et al.*,1990) on pollutant dispersion (CERC, 2006). Furthermore, the complexity of these models allows them to be applied to an array of different geographical locations and environments. For example, AERMOD is applicable to rural and urban areas, flat and complex terrain, surface and elevated releases, and to multiple sources (USEPA, 2004a, 2004b) and ADMS-Urban and Airviro Gauss model take into consideration surface structures such as buildings and trees via the use of local roughness lengths and adjustments to wind speeds (CERC, 2006; SMHI, 2006).

The input data requirements of air quality models have increased in line with their complexity. Early models such as CALINE required few input variables including, a single wind speed and wind direction and an emissions rate (Benson *et al.,* 1972). However, modern dispersion models require a multitude of input parameters. For example, AERMOD requires upper air data, data from site-specific meteorological measurements, boundary layer height, surface albedo, surface roughness, cloud cover, Bowen ratio and a geographically and temporally resolved emissions inventory to be input prior to dispersion modelling (USEPA, 2004a, 2004b, USEPA, 2004c).

Typically road sources are treated as line sources in modern Gaussian air quality models. The line source is decomposed to a number of source elements and the dispersion of pollution from each element is computed. For example, in AERMOD road sources are modelled as a string of volume sources along a line segment (USEPA, 2004a, 2004b) and in ADMS-Urban and the Airviro Gauss model road sources are treated as a series of point sources along a line of finite length (CERC, 2006; SMHI, 2006). Some Gaussian based models have algorithms specifically for modelling the dispersion of pollutants from these elements. These algorithms are modified versions of the simple Gaussian plume formula in Equation 1. For example, ADMS-Urban calculates dispersion from road sources according to the following formulae:

$$\mathrm{C} = \frac{\mathrm{Q_S}}{2\sqrt{2\pi\sigma_Z(X)U}} \exp - \left(\frac{(z-z_p)^2}{2\sigma_z^2}\right) \mathrm{x} \left[\mathrm{erf}\left(\frac{y+L_s/2}{\sqrt{2}\sigma_y}\right) - \mathrm{erf}\left(\frac{y-L_s/2}{\sqrt{2}\sigma_y}\right)\right] \quad + \text{reflection terms}$$

(Equation 3)

Where Q_S is the source strength, Z is the height of receptor above ground, y is the lateral distance from the plume centreline, z_p is the height of the plume above ground, U is the wind speed at the plume height and L_s is the source length. Reflection terms refer to the reflection of the plume when it reaches ground level (CERC, 2006). Some Gaussian models, such as AERMOD and ADMS-Urban take into account physical processes around buildings by modifying σ_y and σ_z. Although, unlike CFD models, they are not able to calculate re-circulation effects caused by multiple buildings or at intersections (Holmes and Morawska, 2006). In addition, in ADMS-Urban initial vertical turbulence emissions heights are altered to account for varying heights of vehicle emissions and an algorithm for extra lateral turbulence accounts for turbulence due to traffic flow:

$$\sigma_{y_{vehicle}} = \sigma_{v_{vehicle}}\ t\left\{1 + \left(\frac{t}{t_d}\right)^2\right\}^{-1/2}$$

(Equation 4)

Where

$$\sigma_{v_{vehicle}} = \mathrm{b.}\left(\frac{\mathrm{N_H U_H A_H + N_L U_L A_L}}{\mathrm{W}}\right)^{1/2}$$

(Equation 5)

The turbulence decay time, t_d is given by

$$t_d = \left(\frac{w}{\tau}\right) / \sigma_{v_{vehicle}}$$

(Equation 6)

Where t is the time to travel to source, b is a constant (0.3) from OSPM street canyon model, τ is a constant (0.1; chosen by CERC after testing), N_H and N_L are the number of heavy and light vehicles per second respectively, $U_H U_L$ and $U_H U_L$ are the speeds of the heavy and light vehicles respectively, A_H and A_L are the areas covered by the heavy and light duty vehicles respectively and w is the road width.

2.6.3 Limitations of Gaussian Air Quality Models

Fundamental Gaussian principles make a number of assumptions that limit the predictive power of the air quality model. The Gaussian formulation does not take time into consideration and pollutants are effectively dispersed from the source to receptor instantaneously (Wagner *et al.*, 2006). Air quality models commonly require data that is averaged over a specific time period, for example AERMOD, ADMS-Urban and the Airviro Gauss model require input data that are resolved to an hourly resolution (USEPA, 2004a, 2004b; CERC, 2006; SMHI, 2006). Gaussian algorithms intrinsic to these models are solved for each line of this input data meaning that the meteorological conditions over the averaging period remain constant and subsequent outputs are representative of the average concentrations per unit of time specified. Therefore, any changes in meteorological conditions during the averaging period will not be reflected in Gaussian calculations (Gurjar *et al.*, 2010). In addition, because Gaussian models are effectively instantaneous they cannot take into account pollution build up over consecutive averaging periods (Lazaridis, 2011). Righi *et al.* (2009) documented ADMS-Urban to underestimate CO concentrations in Ravenna, Italy due to this issue. They applied a correction factor to their data to overcome what they termed the 'memory effect.'

Gaussian models assume that the meteorological data is homogeneous throughout the simulation domain meaning that local meteorological conditions are not considered in dispersion calculations (Tiwary and Colls, 2010). Furthermore, they are inversely dependent on wind speed and perform poorly when predicting the dispersion of pollution under low wind speed conditions (Vallero, 2008; Chock, 1978). As a result in modern air quality models the wind velocity is set to 0.5m/s to 1m/s for zero or very low wind conditions to allow the model to compute (Lazaridis, 2011). Similarly, Gaussian models are sensitive to wind direction and perform better when air-flow is towards the receptor and perform poorly when air-flow is away from the receptor (e.g. Righi *et al.*, 2009; Benson, 1992).

Concentration distributions are Gaussian in stable conditions but the vertical distribution is non-Gaussian in convective conditions to take account of the skewed structure of the vertical component of the turbulence (Harrop, 2002). Therefore, early Gaussian models could not accurately predict pollutant dispersion under convective conditions (see Chock, 1978; Johnson *et al.*, 1973; Zimmerman and Thompson, 1975; Benson *et al.,* 1972). However, most modern air quality models, such as ADMS-Urban, AERMOD and the Airviro Gauss model, use a non-Gaussian formula to calculate pollutant dispersion in convective conditions (see USEPA, 2004a; CERC, 2006; SMHI, 2006) in order to bring material from elevated releases rapidly down to the surface in convective conditions.

A major limitation of the use of Gaussian models to predict pollutant concentrations in an urban environment is that dispersion processes are non-Gaussian in street canyons (Leksmono *et al.,* 2006). To overcome this issue many modern air quality models comprise street canyon models. However, due to long computational times only crude versions of street canyon models are included in modern air quality models. For example ADMS-Urban comprises a simplified version of OSPM that has been shown to poorly represent dispersion processes in the canyon (Westmorelands *et al.,* 2011). In future the integration of Gaussian models with more complex street canyon models will enable pollutant concentrations to be better represented in the urban environment.

2.7 Validation and Evaluation of Dispersion Model Performance

Before air quality model performance can be discussed, it is necessary to highlight the difference between the terms 'validation' and 'evaluation.' According to Jenke (2009) an evaluation study has a set of performance expectations that may or may not be met and a validation study has a set of acceptance criteria that must be met. Kartseva (2008) document that 'the difference between validation and evaluation is that in the former, a technique not yet implemented in practice is investigated, whereas in the latter a technique already implemented in practice is investigated.' When an air quality model is developed it is initially validated through comparison with observed data (e.g. ADMS-Urban; Carruthers *et al.,* 2003a) and it must meet certain criteria before it can be considered fit for purpose. A model validation study may result in a calibration exercise during which model parameters are tuned to improve performance (DEFRA, 2010b). Historically, air quality model validation studies were based on data collected from field experiments (known as 'field grade') (Chang and Hanna, 2010; Hanna, 2010) which were relatively simple in nature, consisting of near ground level continuous point source releases and extensive concentration and meteorological observations over flat or complex terrain (Hanna *et al.,* 1990). These experiments provided more precise data sets with which to validate model performance as parameters, such as emission rates, release heights, topography, meteorological conditions and observed concentrations were accurately recorded at numerous locations, usually along concentric sampling arcs (Hanna *et al.,* 1991). In essence these experiments removed, as far as possible, error due to model input parameters and provided a dataset with which an air quality model's algorithms, code and or calculation procedures could be validated (Chang and Hanna, 2004). Examples of such data sets and a discussion of their use in air quality modelling can be found in Chang and Hanna (2010) and in Hanna (2010).

The wider application and assessment of an air quality model post validation is termed an 'evaluation study' (see Hanna *et al.*, 2011; 2004; 1990; 1991; 1993, Donnelly *et al.*, 2009; Stunder and Sethurama, 1986; Tesche *et al.*, 1987; Mosca *et al.*, 1998; Hanna and Chang, 2001; for examples) and has certain performance expectations e.g. the model should predict within 50% of the observed. The methods by which a dispersion model can be evaluated are discussed in the next section. Chang and Hanna (2004) noted that the performance of a model, when validated with a research grade field experiment dataset, may not be reproduced when the same model is evaluated with input data of lower quality. Consequently it is important that the quality of such input data is of the highest standard prior to modelling (Heinold *et al.*, 1995).

2.7.1 Dispersion Model Evaluation Methods

There have been many statistical measures suggested in the literature for air quality model performance evaluation. For example, Stunder and Sethurama (1986) used variance, total root mean square error and systematic root mean square error to evaluate the performance of two coastal point source dispersion models. In contrast, Tesche *et al.* (1987) used the performance measures ratio of the maximum predicted (C_{pmax}) to the maximum observed concentrations (C_{omax}), bias and gross error to evaluate five grid based models in complex terrain. Desiato (1992) used the correlation coefficient (R), bias, normalised mean square error (NMSE), the proportion of predicted data within a factor of two of the observed (FAC2) and the proportion of predicted data within a factor of five of the observed (FAC5) to evaluate the performance of a puff model used for accident release dispersion modelling. More recently Donnelly *et al.* (2009) used NMSE, FAC2, fractional bias (FB), geometric mean bias (MG) and geometric mean variance (VG) to evaluate the performance of a computation fluid dynamics model (WinMISKAM) using the Mock Urban Setting Test (MUST) field data. All of these statistical descriptors have been used to answer the same two fundamental questions in relation to air quality model performance: in general, by how much is the model over-predicting or under-predicting and; how much deviation is there from the average over-prediction or under-prediction (Duijm *et al.*, 1996). Statistical measures used to answer these questions fall under two main mathematical genres, bias and variance respectively and it is these two descriptors that are well documented in the literature, all be it calculated in different ways. The reason for this is that dispersion is ultimately governed by turbulence, which is random in nature and so cannot be accurately predicted (Chang and Hanna, 2004). Therefore, only basic statistics can be used to compare observed and predicted data. Furthermore, because of the random nature of dispersion, an air quality model will never predict observed concentrations 'perfectly' (Hanna *et al.*, 2004).

Duijm *et al.* (1996) reviewed many statistical evaluation performance measures, namely, bias, mean square error (MSE), FB, NMSE, average absolute gross error (AAGE), fractional standard deviation

(FSD), mean relative bias (MRB), mean relative square error (MRSE), fraction of over-prediction (FOEX), MG, geometric mean, VG, FAC2 and R and concluded that 'One should use at least two performance measures in an evaluation exercise in order to obtain a measure of bias and variance.' In addition, they advised that MG, VG, FOEX, and FAC2 or MRB, MRSE, FOEX, and FAC2 to be the best measures for air quality model performance evaluation. They suggested MG and VG and MRB and MRSE not to be used simultaneously because both provide similar information (i.e. MG and MRB measure bias and VG and MRSE measure variance).

Chang and Hanna (2004) give a comprehensive and in depth review of air quality model performance evaluation methods and procedures and as a result one is not documented here. They first of all review the different applications of air quality models and discuss how these can influence the requirements of an air quality evaluation procedure (e.g. air quality modelling for regulatory purposes are more concerned with high concentration values corresponding to limit value exceedences and evaluation procedures may only consider concentration maxima) and they stress the need to properly define evaluation goals prior to carrying out any statistical analysis. They go on to review the different methods of evaluating air quality model performance presented in the literature, namely Taylors single nonogram method (Taylor, 2001; Gates ,1999), American Society of Testing Materials model evaluation guidelines (ASTM, 2000), Figure of Merit in Space, the Cumulative Distribution Function (CDF) method and the statistical performance measures implemented in the BOOT software (Hanna *et al.,* 1993, 1991). Finally, Chang and Hanna (2004) discuss the different magnitudes of performance measures presented in the literature (and provide a set of values for which outputs from research grade field experiments can be compared) prior to examining the different statistical performance measures in a case study using two Gaussian based models.

In addition to statistical performance measures, graphical presentations are widely acknowledged as being useful for evaluating model behaviour (Hanna *et al.*, 1990, 1991, 1993; Chang and Hanna, 2004). In particular they are most useful when evaluating the results of model sensitivity testing and the use of scatter plots and box plots is common place when assessing performance in relation to independent variables such as mixing depth and horizontal diffusion (e.g. Desiato, 1992).

2.8 Chapter 2 Summary

Emissions factors are combined with traffic data in a model to estimate the emissions from road traffic. Emissions factors can be developed using a number of different techniques namely, dynamometer tests, instrumented vehicles, remote sensing and tunnel experiments. In the UK dynamometer tests are typically used to develop emissions factors. These factors are based on average-speed and vehicle type. Recent research has shown that there are major discrepancies between emissions factors and real world emissions. These differences have been attributed to the inability of the factors to take into consideration congested conditions, the greater uptake of diesel vehicles into the UK stock and a lack of representativeness in dynamometer test cycles from which the factors were developed.

Atmospheric dispersion models allow for the spatial prediction and forecasting of pollution in areas where monitoring equipment is absent. Over the years many different models have been developed. Commonly it is Gaussian models that are used by local authorities for air quality review and assessment in the UK. Gaussians models have now evolved to become much more complex but still retain fundamental Gaussian principles, which mean they comprise a number of assumptions and limitations. These limitations and assumptions can be evaluated using a number of statistical and graphical descriptors that measure bias and variance. In addition, these measures allow for the evaluation of model inputs such as the emissions inventory, which can subsequently be used for strategy modelling.

Chapter 3

3. Background: Reducing Emissions from Road Transport

3.1 Environmental Regulations

In order to prevent and reduce the impact of air pollution on the environment and its constituents many governing bodies worldwide have set air quality standards (or limit values). Air quality standards are ‘concentrations recorded over a given time period, which are considered to be acceptable in terms of what is scientifically known about the effects of each pollutant on health and on the environment (DEFRA, 2012a).’ In the UK air quality legislation is driven by European Union (EU) law and all member states must not exceed EU air quality limit values.

In addition to air quality legislation many governing bodies throughout the globe have set legally binding CO_2 reduction targets following the ratification of the Kyoto Protocol (UNFCCC, 1998). Although road transport is a major source of both toxic air pollutants and CO_2 emissions the legislation enforced in the EU and UK to tackle these issues remains separate. The current air quality and GHG legislation enforced in the UK is described in more detail in the following sections. Then the strategies and technology options available to policy makers to further reduce emissions from road transport is documented.

3.1.1 Air Quality Legislation in the European Union and United Kingdom

In the UK, in 1995 the Environment Protection Act, unlike proceeding Acts (e.g. Environment Protection Act 1990; Clean Air Acts in 1968 and 1956), introduced an effects-based, risk management approach to air pollution abatement (Bell and McGillivray, 2006). It was formulised by a series of air quality standards and regulations (see Table 3). These regulations provided the foundation on which more recent air quality legislation in the UK has been based.

Table 3 Sections of the Environment Protection Act 1995 Relating to Air Quality (Bell and McGillivray, 2006)

Environment Protection Act Section	**Brief Description**
81	Environment agency must take account of the strategy
82	Local Authorities (LAs) must review air quality problems with in their state and assess whether air quality standards are being achieved. Areas of short fall must be identified.
83	LAs assign Air Quality Management Areas (AQMA) in areas where air quality limit values are not met.
84	LAs must assess AQMAs and produce action plans complete with measures and time scales to bring air quality levels back within limits.
85	Reserves the power for assessment to be made in any area and gives instructions to LAs to take specified actions.
86	Role for County Councils to make recommendations to the district on air quality and action plans.
87	Provides Secretary of State (SoS) with powers to make regulations concerning air quality.
88	Provides SoS with powers to make guidance that the LAs should pay due regard to.

In 2005 the European Commission launched the Clean Air for Europe (CAFE) programme with the aim of establishing a long-term, integrated strategy to tackle air pollution and to protect against its effects on human health and the environment (EC, 2005a). The programme's objectives were to set target values for air pollution and national emissions ceilings (negotiated during the 1999 Gothenburg Protocol; see UNECE, 1999), to develop integrated pollution-reduction programmes in targeted areas and to identify specific measures to limit emissions or raise product standards. The European Commission subsequently produced the Thematic Strategy on Air Pollution which is based on the documents produced under the framework of the CAFE Programme (EC, 2005b). The Strategy established interim objectives for air pollution in the EU and proposed appropriate measures for achieving them. It was reviewed in 2010 and a more comprehensive review is due in 2013. However, a number of interim measures have been established from the 2010 review including the necessity to further reduce emissions from vehicles (DEFRA, 2012a).

As a direct result of the documentation produced under the CAFE programme the 2008 European Commission Ambient Air Quality Directive (2008/50/EC) set legally binding limit values for pollutant concentrations in outdoor air (EC, 2008). The 2008 Directive combined nearly all the previous EU air quality legislation (except the fourth Directive 2004/107/EC) and was made law in England through the Air Quality Standards Regulation 2010 (DEFRA, 2011). The Regulation set air quality limit values for SO_2, NO_2, PM_{10}, $PM_{2.5}$, Lead (Pb), Benzene, PAH, 1,3,-butadiene and CO

(Table 4). The main legislative change enforced under the Ambient Air Quality Directive was the introduction of a limit value (25µg/m^3) and an exposure reduction approach for $PM_{2.5}$. The exposure reduction approach adopted is one in which the main aim is to reduce exposure generally with greater reductions required in areas where exposure is the greatest (EC, 2005a). This means that a relatively high concentration cap was set for $PM_{2.5}$ but requires those areas where air pollution is the greatest to achieve much higher reductions (EC, 2012a). In addition, in accordance with the Air Quality Directive member states are eligible to apply for time extensions of three years (PM_{10}) or up to five years (NO_2, benzene) for complying with limit values (EC, 2008). However, despite the extensions many European member states, including the UK, are now facing heavy financial penalties as air quality levels still remain non-compliant (see EC, 2010).

The Ambient Air Quality Directive requires all Secretaries of State to continuously monitor and assess air quality in their authority areas (EC, 2008). In the UK this requirement is passed to local authorities who are responsible for carrying out air quality review and assessment (DEFRA, 2011). Places identified or predicted to be non-compliant with the EU limit values must be defined as an AQMA. The local authority is then required to devise an air quality action plan that aims to reduce toxic air pollution below EU limit levels (NAQS, 2007). This legislation remains the same as that enforced under the old Council Directive 96/62/EC on ambient air quality assessment and management (the Air Quality Framework Directive) and is the strategy documented in the Nation Air Quality Strategy for England, Wales, Scotland and Northern Ireland (NAQS, 2007).

In 2010, in the UK, road transport was responsible for 37%, 43% and 24% of total NO_x, CO and PM_{10} emissions respectively (NAEI, 2012a). The UK is currently failing to meet EU air quality limit values for NO_2 (40µg/m^3 annual average) and PM_{10} (EC, 2010; DEFRA, 2011). A review of local air quality management by Faulkner and Russell (2010) found that in 2009 58% of local authorities across the UK had Air Quality Management Areas (AQMAs) and of these local authorities 92% declared AQMAs due to pollution exceedences due to road transport.

Table 4 Air Quality Limit Values enforced in the UK and in the European Union (DEFRA, 2012b; NAQS, 2007)

<table>
<tr><th>Pollutant</th><th>Applies</th><th>Objective</th><th>Concentration measured as[10]</th><th>Date to be achieved by and maintained thereafter</th><th>European obligations</th><th>Date to be achieved by and maintained thereafter</th><th>New or existing</th></tr>
<tr><td rowspan="5">Particles (PM_{10})</td><td>UK</td><td>50µg.m^{-3} not to be exceeded more than 35 times a year</td><td>24 hour mean</td><td>31 December 2004</td><td>50µg.m^{-3} not to be exceeded more than 35 times a year</td><td>1 January 2005</td><td rowspan="2">Retain existing</td></tr>
<tr><td>UK</td><td>40µg.m^{-3}</td><td>annual mean</td><td>31 December 2004</td><td>40µg.m^{-3}</td><td>1 January 2005</td></tr>
<tr><td colspan="7">Indicative 2010 objectives for PM_{10} (from the 2000 Strategy and 2003 Addendum) have been replaced by an exposure reduction approach for $PM_{2.5}$ (except in Scotland – see below)</td></tr>
<tr><td>Scotland</td><td>50µg.m^{-3} not to be exceeded more than 7 times a year</td><td>24 hour mean</td><td>31 December 2010</td><td></td><td></td><td>Retain existing</td></tr>
<tr><td>Scotland</td><td>18µg.m^{-3}</td><td>annual mean</td><td>31 December 2010</td><td></td><td></td><td></td></tr>
<tr><td rowspan="3">Particles ($PM_{2.5}$)
Exposure Reduction</td><td>UK (except Scotland)</td><td>25µg.m^{-3}</td><td rowspan="3">annual mean</td><td>2020</td><td>Target value 25µg.m^{-3} [12]</td><td>2010</td><td rowspan="3">New (European obligations still under negotiation)</td></tr>
<tr><td>Scotland</td><td>12µg.m^{-3}</td><td>2020</td><td>Limit value 25µg.m^{-3}</td><td>2015</td></tr>
<tr><td>UK urban areas</td><td>Target of 15% reduction in concentrations at urban background[11]</td><td>Between 2010 and 2020</td><td>Target of 20% reduction in concentrations at urban background</td><td>Between 2010 and 2020</td></tr>
<tr><td rowspan="2">Nitrogen dioxide</td><td>UK</td><td>200µg.m^{-3} not to be exceeded more than 18 times a year</td><td>1 hour mean</td><td>31 December 2005</td><td>200µg.m^{-3} not to be exceeded more than 18 times a year</td><td>1 January 2010</td><td rowspan="2">Retain existing</td></tr>
<tr><td>UK</td><td>40µg.m^{-3}</td><td>annual mean</td><td>31 December 2005</td><td>40µg.m^{-3}</td><td>1 January 2010</td></tr>
<tr><td>Ozone</td><td>UK</td><td>100µg.m^{-3} not to be exceeded more than 10 times a year</td><td>8 hour mean</td><td>31 December 2005</td><td>Target of 120µg.m^{-3} not to be exceeded more than 25 times a year averaged over 3 years</td><td>31 December 2010</td><td>Retain existing</td></tr>
</table>

Table 4 Air Quality Limit Values enforced in the UK and in the European Union (Continued)

Pollutant	Applies	Objective	Concentration measured as	Date to be achieved by and maintained thereafter	European obligations	Date to be achieved by and maintained thereafter	New or existing
Sulphur dioxide	UK	266µg.m^{-3} not to be exceeded more than 35 times a year	15 minute mean	31 December 2005			Retain existing
	UK	350µg.m^{-3} not to be exceeded more than 24 times a year	1 hour mean	31 December 2004	350µg.m^{-3} not to be exceeded more than 24 times a year	1 January 2005	
	UK	125µg.m^{-3} not to be exceeded more than 3 times a year	24 hour mean	31 December 2004	125µg.m^{-3} not to be exceeded more than 3 times a year	1 January 2005	
Polycyclic aromatic hydrocarbons	UK	0.25ng.m^{-3} B[a]P	as annual average	31 December 2010	Target of 1ng.m^{-3}	31 December 2012	Retain existing
Benzene	UK	16.25µg.m^{-3}	running annual mean	31 December 2003			Retain existing
	England and Wales	5µg.m^{-3}	annual average	31 December 2010	5µg.m^{-3}	1 January 2010	
	Scotland, Northern Ireland	3.25µg.m^{-3}	running annual mean	31 December 2010			
1,3- butadiene	UK	2.25µg.m^{-3}	running annual mean	31 December 2003			Retain existing
Carbon monoxide	UK	10mg.m^{-3}	maximum daily running 8 hour mean/in Scotland as running 8 hour mean	31 December 2003	10mg.m^{-3}	1 January 2005	Retain existing
Lead	UK	0.5µg.m^{-3}	annual mean	31 December 2004	0.5µg.m^{-3}	1 January 2005	Retain existing
		0.25µg.m^{-3}	annual mean	31 December 2008			

Supplementary to the ambient air quality standards, the UK has legislation specifically aimed at reducing on-road transport emissions. When a new motor vehicle is produced it must comply with all relevant standards, including EU emissions limits or ‘Euro standards,’ before it can legally be sold in the EU. The motor vehicle regulations set out type-approval procedures which are applied to specimen example vehicles prior to general sale (Bell and McGillivray, 2006). The road vehicle regulation requirements relate to a variety of details including catalytic converters, use of unleaded petrol and emissions levels for vehicles. These emission limits are more commonly known as ‘Euro’ standards and regulate carbon monoxide, Non-methane hydrocarbons, total hydrocarbons, NO_x and particulates emissions from tailpipe, evaporation and crank cases (Boulter *et al.,* 2009a). They were introduced in the UK in stages starting with Euro 1 in 1992 and the legislation now lays provisions for Euro 5/V and Euro 6/VI vehicles (EC, 2012b). With each successive standard being introduced the legislation is updated with Regulation (EU) No 459/2012 and Regulation (EU) No 64/2012 recently amending the regulations regarding Euro 6 light duty vehicles (cars and light vans: LDVs) and Euro VI heavy duty vehicles (HDVs) respectively (see EC, 2012b). It should be noted that roman numerals are used when considering Euro standards for HGVs and numbers are used when Euro standards for LDVs are documented.

The current emissions standard for LDVs is Euro 5, which entered into force in 2009 under Regulation (EU) 715/2007/EC. Its main focus was to reduce the emission of particulate matter from diesel cars from 25mg/km to 5mg/km. Euro 6 is scheduled to enter into force in 2014 and aims to reduce the emissions of NO_x from diesel cars from 180mg/km to 80mg/km. Similarly the current legislation in force for HDVs is Euro V which falls under Directive 2005/78/EC and aims to reduce NO_x emissions (40% reduction on Euro IV). Euro VI legislation for HDVs is set to come into force in 2013 and aims to reduce NO_x emissions by 80% relative to Euro V standards. In addition, the Euro VI standard will require diesel HDVs to comply with a particle number threshold as well as a limit value (Regulation (EU) No 582/2011).

The UK annual vehicle Ministry of Transport (MoT) test ensures that the Euro standards are upheld and checks compliance for smoke (diesel vehicles), CO and HC (petrol vehicles) which must not be exceeded (NAQS, 2007). An MoT test is mandatory for most vehicles in the UK over three years old. To comply with the Euro standards, vehicle manufacturers must also ensure that emissions abatement technology fitted to control pollution are able to last for a distance of 160, 000km (Boulter *et al.,* 2009a).

3.1.2 CO_2 Emissions Legislation in the UK

GHG emissions in the UK are primarily controlled by legislation that falls under the Kyoto Protocol. The meeting of world leaders in the city of Kyoto, Japan, in 1997 resulted in 15 EU member states as well as numerous countries worldwide signing a legally binding document confirming their agreement to reduce emissions of six GHGs to or below fixed targets by 2012 (UNFCCC, 1998). Of the 12 countries which have joined the EU since the Kyoto Protocol was agreed, all except Cyprus and Malta have individual emission reduction commitments under the Protocol (EEA, 2012a). The European Commission agreed to an aggregated 8% reduction in GHGs (relative to a 1990/1995 base year) by 2008-2012, requiring the UK to reduce emissions by 12.5% to meet the target (UNFCCC, 2008). In order to comply with the Kyoto targets the EU developed various initiatives through the first European Climate Change Programme (see EC, 2012c) including the European Emissions Trading Scheme (Directive 2003/87/EC), the development of joint implementation and clean development mechanism (see UNFCCC, 2012b). Of direct relevance to road transport was the Directive 2003/30/EC on the promotion of biofuels which required 5.75% of transport fuel to be biofuel by 2011.

The European Environment Agency estimated that the EU member states are currently over-achieving the 12% reduction target despite a lack of change in CO_2 emissions levels from the road transport sector (EEA, 2012a, 2012b). In 2009 a further legally binding commitment to a 20% reduction in EU GHG emissions from 1990 levels by 2020 entered into force through the EU climate and energy package (see Decision NO 406/2009/EC). However, in 2008 the UK set legally binding medium to long term GHG targets that go beyond those laid down in the EU package. The targets came into force under the UK Climate Change Act and require a reduction in GHGs of 34% and 80% by 2020 and 2050 respectively from 1990 base. The plans to meet these targets were documented in the White Paper 'The UK Low Carbon Transition Plan: Nation Strategy for Climate and Energy (Miliband, 2009).' The plans included the introduction of five-yearly carbon budgets to encourage emissions reductions (Table 5). These budgets are emissions caps that provide a benchmark above which GHGs levels must not stray. The budgets cover total GHG emissions from all sectors including road transport and the UK is about to enter into the second Budget (HM-Government, 2011).

Table 5 Carbon Budgets 1 to 4 for the time period 2008 to 2027 and associated % reduction from 1990 levels (HM-Government, 2011)

	Budget 1	**Budget 2**	**Budget 3**	**Budget 4**
Date	2008 - 12	2013 - 17	2018 - 22	2023 - 2027
Carbon Budgets ($MtCO_2e$)	3,018	2,782	2,544	1,950
Reduction below 1990 levels (%)	22	28	34	50

Legislation is currently in force in the EU and UK that specifically targets CO_2 emissions from road transport. In 2009 the Regulation (EU) No 443/2009 of the European Parliament and of the Council set emissions performance standards for new passenger cars as a part of the community's integrated approach to reduce CO_2 emissions from LDVs. The legislation set an average CO_2 emissions value of 130g/km for a manufactures fleet. This allows a manufacture to produce gross emitting vehicles but these must be offset by vehicles which emit below the target value. The legislation was phased-in commencing 2012 and requires 65% of the fleet to meet the 130g/km CO_2 emissions target. The % of a manufacturer's fleet meeting the target is to be tightened with 100% of the fleet complying by 2015. Failure to comply with the legislation results in a fine per car registered that is over the average emissions target value. The long term goal is to reduce the average fleet CO_2 emissions value to 95g/km by 2020. Similar legislation is set to enter into force in 2014 for light commercial vehicles (Regulation (EU) No 510/2011). However, the average fleet value for these vehicles is 175g/km, with 100% compliance by 2016. In the longer term the average fleet value is to be reduced to 135g/km by 2020. At present there are no CO_2 emissions limits for HDVs despite them accounting for 6% of total EU CO_2 emissions (EC, 2012d).

In addition to the average fleet CO_2 emissions targets, in 2008 the European Commission made revisions to the Directive 1999/94/EC on information relating to the fuel economy and CO_2 emissions of new passenger cars offered for sale or lease through the implementation of Regulation (EC) No 1137/2008. Directive 1999/94/EC was put in place to ensure that a consumer is presented with a vehicle's fuel economy and CO_2 emissions information prior to purchase. The revision made to the Directive harmonised the way in which the information is presented to allow for greater consumer awareness.

In order to encourage the uptake of more energy efficient lower carbon vehicles, the excise duty or 'road tax' for vehicles in the UK was calculated from the 1st March 2001 on the basis of engine size or type and CO_2 emissions (VCA, 2012). Owners of vehicle's emitting less CO_2 pay lower tax with owners of cars emitting less than 100g/km paying no road tax (DVLA, 2012).

3.2 Strategies to Reduce the Impacts of Congestion

Congestion occurs when the demand for travel becomes higher than the road network capacity (Hassan *et al.,* 2011). It results in traffic delay, queuing, stop-and-go conditions, low average-speeds and frequent acceleration and deceleration episodes (Stopher, 2004). These traffic characteristics in turn result in greater fuel use and higher tailpipe emissions (Sjodin *et al.,* 1998) and congestion is now prevalent in nearly every major city in the world (see Appendix A for a brief review of road transport's contribution to global and regional air pollution). Historically the UK government increased road capacity in order to reduce congestion and meet increased demand for road travel (Noland and Lem, 2002). However, a report ('Trunk roads and the generation of Traffic') issued to the government in 1994 by the Standing Advisory Committee for Trunk Road Assessment (SACTRA) resulted in a change of thinking due to the existence of a negative feedback mechanism associated with capacity increase (SACTRA, 1994). The report by SACTRA investigated the existence of induced demand in the UK. Induced demand occurs when increases in road capacity attract new traffic resulting in the partial or complete offset of the intent of the capacity increase (Hymel *et al.*, 2010). If the intended capacity increase was to reduce vehicle emissions (and improve air quality levels) then induced demand would directly limit the reductions observed.

The existence of induced demand is now widely accepted amongst researchers, with Goodwin (1992; 1996), Noland and Lem (2002), Kane and Behrens (2000) and Hymel *et al.* (2010) giving reviews of literature concerning induced demand and Noland (2001) documented the different modelling approaches used to estimate induced demand. The level to which induced demand affects road transport is a much debated topic in the literature. Some research has documented capacity increase to result in a substantial (25%>) increase in travel demand (e.g. Su, 2011; Noland, 2001; Downs, 1962; Smeed, 1968) whilst other research has found capacity increase to induce demand for travel only marginally (e.g. Hymel *et al.,* 2010). However, despite the debate the UK government has now switched from its 'predict and provide' approach to a more critical method of evaluating proposals for increased capacity (see Cook, 2011). As a result policy makers have had to switch their focus to invest in strategies that do not rely on capacity increase in order to alleviate congestion, reduce emissions from road transport and improve local air quality.

There are a number of different ways in which the impacts of road traffic congestion can be minimised including, making the vehicle fleet 'cleaner' through technological and fuel advancements, reducing the total amount of vehicle use (VKT) on the network and or decreasing the number of vehicles travelling to a congested area through traffic management strategies (re-routing of traffic, signal optimisation, ramp metering etc). The latter policy measures are less environmentally beneficial as they often involve the relocation of traffic which may result in air quality problems in other parts of the network (May, 1986). Some traffic management strategies aim to smooth traffic flows through signal optimisation (e.g. Li *et al.*, 2004; Chang and Park, 2012; McKenney and White, 2013; Varia *et al.*, 2013). However, such strategies have been documented to have little success in reducing emissions from vehicles in congested areas due to the fact that signal optimisation is ineffective in smoothing traffic flows on a section of the road network that is operating at capacity (Huang and Huang, 2003). As a result an area that is congested will gain no benefits from signal optimisation. In contrast, the introduction of new emissions abatement technology is considered key to reducing emissions from road vehicles. Furthermore, advances in abatement technology are necessary in order for vehicles to comply with stricter EU air quality legislation. Similarly, the uptake of cleaner vehicles, including alternative powertrain vehicles (referred to as 'low emissions vehicles' from here onwards) and those powered with less carbon intense and more efficient fuels, have been documented by King (2007) amongst others to be necessary in order for the UK to reach its legally binding CO_2 emissions targets. Vehicles powered by electricity have been around for many years (Camus and Farias, 2012) but their inability to compete with conventional vehicles (CVs) has meant they have had little uptake in the UK (Oxley *et al.*, 2012). However, recent advances in technology driven largely by legislation have meant that electric vehicles (EVs) and plugin-hybrud electric vehicles (PHEVs) are now highly competitive with internal combustion engine (ICE) vehicles fuelled with petrol or diesel (Gallardo-Lozano *et al.*, 2012). It should be noted that the term 'low emissions vehicle' in this research refers to PHEVs, EVs and 'zero' emissions vehicles (ZEVs).

Policies that aim to reduce VKT have been opposed by some in the literature on the grounds that they negatively impact on economic stability and social equality (see Moore *et al.*, 2010). However, Salon *et al.* (2012) documented that a reduction in VKT generates many benefits including the alleviation of traffic congestion, a reduction in toxic air pollutant and GHG emissions, a reduction in the dependency on foreign oil, and an improvement in public health through increased exercise. Given these benefits there is now more than ever a strong focus on policies that aim to reduce VKT. For example, the UK low carbon reduction strategy for transport set the goal of creating a modal shift from car use to public transport in order to decrease private VKT and subsequently reduce emissions (DfT, 2009b). The US Federal Surface Transportation Policy and Planning Act of 2009 (Commerce Committee, 2009) went a step further and set a specific goal to 'reduce national per capita motor vehicle miles travelled on an annual basis.' Policies that aim to reduce VKT, along with those technologies and fuels that have the potential to reduce emissions from road vehicles are described in more detail below.

3.2.1 Emissions Abatement Technology

Some of the most common emissions abatement technologies available were described in Chapter 2 (section 2.1.1). Their development has come about due to the need of manufacturing companies to comply with legislation. In the future the legislation concerning the emissions of toxic air pollutants from motor vehicles is set to get stricter. Therefore, emissions from road transport are expected to decline based on the assumption that new abatement technology will reduce vehicle emissions further (DfT, 2012b). However, in the past the introduction of emissions abatement technology (e.g. DPFs) and the emissions testing of such technology in some cases has not been successful. In order for maximum emissions reductions to be achieved in the future new abatement technology and dynamometer test cycles must be fit for purpose. This is particularly relevant given that it is expected that in the future the majority of Euro 5 and Euro 6 diesel LDVs and Euro VI HDVs will be fitted with DPFs (Boulter *et al.,* 2009).

3.2.2 Electric Vehicles (EVs)

EVs differ from CVs because they comprise an electric (and not mechanical) powertrain (Smith, 2010). As a result EVs have no tailpipe emissions (Nasai *et al.,* 2002). However, they are responsible for the pollutant and GHG emissions associated with the generation of energy from which they are 'fuelled' (Gould and Golob, 1998). It is this research area that has recently begun to receive more attention in the literature (e.g. King, 2007; Eyre *et al.,* 2002; Brady and O'Mahony, 2011; Oxley *et al.,* 2012; Pasaoglu *et al.,* 2012; Doucette and McCulloch, 2011a; Ma *et al.,* 2012; Smith, 2012; Camus and Farias, 2012; Faria, 2012; Varga, 2012) primarily because the environmental benefits of EVs are dependent on the source of energy from which they derive their power (Samuel, 1992).

For pollutant emissions, according to Deluchi *et al.* (1989), a 100% substitution of conventional passenger cars would result in the near complete elimination of CO and HC emissions and significant NO_x reductions. However, SO_2 emissions may increase if the energy generation is from coal fired power stations (which are the primary source of electricity in the UK). Similar findings to those of Deluchi *et al.* (1989) have more recently been documented by Gould and Golob (1998), Brady and O'Mahony (2011) and Oxley *et al.* (2012).

The CO_2 emissions associated with the introduction of EVs into the road network are very sensitive to the energy generation fuel mix (Doucette and McCulloch, 2011a). It is now acknowledge that in order for substantial (80-90%) GHG emissions reductions to be achieved from EVs a larger portion of the UK's energy generation must come from non-fossil fuel sources, such as nuclear power, geothermal, photovoltaic cells and wind turbines (RAE, 2010; King, 2007). In December 2010 the UK government announced that if 2050 climate change agreements were to be met then CO_2 emissions from the electricity sector must be largely decarbonised by the 2030s (DECC, 2010).

3.2.3 Hybrid Electric Vehicles

Hybrid electric vehicles (HEVs) differ from CVs as they use an ICE powertrain as well as an alternative powertrain (Alvarex *et al.*, 2010). The alternative powertrain is typically an electric motor coupled with an electric storage device, although fuel cells are less commonly used as alternative powertrains in HEVs (Doucette and McCulloch, 2011b). Fuel cells are discussed in section 3.2.3 and as such HEVs that use fuel cells are not discussed here. HEVs can be characterised into 'levels' (micro, mild, full or plug-in) depending on the hybrid components and technology they comprise (Fontaras *et al.*, 2008). Fontaras *et al.* (2008) documented a comparison of the technology and vehicle characteristics associated with the different levels of hybridisation which is shown in Table 6.

Table 6 Hybrid electric vehicle (HEV) characterisation with respect to hybridisation level (Fontaras *et al.*, 2008)

Vehicle operation	Conventional vehicle	Belt/muscle/micro hybrid	Mild hybrid	Full hybrid	Plug-in hybrid
Engine shut-off	Yes	Yes	Yes	Yes	Yes
Regenerative braking		Yes	Yes	Yes	Yes
Smaller IC engine compared to conventional			Yes	Yes	Yes
Electric drive				Yes	Yes
Electric grid battery recharge					Yes

PHEVs differ from conventional HEVs due to their higher battery capacity, the existence of an appropriate electrical output (plug) by which batteries can be recharged and due to the way in which the two powertrains interact (Silva *et al.*, 2009). The way in which the powertrains of PHEVs interact is dependent on their classification. PHEVs can be classed as series or parallel configuration (Kheir *et al.*, 2004). In a series configuration PHEV the ICE mechanical output is converted to electricity, which is stored in an on-board rechargeable battery which in turn is used by an electric motor to drive the vehicle (Adly *et al.*, 2006). In contrast, in a parallel configuration PHEV an electric motor assists the ICE in providing power for the vehicle as well as recapturing energy during deceleration (Zhaiu *et al.*, 2011). When an ICE is in use on-board a PHEV it is in charge sustaining mode (Silva *et al.* 2009). The ICE of a parallel PHEV can be shut off (known as charge depleting mode) allowing battery power to be used at lower speeds and for stop start driving (Eyre *et al.*, 2002). This can significantly reduce toxic pollutant tailpipe emissions and subsequently improve air quality particularly in urban areas where traffic congestion occurs frequently (Kantor *et al.*, 2010; King, 2007; Alvarex *et al.*, 2011; Eyre *et al.,* 2002; Zhaiu *et al.,* 2010). Relative to the ICE of CVs, the ICE for both series and parallel configuration PHEVs is typically downsized, which significantly improves fuel efficiency and can subsequently reduce both CO_2 and pollutant tailpipe emissions (King, 2007; Sioshansi *et al.,* 2010).

Given that PHEVs are charged from the electricity grid, emissions savings from the tailpipe are shifted to the point of energy generation when the vehicle is operated in charge depleting mode (Kong and Recker, 2009). In terms of air quality this is beneficial as power plants are typically located in remote areas away from population dense urban conurbations meaning the risk of human exposure to toxic species is reduced (Sioshansi *et al.,* 2010). However, CO_2 and other GHG emissions are a global problem and as such a shift from tailpipe to power plant is not of any great benefit unless the electricity generation is from low-carbon sources (Jansen *et al.,* 2010; Axsen *et al.,* 2011). As a result emissions from PHEVs are dependent on the energy generation mix (King, 2007). In general, the penetration of PHEVs charged from an electricity generation mix relying predominantly on fossil fuels (e.g. China) increases CO_2 emissions relative to a CV (Doucette and McCulloch, 2011b), those relying predominantly on renewables (e.g. Brazil) decrease CO_2 emissions and those relying predominantly on nuclear power (e.g. France) decrease CO_2 emissions but increase emissions of other GHGs (H_2O) (Silva, 2011). In addition, an energy generation mix with increased capacity of natural gas generators can reduce CO_2 emissions (Sioshansi and Miller, 2011). It should be noted that energy generation mix varies between regions and depending on time of day meaning where, when and how often a PHEV is charged influences emissions (Axsen *et al.,* 2011). It is beyond the scope of this research to document the variation in emissions associated with PHEV charging in detail. However, this subject is well documented in the literature (see Kong and Recker, 2009; Mullan *et al.,* 2011; Wang *et al.,* 2011; Weiller, 2011).

3.2.4 Well-To-Wheel, Well-To-Tank and Tank-To-Wheel Emissions

As mentioned above, PHEVs have point of use emissions (i.e. tailpipe emissions) and are responsible for emissions from electricity generation. The latter emissions are termed 'well-to-tank' (WTT) whilst the former are termed 'tank-to-wheel' (TTW) emissions (GM 2001). The Department of Environment, Food and Rural Affairs (DEFRA) defined WTT emissions as 'the emissions 'upstream' from the point of use of the fuel resulting from the transport, refining, purification or conversion of primary fuels to fuels for direct use by the end user and the distribution of these fuels (DEFRA, 2012c).' WTT emissions are estimated by investigating the different pathways of fuel production (e.g. JEC, 2011). In the case of PHEVs and EVs this involves estimating the emissions from the different pathways of electricity generation (e.g. burning of coal, natural gas, biomass etc.) and distribution and in the case of conventional fuels the different pathways of diesel and petrol production and distribution are explored (GM, 2001). In contrast, TTW emissions are estimated as described in chapter 2, with the UK 2009 emissions factors being estimates of TTW emissions rates (with adjustments for brake and tyre ware emissions).

By summing WTT and TTW the total or 'well-to-wheel' (WTW) emissions can be estimated. EVs have no TTW emissions and subsequently WTW emissions for these vehicles are equal to WTT emissions. WTW emissions for CVs and low emissions vehicles are often reported in the literature (GM, 2001; Wu *et al.*, 2012; Huang and Zhang, 2006; Wang, 2002; Huo *et al.*, 2009; Ma *et al.*, 2012; Bishop *et al.*, 2012). Perhaps the most comprehensive WTW analysis for Europe was documented by JEC (2011) in their research 'Well-to-Wheel Analysis of Future Automotive Fuels and Powertrains in the European Context.' The purpose of the study was to 'guide those who have to make a judgement on the potential benefits of substituting fuels by alternatives.' The study produced three reports. The WTT report established energy and GHG balance for the production, transport, manufacturing and distribution of a number of fuels suitable for road transport powertrains namely, petrol, diesel, Naphtha, compressed natural gas (CNG), liquid petroleum gas (LPG), hydrogen, numerous biofuels and electricity. The TTW report used the ADVISOR model to determine the fuel energy (MJ/km) necessary to perform the New European Driving Cycle (NEDC) and GHG (gCO_2eq/km) emissions during the cycle. The reference vehicle used in the model was typical of a 2002 European 5-door compact saloon car with a 1.6 l engine comparable to a VW golf. The vehicle was modified in the model to test different powertrains and fuels. For both the TTW and WTT reports only technologies that have the potential to become commercially available between 2010 and 2020 were considered. The final report compiled WTW emissions and evaluated the cost and practicality of the technologies considered.

The three JEC (2011) reports were subsequently used by DEFRA (2012c) as a basis for estimating WTT (termed 'scope 3' or 'indirect emissions' in DEFRA (2012)) GHG conversion factors for company reporting. DEFRA (2012c) provide a spread sheet which allows companies to calculate their TTW and WTT GHG emissions which is necessary for certain commitments (see DEFRA, 2010c). The TTW emissions factors used by DEFRA in their reporting spread sheet are single emissions rates weighted by vehicle age and activity of the UK fleet. The JEC (2011) data were used by DEFRA (2012c) to derive WTT emissions for LDVs, HDVs and low emissions vehicles (PHEVs) using simple ratios of TTW:WTT. The conversion factors for PHEVs estimate that WTT emissions account for 15% of WTW emissions. For LDVs and HDVs the % of WTW emissions attributed to WTT ranges from 11% to 17% with a fleet average of 16%.

Current air quality and climate change legislation in the UK covers only TTW emissions from road transport. In the future CO_2 emissions from transport may be extended to included WTT emissions. However, when considering air quality, it is not appropriate to allocate pollutant emissions emitted at one location to an air-shed a considerable distance away as the impacts of toxic air pollutants on the environment and its constituents are predominately confined to the locale in which they are released. Subsequently the inclusion of WTT emissions in air quality review and assessment is unlikely. This causes a significant issue when evaluating co-benefits of strategies and policies. On the one hand WTW CO_2 emissions are to be considered whilst on the other TTW pollutant emissions assessed. Ultimately, until legislation is updated policy makers in the UK remain obligated to meet EU Legislation concerning TTW emissions from road transport. For EVs, WTT emissions are currently assigned to the energy generation sector (DfT, 2011b). Similarly the emissions associated with PHEVs operating in charge depleting mode are assigned to the energy generation sector. In the future, if government plans to decarbonise the electricity grid (DECC, 2010) are implemented then EVs will become zero emissions vehicles.

3.3 Alternative Fuel Vehicles

In general diesel CVs have lower CO_2 emissions than petrol CVs due to the lower carbon content of diesel fuel (Boulter *et al.*, 2009a). However, diesel vehicles are also generally associated with higher NO_x, f-NO_2 and PM_{10} emissions than petrol vehicles (Rhys-Tyler *et al.*, 2011). Over the last decade there has been an increasing dieselisation of the European vehicle fleet (Schipper, 2011). As a result a shift towards research into alternative fuels that offer emissions reductions of both toxic air pollutants and CO_2 has occurred.

There are many fuels that are considered alternatives to conventional petrol and diesel. Those that can be used in CVs with little or no engine modification including LPG, biofuels and hydrogen are at an advantage over other alternative fuels as they can directly compete with petrol and diesel. These fuels are discussed in more detail in the following sections. However, other fuels such as CNG, which require significant cost to convert vehicle engines, remain relatively uncompetitive with CVs (King, 2007).

3.3.1 Liquefied Petroleum Gas (LPG)

LPG has been widely used in commercial vehicles during the last decade (Li *et al.*, 2007) and in the UK there are over 55, 000 LPG vehicles on the roads and in excess of 1,400 filling stations that offer LPG (Eyre *et al.*, 2002). The three major constituents of LPG are propane, iso-butane and n-butane which are together termed LPG alkanes (Lai *et al.*, 2009). The higher butane content of LPG relative to diesel and petrol fuels results in lower NO_x emissions (Saleh, 2008). Similarly, LPG contains less carbon molecules than petrol or diesel which results in a relative reduction in emissions of CO_2 (Saleh, 2008; Myung *et al.,* 2012). Additional benefits of LPG are that it is easily stored, low cost, and has a high combustion efficiency making it an attractive alternative to conventional fuels (Gumus, 2011).

3.3.2 Biofuel

The EU Renewable Energy Directive defines biomass as 'the biodegradable fraction of products, waste and residues from biological origin from agriculture (including vegetal and animal substances), forestry and related industries including fisheries and aquaculture, as well as the biodegradable fraction of industrial and municipal waste.' Biomass can be used to produce biofuels which can be used as an alternative fuel to conventional diesel or petrol (Bernard and Prieur, 2007; Acquaye *et al.,* 2012; Grupta and Demirbas, 2010). There are four main types of biofuels namely; alcohols (e.g. ethanol, methanol), which are made from fermented sugar crops (grain crops); biodiesel, which is made from the esterification of vegetable oils and methanol; natural gas (methane), which is made from the digestion of energy crops and so called second generation biofuels, such as dimethyl ether (DME) and synthetic biodiesel, that are made from the gasification of lignocellulosic biomass and synthetic processes (Biofuels Research Advisory Council, 2006). The latter came about due to growing concerns of increased deforestation and rising food prices as a direct result of the production of biofuels from food crops (see Gallagher, 2008). This topic remains much debated in the literature (see Goldemberg and Guardabarsi, 2009). As a result of these concerns processes were developed that produced biofuels from non-feed stock biomass (Pandey *et al.,* 2011). These biofuels are termed second generation and differ from other biofuels only by the way in which they are produced (see Biofuels Research Advisory Council, 2006).

Emissions from the combustion of biofuels vary depending on the fuel composition (Hammond, 2008). It is beyond the scope of this research to review the associated toxic pollutant and CO_2 emissions from every biofuel or biofuel blend. However, Gaffney and Marley (2009) documented an overview of the general emissions levels from the combustion of biofuels relative to those from conventional petrol/diesel. A summary of the overview can be seen in Table 7. Although emissions of CO_2 from vehicles fuelled with alcohols or biodiesel are generally lower than those of a conventional vehicle, these liquid biofuels contain less energy than petrol or diesel (Biofuels Research Advisory Council, 2006). As a result more fuel has to be burnt to travel the same distance as a conventional vehicle (of similar type and specification) meaning overall alcohols or biodiesel have similar CO_2 emissions to that of petrol or diesel fuelled vehicles (Gaffney and Marley, 2009).

Table 7 Emissions from biofuel combustion relative to emissions from the combustion of conventional petrol/diesel fuel (Gaffney and Marley, 2009)

Biofuel	**Regulated Pollutant Emissions**	**Non-regulated Pollutant Emissions**	**Tailpipe CO_2 Emissions**
Alcohols (Ethanol/methanol)	Decrease except for NO_x which may increase	Significantly increase specifically aldehydes	Similar to petrol/diesel
Natural Gas (Methane)	Decrease CO, HC and NO_x	-	Lower CO_2 (but methane is a potent GHG)
Biodiesel	60% less CO, up to 80% increase in NO_x, PM_{10} and benzene	Increase in aldehydes	Similar to diesel

3.3.3 Hydrogen

Hydrogen can be combined with oxygen in a fuel cell to generate power which can subsequently be used to propel a vehicle (Bento, 2010). These vehicles are known as hydrogen fuel cell vehicles (HFCVs). Hydrogen has high energy efficiency by weight, it can be produced in large quantities and vehicles can be refuelled at speeds comparable to petrol/diesel vehicles, making it a highly competitive fuel for transport (Martin *et al.*, 2009). In addition, HFCVs have zero emissions at the tailpipe and if they are fuelled with hydrogen produced using electricity from renewable sources, then HFCVs emit no emissions at the point of energy generation (Sainz *et al.*, 2012). However, at present only controlled deployment has resulted in the penetration of HFCVs into the global vehicle fleet (Martin *et al.*, 2009). This is because of a number of barriers limiting their uptake primarily surrounding lack of refuelling infrastructure and storage (Hu and Green, 2011). Hydrogen fuel easily leaks and is highly flammable meaning that it is a safety risk (Watanabe *et al.*, 2007; Houf *et al.*, 2012). In addition, hydrogen's low density limits the amount of storage on-board a vehicle (Mori and Hirose, 2009). As a result, advances in storage technologies and the subsequent deployment of such technology in vehicle development and for refuelling are required in order for hydrogen to become a sustainable fuel of the future (King, 2007; Ogden and Nicholas, 2011; Park *et al.*, 2011; Eyre *et al.*, 2002).

3.4 Rebound Effect

Advancement in vehicle technology, fuel and drive trains are seen as primary drivers in meeting air quality limit values and climate change targets. However, it is now widely accepted these advancements are subject to a feedback mechanism termed the rebound effect (Sorrel and

Dimitropoulos, 2007). Berkhout *et al.,* (2000) provide a rigorous definition of the rebound effect and so it is only briefly described here. There are three types of rebound effect which Greene (2012) described as; 1) when improved fuel efficiency reduces the cost of travel inducing travel (direct rebound effect); 2) consumption of other goods and services lowers the cost of travel inducing more demand (indirect rebound effect); 3) when a reduction in the demand for energy reduces its price encouraging increased consumption (economy-wide rebound effect). Studies in the literature have primarily focus on estimating the size of the direct rebound effect (i.e. the per cent of savings offset by the increased demand) on personal transport. For example, Su (2012) estimated the direct rebound effect to be between 11% and 19% for petrol cars in the US using 2009 National Household Transportation Data. Hymel *et al.* (2010) estimated the rebound effect of 4.7% in the short run and 24.1% long run for the USA states using cross-sectional time series data for 1966 through 2004 and Goodwin *et al.* (2004) reported the rebound effect varying between 4% and 89% based on an international survey. However, literature documenting estimates of the rebound effect within the on-road freight sector has been increasing (e.g. Winebrake *et al.,* 2012; Ruzzenenti and Basosi, 2008) and Matos and Silva (2011) found that a 1% increase in diesel fuel efficiency of freight in Portugal resulted in a reduction in energy consumption of 0.759%. This is equal to a direct rebound effect of 24.1%, 0.87 million litres of diesel per year and substantial NO_x and PM_{10} vehicle emissions.

As highlighted above direct rebound effects vary considerably. They are sensitive to the energy service studied (e.g. personal transport or freight, petrol or diesel fuel) the time frame analysed (i.e. long or short run definitions) and the model approach adopted (Matos and Silva, 2011). Current estimates of rebound effects documented in the literature vary due to the way in which researchers incorporate these sensitivities into their investigations. Perhaps the most compressive review and meta-analysis of recent literature concerning direct rebound effects was carried out by Sorrel and Dimitropoulos (2007) who analysed the methods and identified strengths and weaknesses of 17 studies on road transport rebound effects. From the studies they found long run rebound estimates to range between 3% and 87%, with the higher end of the range being associated with data for the US (see Greene (2012) for a review on estimates of rebound effects in the US). Their critical review of the literature allowed Sorrel and Dimitropoulos (2007) to provide a 'best guess' estimate for long run rebound effects of between 10% and 30%. However, they concluded that the 'current research state of knowledge on direct rebound effect is insufficient for policy' and suggested that more empirical work was needed. Since the analysis of Sorrel and Dimitropoulos (2007) further support for long run rebound effects between 10% and 30% have been documented by Matos and Silva (2011), Su (2012), Hymel *et al.* (2010) and Greene (2012) indicating a consensus amongst some researchers. However, other subsequent research does not support the findings of Sorrel and Dimitropoulos (2007). For example Wang *et al.* (2012) estimated a rebound effect of 35% between 1999 and 2009 for the passenger transport sector in Hong Kong. The differences observed between estimates made by Wang *et al.* (2012) and those made by Sorrel and Dimitropoulos (2007) are more than likely due to geographical variation in rebound effects (Sorrel and Dimitropoulos (2007) did not review any studies in Asia) an area in which Sorrel and Dimitropoulos (2007) suggested more empirical research was needed.

3.5 Reducing Vehicle Kilometres Travelled

Given that a rapid increase in VKT has resulted in high emissions and poor air quality throughout the world (Youngkook and Guldmann, 2011), it follows that a reduction in VKT will reverse this trend. The impact of a reduction in VKT on emissions of toxic air pollutants and CO_2 emissions has recently been highlighted with the onset of the global economic crisis. For example, in the UK between 2007 and 2008, total road traffic decreased by 3.6 billion VKT (0.7%) (ITF, 2010b). During the same period DECC (2011a) documented CO_2 emissions from road transport to have fallen by 0.1% and the DfT (2012b) documented substantial reductions in NO_x, CO_2 and PM_{10} emissions from road transport between 2008 and 2010 (see Appendix A, Figure A.2). In addition, the IEA (2009) estimated that growth rates in CO_2 emissions from transport in developed countries dropped sharply in 2008 and absolute emissions of GHGs dropped more in 2009 than in any other time in the past 40 years due to a reduction in VKT. Similarly the benefits of a reduction in VKT have been further highlighted recently by Zhou *et al.* (2010) who found a 32% reduction in VKT in Beijing during the 2008 Olympic Games to have reduced urban VOC, CO, NO_x, and PM_{10} concentrations by 55.5%, 56.8%, 45.7% and 51.6% relative to ambient pollution levels before the games.

As a result of these environmental benefits decision makers have considered and implemented numerous different policy measures in an attempt to decrease VKT many of which were reviewed by Cameron *et al.* (2004). The review by Cameron *et al.* (2004) documented the policy measures introduced by governing bodies in Singapore, Hong Kong, Munich, Stockholm, New York and Perth between the 1960s and 1990s in order to reduce VKT. A summary of these policy options can be seen in Table 8. Broadly the measures for reducing VKT fall under three main policy instruments namely; financial incentive or disincentive, land-use planning and investment in public transport (Perdue *et al.* 2011).

Table 8 Summary of measures introduced by governing bodies between 1960 and 1990 in various cities in order to reduce vehicle kilometres travelled (Cameron *et al.*, 2004)

Measure to Reduce VKT between 1960 and 1990		Singapore	Hong Kong	Munich (Germany)	Stockholm (Sweden)	New York (US)	Perth (Australia)
Fiscal increases in…	Import Taxes	✓					
	Registration Tax	✓	✓				
	Road Taxes	✓		✓			
	Zone Based Charging/Licensing	✓	✓				
	Parking Charges			✓	✓		
	Fuel Tax		✓				
	Vehicle License Fees		✓				
Land-Use Planning	Narrowed Streets			✓			
	Pedestrian only City Centre			✓			
	Limitation of Urban Sprawl				✓		
Public Transport	Modal Integration of Public Transport Services				✓		✓
	Investment in Public Transport	✓	✓	✓	✓	✓	✓

Cameron *et al.* (2004) suggested that those fiscal measures implemented in Singapore and Hong Kong, namely the taxing of fuel, registration and licensing of vehicles and road user charging, appeared to have been the most successful as the traffic volume in Singapore decreased by 45% between 1970 and 1980 and Hong Kong had no significant increase in vehicle ownership between 1980 and 1990. Similar policy measures have been implemented elsewhere in the world (Kenworthy and Laube, 1999; Newman and Kenworthy, 1996; May, 1986) and a substantial amount of literature has focused on evaluating the impact of road user charging on local emissions and air quality (Eliasson *et al.,* 2009; McKinnon, 2006; Mitchell *et al.*, 2005; Beevers and Carslaw, 2005; Mitchell, 2005; Johansson *et al.*, 2009; Borjesson *et al.*, 2012; Santos *et al.*, 2004).

In 2003 congestion charging in London was introduced and in 2007 the zone was extended (Beevers and Carslaw, 2005). A recent report by Transport for London revealed that although early indications suggested decreases in congestion relative to 2002, in 2008 there was no difference in congestion, emissions or air quality levels between pre and post implementation of the charging scheme (TfL, 2008). Furthermore, the report documented that traffic on the boundary of the congestion charging zone increased by 4% due to adjustments in traffic signals. This highlights a major issue with such schemes in that although they aim to reduce the VKT within a specific area through financial disincentives they often result in the build-up of diverted traffic elsewhere in the road network which ultimately maintains or exacerbates air quality problems (May, 1986). Furthermore, Santos *et al.* (2004) documents that the failure of the London congestion charging scheme is due to the fact that the scheme in London, unlike that implemented in Singapore, does not charge users on a per entry basis which suggests that the scheme is not stringent enough to facilitate a modal shift to public transport and subsequently to reduce private VKT. Charge per entry congestion schemes have been implemented elsewhere in the world some of which similarly appear to have been too modest to have resulted in significant air quality benefits. For example, although Johansson *et al.* (2009) found NO_x and PM_{10} emission reductions of 8.5% and 13% to have occurred during the Stockholm congestion pricing trail during January 3 to July 31 2006 exceedences in ambient air quality limit values were still observed on the most densely trafficked streets within the charging area. The congestion pricing scheme in Stockholm in 2007 was made permanent but results to date show that it has had little impact on congestion in the city (Borjesson *et al.*, 2012).

Other zonal based charging schemes include low emissions zones (LEZs) which typically impose a financial penalty on those entering in vehicles which do not meet certain emissions standards (Carslaw and Beevers, 2002). LEZs have now been implemented in 152 cities in nine EU countries (Wolff and Perry 2010). Although the primary aim of these schemes is not to reduce VKT, such a reduction may indirectly occur if financial penalties are high enough to facilitate a modal shift to other modes of transport, such as rail. However, the success of such schemes in substantially improving air quality is not widely documented, for example Jones *et al.* (2012) found that only a small reduction, if any, in particulate number may have occurred as a direct result of the London LEZ and Boogaard *et al.* (2012) documented there to be no air quality improvement in five Dutch cities despite the implementation of LEZs.

It is evident from Table 8 that if road charging, LEZs and other financial measures are to be successful in delivering even small environmental benefits, investments must be made in public transport in order to encourage a modal shift and reduce dependence on private vehicles for road travel. In the UK the 2011 government budgets revealed that funds available for investment in transport are to be cut from £5.5 billion in 2011 to £4.4 billion in 2015 (HM Treasury, 2011). However, during the same year a £560m Local Sustainable Transport Fund was announced which is to be partly used to make alternative modes of transport, including cycling, walking and public transport, viable options for the public (see DfT, 2011a). In addition, in 2012 the UK government agreed to proceed with the development of a new high speed rail network (HS2) which when developed will 'release space on the conventional railway for new commuter, regional and freight services' (see DfT, 2012c). If these new rail services are competitively priced relative to the costs of road travel then the HS2 has the potential to reduce personal car and freight VKT, decrease emissions from the road network and improve air quality.

Recently research has begun to focus on the impact of a VKT specific tax (Greene, 2011; McMullen *et al.*, 2010; Rufolo and Kimpel, 2008). The findings from the research to date suggest that a VKT tax has the potential to reduce VKT, traffic congestion and reduce emissions of toxic air pollutants and CO_2 (Sorenson *et al.*, 2009). In addition, such a policy may have the added benefit of limiting the impact of the rebound effect. However, at present a number of barriers exist, such as large capital investment, that have prevented the wide spread implementation of such policy measures (see Sorenson *et al.*, 2009; Greene, 2011).

A strong relationship exists between land-use and road transport (see Newman and Kenworthy, 1996). Expanding cities fuelled by economic growth have resulted in greater commuter distances and more trips (Zhao, 2010). Large metropolitan areas with high levels of urban sprawl have been shown to have a greater number of pollution exceedences (Stone, 2008) and the correlation between road transport CO_2 emissions and urban sprawl has been documented to be much stronger than correlations between transport emissions and GDP or population data (Bart, 2010). As a result a large amount of research has focused on identifying the impacts of limiting urban sprawl. For example, Heres-Del-Valle and Niemier (2011) documented that a 10% increase in residential density would reduce vehicle miles travelled in California by 1.9% and results from a modelling study by Hankey and Marshall (2010) suggest that cumulative GHG emission from road vehicles could be reduced by 15% to 20% between 2000 and 2020 in the US through restriction of urban sprawl. Similar modelling studies have been documented by Travis *et al.* (2010), Garcia-Palmares (2010), Anas and Pines D, (2008). In addition, Cameron *et al.* (2004) found the development of land with high employment and residential densities in close proximity to public transport hubs to have partly limited the impact of vehicle emissions on air quality in Stockholm. However, despite the air quality and GHG benefits that can be achieved through limiting urban sprawl, policy measures that focus on increasing residential densities are restricted temporally as land-use changes are only effective over the medium to long term (Dulal 2011). Stern (2006) highlighted that in order for significant environmental deficits to be avoided action is needed now and should be sustained in the future. Subsequently land-use change alone cannot be relied upon in order to achieve CO_2 emissions targets from the road transport sector.

In the future it is likely that fiscal measures, land-use planning and investment in public and alternative modes of transport will continue to be used in conjunction in order to reduce VKT. However, to date such policy packages have been ineffective in reducing the VKT in urban areas to levels that result in acceptable air quality. All of the cities documented in Table 8 presently have significant air quality problems to which road transport is a major contributor despite the introduction of measures to reduce VKT (see DEC (2012a) for New York; EPD (2011) for Hong Kong; DEC (2012b) for Perth; DUPBR (2006) for Munich; Johansson *et al.* (2009) for Stockholm). Even Singapore has significant air quality problems which are particularly highlighted when assessing PM_{10}

pollutant concentrations against EU air quality limit values (see NEA, 2012). As a result policy that aims to reduce VKT must get stricter in order for global CO_2 emissions and local air quality targets to be met. Furthermore, a more aggressive reduction in VKT will allow greater environmental benefits from technological advancements to be realised without being offset.

3.6 Modelling the Impact of Road Transport Strategies on Toxic Air Pollutant and CO_2 Emissions

There has been an increase in the number of studies modelling the impact of strategies and policies on vehicle emissions from road transport. Some of these have focused on the impact of low emissions vehicles. For example, Brady and O'Mahony (2011) predicted a 25% substitution of conventional vehicles to EVs by 2020 from a 2008 base-case in Dublin to reduce CO, NO_2 and NO_x emissions by 80%, 69% and 38% respectively. Kantor *et al.* (2010) estimated the penetration of fuel cell plug in hybrid vehicles to reduce GHG emissions in Ontario, Canada, by 3 – 6% and PHEVs and FCVs to reduce GHGs by 3 – 3.5% based on a modelling period between 2008 to 2025. Pasaoglu *et al.* (2012) documented 35%, 45% and 75% reductions in CO_2 due to the low, medium and high penetration of low emissions vehicles into the European fleet over a 40 year period (2010 to 2050). Some of those studies focus solely on the impact of alternative fuels or those that model the impact of improved abatement technology on emissions from road transport. For example Goncalves *et al.* (2009) estimated significant reductions in NO_x, PM_{10}, SO_2, CO and NMVOCs when conventional buses, taxis, heavy duty freight vehicles, LDVs and passenger cars were substituted with vehicles fuelled with CNG and Kassomenos *et al.* (2006) estimated reductions in CO, benzene, PM_{10}, NO_x and VOCs of 41%, 58%, 12%, 23% and 27% respectively when pre-Euro (non-catalytic) vehicles and Euro I vehicles were replaced with vehicles meeting the Euro III emissions standard on selected roads during a typical working day in Athens in 2002. Similar studies concerned with modelling the impact of improved pollutant abatement technology on emissions from road vehicles have been documented by Collet *et al.* (2012) and Ginnouli *et al.* (2011).

Despite the growing body of literature modelling the impact of strategies on vehicle emissions from road transport, those strategy modelling studies that consider both toxic air pollutants and CO_2 remain relatively few in number. Thambiran and Diab (2011) modelled the impact of a change in technology, fuel and VKT on pollutant (NO_x, CO, PM, SO_2) and CO_2 emissions in South Africa. They concluded that a reduction in VKT and the removal of the oldest vehicles in the fleet were the best options for air quality improvement and CO_2 reduction. Brady and O'Mahony (2011) modelled the low medium and high penetration of EVs into the Dublin vehicle stock and found modest reductions in CO_2, CO, VOC, PM, NO_2 and NO_x emissions. Major emissions reductions were observed under the business as usual strategy as a result of the introduction of Euro 5 and Euro 6 technologies. Oxley *et al.* (2012) modelled the impact of numerous strategies on pollutant concentrations and CO_2 emissions for the road network in the UK based on 2008 data and a 2020 target. Their study is distinguishable from other studies because of the large number of strategies modelled namely, changes to the petrol - diesel split, reduced car engine sizes, a reduction in vehicle miles travelled, penetration of EVs and PHEVs, increased use of biofuels and the reduction in average CO_2 emissions from cars. In addition, the modelling approach adopted by Oxley *et al.* (2012) involved the integrated use of an emissions model (IMOVE) and an atmospheric dispersion model (BRUTAL) which allowed air quality policy makers to assess concentration values (although air quality and GHG emissions can only be compared at an emissions level as ambient levels of CO_2 are not toxic to humans).

In general, these studies aimed to evaluate the impact of fixed % strategy changes (relative to the base-case) on vehicle emissions. For example, Thambiran and Diab (2011) modelled 20% strategy changes in vehicle technology, fuel and VKT. Brady and O'Mahony (2011) modelled the low (10%), medium (15%) and high (25%) penetration of EVs and Oxley et al. (2012) modelled a number of fixed % changes e.g. 5% fuel blends of biofuel. Similarly, Schrooten *et al.* (2006), Che et al. (2011), Hao *et al.* (2011), Leighty (2012), Goncalves *et al.* (2009), Pasaoglu *et al.* (2012) and Collet *et al.* (2012) all adopted fixed % strategy change modelling approaches to assess emissions of either toxic air pollutants or CO_2. The % change modelled is typically decided upon using extrapolation of historic data (e.g. Huo *et al.*, 2012c), logistic curves (e.g. Brady and O'Mahony 2011), planned legislation (e.g. Rouston *et al.*, 2011) or socioeconomic models and indicators (e.g. Shakya and Shrestha, 2012). Fundamentally, these types of study ask 'what if questions' i.e. 'what will happen to emissions if I implement a strategy change of..' Such an approach to strategy modelling is adequate for evaluating the impact of imminent policies and legislation. However, as a method for the development and exploration of new policy options this approach is limited as it does not provide flexibility to the policy maker to compare numerous levels of change. Furthermore, given that policy makers are obligated to meet legislation and targets it would be more beneficial for modelling approaches to answer research questions such as 'what change is needed to reach my target of..'. The majority of current fixed % strategy approaches, whilst adding to the air quality and CO_2 policy knowledge base do not enable such a question to be answered. This is perhaps best highlighted in the work of Kromer *et al.* (2010) who adopt a 'what if' approach to assess the impact of vehicle technology (25% or 50% private cars to PHEVs and EVs) on CO_2 emissions in the USA. Their findings were that none of the low emissions vehicle strategies modelled met the target of an 80% reduction in CO_2. Such a conclusion would be adequate if the modelling study was exhaustive i.e. 100% of passenger cars were replaced with PHEVs or EVs. However, this was not the case. The work only informs of those fixed changes that are not able to bring about the required emissions reductions. A flexible and exhaustive approach that allowed for the identification of either those strategies that could meet the target or those that under maximum change could not would be much more beneficial.

Current modelling literature (see those documented above) concerning air quality and climate change typically allows vehicle numbers to increase to represent the demand for road transport. However, a change in vehicle numbers affects vehicle flow which in turn impacts on vehicle dynamics (speed) and ultimately emissions rates. The current literature generally allows vehicle numbers to increase whilst neglecting the change in vehicle dynamics. In an ideal situation traffic simulation models should be re-run for each strategy prior to emissions modelling to allow for changes in vehicle dynamics as a result of a strategy or policy implementation to be represented in the modelling. In reality the computation time of such an approach prevents it from being a viable option. However, a way around this is to fix vehicle numbers at base-case level which would not only prevent changes to vehicle dynamics but would also model a more stringent VKT restriction which the literature suggests is needed for air quality and climate change targets to be met.

3.7 Chapter 3 Summary

Technology, low emissions vehicles, fuels and a reduction in VKT have the potential to reduce emissions of toxic air pollutants and or CO_2 from the road transport sector. Attempts to decrease emissions from road traffic and improve air quality by reducing VKT have been ineffective suggesting more stringent strategies are needed. Furthermore, studies modelling the impacts of strategies on emissions of both toxic air pollutants and CO_2 remain relatively few in number. Those that have been documented do not provide flexibility to the policy maker to compare numerous levels of strategy change. A flexible and exhaustive approach that allows comparison of different levels of change whilst enabling substantive conclusions (about whether or not a strategy has the potential to deliver a 'win-win' for air quality and climate change) would be much more beneficial.

Chapter 4

4. Methodology of Research

In this chapter the method used in this research is described. It should be noted that more detailed descriptions of the work undertaken are laid out in the subsequent relevant chapters of this thesis. The work undertaken focused on road transport in the city of Leicester. Leicester was chosen as a case study for this research due to academic and technical reasons. The academic reasons are; it is a medium sized UK city whose characteristics are typical of other cities in the UK (e.g. dense urban infrastructure, high traffic flows and heavy congestion in the city centre) and; it's CO_2 and air quality policy is similar to that of other local authorities. Therefore, using Leicester as a case study would enable outcomes of this thesis to be applicable throughout the UK. The academic reasons for choosing Leicester as a case study for this research are; 1) comprehensive historic traffic, air quality and meteorological data are readily available; 2) Leicester has a very good air quality monitoring system in place; 3) both traffic and air quality models for Leicester are available for use in this research and; 4) this thesis was funded by the EPSRC under the 4M Project whose primary aim was to model, map, monitor and manage Leicester's carbon footprint. A general description of Leicester is provided below.

Leicester is located in the East Midlands and is one of the largest cities in the region. It is situated on the River Soar ~99 miles north of London by rail. In 1964/65 the M1 was built around Leicester and in 1976/77 the M69 to the West Midlands followed making Leicester a transport hub of the Midlands (LCC, 1995). In 2005 Leicester had a population of 291, 000 people (DECC, 2011b). This is an increase of ~12, 000 people since the 2001 census (LCC, 2001). The census revealed that 38% of households in Leicester owned a car with almost 50% of people travelling to work by this mode and ~15% of people travelling to work by bus, mini-bus or coach (Table 9). On road transport was the dominant travel mode and has had a substantial impact on the air quality and CO_2 emissions in Leicester.

Table 9 Comparison of the percentage travel mode adopted by inhabitants of Leicester in order to get to work in 2001 (LCC, 2001)

Travel Mode	Leicester (%)	England & Wales (%)
People who work mainly at or from home	7.53	9.19
Underground, metro, light rail, tram	0.09	3.01
Train	0.81	4.08
Bus, mini-bus or coach	15.23	7.40
Motorcycle, scooter or moped	0.69	1.09
Driving a car or van	47.47	55.23
Passenger in a car or van	7.59	6.25
Taxi or minicab	0.40	0.52
Bicycle	4.00	2.76
On foot	15.83	10.01
Other	0.38	0.47

As a part of the review and assessment process, in 2000 Leicester City Council (LCC) carried out detailed air quality monitoring followed by pollutant forecasting (LCC, 2000). It was identified that by 2005 the annual EU air quality limit value for NO_2 ($40\mu g/m^3$) would not be met. As such the LCC declared an AQMA within its authority area (see Figure 1, section 4.3 below). In 2005 monitored NO_2 data proved the forecasting to be correct with some places within the city exceeding the limit value by 25% (LCC, 2011a). Further review and assessment found that 95% of local NO_2 was as a result of road traffic. As a result Leicester's 3rd local transport plan (LTP 3) focuses on the development of an improved public transport network and a series of traffic demand management measures in order to encourage the greater use of public transport, less private car use and ultimately to improve air quality within the city (LCC, 2011b).

In addition to the toxic air pollutant emissions limit values, the LCC has set ambitious CO_2 targets. The LCC aim to reduce total carbon emissions by 50% based on 1990 levels by 2025. By 2005 road transport CO_2 emissions in Leicester were 12% lower than 1990 levels meaning an additional 38% reduction is required to meet the 2025 target (LCC, 2011b). In 2005 the dominant source of CO_2 emissions in Leicester was from the industrial and commercial sector (LCC, 2006). The domestic sector was the second highest contributor followed by the road transport sector. However, between 2000 and 2004 road transport in Leicester increased by 8% (LCC, 2006).

Leicester's ambitious CO_2 targets and the city's non-compliance with EU air quality limit values has led to the requirement for road transport strategies that reduced CO_2 emissions and improve air quality ('win-win'). This research investigated the impact of a VKT restriction and a change in technology, vehicle or fuel on emissions from the road transport sector in Leicester. The method used is described below.

4.1 Method

Figure 1 shows a detailed flow diagram of the method used in this research. In addition, the figure shows where each objective was met in the methodology. In summary, a base-case TTW emissions inventory was compiled using data provided from the LCC and using the Platform for Integrated Transport and Health Emissions Modelling (PITHEM; Namdeo *et al.*, 2011). The traffic dataset used in this research and PITHEM are described later in this chapter. The accuracy of the inventory was estimated through the use of an air quality model, ADMS-Urban. In order to compile the base-case inventory factor and cluster analysis were applied to traffic data (provided by the LCC) to classify roads in to groups. This enabled classification specific diurnal flow profiles to be specified prior to air quality modelling. For clarity the fundamental principles of factor and cluster analysis are elaborated further in Chapter 5 in the context of the analysis method.

The emission inventory and diurnal profiles along with meteorological data provided by the LCC were used as input for ADMS-Urban. Air quality modelling was subsequently carried out to estimate the accuracy of the emissions inventory compiled. The base-case emissions inventory was then edited to reflect a change in vehicle, fuel or technology and emissions were recalculated. In addition, a VKT restriction was imposed on the vehicle fleet that did not allow any increase in VKT from the base year. Maintaining VKT at 2005 levels imposed a strict restraint on the Leicester fleet, resulted in the rebound effect being zero and minimised issues concerning changes in vehicle dynamics (e.g. speed and flow change when VKT increases) associated with strategy modelling. The strategy changes to the base-case were made in increments of 5% until 100% was reached (e.g. 5%, 10%, 15% etc. of cars were changed to ZEVs). The changes in emissions relative to the base-case for each strategy were plotted and regression was used to interpolate between the 5% increments. Output of the regression equations allowed any % strategy change to be modelled and subsequent emissions analysed. In addition, the regression equations were used to create data tables which enabled the change required to bring about a 38% reduction in CO_2 (relative to the base-case) to be identified or firm conclusions regarding the ineffectiveness of the strategies to be made. Those strategies that provided a reduction in CO_2 and toxic air pollutants (‘win-win’) were identified and those that resulted in a trade-off were discussed. Finally, the total change in emissions for each road classification relative to the base was calculated for each strategy. This allowed the impact of the strategies to be assessed relative to road classification characteristics and geographical locations.

Figure 1 Method Flow Diagram

Traffic Data from Strategic Transport Model (SATURN)

Leicester City Council (LCC) provided traffic data output from their strategic transport model for the year 2005. In addition, the LCC provided point source and area source emissions data, as well as meteorological data for the same year.

Objective 1

A Novel Application of Factor and Cluster Analysis for Classifying Roads

Factor and cluster analysis were used to classify roads into groups to allow for the assignment of diurnal profiles prior to air quality modelling. Factor analysis was used to infer the number of cluster seeds prior to a cluster analysis (k-means). Roads were subsequently grouped into classifications by the k-means algorithm. The classification specific road characteristics were explored.

Objective 2

Diurnal Traffic Flow Profiles

Halcrow Ltd. provided a set of interpolation factors that were used to calculate traffic flow per hour. Classification specific diurnal profiles were then calculated for weekdays based on average flows. National diurnal profile data was used to construct weekend flow profiles as there were no weekend data available.

Objective 1

Emissions Calculation

Platform for Integrated Transport and Health Emissions Modelling (PITHEM) was used to calculate link based CO_2, NO_2, PM_{10} and f-NO_2 emissions. The software incorporated the DfT 2009 emissions factors and alternative low-carbon vehicle emissions factors from the DfT Low-Carbon Tool. These factors along with average flow and speed data, vehicle fleet composition and diurnal profiles were used to calculate link based emissions rates for the base year 2005.

Objective 1

Dispersion Modelling

An air quality model cannot be evaluated without simultaneously assessing the accuracy of its input data. Therefore, in order to assess the accuracy of the emissions inventory compiled the 2005 base case data was input into an air quality model, ADMS-Urban. The model performance was evaluated through the comparison of model outputs with observed pollutant concentration data according to the evaluation framework described by Chang and Hanna (2004).

Objective 3

Strategy Modelling

The base-case data was edited in 5% increments (until 100% change was reached) to reflect a change in technology, fuel or vehicle within the Leicester fleet using PITHEM (e.g. 5%, 10%, 15% etc. of cars were changed to ZEVs). In addition, VKT was restricted meaning the rebound effect was zero. Emissions changes relative to the base-case were plotted for each strategy and regression was used to interpolate between data points allowing the emissions from any % strategy change to be modelled. Those strategies that provided a win-win for air quality and climate change were identified and those that resulted in a trade-off were discussed. Data tables were compiled using the regression equations allowing a ‘what change is needed to meet my target of…’ approach to be adopted. Subsequently, those strategies that resulted in a 50% reduction in CO_2 were identified and their associated pollutant emissions were assessed.

Objective 4, 5 and 6

4.2 Data and Software Used

The LCC provided a substantial amount data for use in this research, namely traffic activity data from a strategic transport model, geographical co-ordinates of links within the LCC LA area, meteorological data, emission rates for domestic and commercial non-mobile sources and an annual profile that represented fluctuations in Leicester's month by month traffic flow throughout the year (see Appendix D for domestic and non-domestic source locations and month by monthly traffic profile). In addition, Halcrow Ltd (2009) provided interpolation factors that enabled the development of diurnal traffic profiles and national data was used to partially define vehicle fleet composition.

The specialist software used in this work included the PITHEM and ADMS-Urban. In addition, SPSS and Microsoft excel were used for statistical analysis and data manipulation. The software and data used in this thesis are described in the subsequent relevant chapters of this work. However, in the following sections the traffic data set used and the PITHEM software are described.

4.3 The Traffic Data Set

The traffic data used in this research was derived from the Central Leicestershire Transport Model (CLTM) and included transport activity data and road vehicle fleet composition data. The CLTM comprised a number of sub models: transport forecasting, accessibility, modal splits, public transport utilisation and the assignment of vehicles to the highway network. Only the highway sub model (Simulation and Assignment of Traffic to Urban Road Networks; SATURN, Van Vliet 1982) was included in this research. The traffic data derived from SATURN was split into three vehicle types namely, HDVs (aritc and rigid HGVs), LDVs (cars and LGVs) and public transport (buses and coaches). Data for two wheeled vehicles was not available and as a result this vehicle class was not represented in this work. A total of 52 traffic activity variables for these vehicle types were used (see Appendix D). The activity variables included estimates of origin-destination (route-based) traffic flows, network speeds, link delay, link queue length and number of lanes on each road link. All of the traffic data were defined as weekday AM peak, PM peak or inter peak (IP), referring to events occurring between 07.00h-08.00h, 16.00h-17.00h and average hour between 10.00h-16.00h periods respectively for approximately 6000 road links across the Leicestershire area. This work considered only those roads that were located within the LCC LA area. Figure 2 shows the location of Leicester within the UK and the LCC LA area and associated road network. The LCC LA comprised 3748 road links. However, the CLTM was not developed to include every link within the LCC LA. Those links considered by the council to have very low traffic flows were not included in the model and equally were not included in this research. However, it is acknowledged that future work should look to quantify emissions from these missing roads.

Figure 2 The study area of Leicester (a,b,c; OS Maps 2013) and associated road network considered in this research (d,e,f; LCC, 2010)

4.4 Platform for Integrated Transport and Health Emissions Modelling (PITHEM)

A number of emissions models were considered for use in this research, including ADMS-Urban's in built emissions model, the UK government Emissions Factor Tool Kit (see DEFRA, 2009) and PITHEM. PITHEM was considered the most appropriate for use in the research as it was developed specifically to calculate emissions using traffic data directly output from the strategic transport model SATURN which was the source of traffic data in this thesis. In addition, PITHEM is extremely flexible allowing vehicles, technologies and fuels to be easily manipulated using its drop down menus and tick boxes. Therefore, the use of PITHEM substantially reduced data processing times whilst enabling the rapid editing of the base case to reflect various road transport strategies. Furthermore, the emissions factors in PITHEM are readily available (and accessible) meaning they can be compared as part of an assessment and evaluation procedure.

PITHEM enables the calculation of link specific emission rates based on traffic data. It allows for the manipulation of vehicle fleet compositions at the Euro class level. PITHEM uses vehicle flow and speed coupled with the 2009 DfT average-speed TTW emissions factors (see Boulter *et al.*, 2009a) to calculate traffic related emissions. This methodology is consistent with that recommended by the UK Department for Energy and Climate Change (DECC) in the production of their 'Local and Regional CO_2 Emissions Estimates' (DECC 2011b). The UK average-speed emissions factors vehicle fleet composition structure is split into seven levels namely, total fleet (Level 0), vehicle type (Level 1), vehicle type (Level 2), vehicle fuel (Level 3), weight/type (Level 4), engine size (Level 5) and emissions standard (Level 6) (Figure 3). The vehicle fleet composition structure in PITHEM has the same number of levels but is reordered to enable data from transport models to be entered more easily i.e. bus and HGV data are not linked to take into consideration that SATURN provides separate traffic flows for HDVs and public transport (Figure 4). In addition, PITHEM comprises WTW CO_2 emissions factors for PHEVs and EVs from the DfT Local Authority Carbon Tool (DfT, 2011b). The emissions factors for these vehicles differ from those developed by Boulter *et al.* (2009a) as they are based on a single average emissions factor and not on speed (DfT, 2011c). The average emissions factor specified for PHEVs and EVs defined in PITHEM is 97.3gCO_2/km and 53.4gCO_2/km respectively. The vehicles used to derive the average emissions factor for EVs included the Nissan Leaf, Mitsubishi iMiEV, Renault Fluence and Renault Zoe (DfT, 2011c). The average emissions factor for PHEVs was based predominantly on the Plug-in Toyota Prius (DfT, 2011c). Sales data and technical specifications of EVs and PHEVs were used by the DfT to estimate fuel and electricity consumption per km for these vehicles. The UK energy generation mix for 2011 (Table 10) was subsequently used to calculate a sales weighted average CO_2 emissions factor. It should be noted that the sales data and exact vehicle types and specifications used to develop the average emissions factors for low emissions vehicles is not publicly available and would not be released by the DfT.

Table 10 UK Energy Generation Mix (DECC 2011c)

Energy source	**%**
Coal	29.2
Natural Gas	40.7
Nuclear	19.1
Renewables	9.2
Other	1.8

In addition, PITHEM comprises a vehicle class called ‘zero emissions vehicles’ (ZEVs) which release no emissions at the tail pipe or at the point of energy generation. These vehicles can be used as being representative of EVs or PHEVs operating in charge depleting mode when conducting a TTW study.

An average emissions factor for PM_{10} (0.02042 gPM_{10}/km) for ZEVs, EVs and PHEVs is specified in PITHEM in order to take into consideration particulate emissions from brake and tyre ware. There are no further pollutant emissions factors for these vehicles specified in the model.

Figure 3 Vehicle fleet composition structure of the UK 2009 emissions factors

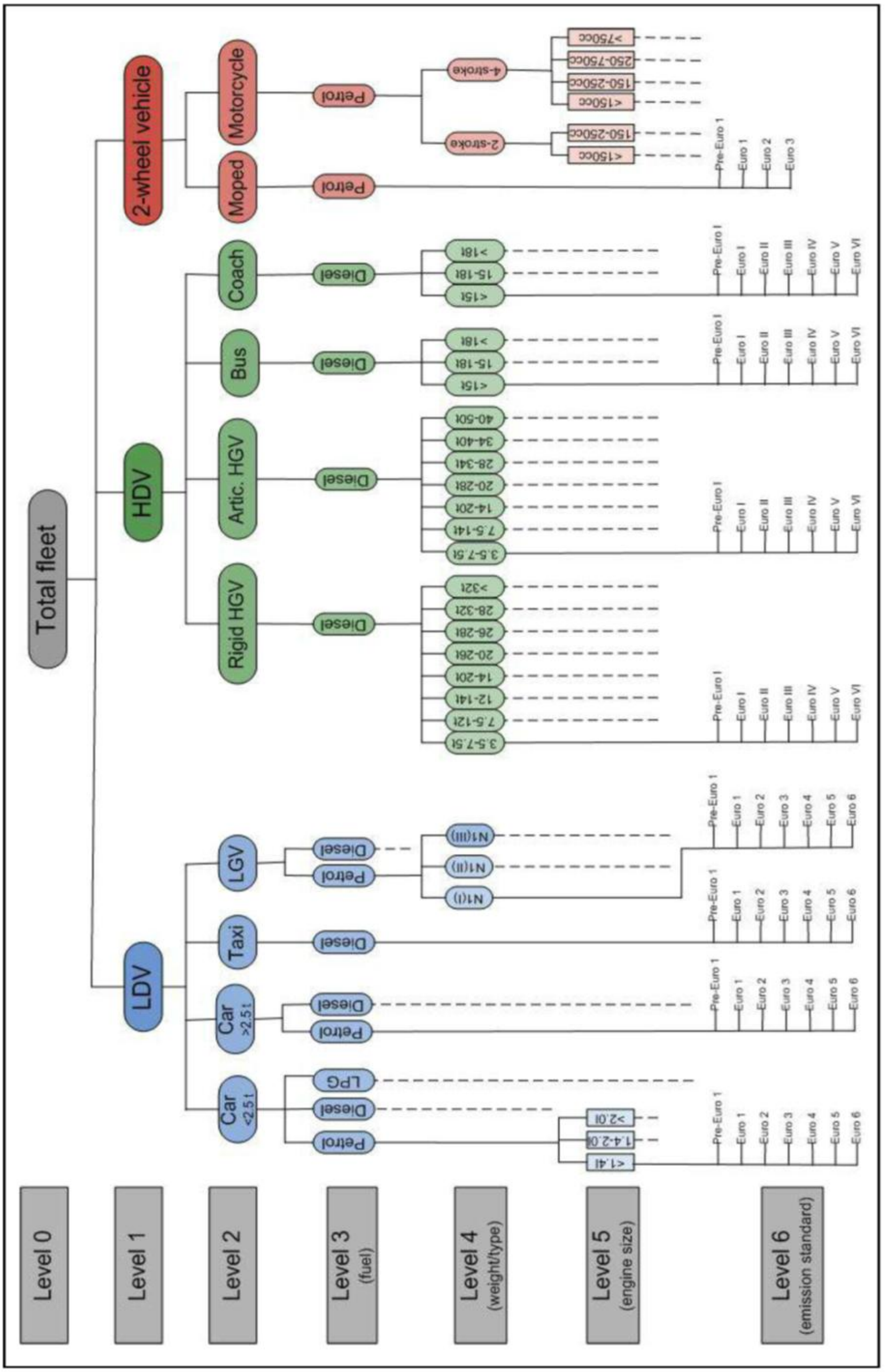
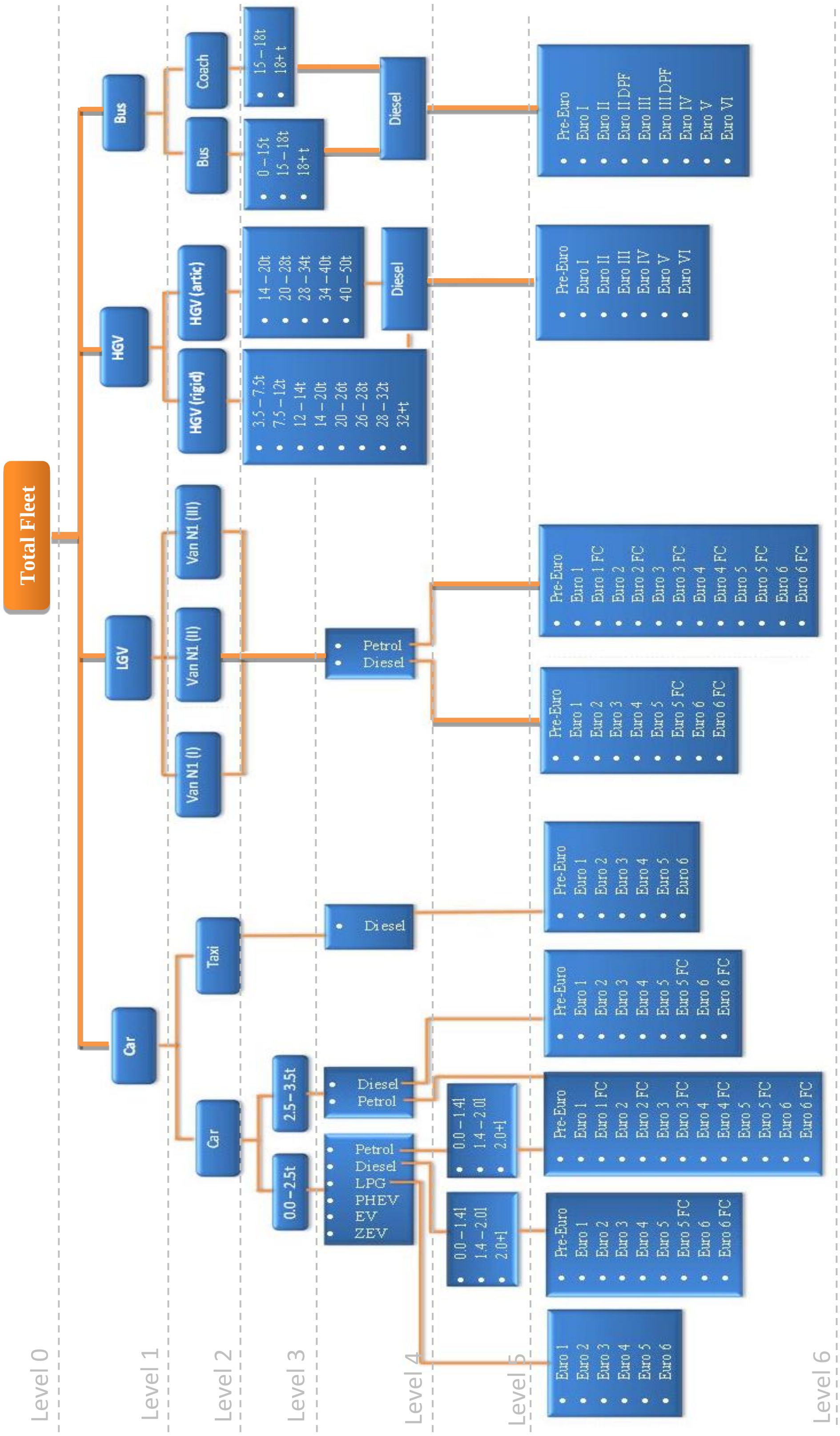


Figure 4 Vehicle fleet composition structure in PITHEM



Chapter 5

5. A Novel Application of Factor and Cluster Analysis to Classify Roads

An important source of data used in air quality emissions and dispersion models is the road traffic flow. Traffic flow is influenced by many factors such as congestion, green light time, number of lanes etc. meaning that each road exhibits fluctuations in flow throughout the day. In an ideal world the fluctuations in traffic flow on every road in a network would be captured in air quality modelling allowing for greater representation of concentrations temporally. However, in reality this is not possible due to large data requirements and computation times. Therefore, air quality models (e.g. AERMOD, AirViro, ADMS-Urban) are limited to a finite number of diurnal flow profiles prior to calculation. As a result there is a requirement for a method that assigns roads into groups (classifications) so that diurnal profiles can be specified to roads with similar characteristics. Therefore, a method that achieves this is explored in this chapter together with a description of the current methods documented in the literature for classifying roads.

In their document 'Traffic Monitoring Guide' the US Department of Transport (US DoT, 2001) suggest three suitable methods for creating road classifications namely, geographical/functional assignment, same road factor application and cluster analysis. The document was constructed as an aid for local authorities to appropriately apply annual average daily traffic (AADT) extrapolation factors to short period traffic counts. Often short period manual traffic counts are carried out at specific times of day e.g. during peak flows and as such the diurnal flow profiles of traffic on such roads is unknown. The US DoT's (2001) 'Traffic Monitoring guide' addresses this issue by providing a methodology that involves classifying roads based on their characteristics such as speed and flow and subsequently applying appropriate AADT interpolation factors to each of these roads depending on their classification.

The document states that geographical/functional assignment involves the grouping of road based on traffic patterns inferred from the knowledge of a traffic professional. However, such a professional requires an in depth knowledge of the road network, including its spatially and temporally variant traffic patterns, which researchers and air quality modellers do not possess. In contrast, air quality modellers and researchers can readily assign roads to classifications using the same road factor application method (see DoT (2001) and references there in) which involves grouping roads that are adjacent to each other. However, it is acknowledged by the US DoT (2001) that this method can be highly unreliable as traffic flows can fluctuate greatly, even between roads that are connected or adjacent to each other. Due to its inaccuracies the same road factor application method of classifying road has little support in the literature and is not considered an appropriate tool for classifying roads. Cluster analysis, on the other hand, has been shown by Chen *et al.* (2008) to be an adequate technique for creating road classifications and is probably the most viable technique available to researchers as it requires little to no knowledge of the physical layout of the road network.

Cluster analysis is a data classification tool that can be used to partition data into meaningful subgroups (Fraley and Raftery, 1998). Cluster analysis techniques can be split into two main categories, hierarchical and non-hierarchical, both of which are well described in the literature (Grimm and Yarnold, 2002, Anderson, 2003, Fraley and Raftery, 1998). Non-hierarchical techniques have a major benefit over hierarchical methods, as they allow multiple passes of the data (Hair *et al.* 1992). With each subsequent iteration data points are allowed to move between clusters (provided they do not increase the within cluster square error) which maximises intra-cluster similarity and inter-cluster dissimilarity (Aldenderfer and Blashfield, 1984). Non-hierarchical techniques are limited in their application as they require the researcher to specify a priori information (Ketcher and Shook, 1996). This limitation is evident in the work of Chen *et al.* (2008) who classified 3263 roads in Leicester according to their traffic conditions, using their traffic characteristics (morning average-speed, hourly flows in hours 9, 12, 18 and 24) and fleet compositions (petrol cars without a catalyst, petrol cars with a catalyst, diesel LGVs, Buses and HGVs). They used the k-means clustering algorithm which has the prerequisite that the user must specify the number of clusters prior to the analysis. In their study the number of clusters specified was six. Although Chen *et al.* (2008) suggest that their method of grouping roads was sufficiently reliable through subsequent analysis with external variables (AURN site and road side pollutant monitoring data) the number of clusters was driven by the requirement of the air quality model rather than justified statistically through rigorous analysis. It is important to allow flexibility for the number of clusters specified so that the cluster analysis can be driven by the data and not restricted by the subsequent applications of the number of clusters.

Therefore, this research investigated the application of a statistical methodology to classifying roads based on traffic conditions that allows the traffic data to drive the classification process. The methodology combines factor analysis and cluster analysis to infer the number of partitions. In this research the method is applied to the road network in Leicester. Initially 52 traffic variables from SATURN were used in the classification process. The variables were defined as weekday AM peak, PM peak or IP, referring to events occurring between 07.00h-08.00h, 16.00h-17.00h and average hour between 10.00h-16.00h periods respectively.

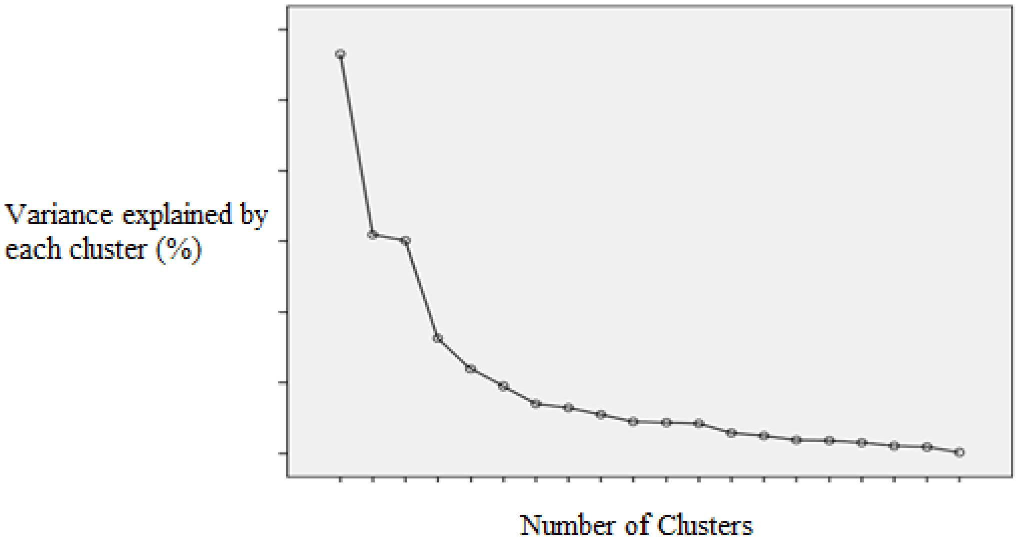
5.1 Factor and Cluster Analysis Method

The use of factor analysis and cluster analysis are standard statistical techniques and the combined use of both factor and cluster analysis is relatively common. In some studies factor analysis is used to validate a cluster analysis structure (e.g. Clark *et al.*, 2003; Berlage and Terwedume, 1988) and in other studies factor analysis is used as a data pre-processor to reduce the number of variables and prevent issues of unequal variable weighting in the clustering process (e.g. Andriotis *et al.*, 2008; Kibicho, 2008). The later method is known as 'factor-cluster' analysis and it has been applied in the medical (Suzuki *et al.*, 2010) and tourism (Cha *et al.*, 1995; Frochot and Morrison, 2000; Ahmed, 1997) sectors. Factor-cluster analysis is used to classify roads in this research. To this author's knowledge the application of factor-cluster analysis to classify roads is unique to this study and so this investigation provides a first step in exploring data-driven road classifications. The method involves factor analysis, producing factor scores and subsequently using these factor scores as input for cluster analysis.

In this research factor analysis is also used to infer the number of clusters to be output by an iterative cluster analysis. There are a number of techniques that have been developed previously in order to determine the number of clusters to be output from a cluster analysis including, the use of a two-stage cluster process (e.g. Peterson, 2002). A two-stage methodology involves initially carrying out a hierarchical cluster analysis to produce a dendogram. The dendogram is then used to infer the number of clusters to be output from a subsequent iterative cluster analysis (e.g. k-means). The dendogram may also be used to determine the initial cluster centres of the iterative analysis. The major issue with such an approach is that hierarchical methods make only one pass through the data set and as such a poor early clustering of the data set is not modified in subsequent clustering steps (Aldenderfer and Bashfield, 1984; McNeil *et al.*, 2005; Suhr and Spitznagel, 2001). This means that a poor initial hierarchical cluster analysis can subsequently infer a poor output from the iterative cluster analysis.

Another technique used to determine the number of partitions of a cluster analysis is the elbow criterion. Mo *et al.* (2010) define this method to involve 'plotting the ratio of the within-cluster variance to the total variance of the data set' (or percentage variance explained by each cluster). The resultant graph has a distinctive shape and when the improvement in per cent of variance explained drops substantially, an elbow-like inflection point is formed and the per cent of variance explained gained by adding more clusters becomes marginal (see Figure 5). Therefore, by looking on the graph for this inflection point the number of clusters to be output can be determined.

Figure 5 Example of elbow criterion graph (based on Mo *et al.*, 2010)



Mo *et al.* (2010) documented this technique to be a satisfactory one. However, the technique itself is very similar to factor analysis but does not have the benefit of determining the key variables that are driving the data set. In factor analysis Catell's (1966) scree plot is used to determine the number of factors to be extracted from the analysis. It involves the plotting of eigenvalues which are matrix based functions (Tabachnick and Fidell, 2001; Field, 2005). The matrices used in factor analysis are of shared common variance and as such the scree plot can be said to be a measure of variable variance. The scree plot works in the same way as the elbow criterion, with an inflection point inferring the number of factors to be extracted. Therefore, the use of factor analysis to infer the number of clusters can be seen as being similar to the elbow criterion, but with the benefit of allowing the user to identify the driving factors within the subject dataset. To this author's knowledge the use of factor analysis to infer the number of clusters is novel to this research.

In this research exploratory factor analysis (EFA) was carried out on 52 variables in order to determine the underlying constructs which describe the data. Various sensitivity tests were conducted during the EFA which were used to inform the appropriate factor analysis (FA) methodology to produce the final solution. Associated factor scores of the final solution were generated and used as predictor variables for cluster analysis. The number of factors extracted during the FA final solution was used as a priori for the number of road classifications to be grouped during the cluster analysis. The road classifications output from the cluster analysis were then analysed statistically to determine their characteristics and as such their internal consistency. In addition, the groupings were visually assessed in a geographical information system (ArcGIS) in order to determine whether or not they conformed to specific expected pattern. All statistical analysis was conducted using the SPSS (17.1) software package.

5.1.1 Data Input

Traffic data for this research was acquired from the CLTM. Predictor variables used in the study were extracted from the 3748 roads within the LCC LA area.

Preliminary statistical analysis (histograms and box plots) of data for each variable revealed that their distributions were all non-normal. Therefore, non-parametric tests at 95% level of confidence were used throughout this chapter.

5.1.2 Factorability of Variables

In order to determine if the data set was appropriate for use in FA the factorability of the variables was assessed through the Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy (MSA) statistics (Kaiser, 1970). Fundamentally the tests compare the magnitudes of the calculated correlation coefficients to the magnitude of the partial correlation coefficients (Pett *et al.*, 2003). The KMO MSA can be calculated for the correlation matrix as a whole or for the individual variables separately. Both were calculated for this research according to equations 7 and 8.

$$MSA = \frac{\sum\sum_{j \neq k} r_{jk}^2}{\sum\sum_{j \neq k} r_{jk}^2 + \sum\sum_{j \neq k} q_{jk}^2}$$

(Equation 7)

$$MSA_j = \frac{\sum_{k \neq j} r_{jk}^2}{\sum_{k \neq j} r_{jk}^2 + \sum_{k \neq j} q_{jk}^2}$$

(Equation 8)

In Equation 7 and Equation 8 q_{jk}^2 is the square of the off-diagonal elements of the anti-image correlation matrix and r_{jk}^2 is the square of the off-diagonal elements of the original correlations. A comprehensive description of KMO MSA procedures is given in Stewart (1981). The anti-image correlation (AIC) matrix reports MSA values for each individual variable on the diagonal, with the negatives of the partial correlations between pairs of variables present on the off diagonals (Tabachnick and Fidell, 2001). KMO MSA values range from 0 to 1. Large MSA values and small negatives of the partial correlations indicate that the data set is factorable (Tabachnick and Fidell, 2001). Kaiser (1974) provided a scale against which to measure KMO MSA values in order to determine if the correlation matrix is factorable. According to Kaiser (1974) a KMO MSA value of 0.90+ is marvellous, 0.80+ meritorious, 0.70+ middling, 0.60+ mediocre, 0.50+ miserable, and a value below 0.50 is considered unacceptable. Kaiser (1974) further suggested a KMO MSA cut-off point for data suitability to be 0.60+ ('mediocre'), with anything below 0.60 indicating a lack of underlying factor structure describing the relationships between the data set variables. Therefore, variables were removed from the EFA if their individual KMO MSA statistics were below 0.60.

In addition to KMO MSA calculations, the communalities (measures of shared variance) between variables were evaluated and the variables correlation matrix was screened. High communality scores (0.30>) suggest that there is a significant proportion of shared common variance between the variables and that FA is appropriate (Fabrigar *et al.,* 1992; MacCallum *et al.,* 1999). Field (2005) suggested that variables that have a correlation coefficient between them greater than 0.90 should be considered as possibly describing the same underlying construct and could in fact be a cause of multicolinearity in the dataset. Therefore, the variables correlation matrix was screened for values above 0.90 and those variables that met this criterion were subjected to sensitivity analysis (see section 5.1.7).

5.1.3 Factor Extraction

There are a number of common factor extraction statistical techniques, principal component analysis (PCA, technically not a FA procedure), principal axis factoring, unweighted least squares, generalised least squares, maximum likelihood, alpha factoring and image factoring. All of these techniques have significant advantages and disadvantages (see Tabachnick and Fidell, 2001, Kline, 1994, Field, 2005) and it is widely acknowledged that there is no definitive extraction method that is beneficial over all other methods (Costello and Osborne, 2005; Fabrigar *et al.,* 1992). Some methods, such as maximum likelihood and generalised least-squares are beneficial in their approach as they allow statistical significance testing of factor loadings, whereas others, e.g. image analysis, are advantageous as they provide a unique solution that accounts for common variance only (Kline, 1994). Fabrigar *et al.* (1992) document principal axis factoring (PAF) to produce results that are comparable to other extraction techniques in terms of reliability as does Bagby *et al.* (1994), Kerns *et al.* (1985), Becker *et al.* (2010) and Greco and Roger (2001). Nunnally and Berstein (1994) compared PAF and PCA extraction techniques and suggested that PAF to perform better than PCA as it lowers the root mean square error (RMS) between the estimated correlations matrix and the actual correlation matrix. They concluded that PAF provides a better fit of the model to the data than PCA does and that PAF is superior to PCA. PAF was chosen as the principal factor extraction method for this research. However, Gorsuch (1983) documented that a dataset with strong underlying constructs will produce the same solution regardless of extraction method. Therefore, in order to assess the strength of the underlying constructs of the final solution PCA, unweighted least squares, generalised least squares, maximum likelihood, alpha factoring and image factoring extraction techniques were compared to those outputs produced using PAF.

5.1.4 Number of Factors Extracted

As with factor extraction, the techniques chosen to determine the number of factors extracted are highly subjective. There is no definitive way in which to determine the number of factors to extract (Ledesma and Valero-Mora, 2007). Kaiser (1974) suggested extracting all factors with eigenvalues higher than 1.0. However, this method has been shown to result in over extraction and occasionally under extraction (Zwick and Velicer, 1986; Tucker *et al.,* 1969; Hakstian *et al.,* 1982; Costello and Osborne, 2005; Patil *et al.,* 2008). Jolliffe *et al.* (1972) documented that Kaiser's value is too strict and suggested that extraction of factors should be based on eigenvalues higher than 0.7. This method, like Kaiser's (1974), however suffers from the same fundamental issues and that both techniques are arbitrary in that an eigenvalue of 1.0 is considered important where as an eigenvalue of 0.99 is not (Field, 2005). In contrast, the 'scree test' (Catell, 1966) does not rely on an arbitrary cut-off value. The scree test involves plotting the eigenvalues against their associated factor in order to determine the relative importance of a factor (Field, 2005). The curve of this graph has a distinct shape and the point of inflection, according to Catell (1966), indicates the cut-off point for selecting factors. It is well documented in the literature that the technique provides fairly reliable results (Gorsuch, 1983; Stevens, 1992; Tucker *et al.*, 1969; Catell and Vogelmann, 1977). Furthermore Monte Carlo investigations by Tucker *et al.* (1969) revealed the scree test to perform consistently better than Kaiser's eigenvalue rule. Therefore, in this research the scree test was used to determine the number of factors to be extracted.

5.1.5 Rotation

Rotation of factor loadings allows for more interpretable results by shifting loadings so that they fall predominately on to a factor (Floyd and Widaman, 1995; Brown, 2009). In the literature rotation is often illustrated as the movement of data points on a graph so that they fall close to one of the axis lines (Field, 2005). In this case the graph's axis represents factors and the plotted points represent factor loadings. The data points plotted can be moved in different ways, e.g. allowed to correlate, in order to make interpretation easier. There are a number of different types of rotation, orthogonal, primarily varimax, is by far the most widely used FA rotation technique documented in the literature (Kline 1994). Oblique rotation, unlike orthogonal rotation, allows factors to correlate (Ford *et al.,* 1986) and in doing so can be seen as a more appropriate technique for EFA. Tabachnick and Fidell

(2001) document that the production of a factor correlation matrix from oblique rotation allows the user to determine if underlying constructs are truly correlated. If the matrix reveals factors to be correlated then the use of oblique rotation is justified. If however, the matrix reveals near zero factor to factor correlation coefficients then it is indicated that orthogonal rotation is applicable. Given these benefits of oblique rotation, oblique direct oblimin was used for the EFA.

5.1.6 Interpretation of Factor Matrices

There is a large volume of literature documenting different ways in which to interpret outputs from FA (Thurstone, 1974; Costello and Osborne, 2005; Gorsuch, 1983; Kline, 1994; Tabachnick and Fidell, 2001; Comrey and Lee, 1992; Cattell, 1978; Stewart, 1981). Perhaps the most cited method for interpreting matrices is that of Thurstone (1974) who proposed five criteria for determining if a loading matrix exhibited 'simple structure.' Thurstone (1974) argued that a FA procedure that produced a loading matrix with simple and interpretable structure is the best fit of the model to the data. Thurstone's (1974) five criteria are as follows; each variable produces at least one zero loading on a factor, each factor has at least as many zero loadings as there are factors, each pair of factors has variables with significant loadings on one factor and zero loadings on the other, each pair of factors has a large proportion of zero loadings on both factors and each pair of factors has only a few variables with significant loading values. Gorsuch (1983) later elaborated on Thurstone's (1974) proposal and suggested that 'zero' loadings are loadings that fall between -0.10 and +0.10. The definition of a 'significant loading' is much debated in the literature. Kline (1994) suggested that a factor loading of 0.30 indicates that 9% of the variance is accounted for by the factor and values equal to or higher than 0.30 should be regarded as significant. In contrast, Cattell (1978) suggested that loadings as low as 0.15 have been viewed as significant. Kline (1994) rejected this theory on the basis that it can cause problems of replication. On the other hand, Comrey and Lee (1992) defined loadings in excess of 0.71 (50% overlapping variance), 0.63 (40% of overlapping variance), 0.55 (30% of overlapping variance), 0.45 (20% overlapping variance) and 0.32 (10% overlapping variance), as excellent, very good, good, fair and poor respectively. Tabachnick and Fidell (2001) suggested that the cut-off point is ultimately a matter of researcher preference and that more often than not a cut-off point is chosen as it makes interpretation of factors easier. In this research a cut-off point of 0.30 was used to determine the significance of factor loadings, as this allowed for a significant proportion of overlapping variance to be considered and enabled interpretation of factor matrices to be carried out with ease.

5.1.7 Sensitivity Analysis

The EFA communalities table and correlation matrix were analysed. Those variables which appeared to be describing the same underlying construct (correlation between variables above 0.9) were removed one at a time from the data set and the EFA was recalculated. Pattern, structure and factor correlation matrices output from the multiple FA were compared and variables were discarded if they resulted in a solution that significantly violated Thurstone's (1974) criteria for simple structure and those criteria of variable factorability documented in section 5.1.2.

5.1.8 Factor Internal Consistency

Internal consistency refers to the interrelatedness of those variables loading on a factor. A solution that has strong variable interrelatedness is deemed to be good as it infers that those variables loading on the same factor share a large proportion of variance and are in fact in part describing the same underlying construct. Cronbach's (1951) coefficient alpha is widely documented in the literature (see Schmitt, 1996, Peterson, 1994) as a mathematical tool for measuring the internal consistency (interrelatedness) of grouped items. Therefore, Cronbach's coefficient of alpha was used to indicate the level of internal consistency of the factors determined from the EFA. Coefficient alpha values range from 0 to 1, with a value of 1 suggesting strong inter-item relatedness and a value of 0 indicating poor interrelatedness. However, it should be noted that a large number of items can result in the inflation of alpha scores (see Cortina, 1993). Therefore, alpha values were used only as an indication of internal consistency. Correlation coefficients were also calculated to further assess the interrelatedness of factor variables.

5.1.9 Factor Scores

According to Field (2005) factor scores are 'a composite score for each individual variable on a particular factor.' That is they are an estimate score of what a subject may have scored on a factor if the underlying construct was measured directly (Tabachnick and Fidell, 2001). In general, factor score procedures can be classified in two ways, refined and non- refined. Non- refined methods, e.g. sum of scores, are simple in their approach (Kline, 1994). In contrast, refined methods, such as Anderson-Rubin and Bartlett's regression techniques are more complex and often yield more reliable results (Lastovicka and Thamodaran, 1991). Field (2005) and Tabachnick and Fidell (2001) give a good basic explanation of factor scores and their uses. In addition, Distefano *et al.* (2009) give a comprehensive review on 'understanding and using factor scores' and provide a useful set of lookup tables which compare factor score algorithms and outputs.

Factor scores are often produced if subsequent analysis is to be carried out using the factored data set (e.g. Funkhouser, 1983). By using factor scores in such analysis (in this case cluster analysis) issues of multicolinearity are addressed and unequal variable weighting is avoided (Ketchen and Shook, 1996). Therefore, factor scores were used as predictor variables in the subsequent cluster analysis.

5.2 Cluster Analysis: k-means algorithm

The k-means algorithm (McQueen, 1967) is one of the most widely used clustering techniques due to its ease of use, simplistic nature, efficiency and empirical success (Jain, 2010). In addition Yiakopouloulos *et al.* (2010) documented the k-means algorithm to be adopted further by its relatively quick computation times, small computational space requirements and the fact that it is not limited by prior knowledge and may produce tighter clusters. K-means is a technique that has been applied successfully within the engineering (e.g. Yiakopouloulos *et al.,* 2010), energy (e.g. Pandit *et al.,* 2011), medical (e.g. Docquier *et al.,* 2009) and electrical (e.g. Mora-Florez *et al.,* 2009) fields, as well as within the transport sector (Chen *et al.,* 2008). It is applied to the dataset used in this research in order to characterise the road classifications.

K-means cluster analysis involves objects moving iteratively from one cluster centre to another, starting from an initial partition (Fraley and Raftery, 1998, Cheung 2003, Chitta and Murty, 2010). Like all non-hierarchical procedures, k-means requires a priori information regarding the number of clusters to be output from the analysis (Grimm and Yarnold, 2002). It initially involves the random selection of cluster centres and the partitioning of objects into the nearest cluster (Ketchen and Shook, 1996). The algorithm then calculates the square error within each of these clusters (Kalyani and Swarup, 2011). Objects are allowed to move between clusters if the square error is minimised (Erman *et al.,* 2006). If an object moves to a new cluster the cluster centre is re-calculated and the whole process starts again in an iterative manner. Only once the clusters become stable (i.e. the square error values for the clusters varies very marginally with further iterations) are the final groupings determined (Hair *et al.*, 1992).

The k-means algorithm is extremely sensitive to the position of initial cluster centres and as such re-ordering of the input data can result in different initial centres and subsequently different solutions (Juang and Wu, 2010). A number of techniques have been presented in the literature to overcome this issue (e.g. averaging the initial seed values) with the ‘multiple restarts’ methods perhaps being the most widely accepted (Likas *et al.,* 2003). The multiple restarts method was adopted in this research primarily due to its ease of use and relatively quick computation time. The method involved a pre-processing procedure whereby the input data was re-ordered 100 times and subsequently grouped using the k-means algorithm. Initial cluster centre values and the assignment of roads to clusters are assessed in terms of frequency. If multiple solutions were produced the most dominant solution was considered the most appropriate for use in air quality modelling due to its greater reproducibility. This approach is similar to that used by Vichi and Kiers (2001) who calculated 100 cluster analysis and retained ‘only the best solution’ for subsequent analysis.

5.2.1 Statistical and Spatial Analysis

Box plots of the within cluster variables were plotted to assess variable data ranges and to help characterise the classifications. Clusters with few outliers (1.5 times the inter quartile ranges) were considered to be more consistent and internally similar. Greater internal similarity indicates a more effective clustering procedure.

Box plots were deemed appropriate as they use median values. The median value is influenced less by extreme values and outliers than other statistical measures such as the mean in non-normally distributed data (Skottowe, 1963) and was considered to be more representative of the classification characteristics in this case. The classifications were then assessed visually using a geographical information system to allow for evaluation of road location in relation to characteristics.

5.3 Results and Discussion

5.3.1 Factor Analysis

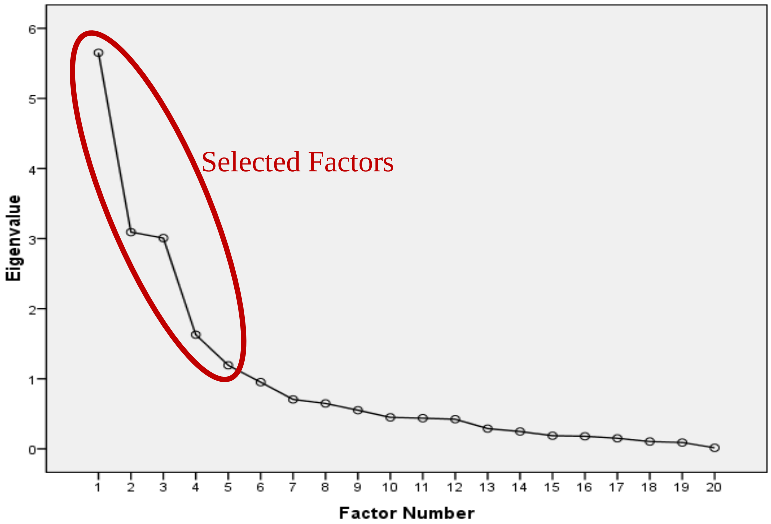
Of the initial 52 variables considered for the EFA, 30 were removed from the analysis due to high correlations (0.90>) and or significantly low (<0.60) individual KMO MSA scores. The 20 variables used as input for calculation of the final solution are shown in Table 11. These variables where extracted from the 52 by 52 correlation matrix of statistical parameters which was studied in detail. This matrix was too large was to be included in the thesis or as an appendix.

All of the variable communalities were significant (0.30≥) which suggested that there was a substantial proportion of shared common variance between the variables and that factor analysis was an appropriate technique. Although using PM Cruise Speed and IP Free Flow speed as predictor variables for the EFA meant including variables with a correlation coefficient above 0.90, the removal of any these variables significantly impacted the stability and interpretability of the FA solution and as a result the speed variables were considered important for the production of the final solution. Also, issues of multicollinearity that may have occurred due to the inclusion of these variables were addressed through the production of factor scores. In addition, speed is an important traffic variable that influences tailpipe emissions which further justifies its retention.

The scree plot output (see justification in section 5.1.4) from the 20 variable EFA is shown in Figure 6. The plot indicated extraction of four, five or six factors. Subsequently the extraction of four, five and sic factors was carried out. The extraction of five factors was deemed the most appropriate. The extraction of four factors doubled the number of non-redundant residuals in the residuals matrix suggesting extraction of another factor. The extraction of six factors was not possible due to the communality of a variable exceeding one which suggested a sixth factor would likely be a replication of a previously defined factor.

The five factor final solution accounted for 72.84% of the total variance in the dataset and as such 27.16% of variance was not extracted. This means that 27.16% of the variance in the dataset was not shared common variance between variables and did not result in significant (0.30≥) factor loading scores. Factors 1 to 5 accounted for 28.25, 15.45, 15.03, 8.15 and 5.96% of the variance respectively. All of the extracted factors had eigenvalues greater than 1.0 indicating that the use of extraction criteria shown by Kaiser (1974) would have yielded the same factor solution. The residuals matrix had 12% non-redundant residuals with absolute values of greater than 0.05. Comparison of the outputs of the 6 extraction techniques (PCA, unweighted least squares, generalised least squares, maximum likelihood, alpha factoring and image factoring) with the PAF solution revealed similar factor loading patterns suggesting that strong underlying constructs within the data were present. This also indicated that the variable factorability analysis carried out was effective.

Figure 6 Scree plot output from the exploratory factor analysis (principal axis factoring, direct oblimin oblique rotation)



The factor pattern loading matrix for the final solution is shown in Table 11. Although there are six cross factor loadings, generally the loading matrix satisfied Thurstone's (1974) criteria for simple structure. All of the factors had an adequate number of significantly high (0.30>) variable loadings and at least 5 loadings between -0.10 and +0.10. The high factor loadings suggested a good model fit to the data and indicated strong internal stability. Furthermore, the FA model provides an easily interpretable output, with factors 1 to 5 describing HDV and LDV flow (1), bus flow (2), delay (3), speed (4) and AM peak network characteristics (5).

Table 11 Communalities scores and factor pattern loading matrix of the final factor analysis solution

		Factor				
	Communalities	1	2	3	4	5
IP Lights	.851	.904				
IP Heavies	.803	.891				
PM Lights	.812	.879				
PM Heavies	.567	.685				
AM Lights	.623	.616				.442
AM Heavies	.479	.504				.330
No. Lanes	.416	.372				.354
PM Bus	.756		-.894			
PM Bus Q	.751		-.830			
IP Bus Q	.748		-.816			
AM Bus	.786		-.758			.359
AM Bus Q	.773		-.743			.417
IP Q Average	.709			.787		
IP Junction Delay	.578			.700		
AM Q Average	.517			.654		
PM Q Average	.461			.617		
AM Network Speed	.464			-.554	.385	
AM Junction Delay	.417			.537		
PM Cruise Speed	.970				.996	
IP Free Flow Speed	.971				.988	

Table 12 shows the 'between factor' correlations (below the diagonal) and Cronbach's Alpha Coefficient score (on the diagonal) for each factor. Factors 1 and 4 are significantly (0.30>) correlated justifying the use of an oblique rotation. This correlation is logical given that factors 1 and 4 describe speed and flow underlying constructs.

The 'within factor' variable correlation coefficients were above 0.60, 0.70, 0.30, 0.30 and 0.40 for factors 1 to 5 respectively suggesting an acceptable level of inter-variable relatedness. Furthermore, generally the alpha scores observed indicated relatively strong factor internal consistency. Nunnally (1978) recommended alpha scores of 0.70 for early stages of research, 0.80 for basic research tools and 0.90 for clinical research purposes. The alpha scores of factor 1 and factor 4 are consistent with Nunally's (1978) criteria for basic research, factor 2 for clinical purposes and factor 5 for the early stages of research. However, the variables loading on factor 3 produced an alpha score of 0.559 suggesting its internal consistency was relatively low. The calculation of Cronbach's (1951) alpha coefficient if one item deleted revealed that removal of AM Network Speed from the factor would have produced an alpha value of 0.790 for factor 3. The removal of AM Network Speed from the FA however substantially impacted the factor loading pattern (given that it is cross loaded) and subsequently the solution structure and interpretability was lost. Therefore, the AM Network Speed remained in the final solution.

Table 12 Factor correlations (below diagonal) and Cronbach's Alpha Coefficient [diagonal]

Factor	**1**	**2**	**3**	**4**	**5**
1	[.898]				
2	-.248	[.904]			
3	.136	-.063	[.549]		
4	.309	.026	-.048	[.812]	
5	.170	-.124	.067	.115	[.746]

5.3.2 Factor Scores

Comparison of the three factor score calculation methods (regression, Anderson-Rubin and Bartlett) showed that the Bartlett technique reproduced scores that most closely matched those in the factor pattern loading matrix. This was consistent with Distefano *et al.* (2009), who suggested that the Bartlett score method is better because it produces estimates that are most likely to represent the true factor scores and also produces high validity estimates between the factor scores and factor. For these reasons the Bartlett method of calculating factor scores was used in this research. The limitation of the Bartlett factor score method is that it may produce factor scores that are correlated in an orthogonal solution (Tabachnick and Fidell, 2001). This was not of major concern, given that the final solution of this FA produced factors that were correlated. However, what was of concern was factor score indeterminacy. Factor score indeterminacy refers to the fact that infinite number of solutions could account for the relationships between variables in a factor analysis (Grice, 2001; Gorsuch, 1983). Therefore, factor scores are imprecise and can only be *estimated* and not *calculated* (Hammon, 1986). Accordingly, factor scores can impact the validity of decisions based on these values (Actio and Anderson, 1986).

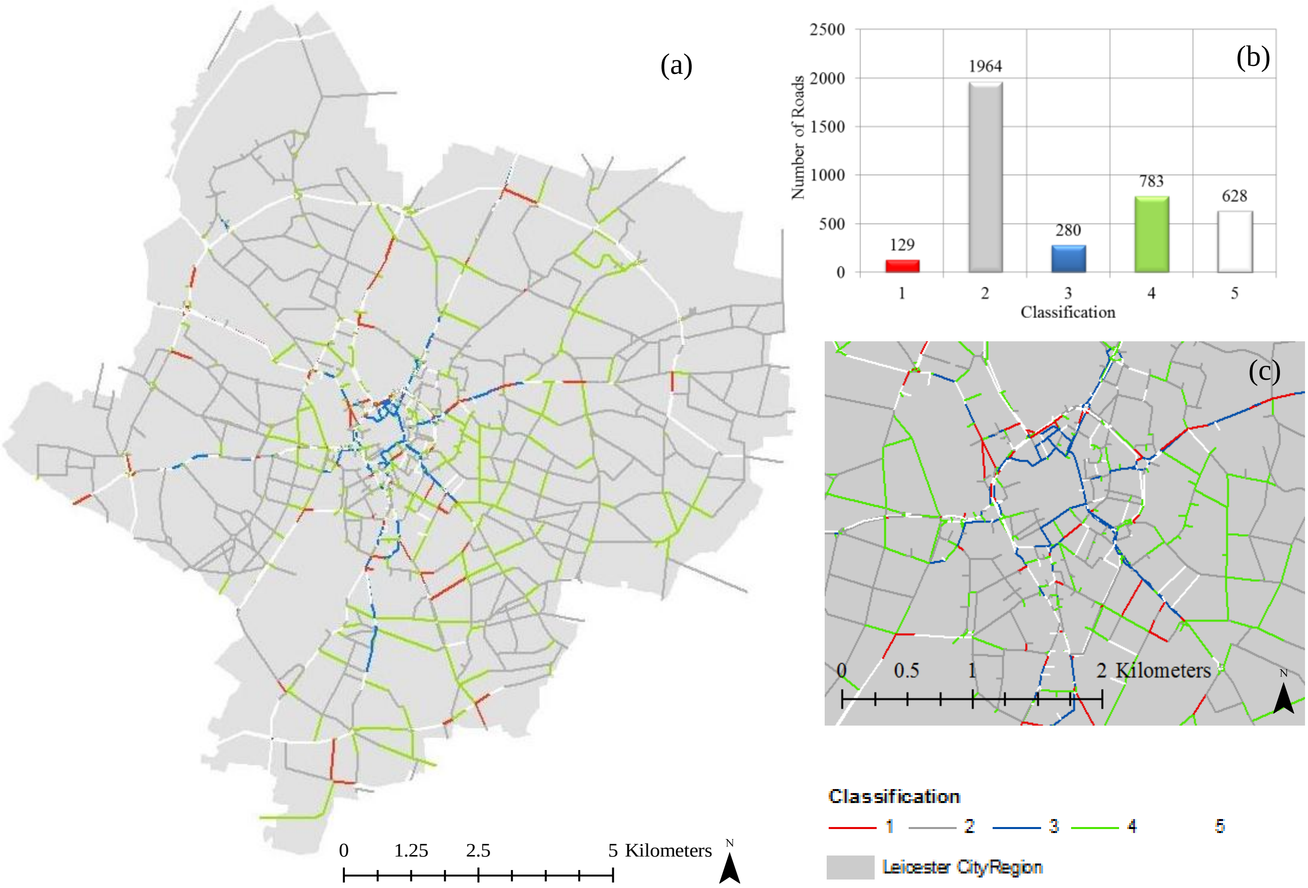
The literature suggests that a solution with high factor loadings, high communality values and a relatively large number of variables loading on factors can reduce the impact of factor score indeterminacy (Gorsuch, 1983; Grice 2001; Actio and Anderson, 1986; Lastovicka and Thamodaran, 1991). The final solution produced in this research appears to meet the above criteria adequately in the sense that all of the factor loading scores were above 0.30, with an average loading value of 0.61, communality estimates were all above 0.40 with an average value of 0.67, and all of the factors had three or more variables loading onto them. This further suggests that the factor scores produced in this research were fit for purpose. However, researchers are reminded that factor scores are estimates and furthermore can be sample specific (Field, 2005). Therefore, the production of factor scores whilst using this methodology may lead to significant errors.

5.4 Cluster Analysis

The completion of factor analysis revealed that five factors could be used to describe the data set. Cluster analysis was carried out in order to group roads in to classifications. The k-means algorithm was used with an a priori of five classifications specified which was inferred from the factor analysis. The multiple starts method, involving the reordering of variable data and re-running of cluster analysis was carried out in order to account for the sensitivity of the k-means algorithm to initial cluster centres. From the 100 cluster analyses computed, it was evident that there were two solutions emerging. Therefore, this research highlights how sensitive the k-means algorithm is to initial cluster seed location. The solutions accounted for 61% (Solution 1) and 39% (Solution 2) of the 100 cluster analyses computed respectively. Therefore, Solution 1 was favoured due to its greater reproducibility.

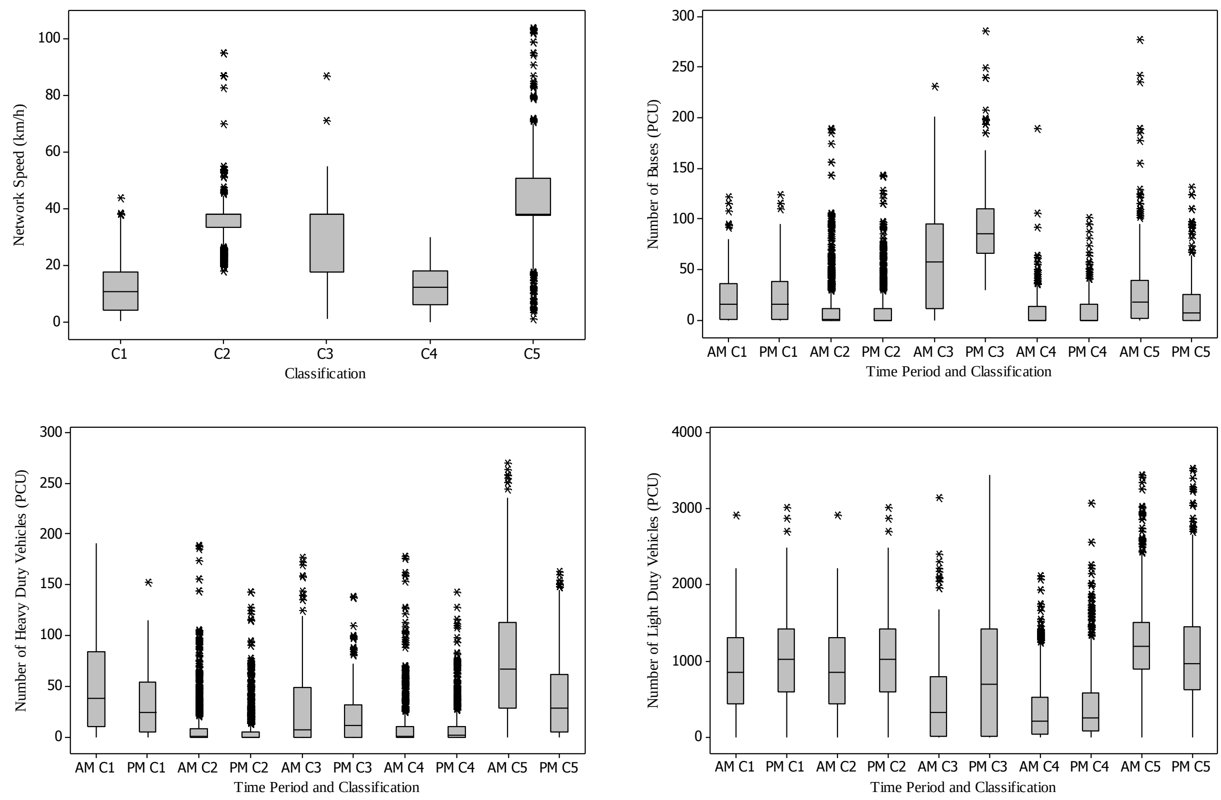
In the Solution over half of the roads were assigned to classification 2 and were evenly spread throughout the city (Figure 7(a)). A total of 784 roads were assigned to classification 4 (Figure 7(b)) and were predominantly located at junctions and intersections with city centre feeder roads. Generally, roads belonging to classification 5 were located on Leicester’s outer ring road and those assigned to classification 3 were located predominantly in the city centre (Figure 7(c)). Classification 1 comprised only 129 roads which were located mainly at junctions.

Figure 7(a) The Leicester City Council (LCC) local authority area road network and associated road classifications; Figure 7(b) number of roads assigned to each classification and; Figure 7(c) the city centre at a finer resolution



The inter-comparison between the road classifications showed their characteristics to vary considerably (Figure 8). Roads belonging to classification 1 were characterised by substantially lower network speeds, bus flows and HDV flows than the other classifications. In addition, the roads in classification 1 were characterised by relatively high LDV flows suggesting that these roads were subject to severe congestion. Classification 2 comprised roads that had low HDV and bus flows and were characterised by LDV flows that were within a similar range to those of classification 1. However, roads belonging to classification 2 were observed to have higher network speeds which were the likely cause of their grouping. Despite 50% of the roads being assigned to classification 2, the data ranges for these roads were relatively small which suggested that they were similar in characteristics. The roads belonging to classification 5 were typically characterised by high network speeds and high HDV and LDV flows. Classification 4 comprised roads that were characterised by low HDV, LDV and bus flows and moderate speeds. Finally, high bus flows and a broad range of speeds were observed for classification 3.

Figure 8 Traffic data comparison between the five road classifications



* Residuals 1.5 times higher or
lower than the inter quartile ranges

Table 13 provides a summary of the typical locations and traffic characteristics of the 5 road classifications.

Table 13 Typical locations and traffic characteristics of the 5 road classifications output from cluster analysis

Classification	Typical Location	Traffic Characteristics
1	City centre junctions	Low speeds, high LDV flows, Low bus and HDV flows
2	Evenly spread throughout the city	High speeds, high LDV flows, Low bus and HDV flows
3	City centre	Broad range of speeds, high bus flows
4	Junctions and Intersections	Low traffic flows, moderate speeds
5	Outer ring road	High speeds, high LDV and HDV flows

Whilst the use of factor-cluster analysis is relatively common for segmentation analysis (Suzuki *et al.*, 2010; Andriotis *et al.*, 2008; Kibicho, 2008; Cha *et al.*, 1995), the use of factor scores as input for cluster analysis is a much debated topic in the literature. Frochot and Morrison (2000) conducted a meta-analysis of segmentation studies and concluded that the factor-cluster analysis approach to be superior to other techniques as it allows the data set to be reduced into 'a smaller set of understandable factors.' Ahmed (1997) found the factor-cluster method to be an advantage over other approaches as it provided ‘richer’ and ‘clearer’ clusters when classifying the climatic regionalization of Saudi Arabia. However, cluster analysis assumes heterogeneity (Grimm and Yarnold, 2002) and variables with a high proportion of shared common variance arguably influence the clustering process. On the one hand, the advantage of using factor scores is that they prevent variables containing unequal weighting (i.e. a large proportion of shared common variance) from being included in the clustering process (Ketchen and Shook, 1996). On the other hand, factor analysis aims to eliminate variables with a small amount of shared common variance and only part of the variance of the dataset is extracted during the analysis (in this research 72.84%). As a result the removal of heterogeneous data during factor analysis may substantially influence the subsequent cluster analysis. In order to estimate the influence of this drawback on the classifications presented, comparison between the outputs of this work (factor-cluster analysis) and those of Chen *et al.* (2008) (cluster analysis) were made. It should be noted that whilst these two studies used slightly different data, their comparison provides insight into the possible influences of factor scores on the classification process in this work. The results show the two outputs to be similar in terms of number of roads assigned which indicates that the use of factor scores in this research did not substantially influence the classification process (Table 14). However, similarities between the two classifications suggested that a limitation common to both the work of Chen *et al.* (2008) and this work was influencing the classification process.

The main similarities between this work and those documented by Chen *et al.* (2008) are that both approaches produced solutions that have a dominant classification containing a large proportion of roads and at least one classification comprising a very small number of roads. This similarity can be explained by the use of simulated traffic data for classification as opposed to the use of real world traffic data. Real world data will inevitably have greater variability than simulated data and is likely to result in a higher number of road classifications. However, it is not only expensive but also impractical to continuously monitor traffic flow and speed on every road within a conurbation. In reality automatic traffic recorders (ATRs) exist only on a relatively small proportion of roads (LCC 2011) meaning that the spatial coverage of real world traffic data does not meet the requirement of regional scale air quality models. Therefore, the use of traffic data from strategic transport models, such as SATURN, has become necessary to allow for estimates of road traffic dynamics, including diurnal profiles, to be included in air quality modelling. However, traffic models comprise assumptions (e.g. capacity-delay curves), limitations (e.g. finite number of routes can be modelled) and often errors (e.g. introduced in input data such as origin destination matrices) which are sometimes evident in outputs. These biases are likely to influence the cluster analysis. The relatively small data ranges of the variables describing the roads assigned to classifications 1 and 2 in this work could be evidence of assumptions made in SATURN influencing the classification process. For example, the small number of roads assigned to classification 1 were characterised by very low network speeds which may, on the one hand, have been the result of capacity-delay assumptions intrinsic to the SATURN model. On the other hand, these speeds may be a reflection of the real world traffic speeds associated with roads located near heavily traffic junctions.

Table 14 Comparison of number of roads assigned for two different methods of classifying roads; factor analysis followed by cluster analysis (this work) and one stage cluster analysis governed by model requirements (Chen *et al.*, 2008)

Classifications in This Work	Roads (%)	Classifications in Chen *et al.* (2008)	Roads (%)
1	3.4	**1**	0.4
2	51.9	**2**	23.1
3	7.4	**3**	0.8
4	20.6	**4**	0.4
5	16.6	**5**	34.9
		6	40.2

In some cases it is possible that many variables output from a traffic model contain a large proportion of shared bias. In such a case, the use of the method presented here to classify roads can be seen as an advantage over other approaches as variables containing multicolinearity and unequal weighting are removed from the classification process. However, it should be noted that the use of factor scores as input for cluster analysis may in some cases influence the classification process (see above). The use of the factor and cluster analysis method presented here also has an advantage over other methods as it allows the classification process to be driven by the data and not restricted by the subsequent applications of the number of clusters.

5.5 Chapter 5 Summary

A statistical method of classifying roads was presented. Factor analysis was used to determine the underlying constructs of the road traffic data for the LCC road network. Factor analysis was used to infer the number of cluster seeds for the k-means algorithm. Some traffic variables were found to be unsuitable for factor analysis and were removed. The factor analysis revealed five underlying constructs. Therefore, five initial seed functions were specified for the cluster analysis allowing the clustering process to be driven by the data itself. Multiple cluster analyses were calculated to test the stability of the solution. Two predominant solutions emerged due to different initial cluster seed locations. Solution 1 was favoured as it had greater reproducibility. The use of factor scores as input for cluster analysis was discussed and the road classifications produced were compared to those produced in previous work using a different classification technique. The classifications produced in this work were similar in terms of number of roads assigned to a direct cluster analysis approach which suggested that the use of simulated traffic data was influencing the classification process.

CHAPTER 6

6. Air Quality Modelling: Evaluation of the Emissions Inventory

The approach recommended by the government to monitor the air quality of a city is to identify a suitable (often a single) fixed site for a monitoring station to record concentration levels continuously over time (DEFRA, 2007). Monitoring locations are only capable of providing insight into the impact of previous and current abatement policies and strategies on pollutant concentration levels and cannot be used for evaluating the effectiveness of future action plans. Instead, atmospheric dispersion models have been developed to carry out this task. Concentration levels are predicted based on input data that can be manipulated and edited to reflect a range of strategies and policies depending on user preference. In order to assess the impact of these policies such pollutant 'forecasts' are compared to a 'base-case' which represents pollutant concentrations predicted using current fleet characteristics, traffic and base year meteorological data. The air quality model allows the emissions inventory compiled for the base year (in this research 2005) to be evaluated and subsequently systematically changed to reflect planned strategies. Comparison with the base-case benchmark allows the effectiveness of such strategies to be estimated prior to implementation. In this way more effective use of resources is achieved ensuring that policy decisions taken deliver their objectives. Therefore, the next step in this research was to create, evaluate and test the robustness of the air quality model to replicate the base-case. In this chapter the emissions inventory compiled for the LCC region is presented and the ability of the ADMS-Urban dispersion model to predict concentrations of NO_2 and PM_{10} at fixed locations throughout the city evaluated. Predicted concentration levels are compared to observed data and model performance is quantified on a statistical basis.

6.1 Study Methodology

Diurnal profiles were developed using the five road classifications documented in Chapter 5. Vehicle fleet composition was defined using data from SATURN and national data (DfT, 2009b). The vehicle fleet composition, traffic flow data and link average-speed were subsequently used in PITHEM to calculate road transport emissions. The LCC provided emissions values that were representative of the non-mobile source emissions in the LA area. The emissions inventory along with meteorological data was used as input for ADMS-Urban. The dispersion model was used to predict concentrations of NO_2 and PM_{10} at seven and five receptor locations across the city of Leicester respectively. These receptor locations are representative of the pollutant monitoring sites within the LCC LA area. Model performance was subsequently evaluated through comparison of predicted with observed concentrations according to methods suggested by Chang and Hanna (2004). It should be noted that measured (termed 'observed' as specified from here on in) concentration data were assumed to accurately represent actual pollution concentrations.

6.1.1 Diurnal Profiles

Halcrow Ltd (2009) provided interpolation factors that allowed for the calculation of AADT flow and diurnal profiles (Table 15). The interpolation factors were derived from empirical data and enabled the interpolation of the AM peak, IP period and PM peak hour values. The AM and PM interpolation factors were easily applied to the corresponding peak flows obtained from SATURN. In contrast, the interpolation factor for the IP period was a composite value for the pre 07.00h (00.00h - 07.00h), 10.00h - 16.00h and post 19.00h (19.00h - 00.00h) periods. LCC provided the breakdown of the IP period. The pre 07.00h, 10.00h-16.00h and post 19.00h periods accounted for 7%, 37% and 56% of the total IP period respectively. Therefore, the interpolation factor was used to calculate the IP total and the data from the LCC was subsequently used to breakdown the IP period into the three time scales.

Table 15 Interpolation factors provided by Halcrow Ltd (2009) used to calculate annual average hourly traffic flows

Period	**Factor**	
	Highway	Public Transport
AM Peak Hour to 07.00-09.00h	2.6	2.4
IP Average Hour to Period pre 07.00h,10.00h-15.00h, post19.00h	7.5	7.0
PM Peak Hour to Period 16.00-18.00h	2.7	2.6

Halcrow Ltd (2009) provided different interpolation factors for public transport. Analysis of the Leicester bus timetable revealed bus traffic to occur on the roads between 05.00h - 00.00h only (LCC 2011c). Subsequently the pre 07.00h traffic flow period was shortened from 00.00h - 07.00h to 05.00h - 07.00h to accommodate public transport flows. This meant that there were zero bus flows between the hours of 00.00h and 05.00h.

The highway (HDV and LDV) flows and public transport flows were summed to give total hourly traffic flows for each link. The links were then assigned to their appropriate classifications and the average hourly traffic flow of the links within each road classification was calculated and used to create classification specific diurnal profiles. The profiles were then transformed to meet the input requirements of AMDS-urban (profiles must average one and add up to 24; CERC 2011). The profiles created can be seen Appendix E.

Interpolation factors that enabled the development of Saturday and Sunday profiles were not available. Therefore, the 2005 DfT national flow profiles for the weekend days were used (DfT, 2009b).

All of the weekday profiles developed were characterised by two peak flow periods (AM and PM peaks) and by low flows during the early morning and night. In general, classifications 1 and 5 and classifications 4 and 2 respectively exhibited similar diurnal variation. However, road classification 3 had a profile dominated by PM peak flows with only a small AM peak period.

6.1.2 Vehicle Fleet Composition

Vehicle fleet compositions were developed according to the structure of PITHEM (see Chapter 4 Figure 4) using data from SATURN and national data (DfT 2009b). Level 1 of the vehicle fleet composition structure for each link was partly defined using the HDV, LDV and bus compositions from SATURN. National vehicle fleet composition data was used to further characterise the LDV vehicles into cars and LGVs at Level 1. All other levels of vehicle fleet composition were defined using national data.

6.1.3 Emissions Data

The LCC provided NO_x (285t/yr) and PM_{10} (10t/yr) emissions data for point and area sources. These emissions were considered representative of the commercial and domestic contributions to local air pollution in Leicester. Link based NO_x and PM_{10} emissions were calculated using vehicle fleet composition, AADT and average network speed. The AM, IP and PM Network Speeds were used to calculate the average-speed for each link. In addition, an annual profile for month by month traffic flow provided by the LCC was defined in the emissions inventory. However, the temporal variation of point and area source emissions were not defined due to a lack of available data.

It should be noted that ADMS-Urban assumes that 10% of NO_x from all sources is emitted as NO_2.

6.2 ADMS-Urban

A number of models in addition to ADMS-Urban were available for use in this research, namely AERMOD and Airviro. AERMOD was not used in this research as it requires substantially more meteorological data (e.g. upper air data, surface albedo, Bowen ratio etc.) than either Airviro or ADMS-Urban. This meteorological data was not readily available for Leicester and therefore the requirements of the model could not be met. In contrast to AERMOD, ADMS-Urban requires only a basic set of meteorological data from which it calculates more complex meteorological parameters. The meteorological data available for use in this research were sufficient enough to meet the requirements of ADMS-Urban. Airviro was not used in this research as it is split into a number of modules (e.g. emissions module, dispersion module and chemistry post processing module) which have to be manually set up one after another. This is extremely time consuming. In contrast, ADMS-Urban requires only a single initial set up as all modules (e.g. meteorological pre-processing and emissions, dispersion and chemistry calculations) are automatically run once a preceding calculation has finished. Therefore, manual set up times are significantly reduced when using ADMS-Urban.

ADMS-Urban has been validated in numerous studies (Carruthers *et al.,* 1998; Blair *et al.,* 2003; Carruthers *et al.,* 2003a) and it has been shown to perform within a factor of two when predicting pollutant concentrations in Taiwan (Carruthers *et al.,* 2008), China (McHugh *et al.,* 2005), France (Soulac *et al.,* 1997), Italy (Righi *et al.,* 2009) and the UK (Carruthers *et al.,* 1999). In addition, its performance has been shown to be comparable, if not better than other dispersion models and approaches by Hanna *et al.* (1999), Leskmono *et al.* (2006), Carruthers *et al.* (2003b) and Riddle *et al.* (2004). Therefore, ADMS-Urban was considered the most appropriate regional scale dispersion model for use in this research.

The treatment of road sources in ADMS-Urban has already been described in Chapter 2 along with an overview of its Gaussian principles and limitations. The following sections document the model set-up carried out in this work and ADMS-Urban is further described. However, a comprehensive description of the model is given by CERC (2006). It should be noted that canyon width and canyon height data were not available for use in this research and it was for this reason that ADMS-Urban's canyon model was not used in this study.

6.2.1 Model Input Limitations

The maximum number of road sources that can be defined in ADMS-Urban in any single set-up prior to calculation is 3000 and so it was not possible to model the whole of the simulation domain in one. Therefore, the road network was divided spatially into three segments (top, bottom and middle) and the model was executed in two ways. The first run (Figure 9) comprised point, area and road emissions sources aggregated to a shallow grid source (300m x 300m resolution; 2025 grid cells) for the entire area (all three segments) whilst the middle of the road network was explicitly defined at a much higher resolution as a road source. Predicted concentrations at three receptor locations (Bassett Street, New Walk Centre (NWC) and Uppingham Road) were output for the first run. It should be noted that ADMS-Urban subtracts the emissions from explicitly defined sources (in this case road sources) from the grid source prior to calculation preventing double counting. The second run (Figure 10) comprised point, area and road source emissions aggregated to a shallow grid source (300m x 300m resolution; 2025 grid cells) of the entire area whilst the top and bottom segments of the road network were explicitly input as road sources. Predicted concentrations at four receptor locations (Abbey Lane, Melton Road, Imperial Avenue and Glenhills Way) were output for the second run. This methodology is based on the approach of Owen *et al.* (1999 and 2000) who defined links both explicitly and aggregated to grid level when predicting pollution concentrations at fixed locations throughout London using ADMS-Urban.

Figure 9 ADMS-Urban model run 1 set up for the Leicester City Council (LCC) Local Authority (LA) area

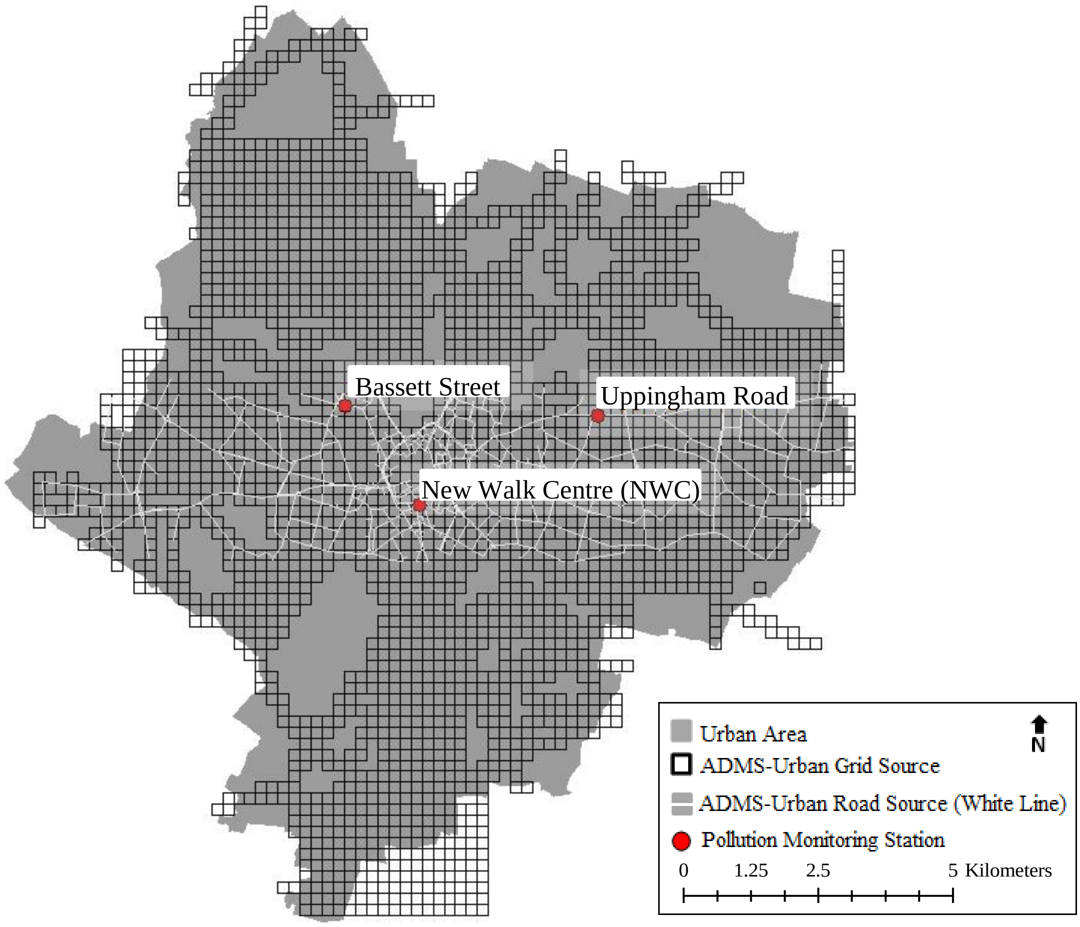
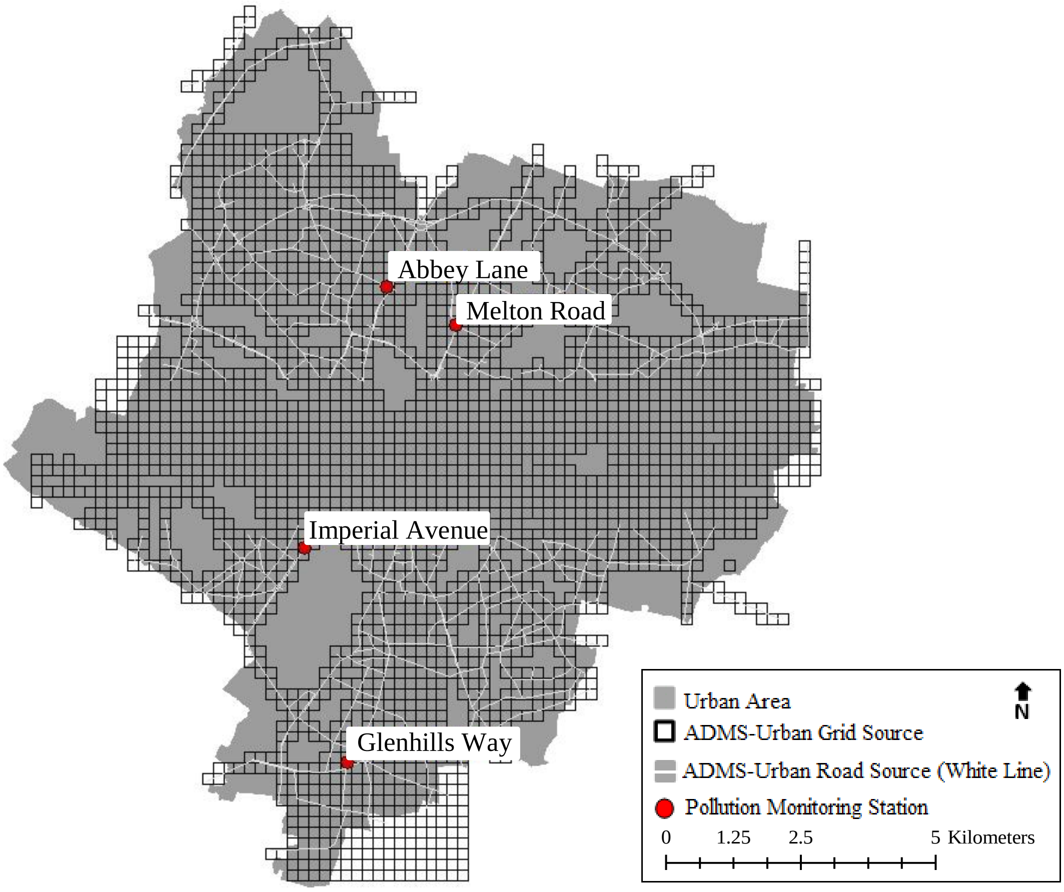


Figure 10 ADMS-Urban model run 2 set up for the Leicester City Council (LCC) Local Authority (LA) area



In ADMS-Urban a grid source is treated in a similar manner to a line source. Like a road source, a grid source has no plume rise but the user must specify a grid depth which represents the depth within which the source is well mixed. A grid depth of 10m is advised by CERC (2011) for large urban conurbations and was the value used in this study. Similarly, like a road source a grid source is decomposed to a maximum of 10 source elements. The contribution from each element is approximated by a crosswind vertical slice of finite length and height (CERC, 2006). The expression for the concentration from a crosswind vertical slice of length L_s and height L_1 is given by Equation 9.

$$C = \frac{Q_S}{4U}\left[\mathrm{erf}\left(\frac{y+L_S/2}{\sqrt{2}\sigma_y}\right)-\mathrm{erf}\left(\frac{y-L_S/2}{\sqrt{2}\sigma_y}\right)\right] \text{ x } \left[\mathrm{erf}\left(\frac{\frac{z+L_1}{2-Z_S}}{\sqrt{2}\sigma_z}\right)-\mathrm{erf}\left(\frac{\frac{z-L_1}{2-Z_S}}{\sqrt{2}\sigma_z}\right)\right] \text{ +Reflection terms}$$

(Equation 9)

Where C is the pollutant concentration, U is the mean wind speed affecting the plume, Q is the emissions rate, h the effective emissions height above the ground, σ_y and σ_z are the values of horizontal (y) and vertical dispersion (z) coefficients.

6.2.2 Chemical Reaction Scheme

ADMS-Urban has a simple Generic Reaction Set (GRS) that is used to define NO_x chemistry. It should be noted that the scope of the dispersion model does not extend to include all the chemical reactions that take place in the atmosphere. The GRS takes into account eight chemical reactions (see CERC, 2006; Venkatram *et al.*, 1996). The model requires the input of NO_x, NO_2 and O_3 background concentrations (see section 6.2.3) prior to modelling chemistry.

There are two separate chemistry modules in ADMS-Urban, both of which employ the same GRS. The simpler of the two modules uses the GRS only and assumes that background pollutant levels and associated reactions do not vary spatially throughout the study area. In contrast, the Chemical Reaction Scheme with Trajectory (CRST) model takes into account differences in surface and background ozone levels that may occur over large conurbations through the use of a Lagrangian box model. The trajectory model requires the specification of a grid source. This allows for a more spatially variable ozone field to be calculated. The average lifetime of pollutants at each receptor point is used to calculate the time scale over which the eight reactions take place (Owen *et al.,* 2000). Background gases are assumed to enter the simulation area at the upwind edge of the domain. The trajectory module then aggregates the emissions, meteorological conditions and deposition rates into 5km x 5km grid squares and then uses the GRS to calculate local pollutant concentrations. Therefore, to allow for spatial variability in photochemical reactions the CRST was used in this investigation.

6.2.3 Background Data

The UK has an extensive network of air quality monitoring stations. The AURN is the main air quality compliance network for DEFRA and devolved administrations. In their local air quality management technical guidance, DEFRA state the use of background data from a rural monitoring station is appropriate if all local sources are explicitly modelled (DEFRA, 2009). Therefore, background data from a rural monitoring station was used in this investigation. NO_x, NO_2, PM_{10} and O_3 background concentration data was collated from Harwell rural background monitoring station which is located 125km> from Leicester. This site was chosen based on advice from the LCC (2011d) who use data from Harwell when conducting air quality review and assessments. The site was considered appropriate because it provided data of good quality, there was sufficient data capture and because of its location downwind of Leicester (LCC, 2011d). Although the background data from the Harwell site met the requirements of ADMS-Urban it was envisaged that due to its distance from Leicester it would not be representative of the city's urban background pollution concentrations. However, a number of other rural background sites (namely Ladybower and Market Harborough) were considered for use in this research, but the data capture at these locations was found insufficient to meet the requirements of ADMS-urban. Therefore, the background site located at Harwell was at the time considered the best appropriate option for use in this research.

6.2.4 Meteorological Data Set and Pre-processing

Meteorological data for the parameters wind speed (m/s), wind direction (^{o}), solar radiation (W/m^2), temperature (^{o}C) and precipitation (mm/h) for the year 2005 were provided by LCC for use in this study. The data used was recorded in central Leicester at a height of 10m. It is widely accepted in the literature that meteorological conditions vary on the microscale, with the construction of every building, bridge, road etc. effectively creating a new microclimate which has its own set of meteorological parameters governing pollutant dispersion (Vallero, 2008). Therefore, the use of meteorological data collected from a single point in Leicester was not considered representative of the meteorological conditions immediately within the vicinity of the pollution monitoring sites. However, meteorological data of this resolution was not available for use in this research and the data provided by the LCC collected from a single central location in Leicester was considered the best available at the time of research.

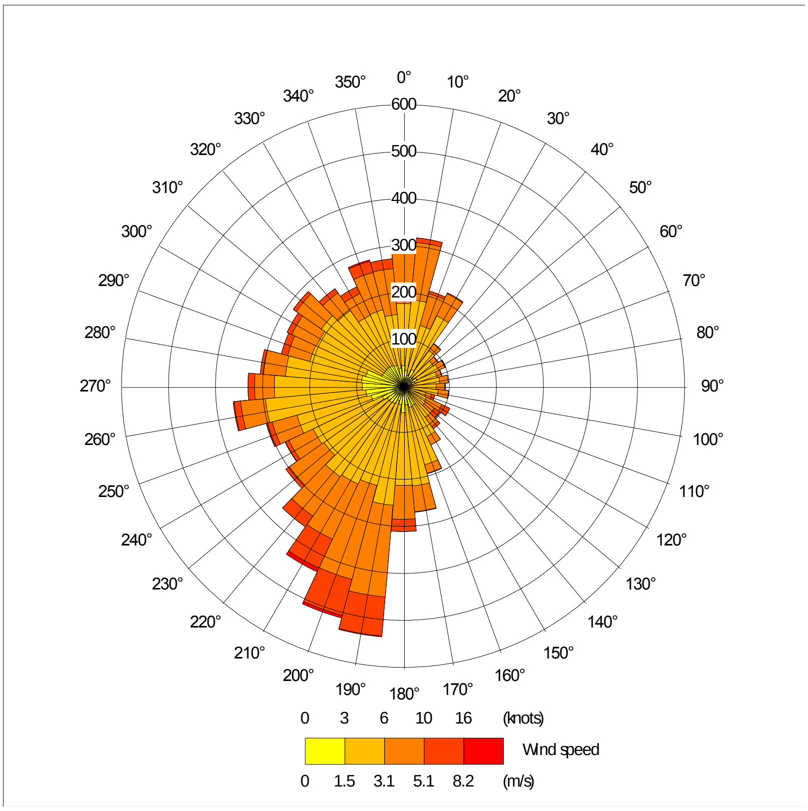
A constant surface roughness length of 1.5m was used to describe the simulation area, as this value is suggested by CERC (2006) for large urban conurbations.

The meteorological data was characterised by mixed patterns of wind (Figure 11), with 3% of the hourly sequential data exhibiting wind speeds of $\leq$1m/s and 1% of the data exhibiting wind speeds of $\leq$0.75m/s. Table 16 shows a summary of meteorological conditions for the city of Leicester for the year 2005. The maximum wind speed (23m/s) was recorded on 24th February at 19.00h. The prevailing wind was from the south/south westerly direction. Peak solar radiation (1 W/m^2) values were frequently achieved throughout the year and were not season specific. Higher temperatures were observed between the months of April and August which corresponded to the UK summer time.

Table 16 Summary of meteorological conditions for the city of Leicester for the year 2005

	Temperature (°C)	**Wind Speed (m/s)**	**Solar Radiation (W/m^2)**	**Precipitation (mm/h)**
Average	10.57	2.92	0.13	0.07
Maximum	34.00	23.00	1.00	3.10
Minimum	-6.00	0.00	0.00	0.00

Figure 11 Wind rose (wind speed [m/s] and wind direction [°]) for the city of Leicester 2005



ADMS-Urban has algorithms to compute the rates of dry deposition (F) and wet deposition (F_{wet}). Both were used in this investigation. F is defined by the following formula.

$$F = v_d C$$

(Equation 10)

Where:

$$v_d = \frac{v_s}{1 - \exp(-v_s / v_d')}$$

(Equation 11)

Where $\mathrm{v_d}$ is the deposition velocity which is defined in Equation 11, v_s the terminal velocity (a function of gravitational settling) and v'_d the deposition velocity as a function of diffusion. When dry deposition is specified in ADMS-Urban the airborne concentration is modified to reflect a reduction in plume strength with distance and by adjusting the vertical profile as removal only occurs at the surface.

F_{wet} is modelled using a washout coefficient Λ which is dependent on a large number of parameters including; the nature of the pollutant, concentration in air raindrops, rainfall rate and droplet size distribution. These parameters can be input by the user or estimated by ADMS-Urban. The default values in ADMS-Urban were used to calculate the wet deposition rates in this investigation as information on droplet size distribution and concentration in raindrops was not known. F_{wet} is calculated in ADMS-Urban according to the following formula:

$$F_{wet} = \int_0^\infty \Lambda \mathrm{C}\, dz$$

(Equation 12)

Where dz is the deposition height. As with dry deposition, the wet deposition algorithm reduces the plume strength with distance from the source.

6.3 Observed Concentration Data

Observed PM_{10} and NO_2 concentration data was compiled for five and seven monitoring locations within the LCC LA area respectively. All the sites are AURN accredited. Table 17 shows a summary of the monitoring station characteristics. All of the stations were situated on the road side except for the NWC which was located 30m from the nearest road and is classified as an urban background station. Monitoring stations at Abbey Lane, Bassett Street, and Melton Road were located close to heavily trafficked junctions and the station at Glenhills Way was located adjacent to a junction characterised by high delay. The remaining stations (Imperial Avenue and Uppingham Road) were located on road links that were considered to be on a primary traffic corridor into Leicester city centre (city centre feeder roads). These city centre feeder roads were characterised by high vehicle flow and high junction delay.

Table 17 Summary of monitoring station characteristics

Site Name	Pollutants Monitored	Distance to Nearest Road (m)	Nearest Link AADT (PCU)	Nearest Link Average Traffic Speed (km/h)	Site Location Description
New Walk Centre (NWC)	PM_{10} and NO_2	30	23923	27	Surrounded by Buildings on three sides
Abbey Lane	PM_{10} and NO_2	7	2658	33	40m from a heavily trafficked junction
Basset Street	NO_2	12	3013	27	95m from extremely large junction
Melton Road	PM_{10} and NO_2	3	10545	38	70m to heavily trafficked junction
Glenhills Way	PM_{10} and NO_2	3	16058	27	68m from a junction characterised by delay
Imperial Avenue	PM_{10} and NO_2	7.5	15533	38	On a city centre feeder road
Uppingham Road	NO_2	2	9828	38	On city centre feeder road, 64m to nearest junction

In 2005, monitoring sites at Abbey Lane, Glenhills Way and Melton Road recorded annual mean concentration values that failed to comply with EU NO_2 limit values (40µg/m^3 annual average). In contrast, PM_{10} pollution levels were well under the EU limit values (50µg/m^3 24 hour average and 40µg/m^3 annual average).

Figure 12 and Figure 13 show the monthly mean NO_2 and PM_{10} concentrations at the seven and five monitoring sites respectively. All sites had a data capture greater than 90% for the year. In general, the monitoring station at Glenhills Way recorded the highest NO_2 and PM_{10} concentrations. The NWC monitoring station, which was surrounded by buildings on three sides, recorded the lowest NO_2 concentration values. However, the NWC site recorded the third highest PM_{10} pollution levels. The monitoring station at Imperial Avenue recorded the lowest PM_{10} concentrations. Recorded NO_2 levels, with the exception of data recorded at Glenhills Way, showed relatively strong seasonal (spring, summer, autumn and winter) variation, with pollution levels peaking in the winter in November and again in February and tailing off in the summer. In contrast, trends in pollution levels recorded at Glenhills Way remained steady between January and May but increased rapidly between

June and December. Similarly PM_{10} concentration levels showed strong seasonal variation at all monitoring sites with higher concentrations in winter and spring than in summer and autumn.

Figure 12 Monthly mean NO_2 concentrations (µg/m^3) at Abbey Lane, Bassett Street, Glenhills Way, Uppingham Road, Melton Road, Imperial Avenue, and New Walk Centre (NWC)

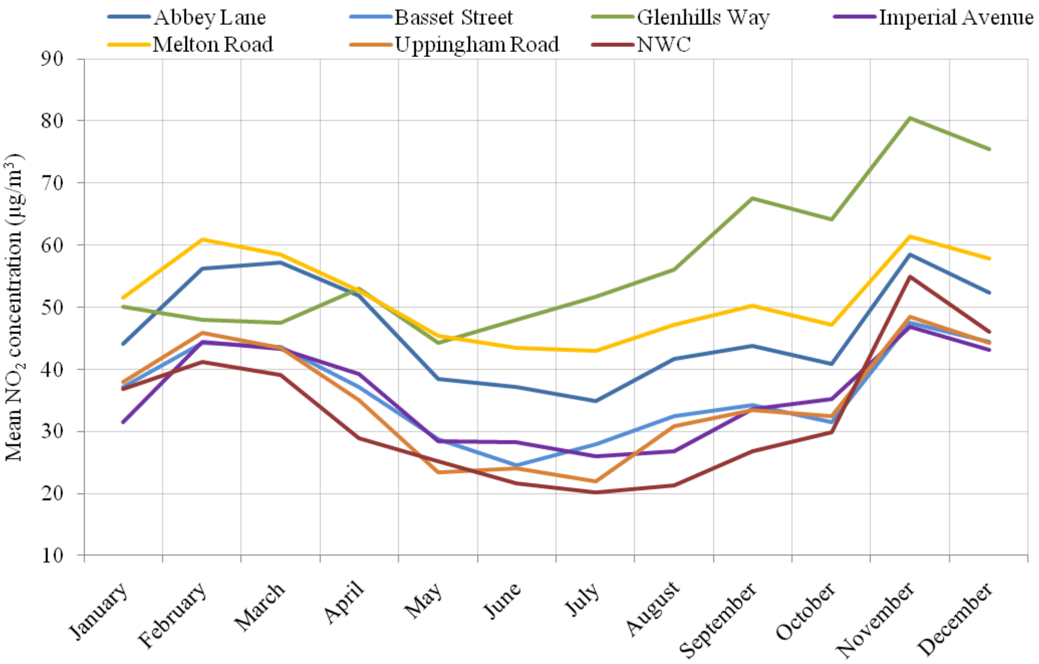
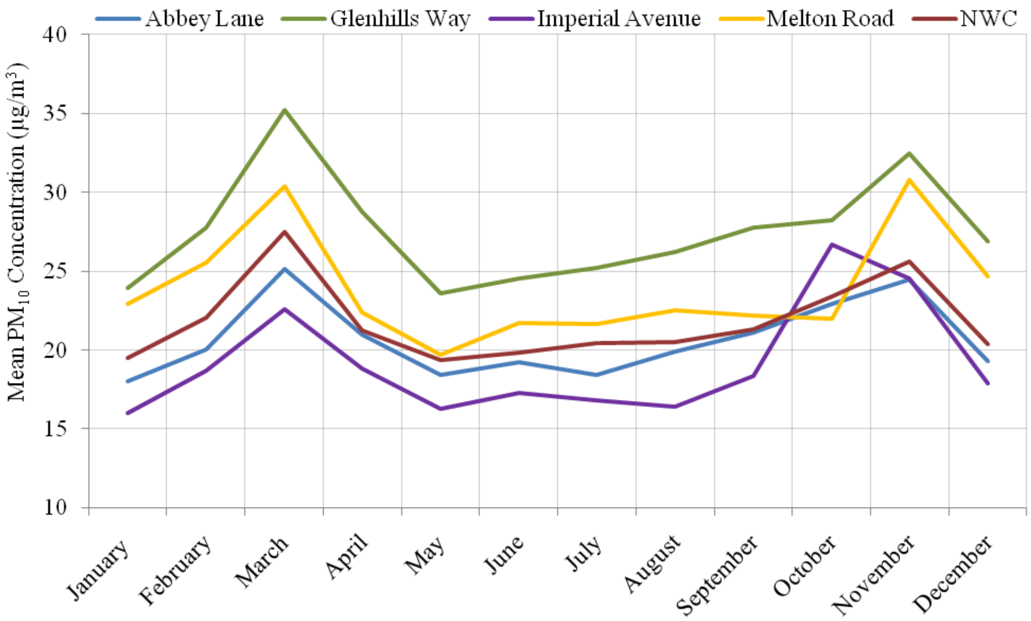


Figure 13 Monthly mean PM_{10} concentrations (µg/m^3) at Abbey Lane, Glenhills Way, Melton Road, Imperial Avenue and New Walk Centre (NWC)



6.4 Comparison of Predicted and Observed: Statistical Analysis Method

Chang and Hanna (2004) give a comprehensive review of the different statistical evaluation methods presently available to air quality modellers. Based on their review the ASTM, CDF and Taylor's nonogram were considered to be inadequate for evaluation of data in this work due to the following reasons. A CDF approach provides a qualitative comparison of predicted and observed concentration and did not meet the quantitative comparison criteria defined in this research goal. Taylor's nonogram (Taylor, 2001, Gates, 1999) comprises three quantitative performance evaluation measures (NMSE, normalised standard deviation - NSD, R: where R is the square root of the correlation coefficient R^2) which are presented on one diagram. However, the performance measure R is described in the literature as a poor indicator of model performance (Stunder and Sethurama, 1986). Duijm *et al.* (1996) document that R 'merely determines whether the variance in the predicted (Cp) and observed (Co) concentrations is in some way correlated….the correlation tells nothing about the agreement between the two sets of data.' Finally, the ASTM procedure does not directly compare predicted and observed data (ASTM, 2000). Instead, prior to performance evaluation, predicted and observed data are placed separately into groups (called regimes in the user guide) defined based on independent factors such as wind speed or downwind distance. These regimes are then averaged and it is these average values which are compared. However, although Chang and Hanna (2004) describe the ASTM procedure as 'a promising approach,' they concluded that there are a number of issues with the methodology that need to be addressed before it can be useful. These include the fact that comparisons are sensitive to the regimes in which they are placed, there are only a finite number of regimes, which limits the number of comparisons, and the procedure has only been used with short range dispersion experiments with concentric sampling arcs.

In contrast to the ASTM methodology, the statistical procedures implemented in the BOOT Software (Hanna *et al.,* 1991, 1993; Chang and Hanna, 2004) evaluate model performance by coupling predicted and observed concentrations. Concentrations can be coupled in time, in space or both. The original BOOT software (Hanna, 1991) was developed under the European Initiative on Harmonisation within Atmospheric Dispersion Modelling for Regulatory Purposes to provide a common set of quantitative performance measures with which an air quality model's performance could be assessed (see HARMO, 2012). Use of the standard set of statistics is well documented in the literature (Hanna, 1989; Owen *et al.*, 1999, 2000; Ichikawa and Sada, 2002; Nappo and Essa, 2000; Mosca *et al.,* 1998) and the software is widely accepted as a tool to evaluate model performance. However, literature concerning its application to evaluate air quality performance relating to mobile sources is relatively limited.

The latest version of the BOOT software (Chang and Hanna, 2005) not only provides an improved set of standard statistical descriptors but also suggests a framework for model performance evaluation; a clear goal should be defined for the evaluation method, the BOOT statistical software (Chang and Hanna, 2004) should be used to quantitatively evaluate the performance of the air quality model and exploratory data analysis should be carried out on the observed and predicted data in relation to independent variables (e.g. wind speed and direction). The framework was followed in this research.

6.4.1 Evaluation Goal

The goal of the evaluation procedure carried out in this work was to quantitatively compare predicted and observed concentrations of NO_2 and PM_{10} so that the performance of ADMS-Urban could be assessed and the accuracy of the emissions inventory compiled estimated.

6.4.2 Statistical Performance Measures

The BOOT statistical software (Chang and Hanna, 2004) was used to calculate the performance evaluation measures; FAC2, FB, MG, fractional bias false negative (FB_{fn}), fractional bias false positive (FB_{fp}) NMSE and VG. FAC2 is documented in the literature as being the most robust measure of a model's performance because FAC2 is not influenced by extreme high or low values and as a result is a completely unbiased evaluation performance measure (Chang and Hanna 2005). It is calculated according to Equation 13.

$$\text{FAC2} = \text{fraction of data that satisfy}$$
$$0.5 \leq \frac{C_p}{C_o} \leq 2.0$$

(Equation 13)

Where C_o denotes the observed concentration values, and C_p denotes predicted concentration values. In all statistics defined in the BOOT framework, C_o and C_p data are coupled in time (averaging time, T_a, was defined as hourly in this study) and space (at the same receptor location).

FB and MG are measures of mean bias. They indicate the mean under or over-prediction (Hanna *et al.* 2004) and are calculated according to equations 14 and 15 respectively.

$$FB = \frac{(\overline{C_o} - \overline{C_p})}{0.5(\overline{C_o} + \overline{C_p})}$$

(Equation 14)

$$MG = \exp\left(\overline{\ln C_o} - \overline{\ln C_p}\right)$$

(Equation 15)

In equations 14 and 15 $\bar{C}$ denotes the average of the data set. FB ranges from -2 (over-prediction) to +2 (under-prediction) and a perfect model has an FB of zero (Hanna *et al.*, 2004). However, because FB is a measure of mean bias, predictions that do not closely match those of the observed can still result in a FB close to zero. To overcome this issue Chang and Hanna (2004) suggested the calculation of the false negative (FB_{fn}) and false positive (FB_{fp}) parts of FB. FB_{fn} and FB_{fp} are calculated according to equations 16 and 17 respectively.

$$FB_{fn} = \frac{0.5[\overline{|C_o - C_p|} + (\overline{C_o} - \overline{C_p})]}{0.5(\overline{C_o} + \overline{C_p})}$$

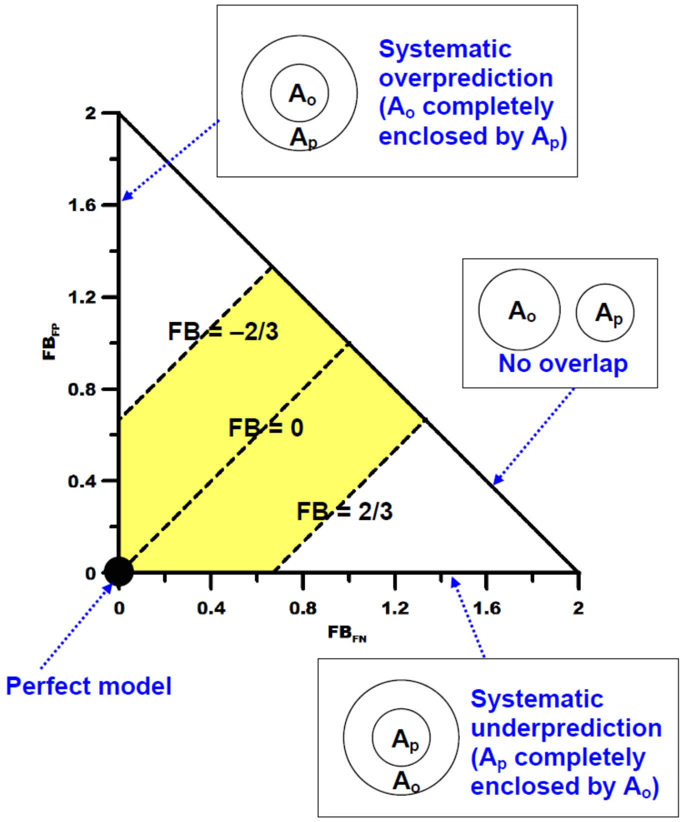
(Equation 16)

$$FB_{fp} = \frac{0.5[\overline{|C_o - C_p|} + (\overline{C_p} - \overline{C_o})]}{0.5(\overline{C_o} + \overline{C_p})}$$

(Equation 17)

FB_{fn} only considers pairs of predicted and observed data where $C_p<C_o$ and as such FB_{fn} is a measure of under-prediction of the model. On the other hand FB_{fp} considers only pairs of data where $C_p>C_o$ and as such is a measure of over-prediction of the model. Chang and Hanna (2005) illustrated that plotting FB_{fn} against FB_{fp} can be a useful way to evaluate a model's performance. They presented a two dimensional diagram with the x and y coordinates defined as FB_{fn} and FB_{fp} respectively (Figure 14). The diagram can be used to determine if a model's fractional bias falls within a factor of two (indicated by the shaded area between FB = -2/3 and FB = 2/3), if there is no overlap between the predicted and observed concentrations (the hypotenuse of the triangle) and if there is systematic under or over-prediction between the observed (A_o) and predicted (A_p) contour areas. Chang and Hanna (2004) documented the relationship between FB and contour area and it is not presented here. The two dimensional FB diagram was plotted in this investigation. It should be noted that the Figure of Merit in Space (FMS) compares A_o and A_p (see Chang and Hanna, 2004) and therefore it was not necessary to calculate FMS in this work as the two dimensional FB diagram accounts for this relationship.

Figure 14 Two dimensional FB diagram*



* The x axis indicates under-prediction and the y axis over-prediction. Perfect agreement between observed and predicted data lies at $FB_{fn} = FB_{fp} = 0$. FB = -2/3 and FB = 2/3 represent a factor of two over and under-predicted respectively. The shaded area represents a mean bias that is within a factor of two of the observed. The hypotenuse of the triangle represents no overlap between the predicted and observed concentrations.

NMSE and VG are measures of variance or scatter and indicate the overall deviation between the predicted and observed (Hanna *et al.*, 1999). They are calculated according to Equations 18 and Equation 19 respectively.

$$\mathrm{NMSE} = \frac{\overline{(C_o - C_p)^2}}{\overline{C_o}\,\overline{C_p}}$$

(Equation 18)

$$VG = \exp\left[\overline{(\ln C_o - \ln C_p)^2}\right]$$

(Equation 19)

Both MG and VG are based on a logarithmic scale and their measure of bias refers to the ratio of C_p to C_o (Chang and Hanna, 2005). However, due to their measure on a log scale, MG and VG are sensitive to low values. For example Dijum *et al.* (1996) documented that coupled data with values lower than 10ppm removed to have a MG of 2.22 and VG of 11.9 but when values lower than 20ppm were removed the same model was documented to have a performance equal to MG 1.97 and VG 9.9. To overcome this issue Chang and Hanna (2004) suggested removing data below the lowest limit of detection (LOD) of the instruments used to record the observed data prior to calculating MG and VG. Therefore, in this research observed and predicted NO_2 and PM_{10} concentration values lower than 0.4ppb (see Teledyne Instruments 2011) were removed from the data sets prior to calculating MG and VG.

FB and NMSE are calculated on a linear scale and as a result can be influenced by extreme high values (Dijum *et al.*, 1996). A relatively high FB (e.g. FB = ±2) and or NMSE (e.g. NMSE =4) value but a lower MG (e.g. 0.5> MG < 2) and or VG (e.g. VG = <1.6) value can indicate the presence of infrequent high values and that the predicted or observed (or both predicted and observed) data is (are) not normally distributed (Donnelly *et al.*, 2009). In such a case the use and interpretation of MG and VG is more appropriate as they give equal weighting to over or under-predictions (Mosca *et al.*, 1998; Hanna *et al.*, 2004). MG and VG values are always greater than zero. An MG value <1 indicates model over-prediction whilst an MG of 1> suggests model under-prediction and a perfect model has an MG of 1 (Chang and Hanna, 2005). An MG of 0.5 indicates a factor of two over-prediction and an MG of 2 indicates a factor of two under-prediction (Chang and Hanna, 2004). In contrast, a model with a VG of 1.6 indicates that on average there is a factor of two scatter between coupled predicted and observed data (Hanna *et al.*, 1993). As VG is a measure of variance it does not indicate over or under-prediction as is the case for its linear counterpart, NMSE.

The BOOT software was used to calculate whether the statistical performance measures FB, NMSE were significantly different from zero and MG, VG and FAC2 significantly different from one. The BOOT software comprises a bootstrap or Jackknife resampling procedure (Efron, 1987) that resamples the coupled observed and predicted data a 1000 times, with the possibility of the same pair being sampled more than once (Mosca *et al.*, 1998). Statistical performance values are calculated for each sample taken and the distribution of each performance measure is determined. The standard deviations of these distributions are subsequently used to determine the 95% confidence limits of the measures (Hanna *et al.*, 1991).

From extensive experience in evaluating air quality model performance Chang and Hanna (2004) suggested a range of values within which a ‘good’ model’s performance measures should lie (FAC2 > 0.5, FB<0.3 or 0.7<MG<1.3, NMSE <1.5 or VG<4). However, these acceptance criteria were set for research grade field experiments and it was further documented by Chang and Hanna (2004) that ‘model performance would be expected to deteriorate as the quality of inputs decreases or as more stringent data pairing options (paired in time and space) are used.’ There has been no acceptance criteria suggested in the literature for non-field grade experiments.

6.4.3 Exploratory Data Analysis

Time series analysis of observed and predicted concentrations were plotted to help assess the ability of ADMS-Urban to predict concentrations in time. It should be noted that predicted data are plotted on the negative scale for time series comparisons. In addition, observed versus predicted scatter plots were drawn to further assess agreement in time. Residual values (ratio of C_p to C_o) were calculated and grouped according to independent variables, namely wind speed, wind direction, time of day and time of year (summer or winter). Residuals were grouped if they occurred at wind speeds of 1m/s to 6m/s and 7m/s and above, according to units of 45^o angles of wind direction (orientated to Figure 9 and Figure 10) and for each consecutive hour of the day for diurnal trend analysis. Finally, residuals were grouped based on time of year, with September to March classed as the UK winter time and April to August as the UK summer time. Perfect agreement between predicted and observed results in a residual of one. Residuals less than 0.5 indicate a factor of two under-prediction, whilst residuals greater than two indicate a factor of two over-prediction.

6.5 Results

The statistical performance measures NMSE and FB calculated were significantly different from zero at 95% confidence interval. Similarly the statistical performance measures VG, MG and FAC2 were significantly different from 1 at 95% confidence. ADMS-Urban significantly under-predicted NO_2 concentrations. Predicted concentrations of NO_2 and PM_{10} were dependent on wind speed, wind direction, season and time of day. The results for NO_2 and PM_{10} are presented in the next sections.

6.5.1 Statistical Performance Measure for NO_2

All sites had positive FB values and VG and MG values significantly (95% confidence) greater than 1 suggesting ADMS-Urban under-predicted NO_2 concentrations (Table 18). FB values were within a factor of two (-2/3> FB <2/3) and MG values, with the exception of Glenhills Way, were also within a factor of two (0.5>MG <2) of the observed. Only VG values for Bassett Street and Imperial Avenue fell within a factor of two scatter and NMSE values for these sites were comparatively low further indicating a relatively small spread of predicted data around the observed. In contrast, all other sites were found to have VG and NMSE values that suggested a large spread of predicted data around the observed data.

The predicted data at all of the sites except those of Glenhills Way and Melton Road had FAC2 values of 60% or greater. Only 44% and 53% of predicted NO_2 concentrations at Glenhills Way and Melton Road respectively were within a factor of two of the observed. A greater proportion of predicted data fell within a factor of two of the observed at Imperial Avenue (FAC2 73%), Bassett Street (FAC2 72%) and Uppingham Road (FAC2 69%). Similarly, 66% of predicted urban background NO_2 concentrations were within a factor of two at the NWC site. NO_2 concentrations at this site were under-predicted by an average of only 4% (FB = 0.04) over the year which is comparable to the mean under-prediction (2%; FB=0.02) found at Bassett Street.

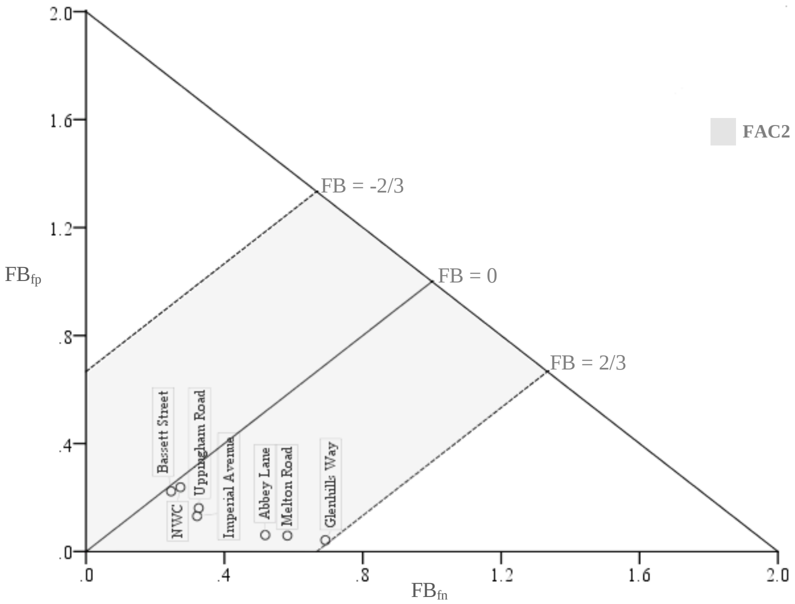
Table 18 Statistical performance measures mean, standard deviation (SIGMA), normalised mean square error (NMSE), the proportion of data that is within a factor of two of the observed (FAC2), fractional bias (FB), geometric mean variance (VG), geometric mean bias (MG) for observed and predicted NO_2 concentrations at the seven monitoring locations respectively

Site Name	Model	MEAN	SIGMA	NMSE	FAC2	FB	VG	VG within a factor of 2 (VG<1.6)	MG	MG within a factor of 2 (0.5 >MG< 2)
Abbey Lane	Observed	46	24	0	1	0	1	-	1	-
	Predicted	29	17	0.58	0.60	0.46	1.82	No	1.63	Yes
New Walk Centre (NWC)	Observed	33	21	0	1	0	1	-	1	-
	Predicted	32	18	0.46	0.66	0.04	1.79	No	1.03	Yes
Bassett Street	Observed	36	19	0	1	0	1	-	1	-
	Predicted	35	23	0.39	0.72	0.02	1.55	Yes	1.09	Yes
Glenhills Way	Observed	57	29	0	1	0	1	-	1	-
	Predicted	29	20	0.95	0.44	0.65	2.80	No	2.14	No
Imperial Avenue	Observed	36	18	0	1	0	1	-	1	-
	Predicted	29	19	0.36	0.73	0.19	1.50	Yes	1.3	Yes
Melton Road	Observed	52	22	0	1	0	1	-	1	-
	Predicted	30	19	0.68	0.53	0.52	2.33	No	1.86	Yes
Uppingham Road	Observed	35	20	0	1	0	1	-	1	-
	Predicted	30	20	0.41	0.69	0.17	1.63	No	1.25	Yes

The observed data for Abbey Lane, Melton Road and Glenhills Way showed annual mean exceedences of the NO_2 EU air quality limit value (40µg/m^3). These exceedences were not found in the predicted concentrations as annual mean values were significantly under-predicted at these sites. Neither observed or predicted NO_2 concentrations exceeded 200µg/m^3 more than 18 times a year.

Figure 15 shows the two dimensional FB diagram for NO_2, where perfect agreement between predicted and observed data lies at FB_{fn} = FB_{fp} =0. All of the predicted data comprised over and under-prediction. Generally, the model showed a greater tendency to under-predict rather than over-predict as FB_{fn} values were found to be higher than FB_{fp} values. ADMS-Urban over-predicted concentrations at Glenhills Way the least, but under-predicted concentrations at this site the most. The diagram suggests that there was overlap between the predicted and observed concentration contour lines as the data points did not fall close to the triangle hypotenuse. Predicted NO_2 concentrations at Bassett Street and NWC had FB values close to zero, but both comprised under and over-prediction.

Figure 15 Two dimensional FB diagram for NO_2



6.5.2 Exploratory Data Analysis for NO_2

All of the modelled percentile values were under-predicted (Table 20Table 19). However, the level of under-prediction was dependent on site location. The predicted data for Bassett Street and Uppingham Road showed an under-prediction of ~10µg/m^3 for the lower percentiles (50th to 98th), whilst the level of under-prediction increased linearly at these sites in line with the 99th, 99.8th, 99.9th and 100th observed percentiles. In general, the modelled percentiles for Melton Road showed an under-prediction of ~25µg/m^3 but the 99.9th and 100th percentiles were under-predicted by only ~10µg/m^3.

The modelled percentiles at Glenhills Way were under-predicted the most with the 50th percentile found to be under-predicted by more than a factor of two. Similarly, a factor of two under-prediction was found for the 100th percentile at Imperial Avenue. However, unlike Glenhills Way, generally good agreement between observed and predicted percentiles was found for Imperial Avenue. Similarly, predicted percentiles at the NWC site showed generally good agreement with the observed. However, the model significantly under-predicted peak percentiles at the NWC location and showed ~45μg/m^3 under-prediction for the 99.9th and 100th percentiles. A similar trend was found at Abbey Lane with the 99.8th and 99.9th percentiles under-predicted by as much as ~50μg/m^3.

Table 19 The 50th to 100th percentiles respecitvely for the observed and predicted NO_2 concentrations (μg/m^3) at the New Walk Centre (NWC), Bassett Street, Uppingham Road, Abbey Lane, Glenhills Way, Melton Road and Imperial Avenue

Monitoring Site	**Model**	**Percentile (μg/m^3)**								
		50th	*84th*	*90th*	*95th*	*98th*	*99th*	*99.8th*	*99.9th*	*100th*
New Walk Centre (NWC)	Observed	29	52	59	69	86	101	136	153	201
	Predicted	28	50	58	67	76	84	103	108	148
Bassett Street	Observed	33	55	63	72	85	93	119	127	168
	Predicted	21	42	49	58	68	74	87	91	114
Uppingham Raod	Observed	31	55	64	75	88	95	110	115	143
	Predicted	21	42	50	61	72	79	93	101	113
Abbey Lane	Observed	44	69	77	90	103	116	146	164	181
	Predicted	25	46	54	63	74	80	94	102	157
Glenhills Way	Observed	54	85	96	112	131	144	174	181	202
	Predicted	24	49	58	70	81	87	102	110	133
Melton Road	Observed	50	75	82	91	99	105	119	125	176
	Predicted	26	49	56	68	79	86	101	113	165
Imperial Avenue	Observed	33	54	60	68	78	85	101	114	307
	Predicted	25	48	57	69	80	87	99	106	145

The time series and scatter plots confirmed the trends in the descriptive statistics, with sites found to have NMSE and VG values respectively closer to zero and one to have better agreement with the observed data in time. The time series and scatter plots not presented below can be found in Appendix F. In general, predicted NO_2 concentrations at Glenhills Way showed poor hour by hour agreement (Figure 16(a)) with a large proportion of data under-predicted (Figure 16(b)). A similar trend was found for Abbey Lane and Melton Road. Model over-predictions were more prominent at NWC (Figure 17(a) and Figure 17(b)), Uppingham Road, Bassett Street (Figure 18(a)) and Imperial Avenue, particularly during the summer months. ADMS-Urban had a greater tendency to over-predict NO_2 concentrations at Bassett Street than at any other location (Figure 18(b)).

Figure 16(a) Time series graph of observed and predicted NO_2 concentrations ($\mu g/m^3$) and Figure 16(b) observed vs predicted NO_2 concentrations ($\mu g/m^3$) at Glenhills Way from the 1st of January 2005

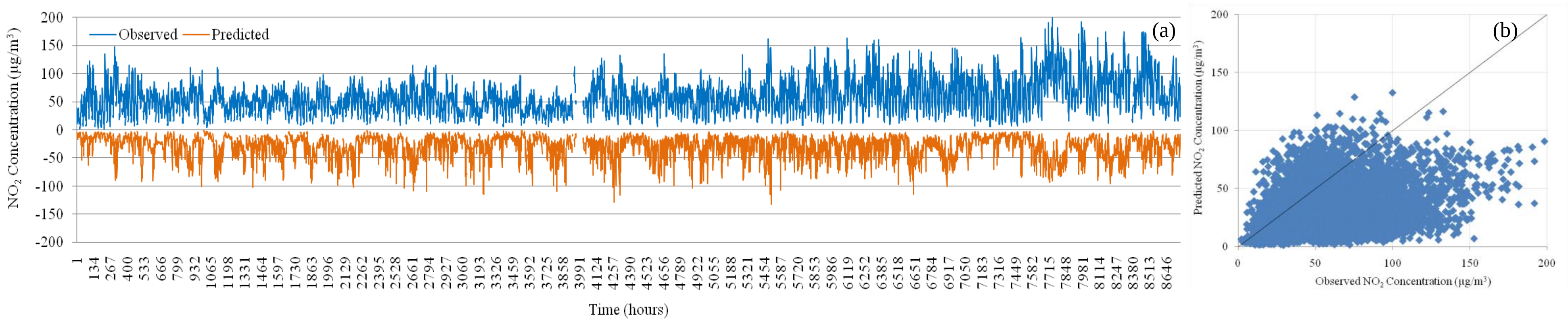


Figure 17(a) Time series graph of observed and predicted NO_2 concentrations ($\mu g/m^3$) and Figure 17(b) observed vs predicted NO_2 concentrations ($\mu g/m^3$) at NewWalk Centre (NWC) from the 1st of January 2005

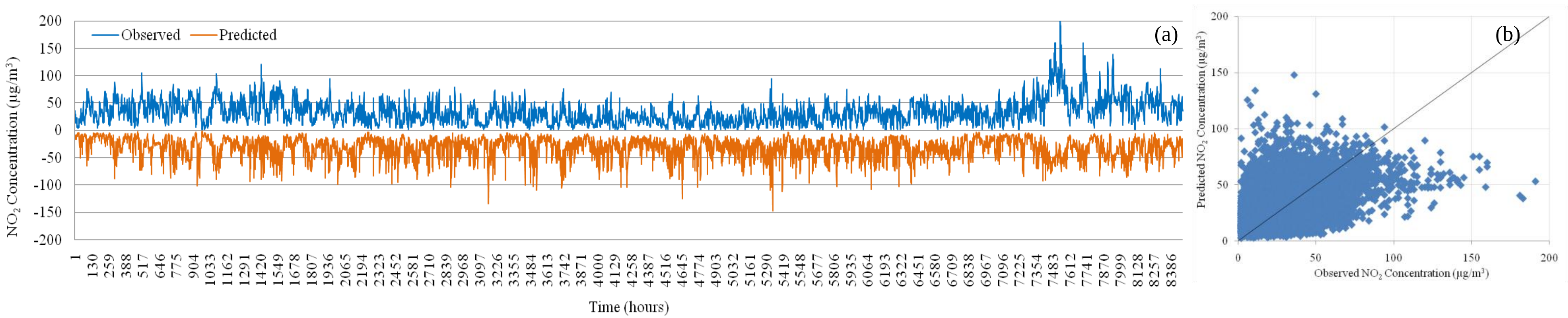
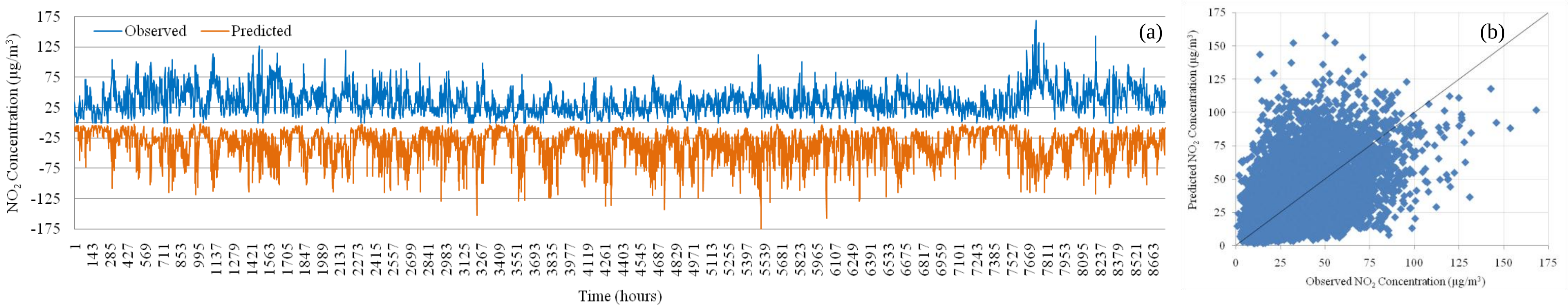


Figure 18(a) Time series graph of observed and predicted NO_2 concentrations (µg/m^3) and Figure 18(b) observed vs predicted NO_2 concentrations (µg/m^3) at Bassett Street from the 1st of January 2005



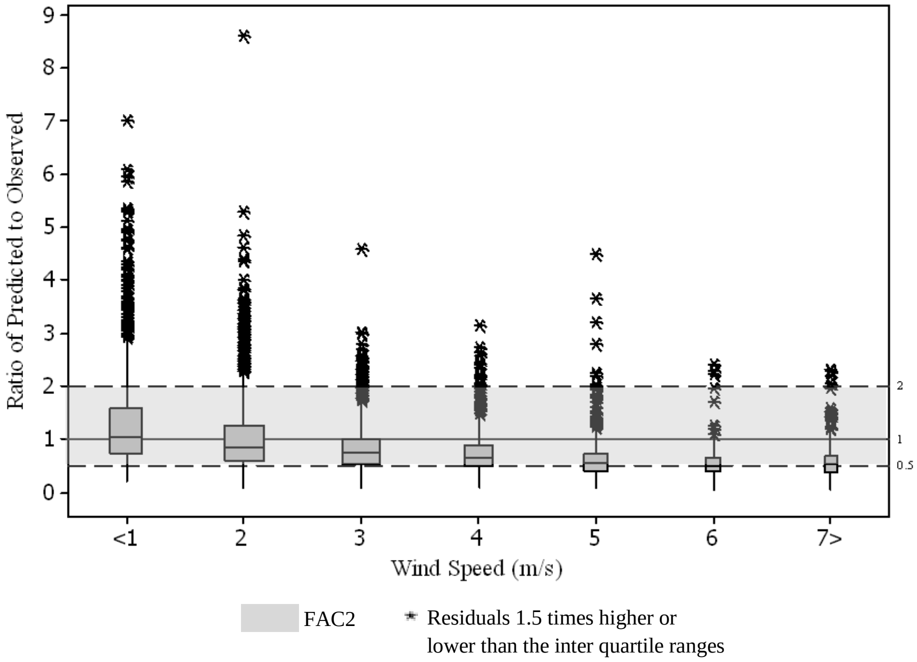
The ability of ADMS-Urban to predict NO_2 concentrations was dependent on wind speed, wind direction, season and time of day. The box plots of residuals versus independent variables for NO_2 and PM_{10} are presented in Appendix G. It should be noted that the box plot size is proportional to the number of residuals for the particular variable. Although the overall trend was one of under-prediction, in general the model had a greater tendency to over-predict during low wind speed conditions (<1m/s) and the model's performance deteriorated in favour of under-prediction as wind speeds increased (e.g. Figure 19). The tendency of the model to over-predict during low wind speed conditions resulted in a greater number of residuals falling within a factor of two.

ADMS-Urban's sensitivity to wind direction was dependent on wind speed. Generally, the model had a tendency to over-predict NO_2 concentrations during wind directions between 0° and 90° (Table 20), which typically exhibited low wind speed conditions (see Figure 11). In contrast, the model under-predicted during wind directions between 180° and greater than 315°, which typically had higher wind speeds. The best performance for all sites was found during wind directions that were associated with low wind speed conditions (<1m/s) as the model had a greater tendency to over-predict during these conditions resulting in a greater number of residuals falling within a factor of two.

Table 20 Sensitivity of ADMS-Urban to wind direction when predicting PM_{10} concentrations at Abbey Lane, Gelnhills Way, Imperial Avenue, Melton Road, New Walk Centre (NWC), Bassett Street and Uppingham Road

Location	Wind Direction (°)		
	Under-prediction	Over-prediction	Best Performance
Abbey Lane	225<270	0<45	0<45
Glenhills Way	180<225	45<90	45<90
Imperial Avenue	225<270	45<90	0<45
Melton Road	315>	45<135	45<135
New Walk Centre (NWC)	180<225	45<90	0<45
Bassett Street	180<225	45<90	315>
Uppingham Road	180<225	45<90	0<45

Figure 19 Ratio of predicted to observed (Cp/Co) NO_2 concentrations and wind speed (m/s) at Imperial Avenue



The performance of ADMS-Urban varied by time of day showing a greater tendency to over-predict at night (~20.00h to ~3.00h) and a tendency to under-predict between 4.00h and 6.00h (e.g. Figure 20). The models tendency to over-predict at night resulted in a greater number of residuals falling within a factor of two. In addition, a greater tendency for the model to under-predict between 10.00h and 12.00h was found at NWC, Bassett Street and Imperial Avenue.

The model generally over-predicted NO_2 concentrations more in the summer months and under-predicted during the winter period (Figure 21). These seasonal trends were the most pronounced when the model predicted concentrations at Uppingham Road, Bassett Street, Imperial Avenue and NWC. When the model predicted concentrations at Melton Road, Abbey Lane and Glenhills Way it showed much less dependence on season and had only a marginal tendency to over-predict more in the summer than in the winter.

Figure 20 Ratio of predicted to observed (Cp/Co) NO_2 concentrations and time of day (hours) at Glenhills Way

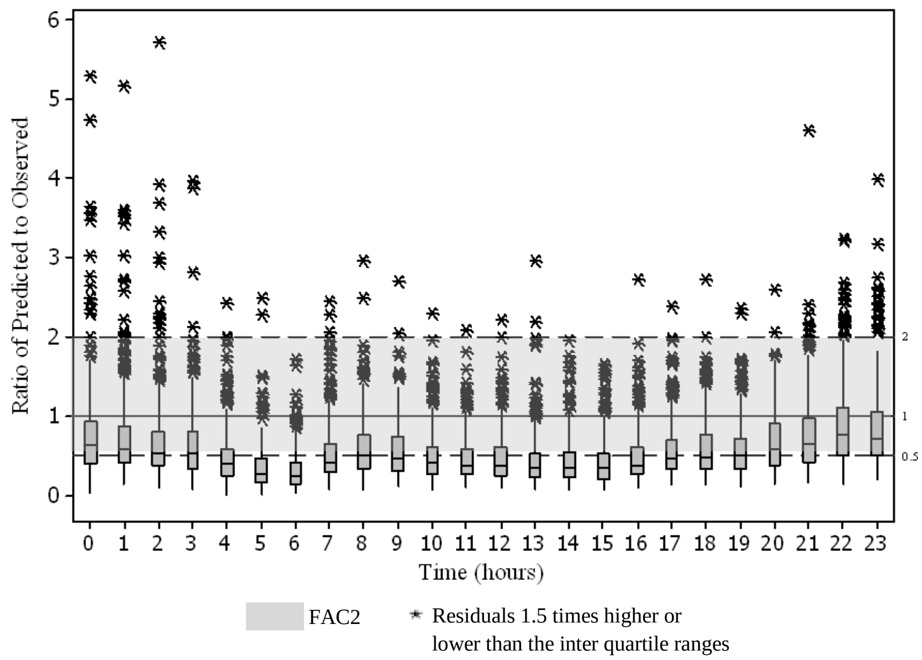
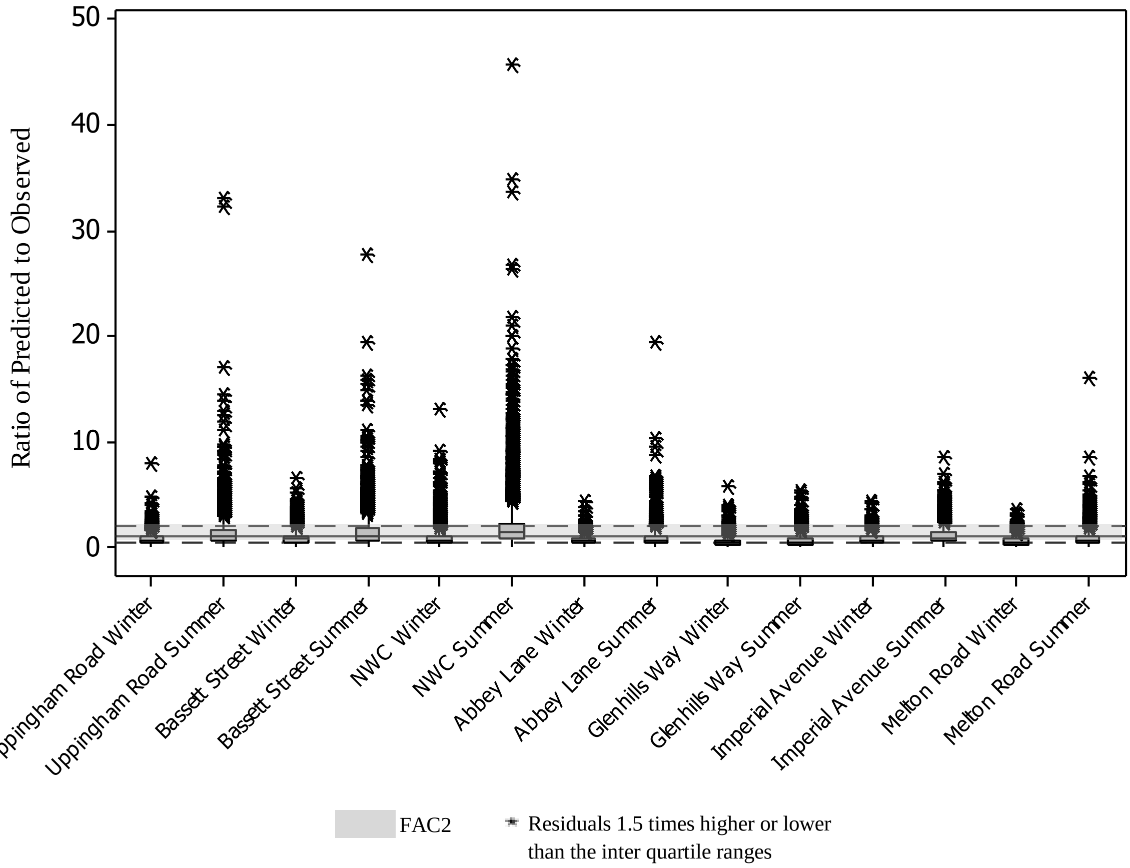


Figure 21 Ratio of predicted to observed (Cp/Co) NO_2 concentrations and Season (Summer and Winter) for Uppingham Road, Bassett Street, New Walk Centre (NWC), Abbey Lane, Glenhills Way, Imperial Avenue and Melton Road



6.5.3 Statistical Performance Measures for PM_{10}

More than 80% of the predicted PM_{10} data was within a factor of two of the observed at all locations (FAC2 values ranged from 0.84 to 0.90; Table 21). NMSE values ranged from 0.22 to 1.34 and VG values ranged from 1.21 to 1.30 which indicated a relatively small spread of predicted data around the observed. The model had a tendency to over-predict concentrations at Abbey Lane and Imperial Avenue. In contrast, the model had a tendency to under-predict at NWC, Melton Road and Glenhills Way. All of the FB, VG and MG values were within a factor of two of the observed ($0.5 > MG < 2$, $VG < 1.6$, $-2/3 > FB < 2/3$).

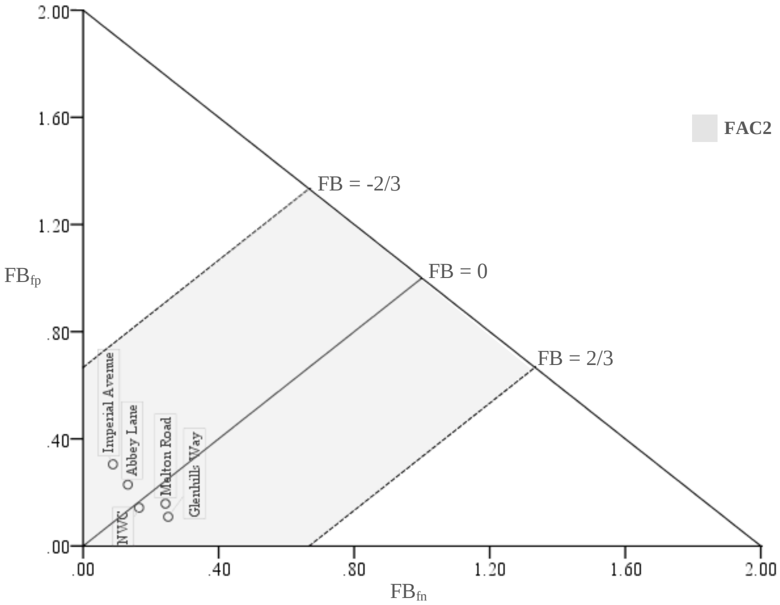
With the exception of predictions made at Imperial Avenue, all NMSE values were within a factor of two ($NMSE < 0.5$). A NMSE value of 1.34 was found for predictions at Imperial Avenue. However, its log normal counterpart, VG was found to be relatively low (1.29). This suggested greater influence of extreme values on peak concentrations.

Figure 22 shows the two dimensional FB diagram for PM_{10}. Both over and under-prediction was evident at all locations. The diagram further highlights that all of the predicted data fell within a factor of two mean bias. In addition, the diagram suggested that there was overlap between the predicted and observed concentration contour lines because the data points did not fall close to the triangle hypotenuse. On average the model had a greater tendency to under-predict at NWC, Glenhills Way and Melton Road and over-predict at Abbey Lane and Imperial Avenue which is reflected in the respective FB values.

Table 21 Statistical performance measures mean, standard deviation (SIGMA), normalised mean square error (NMSE), the proportion of data that is within a factor of two of the observed (FAC2), fractional bias (FB), geometric mean variance (VG), geometric mean bias (MG) for PM_{10} concentrations at the five monitoring locations respectively

Site Name	Model	MEAN	SIGMA	NMSE	FAC2	FB	VG	VG within a factor of 2 (VG<1.6)	MG	MG within a factor of 2 (0.5 >MG< 2)
Abbey Lane	Observed	21	12	0	1	0	1	-	1	-
	Predicted	23	10	0.32	0.86	-0.10	1.27	Yes	0.87	Yes
New Walk Centre (NWC)	Observed	22	11	0	1	0	1	-	1	-
	Predicted	21	10	0.22	0.90	0.02	1.21	Yes	1.01	Yes
Glenhills Way	Observed	27	14	0	1	0	1	-	1	-
	Predicted	24	11	0.28	0.87	0.14	1.24	Yes	1.12	Yes
Imperial Avenue	Observed	19	24	0	1	0	1	-	1	-
	Predicted	24	10	1.34	0.84	-0.22	1.29	Yes	0.76	Yes
Melton Road	Observed	24	14	0	1	0	1	-	1	-
	Predicted	22	11	0.41	0.84	0.09	1.30	Yes	1.05	Yes

Figure 22 Two dimensional FB diagram for PM_{10}



6.5.4 Exploratory Data Analysis: PM_{10}

The model had a tendency to under-predict 99.8th and 99.9th modelled percentile values at all locations and a factor of two under-prediction was found for the 99th percentile at Melton Road (Table 22). In contrast, generally better agreement was found for the lower percentiles. With the exception of Imperial Way and Abbey lane, the model had a tendency to over-predict the 100th percentile value and the peak predicted concentration at the NWC site (356µg/m^3) was more than a factor of three higher than the observed. The observed 100th percentile at Imperial Avenue (1428µg/m^3) was almost a factor of four higher than that of the predicted (361µg/m^3). This high value for the observed 100th percentile was the likely cause of the high NMSE value observed in Table 21.

Table 22 The 50th to 100th percentiles for the observed and predicted PM_{10} concentrations at the New Walk Centre (NWC), Abbey Lane, Glenhils Way, Melton Road and Imperial Avenue monitoring sites respectively

Monitoring Site	Model	Percentile (μg/m^3)								
		50th	*84th*	*90th*	*95th*	*98th*	*99th*	*99.8th*	*99.9th*	*100th*
New Walk Centre (NWC)	Observed	20	31	35	42	52	59	81	86	113
	Predicted	20	29	32	38	47	52	63	66	356
Abbey Lane	Observed	19	30	34	40	48	53	76	86	418
	Predicted	21	31	34	40	48	54	64	69	357
Glenhills Way	Observed	25	39	45	54	63	70	90	102	226
	Predicted	22	33	37	43	51	57	69	70	364
Melton Road	Observed	21	33	39	46	60	72	106	134	304
	Predicted	20	30	34	40	49	54	65	67	361
Imperial Avenue	Observed	17	26	30	36	45	52	74	106	1428
	Predicted	22	32	36	42	51	56	66	70	361

Time series analysis revealed that predicted data for all sites had similar temporal variation (see Appendix F). Comparison with the background data revealed strong agreement between predicted and background PM_{10} concentrations temporally (e.g. Figure 23(a) and Figure 23(b); Figure 24(a) and Figure 24(b)). However, less agreement was found between observed concentrations and background concentrations (e.g. Figure 23(c) and Figure 23(d)), which in turn meant that predicted and observed data had less hour by hour agreement (e.g. Figure 23(e) and Figure 23(f) and Figure 24(c) and Figure 24(d)).

Figure 23(a) Time series of background and predicted PM_{10} concentrations (µg/m^3); Figure 23(b) predcited vs background PM_{10} concentrations; Figure 23(c) observed and background PM_{10} concentrations; Figure 23(d) observed vs background PM_{10} concentrations; Figure 23(e) observed and predicted PM_{10} concentrations (µg/m^3) and; Figure 23(f) observed vs predicted PM_{10} concentrations at Melton Road

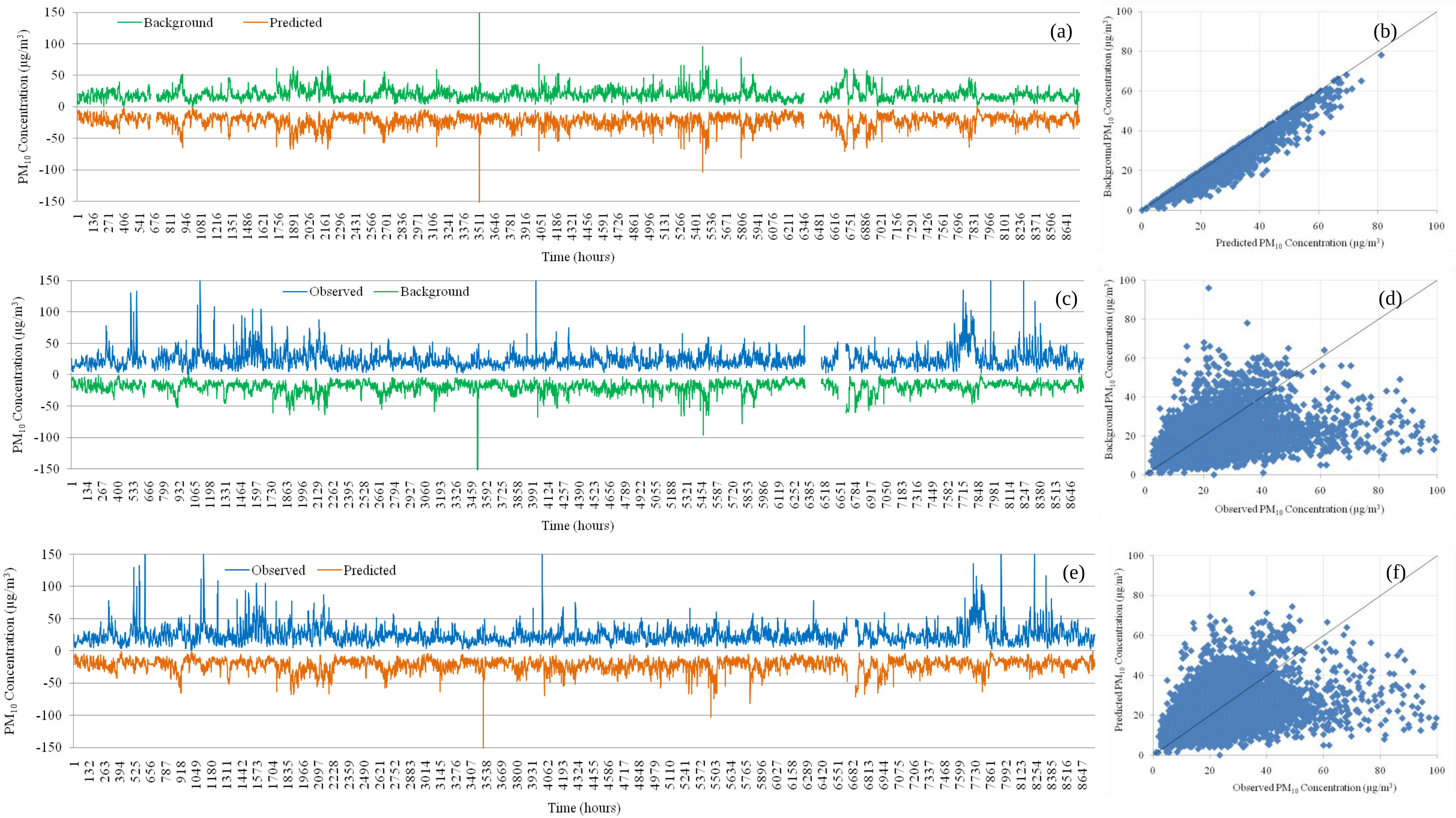
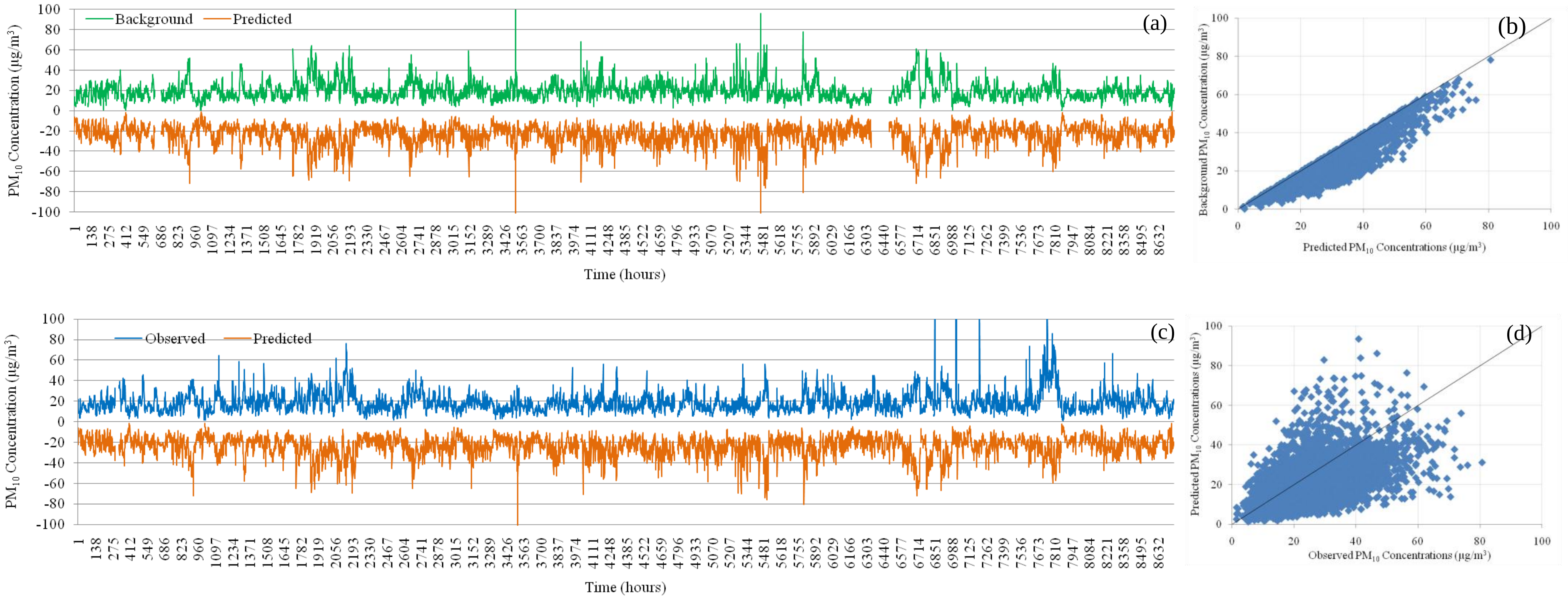
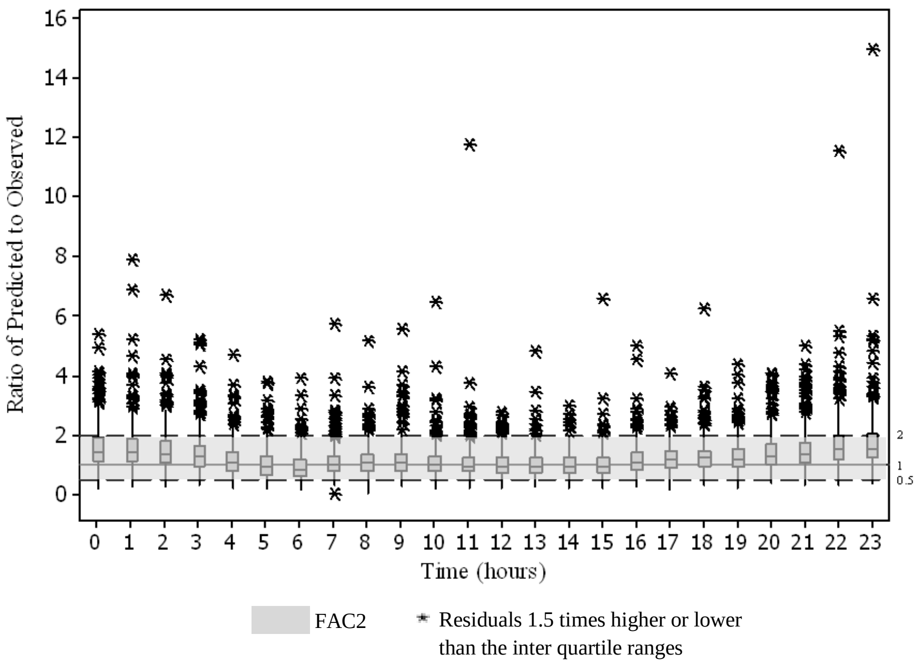


Figure 24(a) Time series of background and predicted PM_{10} concentrations (μg/m^3); Figure 24(b) predcited vs background PM_{10} concentrations; Figure 24(c) observed and predicted PM_{10} concentrations (μg/m^3) and; Figure 24(d) observed vs predicted PM_{10} concentrations at Imperial Avenue from 1st January 2005



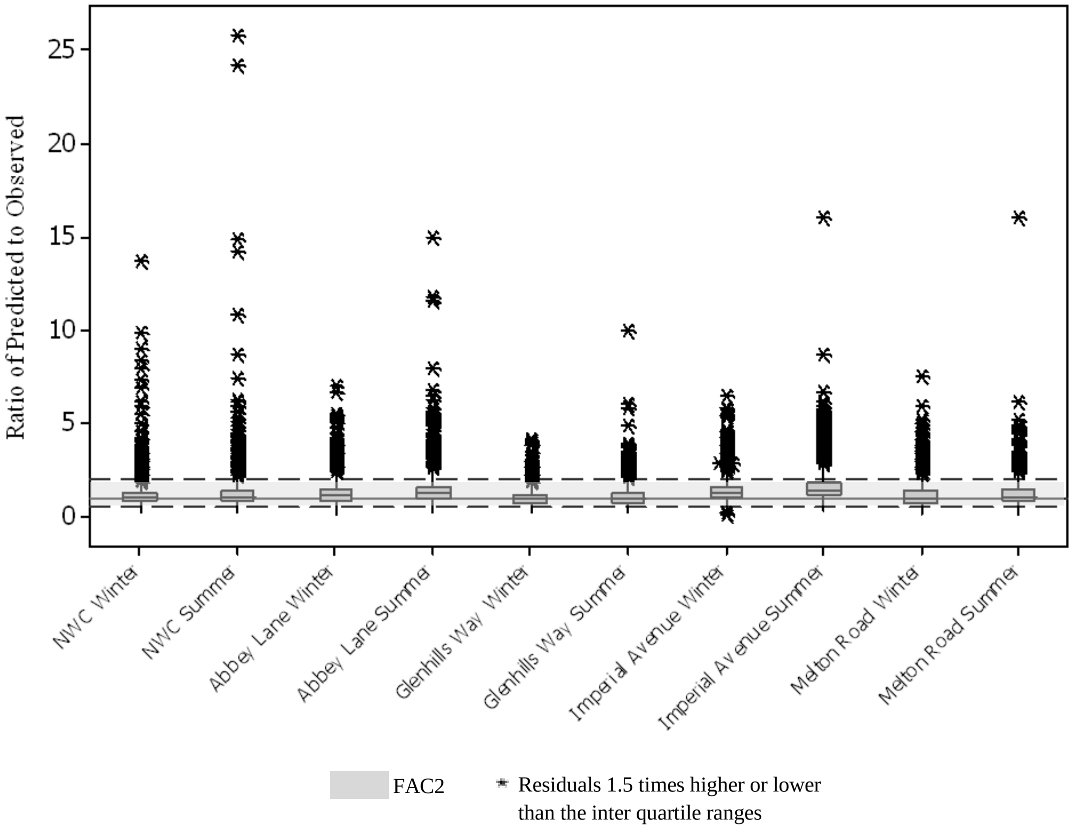
The ability of ADMS-Urban to predict PM_{10} concentrations varied depending on wind direction, season, wind speed and time of day. Although the overall trend found at NWC, Glenhills Way and Melton Road was one of under-prediction and the model typically over-predicted PM_{10} concentrations at Abbey Lane and Imperial Avenue, ADMS-Urban had a greater tendency to over-predict PM_{10} concentrations between 20.00h to 3.00h which resulted in a greater number of residuals falling within a factor of two of the observed at those sites that exhibited a general trend of under-prediction. In contrast, the model had a greater tendency to under-predict between 4.00h and 6.00h (e.g. Figure 25) and model under-prediction was found between 10.00h and 12.00h at all sites with the exception of the Abbey Lane location. Model performance when predicting PM_{10} concentrations at the NWC site was much less dependent on time of day.

Figure 25 Ratio of predicted to observed (Cp/Co) PM_{10} concentrations and time of day (hours) at Abbey Lane



The trends in model performance with season for PM_{10} were similar to those found for NO_2, with a greater tendency for model over-prediction during the summer and under-prediction during the winter (Figure 26). The trend of under-prediction in winter was most pronounced at Glenhills Way, whilst ADMS-Urban's tendency to over-predict in summer was the most evident at Imperial Avenue and Abbey Lane.

Figure 26 Ratio of predicted to observed (Cp/Co) PM_{10} concentrations and Season (Summer and Winter) for New Walk Centre (NWC), Abbey Lane, Glenhills Way, Imperial Avenue and Melton Road



ADMS-Urban had a tendency to under-predict at Glenhills Way during high wind speeds and during wind directions associated with these conditions (between 180° and 270°; Table 23). Model over-predictions were typically found at Glenhills Way during wind directions between 45° and 90° corresponding to low wind speed conditions (<1m/s; see Figure 11). In contrast, trends in PM_{10} predictions and wind conditions were less pronounced at Imperial Avenue as almost 75% of the residuals were found to be systematically over-predicted irrespective of wind speed (e.g. Figure 27) or direction. Similarly, ADMS-Urban was less sensitive to wind speeds when predicting PM_{10} concentrations at Abbey Lane as all median values were marginally over-predicted irrespective of wind speed (Appendix G). The model had a slight tendency to over-predict at Abbey Lane during wind directions associate with low wind speed conditions (greater than 315° and between 0° and 45°).

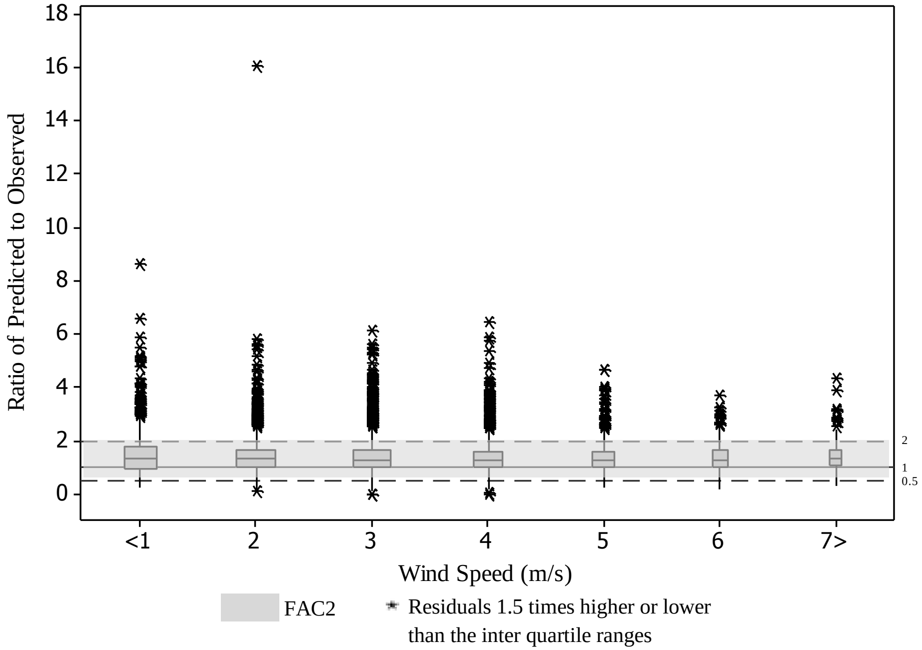
Low wind speeds (<1m/s) and wind directions between 0° and 45° resulted in greater under-prediction at the NWC location and over-predictions at the same site were found at high wind speeds and for wind directions between 225° and 270°. ADMS-Urban had a greater tendency to under-predict PM_{10} concentrations during wind speeds of 4m/s and wind directions between 270° and 315° at Melton

Road. The performance of the model deteriorated in favour of over-prediction during wind speeds greater than 7m/s and for wind directions between 45° and 135° at the same location.

Table 23 Sensitivity of ADMS-Urban to wind speed and wind direction at Glenhills Way, Imperial Avenue and New Walk Centre (NWC)

Location	Overall Trend	Wind Speed (m/s)			Wind Direction (°)		
		Under-prediction	Over-prediction	Best Performance	Under-prediction	Over-prediction	Best Performance
Glenhills Way	Under-prediction	6>	<1	<1	180<270	45<90	45<90
Melton Road	Under-prediction	4	7>	2, 3	270 to 315>	45<135	180<225
NWC	Under-prediction	<1	7>	7>	0<45	225<270	225<270

Figure 27 Ratio of predicted to observed (Cp/Co) PM_{10} concentrations and wind speed (m/s) at Imperial Avenue



6.6 Discussion: Comparison with the Literature

Table 24 shows a comparison of the FB, MG, VG, NMSE and FAC2 ranges found in this research with some of those documented in the literature. The table shows statistical performance measures from a range of air quality model experiments, such as studies that only considered maximum plume centre line concentrations (e.g. Hanna *et al.*), those that conducted model sensitivity tests (e.g. Hanna and Chang 2001) and those that coupled observed and predicted concentrations in time, in space and or both (e.g. Donnelly *et al.*, 2009; Duijum *et al.*, 1996). Furthermore, the table comprises investigations that used different air quality model types such as Gaussian, dense gas and CFD models. It should be noted that many of the experiments listed in Table 24 contain bias and comparisons should be made with caution. However, in general, comparison with research grade field investigations show the performance of ADMS-Urban in this study was comparable (e.g. Chang and Hanna, 1990; Desiato, 1992) to previous studies found in the literature. A study of particular relevance is that of Hanna *et al.* (2000) which evaluated the ability of ADMS, AERMOD and ISC3 to predict arc maximum tracer concentration values and concentration values at points above the tracer release height using various field grade data sets, namely OPTEX, Duke Forest, Kincaid power plant, Indianapolis power plant and Lovett power plant. The datasets were compiled from research grade experiments that were carried out in very different environments and comprised very different elements such as buoyant or non-buoyant tracer plumes and flat or urban terrain and as such evaluated model performance under changing conditions. Hanna *et al.* (2000) documented ADMS to under-predict by ~20%, AERMOD by ~40% and ISC3 was shown to perform least well having only 33% of predicted data within a factor of two of the observed. However, the model was shown to have a 40% bias (towards under-prediction) when predicting maximum SO_2 concentrations at 12 continuous monitors, not arranged in an arc, located on a mountain at a distance of 2000m and 3000m from a 145m stack. This suggested that the model performed better when predicting maximum concentrations along an arc and that model performance deteriorated when predicting pollution levels at random spatial locations. The under-predictions recorded by Hanna *et al.* (2000) are comparable to the NO_2 under-predictions in this research. The research of Hanna *et al.* (2000) considered only fixed emissions sources and was based on field grade data, which provided emissions and concentration measurements at a greater level of detail than the data used in this work.

The statistical values describing the performance of ADMS-Urban calculated by Carruthers *et al.* (2003a) show the model to have exceptional performance and comparatively, the performance of ADMS-Urban in this work is poor. The validation study carried out by Carruthers *et al.* (2003a) involved the assessment of ADMS-Urban to predict pollutant concentrations at both roadside and urban background locations in London. The model run for the validation study included the use of the CRST, canyon model and background data from four different rural monitoring stations chosen based on wind direction. In addition, the study adopted a nested approach in which the main simulation area (Greater London) was modelled explicitly and surrounding areas (within 3km) were modelled as grid sources to take into consideration background emissions immediately adjacent to the simulation domain. Furthermore, the model inputs were adjusted to take into consideration local PM_{10} from construction. Therefore, the quantity and quality of input parameters used by Carruthers *et al.* (2003a) were significantly greater than those used in this research and the model performance documented can subsequently be considered 'best case.' Information on canyon parameters, emissions sources adjacent to the simulation domain, PM_{10} emission rates from construction and background concentrations relative to wind direction were not available for use in this research which significantly (95% confidence) impacted the performance of ADMS-Urban.

The performance of ADMS-Urban in this work was more comparable to the non-field grade evaluation investigations documented by Owen *et al.* (1999; 2000) and Righi *et al.* (2009). These investigations were found to have used input data and set up the model in a similar way to that described in this research and subsequently were of lower quality than those of Carruthers *et al.* (2003a). Therefore, the literature suggested model inputs were the cause of predictive error in this research. The cause of the error in prediction is discussed in more detail in the following section.

Table 24 Comparison of statistical descriptors used for air quality model performance evaluation

Author and Date (*data set type*)	Model	Pollutant	Statistical Performance Measure Ranges				
			FB	MG	VG	NMSE	FAC2
This Work (*Non-Field Grade*)	ADMS-Urban	NO_2	0.02 to 0.73	1.03 to 2.14	1.50 to 2.80	0.36 to 0.95	0.44 to 0.73
	ADMS-Urban	PM_{10}	-0.22 to 0.14	0.76 to 1.12	1.21 to 1.30	0.22 to 1.34	0.84 to 0.90
Non-Field Grade							
Carruthers *et al.* 2003a	ADMS-Urban	NO_2	-0.14 to 0.20	-	-	0.12 to 0.28	0.78 to 0.95
Carruthers *et al.* 2003a	ADMS-Urban	PM_{10}	-0.06 to 0.03	-	-	0.13 to 0.71	0.90 to 0.95
Owen *et al.* 2000	ADMS-Urban	NO_x, NO_2	-	-	-	-	0.28 to 0.79
Owen *et al.* 1999	ADMS-Urban	NO_x,	-0.45 to 0.34	-	-	2.57 to 10.6	0.13 to 0.46
Righi *et al.* 2009	ADMS-Urban	CO	0.17 to 0.21	-	-	0.65 to 0.92	0.45 to 0.59
Field Grade							
Hanna *et al.* 2011	4 wind flow models	Tracer Release	-1.32 to 0.60	0.12 to 2.76	3.30 to 10^4	0.75 to 19.3	0 to 0.45
Hanna *et al.* 2004	FLACS (CFD)	Tracer Release	-1.32 to 0.61	0.35 to 2.63	1.07 to 17.9	0.07 to 2.03	0.47 to 1.00
Donnelly *et al.* 2009	WinMISKAM (CFD)	Tracer Release	0.21 to 0.43	1.17 to 2.00	7.68 to 50.8	1.39 to 2.79	0.43 to 0.50
Desiato 1992	Apollo (based on puff model)	Tracer Release	-	-	-	3.5 to 7.4	0.32 to 0.35
Hanna and Chang 2001	HEGADAS 3+ (Dense gas dispersion model)	Tracer Release	-	0.49 to 0.96	1.15 to 2.00	-	0.52 to 0.92
Chang and Hanna 1990	3 simple Gaussian plume models	Tracer Release	-	-	-	0.14 to 5.75	0.49 to 0.92
Duijum *et al.* 1996	Britter and McQuad model, 3 Gaussian plume models	Tracer Release	-	(ln) 0.04 to 2.87	(ln) 6.61 to 20.2	-	0.27 to 1
Hanna *et al.* 1991	14 hazardous gas models	Tracer Release	-1.54 to 1.24	-	-	0.03 to 6.17	0 to 1
Mosca *et al.* 1998	long range dispersion models	Tracer Release	-	0.36 to 1.26	6.29 to 111.37	9.95 to 1091.15	0.28 to 0.37
Chang and Hanna 2004	2 Gaussian plume models	Tracer Release	-0.04 to 0.52	0.84 to 15.52	1.2 to 306520	0.46 to 3.47	0.24 to 0.89
Hanna *et al.* 2000	ADMS, AERMOD, ISC3	Tracer Release	-	-1.68 to 2.47	0.7 to 11.6	-	0.06 to 0.80

6.7 Discussion: Performance of ADMS-Urban

According to Hanna (2007) the total error in a model output is made up of four components; errors and unrepresentativeness in observed data, errors and unrepresentativeness in inputs to the model, model errors such as assumption in model algorithms and stochastic fluctuations in observed data. Stochastic fluctuations in observed data come about due to random turbulence in the atmosphere (Chang and Hanna, 2004). It is not possible to fully account for this random turbulence in an air quality model's algorithms. As a result stochastic errors are always present in a model's output (Chang and Hanna, 2005). Furthermore, it is due to stochastic fluctuations that there can never be a model that predicts pollutant concentrations perfectly. Therefore, the model predictions in this research comprised an element of stochastic error. However, given the level of total predictive error found it was unlikely that this was the main cause of under-prediction and over-prediction. Similarly it was unlikely that errors (e.g. monitoring equipment calibration errors) and unrepresentativeness in observed data (i.e. observed data does not reflect the pollutant concentrations in the surrounding area) were the major cause of under-prediction in this case, although it is acknowledged that they will have contributed to total model predictive error.

The data analysis and comparison with the literature (see section 6.6 above) indicated the major source of model error in this research came about due to errors and unrepresentativeness of inputs to the model. It is possible that errors in input data resulted in model compensating errors which in turn resulted in better model performance. Compensating errors are when a model's performance is improved due to errors in input data, model algorithms etc. (Chang and Hanna, 2004). Compensating errors were seen in the predicted NO_2 data and predicted PM_{10} data sets. The model had a greater tendency to over-predict NO_2 concentrations between ~20.00h and 3.00h, during wind speeds <1m/s and during wind directions between 45° and 90° which resulted in a higher proportion of the model residuals falling within a factor of two. Similar, compensating errors were found for predicted PM_{10} concentrations but these were more dependent on location. The source of these errors are documented below, where the input variables (emissions inventory data - simulated traffic data, interpolation factors, diurnal profiles and emissions factors; meteorological data; and background concentration data) and the method used to model chemical reactions in the atmosphere are discussed.

6.7.1 Simulated Traffic Data, Interpolation Factors and Diurnal Profiles

The data from the strategic transport model (SATURN) used in this investigation did not include all of the roads inside the study area and emissions from these roads were not resolved in the inventory. Therefore, the compiled emissions inventory was incomplete, which would in part account for the under-predictions observed. Failure to account for emissions sources is well documented in the literature as a significant cause of predictive error (see Taghavi *et al.*, 2005; Hsu *et al.*, 2010; Zang *et al.*, 2008). The roads within the LCC LA area not modelled in this research were considered by the council to have very low traffic flows and therefore are unlikely to have been the primary cause of the model error in prediction found. However, point and area source data provided by the LCC may have been imprecise which would account for part of the model error observed.

SATURN was developed using ATR data and manual count data (LCC 2011e). ATRs and manual counts provide data that is a snap-shot of the traffic flow at the time of the recording. It is restricted temporally meaning that its representativeness over a longer time period is questionable. On a similar note, a traffic model requires the user to specify origin-destination data and the model then assigns traffic to roads based on this data (Van Vliet, 1982). It is impossible for the user to know every origin and destination within a network (given their diversity and dynamic nature) and so traffic models can comprise significant error (e.g. Namdeo *et al.,* 2002). Furthermore, the assignment of vehicles to roads by a traffic model ultimately determines the vehicle fleet composition on each road. Therefore, errors in assignment due to imprecise and unrepresentative origin destination matrices in turn result in errors in vehicle fleet composition. In this research, vehicle fleet composition at Level 1 was defined using data from SATURN and subsequently vehicle fleet characteristics were a source of error. In addition, the use of national data to represent local fleet compositions in this work will have further contributed to the model error. Namdeo *et al.* (2002) estimated that the potential error for vehicle fleet composition when using an air quality model to typically range from ±5% to ±10%.

Traffic models are steady-state assuming traffic flow remains constant over a single hour (Van Vliet, 1982). However, in reality traffic flows are unlikely to remain static over such a time scale. An increase in traffic volumes and or changes in travel-related characteristics increase vehicular emissions significantly (Nesamani *at al.*, 2007). Namdeo *et al.* (2002) suggested that SATURN has a potential error of ±12% for vehicle flows. Similar error margins for SATURN were documented by Matoros *et al.* (1987) and Nejadkoorki *et al.* (2008). Therefore, the use of simulated traffic data in this research was responsible for part of the model error found.

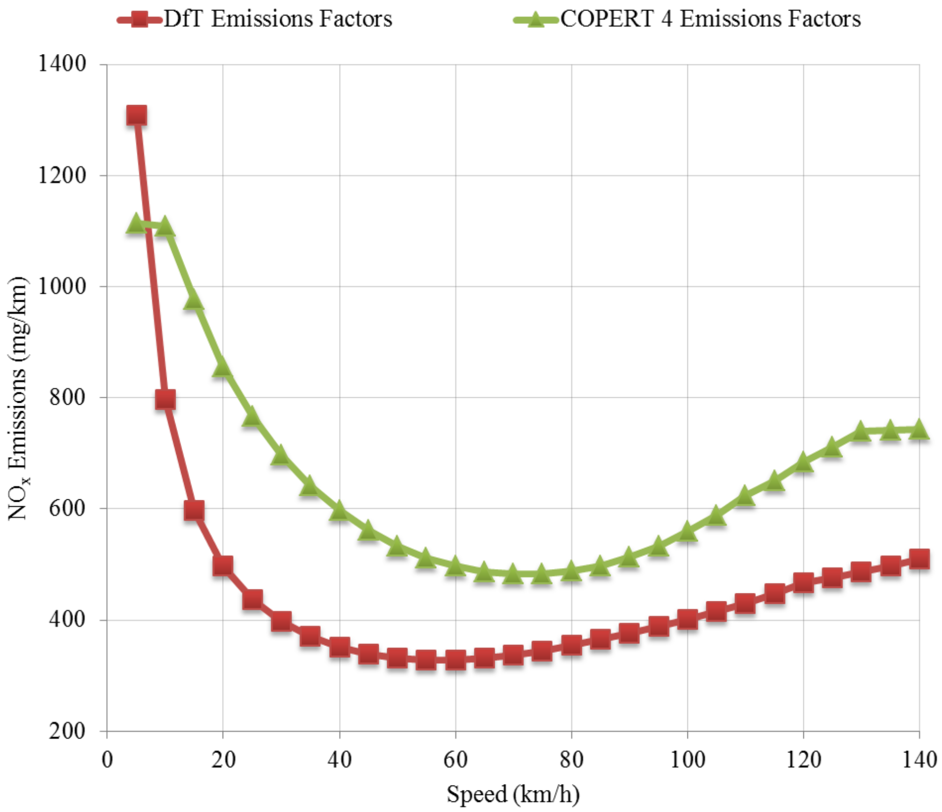
Time series analysis revealed that predicted NO_2 failed to accurately follow observed values in time. Under-predictions between 4.00h and 6.00h and during the IP period, particularly at NWC, Bassett Street and Imperial Avenue between 10.00h and 12.00h suggested an underestimate in the duration of peak emissions time. The diurnal profiles used in this research were developed using three different sets of interpolation factors, namely a set for constructing the AM, PM and IP periods respectively. Therefore, the profiles created did not model the transitions between periods and may have resulted in peak periods being shorter than in reality. This was a likely cause of predictive error. Future research should look to smooth the diurnal profiles to better represent diurnal variations in traffic flow and resulting congestion.

6.7.2 Emissions Data

The use of a coarse grid resolution has been well documented in the literature as a significant source of emissions and dispersion modelling error (Tang, 2002; Brucher *et al.,* 2000; Pangprueka *et al.,* 2008; Gilani and Pieim, 1996; Liang and Jacobson 2000), which tends to increase when chemically reactive species (e.g. NO_x) are considered (Jang *et al.,* 1995; Brant *et al.,* 2006). It is possible that the grid resolution used in this research (300m x 300m) may have resulted in the spatial dilution of emissions sources. However, given that in the two ADMS-Urban model runs the roads immediately adjacent to the monitoring sites were modelled explicitly it is unlikely that the grid resolution was a major cause of predictive error.

Since the completion of the modelling work carried out in this research the DfT released an updated set of interim emissions factors (DEFRA, 2012d). The factors incorporated changes to PM_{10} and NO_x emissions rates as the 2009 functions describing these emissions were considered not to be representative of real world emissions. The NO_x emissions factors developed by Boulter *et al.* (2009a) on behalf of the DfT were replaced with functions from COPERT 4 v8.1. The changes to the NO_x factors included adjustments to emissions degradation rates as well as changes in baseline speed - emissions functions. In addition, changes were made to the vehicle fleet composition to also take into account new vehicle sales projections, revised figures on the likely penetration of diesel cars and evidence from DfTs Automatic Number Plate Recognition data on the age mix of vehicles on the road across the country. Figure 28 shows the fleet weighted NO_x emissions factors used in PITHEM and the interim corrected factors released by the DfT in 2012 (DEFRA, 2012d). It should be noted that the factors in Figure 28 are for the year 2012. The latest interim factors do not include emissions rates for the year 2005 and are not publicly accessible. Personal correspondence provided access to the new factors for 2012 as they were readily available (see NCL, 2012). On average the COPERT 4 v8.1 are higher than the DfT factors by 35%. Therefore, the new interim COPERT 4 factors indicate that unrepresentative emissions factors were a primary cause of model error in this study.

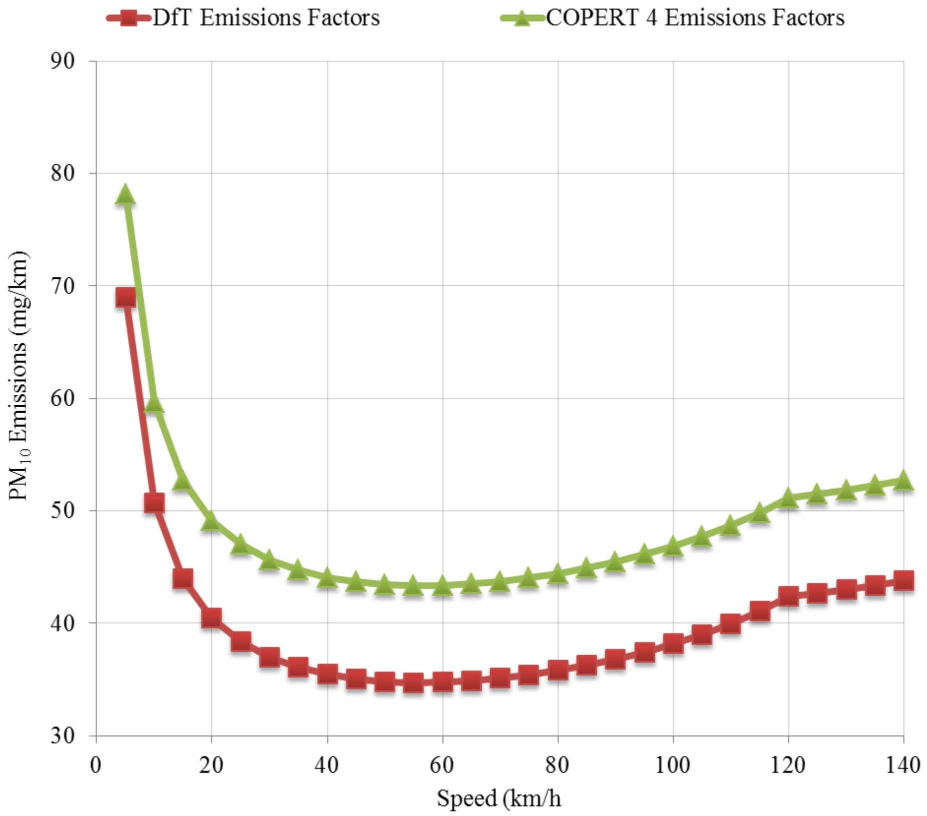
Figure 28 Fleet weighted speed-dependent NO_x emissions factors used in PITHEM and the speed-dependent NO_x emissions factors used in COPERT 4 v8.1 for the year 2012 (NCL, 2012)



ADMS-Urban was shown to adequately predict mean PM_{10} concentrations and consequently the evaluation statistics (MG, VG and FB) showed ADMS-Urban to perform within acceptable ranges (0.5> MG <2, VG<1.6, -2/3> FB <2/3). However, it failed to predict PM_{10} concentrations in time accurately. The recently released interim PM_{10} COPERT 4 tailpipe and brake and tyre wear emissions factors remain unchanged compared to the DfT 2009 emissions factors. However, road abrasion emission factors have been added to the revised data resulting in an average increase in fleet weighted emission factors of 9% based on the year 2012 (Figure 29). Therefore, the interim emissions factors suggest that failure to take into consideration road abrasion was a cause of PM_{10} under-prediction in this research.

It is likely that the average-speed emissions factors used in this work failed to represent real-world short-lasting peaks caused by changing vehicle ‘dynamics’ (e.g. rapid acceleration, late gear change etc) (see Dee Hann and Keller, 2000; Jourmard *et al.*, 1995; Sturm *et al.*, 1997). A major fundamental issue with the average-speed approach is that trips having very different vehicle operation characteristics (and emissions) can have the same average-speed (Balrow and Boulter, 2009). Consequently a trip with low speeds but a few short sharp changes in dynamics are ‘smoothed out’ by the continuous functions used in the average-speed method (Boutlter *at al.*, 2009a). Therefore, the use of average-speed emission factors was considered a cause of model under-prediction in this research.

Figure 29 Fleet weighted speed-dependent PM_{10} emissions factors used in PITHEM and the speed-dependent PM_{10} emissions factors used in COPERT 4 v8.1 for the year 2012 (NCL, 2012)



6.7.3 Meteorological Data

It is well documented in the literature that meteorological conditions govern the dispersion processes in the atmosphere (Than *et al.*, 2008, Alabiso and Parrini, 1998, Tu *et al.*, 2007, El-Shobokshy *et al.*, 1990; Elminir, 2005). Therefore, it is important that the meteorological data input to an air quality model is representative of the simulation domain. The meteorological data used in this research was recorded in the centre of Leicester and was considered representative of the study area. However, Carruthers *et al.* (2003a) found ADMS-Urban to be extremely sensitive to meteorological monitoring site location and documented ±8% error when conducting sensitivity tests using two different meteorological data sets. The error occurred when meteorological data from an airport was switched with a data set from a central urban monitoring site. These findings highlighted that meteorological conditions vary on the microscale, with the construction of every building, bridge, road etc. effectively creating a new microclimate which has its own set of meteorological parameters governing pollutant dispersion (Vallero, 2008). All of the monitoring sites in this research were located in an urban street. However, the dimensions of the local area (canyon width and canyon height) in which the monitoring stations were located were not known, meaning the use of ADMS-Urban's integrated street canyon model was not possible. Leksmono *et al.* (2006) found an ADMS-Urban model run using the street canyon module to result in higher NO_2 concentrations (maximum 47.8μg/m^3) than a model run considering NO_2 for an open road (maximum 31.2μg/m^3). They concluded that NO_2 concentrations were higher as 'air is trapped in the canyon leading to a pollution build up.' Therefore, failure to consider changes in meteorological conditions due to the canyon effect in this research may have resulted in model under-predictions as high as 35% for maximum concentration values. Similar under-predictions were observed for the 99th, 99.8th and 99.9th NO_2 percentiles at Abbey Lane. Furthermore, it is suggested that the outliers (stars on the residual box plots presented in sections 6.5.2 and 6.5.4) in the predicted data were caused by stochastic fluctuations in meteorological conditions on the microscale which the model could not predict.

The residual box plots for PM_{10} and NO_2 and time of day revealed ADMS-Urban had a greater tendency to over-predict pollutant concentration values at night (~20.00h to ~3.00h). On the one hand it is possible that this was caused by unrepresentative vehicle fleet compositions, vehicle flows or speeds on roads in close proximity to the monitoring sites over these time periods. On the other hand it is possible that this error resulted from ADMS-Urban's inability to accurately predict pollutant concentrations during stable conditions (see Owen *et al.,* 1999). Gaussian models are inversely dependent on wind speed and perform poorly when predicting the dispersion of pollution under low wind speed, calm conditions such as those that form at night during a temperature inversion (Vallero, 2008; Chock, 1978; Lazaridis, 2011). In ADMS-Urban the wind velocity is set to 0.75m/s for zero or very low wind speed conditions to allow the model to compute (CERC, 2006). Therefore, a greater rate of dispersion is calculated between ~20.00h and ~3.00h resulting in error in the prediction. This hypothesis is supported by the NO_2 residuals box plots for wind speed which showed ADMS-Urban to have a greater tendency to over-predict NO_2 concentrations during wind speeds <1m/s. In addition, ADMS-Urban is effectively instantaneous and cannot take into account pollution build up over consecutive hours (Lazaridis, 2011; Righi *et al.*, 2009). Therefore, under low wind speed conditions when dispersion is relatively small any pollution build up cannot be included in model calculations which results in under-prediction. Namdeo *et al.* (2002) estimated that errors due to ADMS-Urban model algorithms may be as high as ±20%.

ADMS-Urban's sensitivity to wind direction was dependent on wind speed. The model showed a tendency to over-predict NO_2 concentrations when wind directions were between 0° and 90°. From the windrose (Figure 11) it can be seen that when the air flow was in the direction between 45° and 90° wind speeds were low suggesting ADMS-Urban's inverse dependence on wind speed was the cause of over-prediction. In contrast, ADMS-Urban had a greater tendency to under-predict NO_2

concentrations during wind directions of 180° and greater than 315°, which correspond to higher wind speeds. On the one hand, this could have been because ADMS-Urban set a lower rate of dispersion during these conditions than was found in reality. On the other hand, this may have been due to unrepresentative background emissions. Under high wind speeds greater dispersion of pollution from sources directly adjacent to the study area will have passed into the local air-shed. Therefore, a failure to take into account these sources in the model resulted in under-prediction. This is discussed in more detail in the next section.

Owen *et al.* (1999) found ADMS-Urban to under-predict NO_x and NO_2 concentrations during the winter when modelling air quality in London. They documented that during winter a greater number of stable conditions prevailed further highlighting that Gaussian models perform poorly when predicting concentrations in calm, low wind speed conditions (Vallero, 2008; Chock, 1978; Lazaridis, 2011). In this research a marginally greater proportion (53%) of calm conditions were found in winter than in summer which indicated a possible reason for the seasonal trends observed.

6.7.4 Background Pollutant Concentration Data

The background data used in this investigation was recorded at Harwell rural monitoring station which, given its distance from Leicester (125km>), will probably have failed to take into account the background emissions attributed to the road, point and area sources immediately adjacent to the study area. This would, in part, account for the under-predictions in pollutant concentrations observed. The influence of the unrepresentative background emissions was highlighted in the predicted data at Glenhills Way. ADMS-urban consistently under-predicted NO_2 concentrations at Glenhills Way and the model had poor performance when predicting both PM_{10} and NO_2 concentrations at this site. The monitoring station was situated <1.5km from the south, west and eastern edges of the simulation domain boundary and therefore failure to take into account adjacent emissions sources was more pronounced at this location. Furthermore, to the west of Glenhills Way is situated the M1 Motorway, a source of substantial emissions. A similar issue was observed by Owen *et al.* (2000) who document that ADMS-Urban under-predicted NO_x and NO_2 concentrations at Bexley, which was located on the eastern extreme of their Greater London study area. No account was taken of emissions immediately outside Greater London in their investigation and as a result the model under-predicted the mean NO_2 concentration by 25% when the GRS was used. Therefore, the relatively large bias and spread of predicted NO_2 data observed at Glenhills Way, and to a lesser extent at the other monitoring site locations, can be explained by the unrepresenative background emissions.

Although predicted PM_{10} concentrations appeared to be sensitive to the independent meteorological variables specified in the model setup, concentrations were found to follow the temporal variation in the background data. Predicted concentrations deviated only marginally from background values and as a result were less sensitive to meteorological conditions. It is well documented in the literature that background concentrations can contribute a significant proportion of the total pollution within an air-shed (see McHugh *et al.,* 2004; Richmond-Bryant *et al.,* 2009; Mensink *et al.,* 2003). In such situations local policy is likely to have a limited impact on reducing PM_{10} concentrations. Regional, national or international policy would be required for reductions to be achieved. However, in this research the observed data was found to deviate substantially from the background PM_{10} concentrations, which indicated; a) the presence of local emissions sources and; b) that local sources were not properly represented in the model. In future the inclusion of road abrasion emissions rates in the emissions inventory will help to better represent local traffic emissions sources and more representative background data would likely improve the agreement between the predicted and observed.

ADMS-Urban significantly over-predicted PM_{10} concentrations at Imperial Avenue and Abbey Lane, particularly during the summer period. Over-prediction at these locations typically occurred when estimates were made for lower PM_{10} concentrations. This suggested that the lower percentiles of the background data were not representative of the local pollution at these sites.

6.7.5 Chemical Reactions in the Atmosphere

Atmospheric chemistry was modelled in this research using ADMS-Urban's CRST which comprises a GRS. The GRS in turn comprises only 8 chemical reactions and is therefore a crude representation of the complex processes that occur in the atmosphere (CERC, 2006). Generally, the GRS has been shown to perform adequately in the literature (e.g. Carruthers *et al.,* 1999; Owen *et al.,* 2000). However, there is some debate in the literature as to whether empirical based approaches should be adopted for predicting NO_x chemistry rather than semi empirical methods, such as the GRS. A comparative study of the GRS with two empirical based approaches (National Environmental Technology Centre (NETCEN) and the Environment Research Group of King's College (ERG) empirical approaches) by Carruthers *et al.* (2003b) found all three methods to be in good agreement with the observed when predicting roadside NO_2 concentrations in London. However, Carruthers *et al.* (2003b) concluded that although empirical approaches have the advantage of speed of calculation and providing a close link of the model to observed data they are limited in their applicability geographically, have uncertainties surrounding the validity of the relationships for future years and exhibit difficulty with ensuring continuity in the spatial distribution of NO_2 (see Chaney *et al.,* 2011 for the latter). Leksmono *et al.* (2006) conducted a similar comparative study and found the empirical based Derwent-Middleton (1996) function to predict higher NO_2 concentrations (by 4% to 38%) than those observed when ADMS-Urban's GRS was used. However, the highest differences between the two methods were found when predicting concentrations in a rural street canyon suggesting that dispersion processes were the cause of the differences observed. Similarly, Soulac *et al.* (1997) initially found the GRS perform poorly relative to the Derwent-Middleton function when predicting NO_2 concentrations in Lyon, France. However, closer inspection of the analysis revealed that the differences in performance found were due to dispersion calculations and not the GRS. The GRS assumes that the ambient air mixing into the plume as it is transported downstream is uniformly mixed across the plume (CERC, 2006; Carruthers *et al.*, 2003c). Therefore, the GRS is inappropriate for canyon modelling (Leksmono *et al.*, 2006; Westmorelands *et al.*, 2011). The canyon model was not used in this research and subsequently error in prediction could not be attributed to these short falls. However, the GRS is a post processor that uses the predicted NO_x concentrations as input for subsequent calculations (Owen *et al.*, 2000). Therefore, the performance of the GRS is dependent on the ability of the dispersion model to predict NO_x concentrations accurately in time and space. A failure to represent emissions rates accurately in this research resulted in the under-prediction of NO_x concentrations which were used as input for the GRS.

ADMS-Urban assumed 10% of NO_x to be emitted as f-NO_2 (CERC, 2006). However, recent research suggests this value is a gross underestimate. For example, Carslaw and Beevers (2004) and Jenkin (2004) estimated diesel LDVs to have a mean f-NO_2 fraction of 12.7% and 11.8% respectively, AQEG (2007) documented f-NO_2 values in the range of 20-70% for Euro 3 diesel cars and Carslaw *et al.* (2007) found diesel vehicles equipped with DPF to have f-NO_2 fractions of ~40-50%. Therefore, the NO_X:NO_2 assumptions made by ADMS-Urban resulted in error in the prediction. A study by Westmorelands *et al.* (2011) revealed that changing the f-NO_2 fraction in ADMS-Urban from 10% to 20% (a value observed at numerous sites in the UK, see AQEG, 2007) reduced annual mean NO_2 predictive error by 16% and resulted in predicted values that were within 5% of the observed.

Unrepresentative solar radiation data is a possible cause of the seasonal NO_2 trends found in this research. Equations 20 and Equations 21 show the two primary chemical reactions used by ADMS-Urban to represent NO_x chemistry in the atmosphere.

$3NO_2 + hv \rightarrow 3NO + O_3$
(Equation 20)

$NO + O_3 \rightarrow NO_2 + O_3$
(Equation 21)

Where hv is solar radiation. Overestimation of hv data would result in model under-predictions as this would enhance O_3 formation. In this research, model under-predictions were found during the winter months indicating that overestimation of hv data was a possible cause of error. In contrast, the model was found to over-predict during the summer months suggesting that hv data may have been underestimated. In addition, an overestimation of background O_3 levels in summer may have contributed to the NO_2 over-predictions found in summer.

6.8 Chapter 6 Summary

An emissions inventory was compiled and was subsequently evaluated using an air quality model, ADMS-Urban. The dispersion of toxic air pollutants, NO_2 and PM_{10} were modelled over the Leicester area and air quality model performance was evaluated through comparison with observed data at seven fixed locations. Graphical and statistical descriptors revealed that both under and over-prediction was evident in modelled data. However, overall ADMS-Urban under-predicted mean NO_2 concentrations. Relatively good agreement between predicted and observed mean PM_{10} concentrations was found at some locations, whilst at others the model had a tendency to over-predict. Hour by hour agreement between predicted and observed pollutant concentrations was relatively poor. The use of simulated data and an unrepresentative vehicle fleet composition were considered to contribute substantially to the model error observed. Street canyon data was not available for use in this research which meant that local microscale meteorological conditions were not accurately represented in the air quality modelling carried out. This may have resulted in errors of ±35% for peak concentrations.

When predicting NO_2 concentrations the model performance was found to be sensitive to wind speed, wind direction, season (summer and winter) and time of day. The model had a greater tendency to over-predict during low wind speed (<1m/s) conditions (which were typically found at night between ~20.00h to ~3.00h) due to ADMS-Urban's inverse dependence on wind speed and in ability to take into account pollution build up over consecutive hours. In addition, the model's performance deteriorated in favour of under-prediction as wind speeds increased. Under high wind speeds greater dispersion of pollution from sources directly adjacent to the study area will have resulted in higher pollution over the Leicester air-shed. These emissions sources were not modelled in this research and thus NO_2 under-prediction was found and had particularly influence during high wind speeds. In contrast, PM_{10} predictions were less dependent on meteorological conditions as they were found to follow background concentrations temporally. The observed data were found to deviate from the background values substantially, which suggested the local emissions sources defined in the model were not representative of real world conditions. The inclusion of road abrasion PM_{10} emissions rates in the emissions inventory may help to better represent local traffic emissions sources and more representative background data would likely improve the agreement between the predicted and observed.

ADMS-Urban had a tendency to under-predict between 4.00h and 6.00h and 10.00h and 12.00h respectively. This was likely caused by the use of AADT interpolation factors which did not accurately represent diurnal variations in traffic flow and resulting congestion. The model generally under-predicted during the winter period which was attributed to a greater proportion of calm conditions prevailing in winter than in summer. In the summer the model had a greater tendency to over-predict NO_2 concentrations which was possibly caused by an underestimate of solar radiation and or an overestimation of background O_3 concentrations.

During the air quality modelling calculations ADMS-Urban assumed 10% of NO_x to be emitted as f-NO_2 which has been shown in the literature to be a gross underestimate. Therefore, under-prediction was evident in this research due to this assumption. In addition, the NO_x emissions factors used to calculate link based emissions rates in this work have recently been updated due to relatively poor representation of real world emissions. New NO_x emissions factors were found to be on average 35% higher than those used in this study. Therefore, the use of the 2009 DfT emissions factors were a major cause of error in prediction.

The overall error due to the use of unrepresentative vehicle fleet composition, traffic flows, emissions factors, background data and meteorological data and the error due to ADMS-Urban assumptions and limitations are summarised in Table 25. The error attributed to the emissions inventory was estimated to be between 13% and 57% of the total error found depending on location and pollutant considered. A large proportion of the emissions inventory error was attributed to the use of unrepresentative emissions factors. In this research the difficulty in compiling an emissions inventory that is representative of real world emissions was demonstrated and the need for emissions factors that are representative of real world driving conditions and not just dynamometer test cycle conditions was highlighted.

Table 25 Estimated cause and proportion of air quality model predictive error

Cause of Error	Estimated Error (%)	Reference
Unrepresentative Vehicle Fleet Composition	±5 to ±10	(Namdeo *et al.* 2002)
Simulated Traffic Flows	±12	Matoros *et al.* (1987) Namdeo *et al.* (2002) Nejadkoorki *et al.* (2008)
Unrepresentative emissions factors	-35 for NO_X, -9 PM_{10} 4 to 35 Depending on pollutant	DEFRA (2012d) Namedo *et al.* (2002)
Unrepresentative meteorological data (failure to model street canyon meteorology)[1]	-8 annual mean [1](-35 for maximum concentrations)	Carruthers *et al.* (2003) [1]Leksmono *et al.* (2006)
ADMS-Urban model algorithms/assumptions (sensitivity to wind speed and wind direction; inability to model pollution build up; 10% NO_x emitted as NO_2*)	±20 (-16*)	Namedo *et al.* (2002) *Westmorelands *et al.* (2011)
Unrepresentative background Concentrations	-25 (for NO_2)	Owen *et al.* (2000)
Estimated maximum error attributed to NO_x emissions inventory	-57	
Estimated maximum error attributed to PM_{10} emissions inventory at sites where under-prediction was found	-31	
Estimated maximum error attributed to PM_{10} emissions inventory at sites where over-prediction was found	13	

Having developed a thorough understanding of the influence of the different parameters in, and the limitations of, the air quality model this chapter provided a quality check on the emissions resulting from the LCC traffic model. The next chapter draws together the outputs of this research and presents ideas for the future.

CHAPTER 7

7. Emissions Abatement Technology, Fuels and Low Emission Vehicles: Win-Win for Air Quality and Climate Change?

In Chapter 6 a base-case of emissions for the LCC region was developed and the accuracy of the inventory compiled estimated. In addition, the impact of road traffic on air quality in Leicester and issues with current dispersion modelling practices were highlighted. It is the aim of this chapter to edit the base-case to reflect various hypothetical strategies assuming that the flows and speeds remain unchanged which means that the VKT remains the same. It should be noted that only TTW emissions were modelled in this research as it is not appropriate to allocate pollutant emissions emitted at one location to an air-shed a considerable distance away as the impacts of toxic air pollutants on the environment and its constituents are predominately confined to the locale in which they are released. Furthermore, WTT emissions are typically out of the remit of control for local authority policy makers. Therefore, considering only those emissions that can be reduced by local action is beneficial as it allows money to be spent wisely. In the following text, the term 'emissions' refers to TTW unless stated otherwise, 'win-win' refers to a reduction in both CO_2 and toxic air pollutant emissions as a result of a change to the Leicester fleet and the term 'trade-off' refers to a situation where a win-win is achieved but at the cost of greater reductions in either toxic air pollution or CO_2 emissions as a result of another strategy.

7.1 Strategy Modelling Methodology

The base-case was edited to reflect 13 strategies involving changes to the vehicle fleet composition. Each strategy was modelled separately and a VKT restraint was imposed on the vehicle fleet. Emissions of CO_2, NO_x, f-NO_2 and PM_{10} were calculated and comparisons between the base-case and strategy were made in each case. The strategies modelled included the introduction of vehicles fitted with new emissions abatement technologies (e.g.EURO VI) or with low emissions vehicles (e.g. ZEVs) and through changes to the fuel type used by vehicles (e.g. introduction of LPG).

Figure 30 shows a flow diagram of the method used to model the 13 strategies in this research. All strategies were modelled using PITHEM. Changes to the fleet composition were implemented in 5% increments (e.g. 5%, 10%, 15% etc. of conventional cars were replaced systematically with electric vehicles) to allow the relationship between strategy and emissions change to be identified. IBM (2012) suggested that more than 15 pairs of data are required for a regression analysis. Given that choice of incremental changes of typically one or two per cent would result in substantial computational time, a compromise was reached at 5% increments providing 21 pairs of data to be output. It should be noted that regression analysis, including the fitting of linear and polynomial trend lines to data sets of less than 21 pairs is common practice in the literature (e.g. Khan and Kockleman, 2012; Fontaras *et al.*, 2008; Cheng *et al.*, 2006). Once the 5% incremental change was made the remaining vehicle fleet proportions were redistributed with the earliest vehicle types being reduced first. An example of this is presented in Figure 31 below.

Figure 30 Strategy modelling method flow diagram

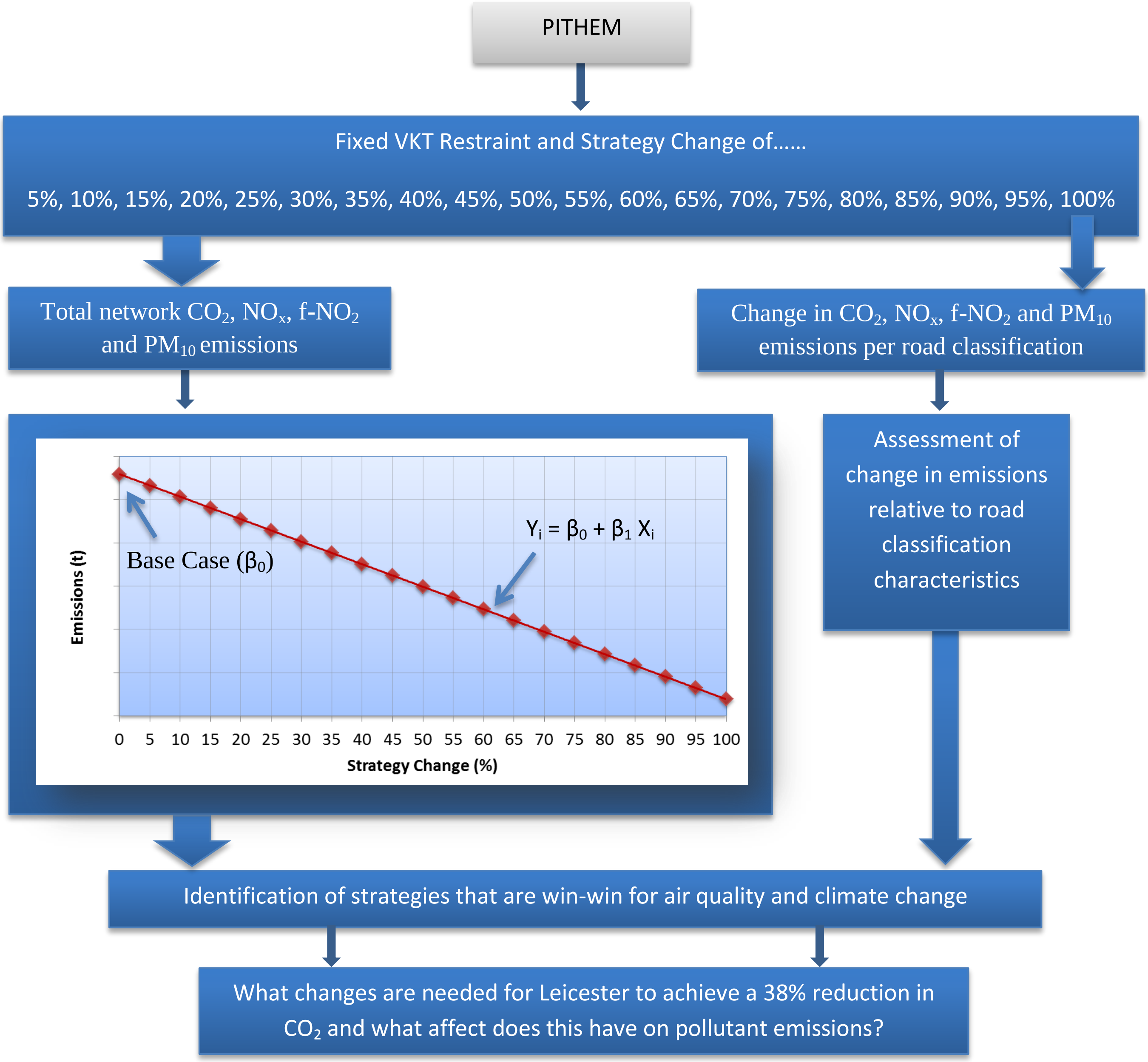


Figure 31 Example of vehicle fleet redistributions associated with modelling 5% incremental introductions of Euro 6 vehicles into the fleet

Vehicle Standard	**Vehicle Fleet Composition (%)**			
	Base Case	**5% Euro 6 Strategy**	**10% Euro 6 strategy**	**15% Euro 6 strategy**
Pre-Euro	5 -5	0	0	0
Euro 1	10	10 -5	5 -5	0
Euro 2	15	15	15	15
Euro 3	70	70	70	70
Euro 4				
Euro 5		+5	+5	+5
Euro 6		5	10	15

The total network emissions from each strategy were plotted against the % change in the vehicle fleet. Those strategies that offered a win-win for air quality improvement and CO_2 reduction were identified and those that resulted in a trade-off were discussed. Subsequently 'best fit' linear or polynomial trend lines were used to interpolate between the incremental changes in emissions output from each strategy. This allowed the statistical relationship between emissions and strategy to be output in the form of a regression equation. The regression equations enabled any % change (e.g. 3%, 4%, 6% etc.) to be derived and associated emissions assessed. They were subsequently used to create data tables of emissions outputs resulting from 1% to 100% strategy changes which allowed research questions such as 'what change is needed to meet my emissions target of…' to be answered. To demonstrate the use of these tables the level of change needed for Leicester to achieve a 38% reduction in CO_2 emissions from strategy options were explored. A 38% reduction in CO_2 based on 2005 is the equivalent of a 50% (LCC's target) reduction in CO_2 based on 1990 levels. The resulting pollutant emissions from these strategies were investigated.

The emissions per road classification were calculated for the base-case and for each of the 100% change strategies (e.g. 100% cars changed to ZEVs). The extreme case was chosen as the LCC has set very ambitious targets for CO_2 and has widespread pollution exceedances throughout the city. Therefore, it was envisaged that significant and substantial changes would be necessary in order for Leicester to meet targets and comply with air quality limit values. The % change in emissions was calculated for each road classification for each strategy relative to the base and those strategies that resulted in the greatest reduction in toxic air pollutants and CO_2 were identified. This allowed the effectiveness of each of the strategies to be analysed spatially and for the relationship between emissions change and road characteristics to be assessed.

A description of the base-case was documented in Chapter 6. The development of the strategies is described in more detail in the following sections and examples of the vehicle fleet compositions modelled are documented below.

7.1.1 Vehicle Kilometers Travelled (VKT) Restriction

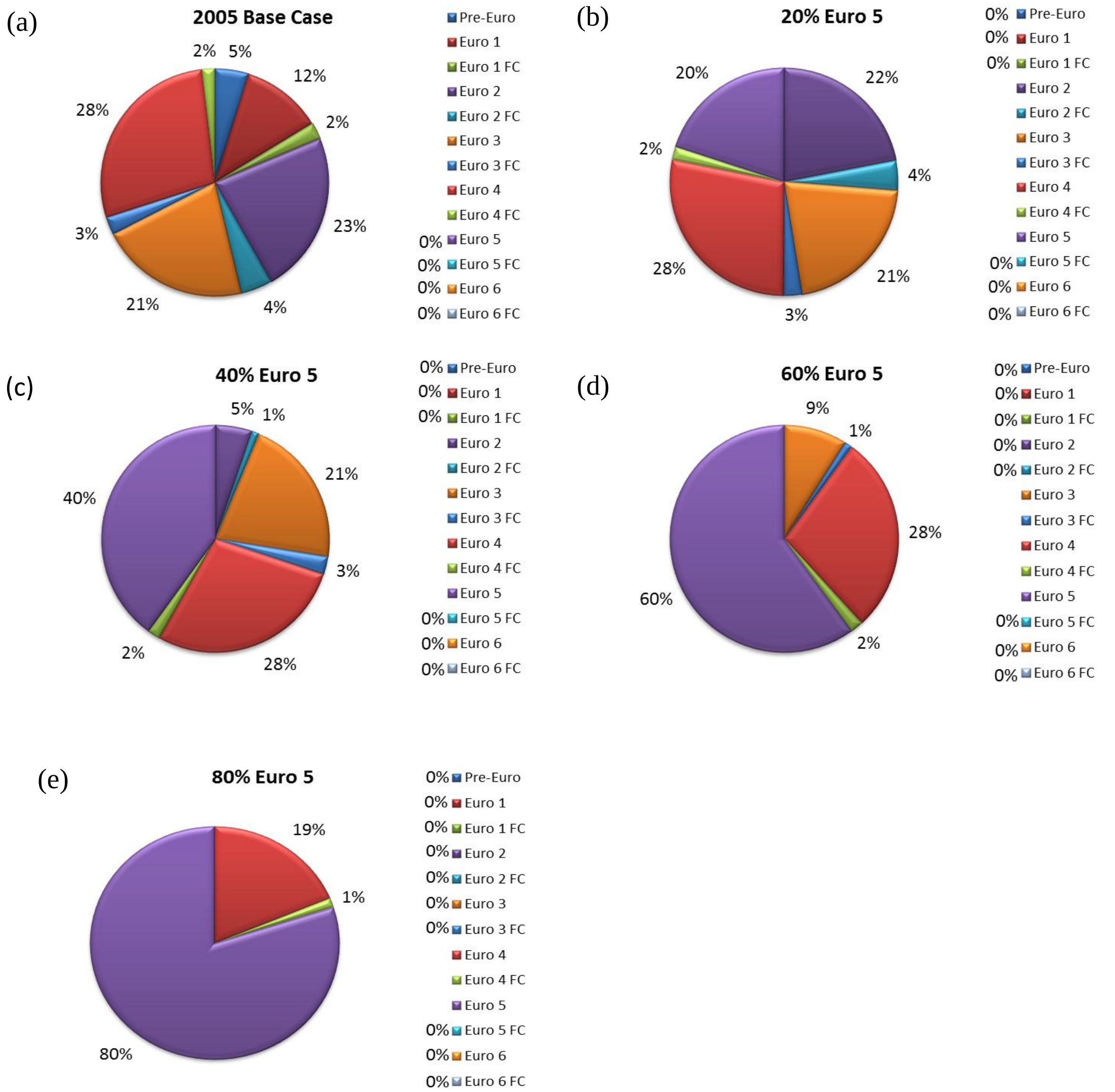
A VKT restriction was imposed on the vehicle fleet which provides assessments that assume there is no change from the base year in the VKT. In this way the modelling provides a consistent base against which the changes in emissions are assessed. The literature suggests a stricter VKT restraint is needed to reduce emissions from road vehicles (see Chapter 3, section 3.5). Therefore, maintaining VKT at 2005 levels imposes a strict restraint on the Leicester fleet. It is acknowledge that this restraint is unlikely to happen. However, it was the intension of this work to investigate whether such an extreme case coupled with other strategies and policies could provide a win-win for air quality and climate change thereby providing insight into the level of change required in order for ambitious targets to be met and compliance with legislation achieved. In addition, modelling such a VKT restriction has two other implications. The first is that any emissions reductions are not offset by an increase in VKT allowing the 'true' impact of a change in technology, fuel or vehicle on emissions to be assessed i.e. the rebound effect is zero. Secondly by restricting the VKT to 2005 levels issues concerning changes in vehicle dynamics (e.g. speed and flow) associated with strategy modelling are minimised.

7.1.2 Emissions Abatement Technology

A total of eight strategies were modelled to reflect improved emissions abatement technology. This primarily involved the introduction of Euro 5/V and Euro 6/VI technology to the private car (shortened to 'car' from here on in), LGV, HGV and bus vehicle fleets. Petrol and diesel cars that represented the oldest (in terms of Euro class) portion of the car fleet were changed with cars equipped with Euro 5 and Euro 6 technology respectively. Similarly pre-Euro/Euro petrol vans class N1 (I) and diesel vans classes N1(I), N1(II) and N1(III) vehicles were changed with vans equipped with Euro 5 and Euro 6 technology and pre-Euro/Euro Artic and rigid diesel HGV vehicles were retired in favour of Euro V and Euro VI vehicles. Finally, buses of weight category 0-15t, 15t-18t, 18t+ and coaches of weight category 15-19t and 18t+ were changed with vehicles fitted with Euro V and Euro VI technology.

Figure 32(a) to Figure 32(e) shows an example of the vehicle fleet composition that was modelled to reflect the introduction of Euro 5 technology into the Leicester car stock. The introduction of 20% vehicles with Euro 5 technology (Figure 32(b)) resulted in the removal of pre-Euro and Euro 1 cars from the vehicle fleet. A 60% introduction of Euro 5 cars (Figure 32(d)) resulted in the additional removal of Euro 2 vehicles and an 80% change in the fleet (Figure 32(e)) in favour of Euro 5 resulted in the further removal of Euro 3 cars. It should be noted that as the 5% incremental changes were implemented the ratio of failed catalyst to non-failed catalyst vehicles remain constant for each particular Euro class.

Figure 32(a) to Figure 32(e) Vehicle fleet composition resulting from 20% increases in Euro 5 petrol cars



7.1.3 Low Emissions Vehicles

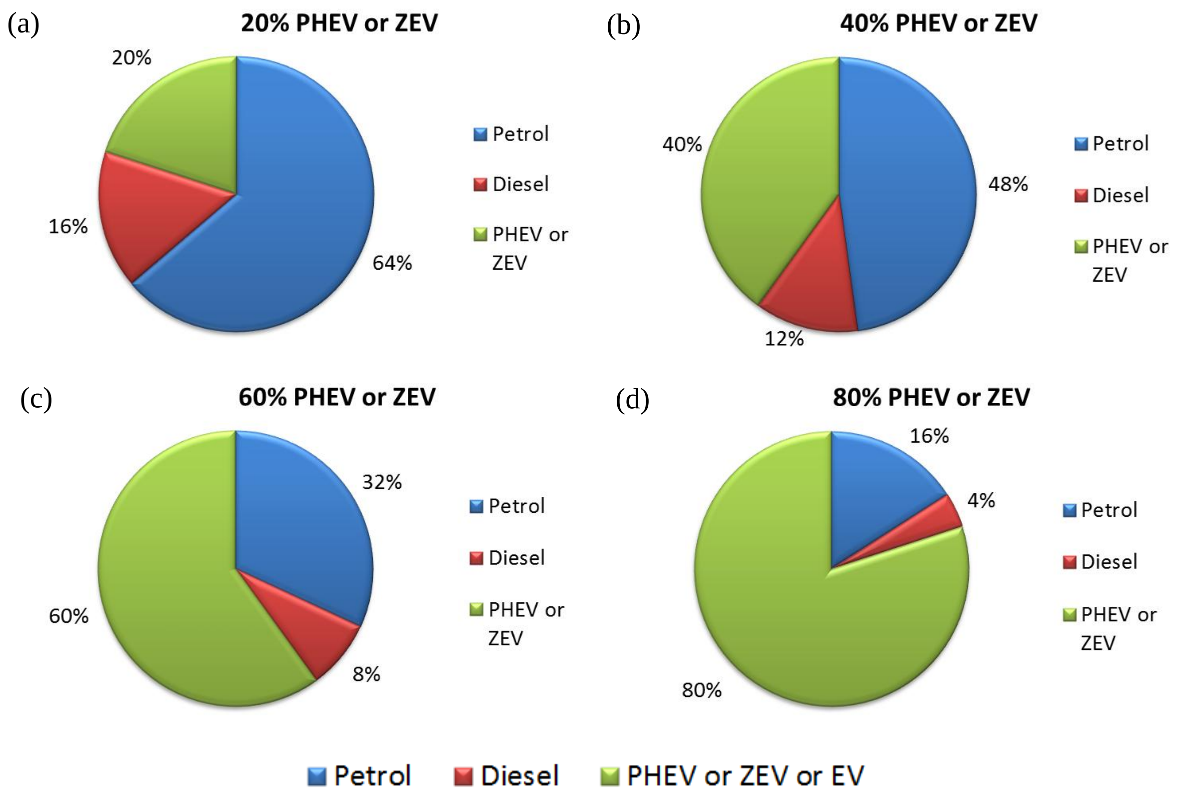
The penetration of PHEVs or ZEVs was modelled. It should be noted that ZEVs are representative of EVs under current legislation i.e. zero emissions vehicles. In addition, ZEVs are representative of PHEVs operating in charge depleting mode. The ratio of petrol to diesel cars remained the same as the base-case, but the % of cars running on conventional fuel was reduced in 5% increments in favour of low emissions vehicles (see Figure 33 for an example of the compositions modelled).

The CO_2 emissions factors for PHEVs in PITHEM are estimates of WTW emissions rates. Therefore, it was necessary to calculate the proportion of these emissions that were TTW emissions (i.e. tailpipe emissions from PHEVs whilst in charge sustaining mode). The DEFRA (2012c) GHG conversion factors based on the JEC (2011) WTW analysis estimate WTT emissions from PHEVs to account for 15% of WTW emissions. The GHG conversion factors provided by DEFRA (2011c) are a composite factor for N_2O, CH_4 and CO_2 emissions. However, CO_2 accounts for 99%> of these emissions and therefore it was concluded that N_2O and CH_4 emissions have a negligible impact on the % of WTW emissions that are WTT. Therefore, CO_2 emissions associated with the introduction of PHEVs into the Leicester fleet were reduced by 15% allowing TTW emissions to be estimated and subsequently compared to the base-case and other strategies. This is equivalent to a TTW emissions rate of 82gCO_2/km which is within the range (60 to 90gCO_2/km) estimated by Hagman and Assum (2012) who calculated TTW emissions from nine instrumented PHEV Toyota Prius' operating under real-world driving conditions in the Nordics (Denmark, Finland and Norway) from 2010 to 2012. In the same study 'barely detectable' pollutant (PM_{10}, NO_x and VOCs) emissions were found when a dynamometer test of a 2.1litre/4.4kWh battery PHEV Toyota Prius was carried out using the Helsinki urban driving cycle.

PITHEM does not include emissions factors for PHEV TTW pollutant emissions. This is because a comprehensive database of factors does not exist and estimates of PHEV tailpipe emissions documented in the literature are very few in number. The findings of Hagman and Assum (2012) are applicable to the Nordics driving conditions but indicate that PHEVs have very small emissions rates when operating under urban conditions. Fontaras *et al.* (2008) conducted dynamometer tests of a 2005 hybrid electric Prius over the ARTEMIS real world driving cycle. The Prius was found to operate very close to the manufacturer's specifications for type approval over the New European Driving Cycle (NEDC) with an average NO_x emissions rate of 0.01gNO_x/km. Although the Prius tested in the work of Fontaras *et al.* (2008) was a 2005 HEV it's average NO_x emissions rate was found to be well below Euro 4 (0.08gNO_x/km) and Euro 5 (0.06gNO_x/km) standards. Both plug-in hybrid electric and hybrid electric Toyota Prius' have the same 'synergy drive' hybrid engine technology (Toyota, 2012). Subsequently, it was assumed that the NO_x emissions rates for the Toyota hybrid Prius range are similar. Therefore, PITHEM was modified to include a constant emissions rate of 0.01gNO_x/km for PHEVs in this work.

PM_{10} and f-NO_2 exhaust emissions factors for PHEVs were not available for use in this research and were not modelled. However, PM_{10} emissions from brake and tyre wear were calculated for the low emissions vehicle strategies.

Figure 33(a) to Figure 33(d) Vehicle fleet composition modelled to reflect a change from car to low emissions vehicle



7.1.4 Fuels

A strategy was developed that reflected a replacement of petrol or diesel cars in the fleet with cars fuelled by LPG. This was carried out for diesel and petrol cars separately. When petrol (diesel) cars were changed the vehicle fleet composition (at the Euro class level) associated with the petrol (diesel) cars were switched to LPG. However, no pre-Euro LPG car emissions factors are available in the NAEI and as a result it was not possible to model them using PITHEM. Therefore, pre-Euro cars were assumed to be replaced with Euro 6 LPG vehicles. In the case of petrol cars this resulted in 5% of total LPG vehicles modelled as Euro 6 and for diesel 2% of the total LPG vehicles were Euro 6

(Figure 34(a) and Figure 34(b)). Similarly there are no emissions factors for cars with failed catalysts fuelled by LPG in the NAEI. Therefore, petrol cars were modelled to be replaced with cars with non-failed catalysts fuelled by LPG.

Figure 34 Euro classification breakdown modelled for the replacement of petrol (a) and diesel (b) cars with LPG cars

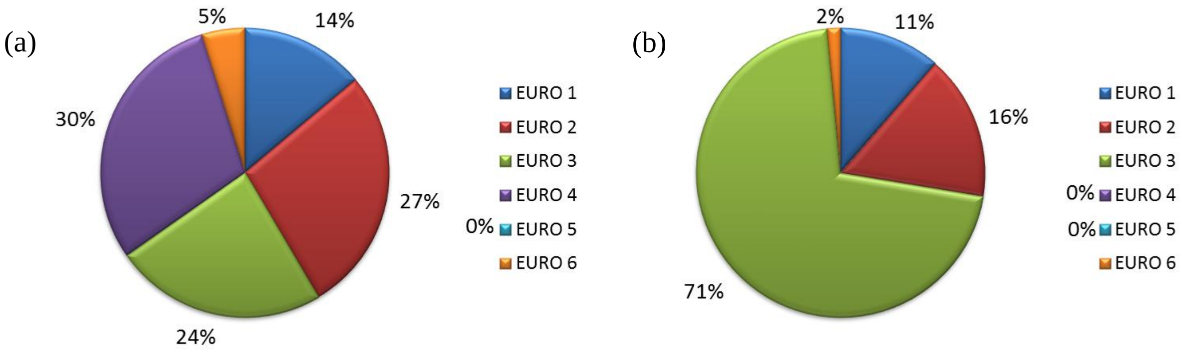
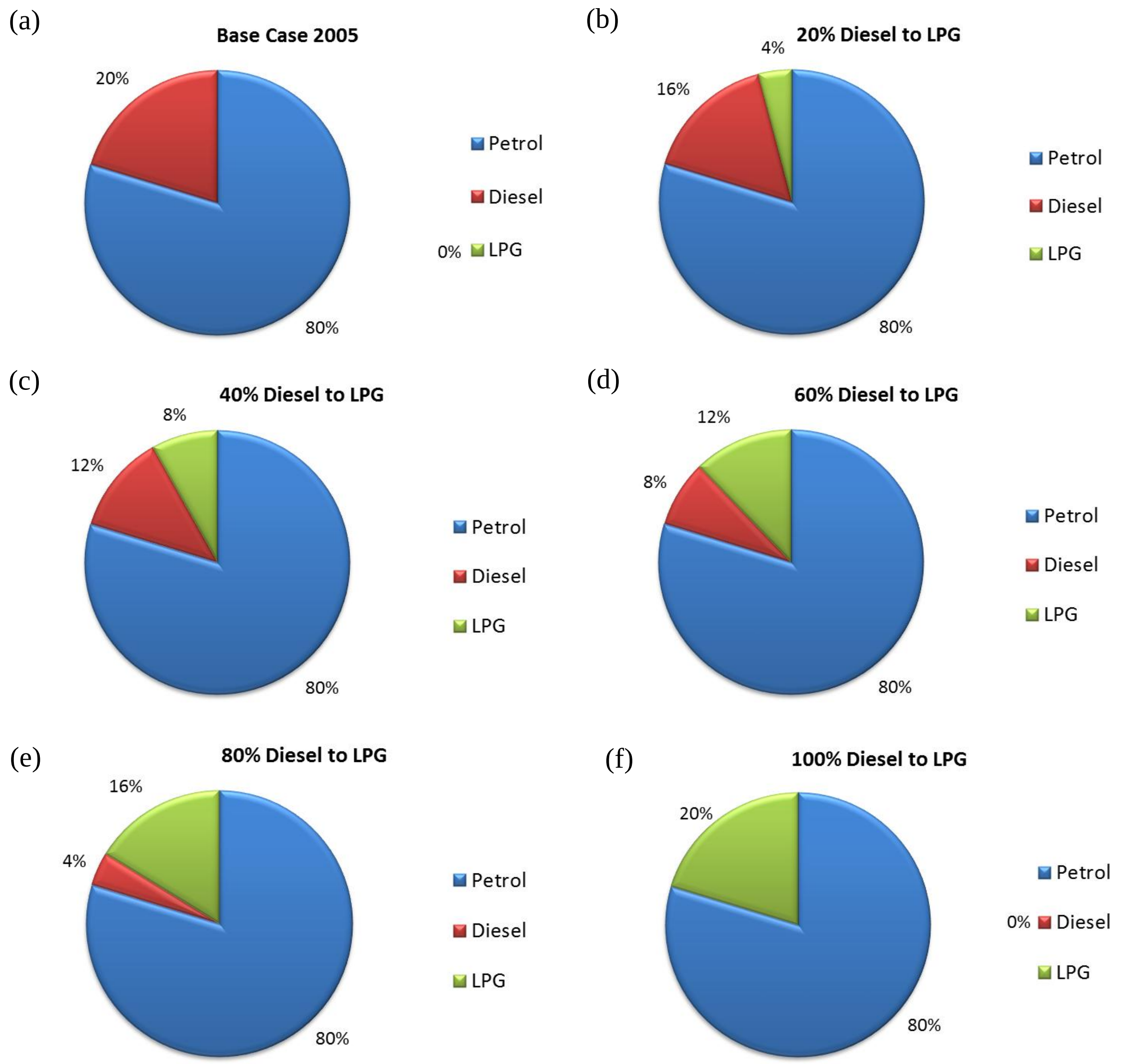


Figure 35(a) to Figure 35(f) show the car fuel split that was modelled to reflect a switch from diesel to LPG fuelled vehicles. 100% removal of diesel fuelled cars in favour of LPG fuelled cars resulted in a 20%-80% LPG-petrol split. In contrast 100% switch from petrol fuelled cars to LPG resulted in an 80%-20% LPG-diesel split.

An additional strategy was developed to reflect changes to the car petrol diesel fuel split. The % of cars that were fuelled by diesel (petrol) was changed in 5% increments until 100% diesel cars (petrol) were modelled. It should be noted that the car base-case fleet composition was 80%-20% petrol-diesel split.

Figure 35(a) to Figure 35(f) Car fuel split modelled to reflect a switch from diesel to LPG by 20% increments



7.2 Statistical Analysis

Least Squares Regression analysis was used to fit linear or polynomial trend lines to scatter plots of emissions versus strategy change. Regression analysis was considered appropriate as they provide equations that allow interpolation between the 5% steps modelled using PITHEM. The resulting equations can be used to estimate values over the range of the independent variable over which the trend line (or model) was fitted (Montgomery *et al.*, 2012) i.e. it allows a value of Y (dependent variable), which in this research is the emissions change (t) to be estimated from a given value of X (independent variable), in this case % change imposed by the strategy.

In the following sections least squares regression is explained and the method used to fit linear or polynomial trend lines using least squares regression is documented.

7.2.1 Least Squares Regression

The simplest linear model involves one independent variable and states that the dependent variable changes at a constant rate as the value of the independent variable increases or decreases (Rowlings *et al.* 2001). The statistical relationship describing a simple linear model is given by the following equation;

$$Y_i = \beta_0 + \beta_1 X_i$$

(Equation 22)

Where β_0 is the intercept, the value of Y when X = 0, β_1 is the slope of the line, the rate of change in Y per unit change in X and i is the observational unit. Both β_0 and β_1 are estimated from the data and are treated as pairs for each i. In some cases a constant rate of change as described by a simple linear model does not represent the relationship that exists between the dependent and independent variables. In such a case it is necessary to extend the straight line model to a second-order, or quadratic polynomial which takes the form;

$$Y_i = \beta_0 + \beta_1 X_i + \beta_2 X_i^2$$

(Equation 23)

Higher order polynomial models are a further extension of the linear model and take the form;

$$Y_i = \beta_0 + \beta_1 X_i + \beta_2 X_i^2 + \beta_3 X_i^3 + \ldots \beta_p X_i^p$$

(Equation 24)

Where p is the number of rates of change in Y per unit change in X. A polynomial with two degrees is known as a quadratic model, those with three degrees a cubic, four a quartic and five a quintic model. Random variation in Y_i causes each pair of β_0 and β_1 (or $\beta_0 ... \beta_p X_i^p$ if a polynomial model is considered) to give different results (Rowlings *et al.* 2001). These differences are known as residuals (e) which represent the difference between the observed value of Y and the value of Y that is estimated by X using the regression equation ($\hat{Y}$) (Weisberg 2005). If $\widehat{\beta_0}$ and $\widehat{\beta_1}$ are numerical estimates of the parameters β_0 and β_1 respectively then $\widehat{Y_i}$ can be calculated from;

$\widehat{Y_i} = \widehat{\beta_0} + \widehat{\beta_1} X_i$
(Equation 25)

Therefore, e_i can be calculated from;

$e_i = Y_i - \widehat{Y}_i$
(Equation 26)

The Least Squares Regression principle chooses $\widehat{\beta_0}$ and $\widehat{\beta_1}$ that minimise the sum of squares of the residuals ($ss(Res)$) (Miles and Shevlin 2001) which is estimated from;

$ss(Res) = \sum {e_i}^2$
(Equation 27)

The Least Squares procedure has a number of assumptions the majority of which must be met if the regression is to be deemed appropriate (Table 26). Small violations of the underlying assumptions do not invalidate the model in a major way, but large violation of the assumptions indicates the regression model is inappropriate (Chatterjee and Hadi, 2006).

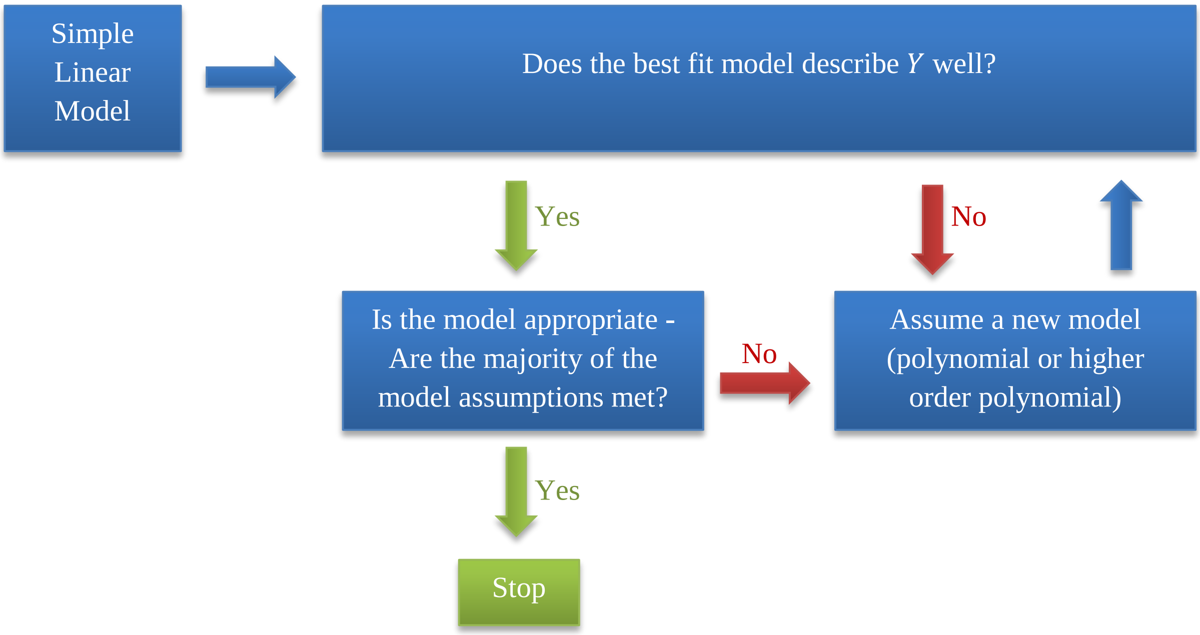
Table 26 Least Squares Regression assumptions (constructed from text of Chatterjee and Hadi 2006)

Regression Component	**Assumptions**
X_i	Non-random
	Measured without error
Y_i	Equally reliable and have approximately equal role in determining regression results and influencing conclusions
(e)	Normally distributed
	Average of zero
	Errors have same variance
	Errors are independent from each other

7.2.2 Fitting Linear and Polynomial Regression Models

Kleinbaum *et al.* (2008) described three methods that can be used to fit regression models to data. The first is the forward method which begins with a simple linear straight line model and then adds more complexity to the model in successive steps if necessary. The reverse of this method by which a complex model is successively reduced until an appropriate fit is found is called the backward method. The third approach is based on experience or theory and requires some prior knowledge of the relationship between X and Y. In this research the forward method of model or trend line fitting was used as its logical 'start simple' approach was favoured (Figure 36).

Figure 36 Flow diagram of forward method used to determine appropriate regression model fit



Initially a simple linear model was fitted to the data. The standard error of the estimate (SEE) was calculated in order to determine if the model described Y well. SEE measures how precise the prediction of $\hat{Y}$ is based on the regression of Y on X (Shenoy *et al.*, 2002). It takes the form;

$$SEE = \sqrt{\frac{\sum(e_i)^2}{n-2}}$$

(Equation 28)

Where n is the number of observed values. A low SEE value indicates that the typical distance between $\hat{Y}$and Y is small and suggests that the model is a good fit to the data (Gravetter and Wallnau, 2011). In addition to SEE the value of R^2, was calculated using the formula;

$$R^2 = 1 - \frac{SS(Res)}{\sum(Y_i - \bar{Y})^2}$$

(Equation 29)

Where $\bar{Y}$ is the mean of Y. R^2 determines if the variance in Y can be explained by the variance in X (Montgomery *et al.,* 2012). However, it does not mean that variance in X is the cause of variance in Y (Draper and Smith, 1998). For this reason unless X and Y come from a controlled experiment where the relationship between X and Y is known to be strong then R^2 should be viewed with caution (Rowlings *et al.,* 2001). In this research X and Y came from a controlled experiment during which incremental changes were made to a single variable (X) and no other variables had influence on Y. Therefore, any change in emissions was known to be caused by the strategy change. As a result the use of R^2 in addition to SEE as a measure of model fit was appropriate. R^2 values range from zero to one and a value of one indicates a perfect model fit i.e. $SS(Res) = 0$.

If a high value of SEE and a low value of R^2 were observed then a higher order regression model was fitted to the data and the goodness of fit test was recalculated. In contrast, if a low value of SEE and a high $R^2$was observed then the model was tested to determine if it violated the Least Squared Regression assumptions (Table 26). From preliminary assessment of the X and Y variables it was clear that they did not violate the assumptions; the X values were non-random and were measured without error as this investigation was a controlled experiment and each Y_i had equal role in determining regression results. However, it was necessary to test that the model residuals were compliant with the majority of the regression underlying assumptions. The residuals were tested for normality using the Anderson-Darling goodness of fit test (Anderson and Darling 1954). The Anderson-Darling test is currently considered to be superior over other normality tests as it emphasizes the quality of fit in the tail of its distribution more than other methods (such as the Kolmogorov-Smirnov test; Massey 1951) (Grace and Wood 2012). The Anderson-Darling test is well described by Thas and Ottoy (2003). The test determines whether or not there is a significant (p-value 0.05>) relationship between a given distribution and a normal distribution (Thas and Ottoy, 2003).

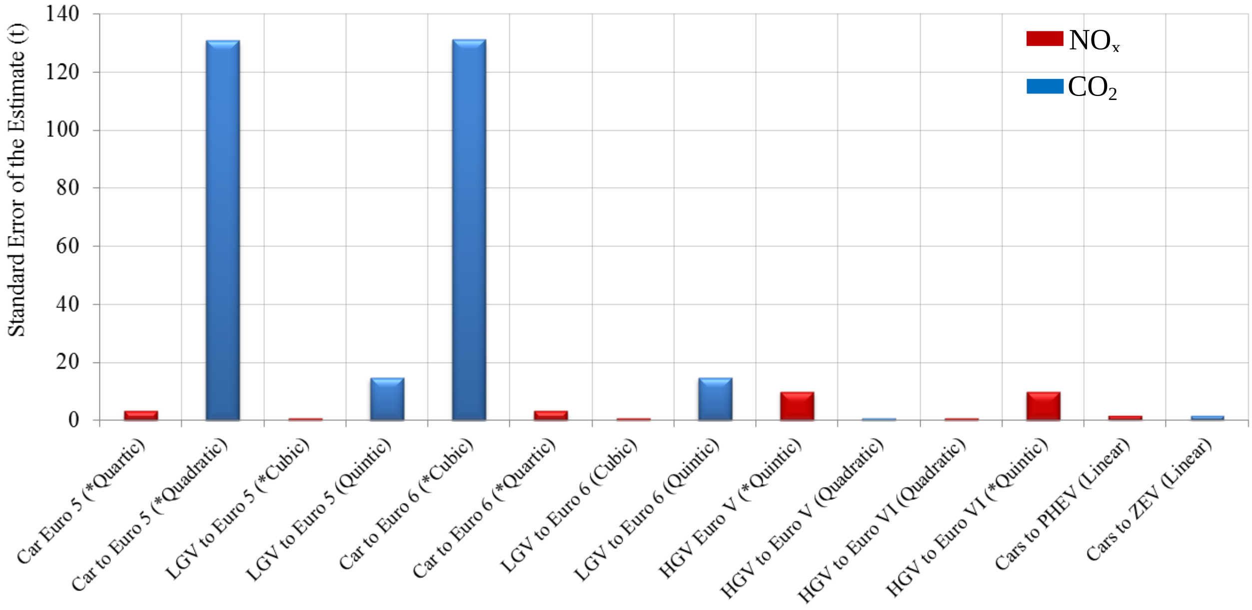
In addition to goodness of fit tests the mean of the residuals were calculated. Scatter plots of e_i versus $\widehat{Y_i}$ were plotted and subsequently visually assessed in order to determine if the values of e_i had the same variance (equal scatter around the x axis) and were independent from each other (no clustering of data points on the plots). A scatter plot of e_i versus $\widehat{Y_i}$ that shows a non-random scatter may indicate that a higher degree regression model may provide a better fit to the data (Montgomery *et al.,* 2012). Therefore, a higher degree model fit was tested. Small violations of the underlying assumptions were considered acceptable and a model was only deemed to be a poor fit to the data if it had a high SEE, low R^2 and its residuals had a mean 0> and were non-normally distributed.

The regression equations describing the statistical relationships between strategy and emissions were subsequently used to identify which strategy, if any, could achieve a 38% reduction in CO_2. The resulting pollutant emissions from such strategies were analysed.

7.3 Results

All of the models had R^2 values of one and normally distributed residuals (p-value = 0.05>). In addition, the model residuals for each of the strategies had means of zero. A total of 20 models were linear, six were quadratic, eight cubic, nine quartic and four were quintic. Figure 37 shows a bar chart of those strategies that had SEE scores greater than zero. It should be noted that the model type fit to each of these data sets is given in brackets on the x-axis label. Only models fitted to CO_2 and NO_x emissions data sets had SEE scores greater than zero. The linear models describing the statistical relationships for the low emissions vehicles had SEE values ±1t. Similarly four out of the five quadratic models had SEE scores that were equally small. The models describing the statistical relationship between % change in cars to Euro 5 or Euro 6 and CO_2 emissions were quadratic and cubic respectively and both were observed to have an SEE of ±131t. The cubic models fit to the LGV to Euro 5 and Euro 6 data set for NO_x had a small SEE of ±1t. Quartic models were fit to the car to Euro 5 and car to Euro 6 NO_x emissions datasets and were observed to have SEE values of ±3t. The second highest SEE scores (±15t) were observed for the quintic models applied to describe the CO_2 emissions resulting from the introduction of new abatement technology to the LGV fleet. A similar SEE of ±10t was observed for the quintic models describing the CO_2 emissions resulting from a change in HGV vehicles in favour of Euro V/VI technology.

Figure 37 Standard error of the estimate of those models fit to the NO_x and CO_2 emissions datasets



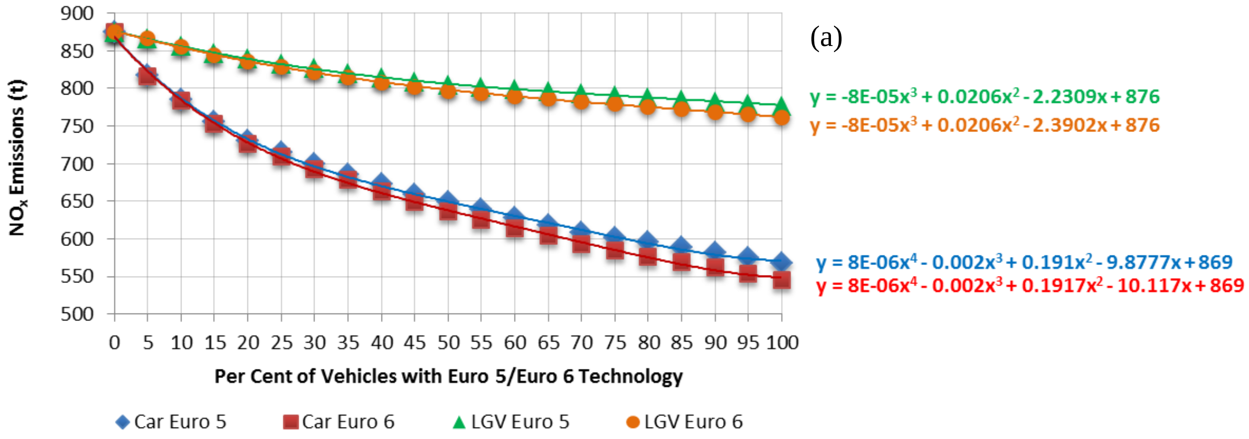
*indicates higher residuals in absolute terms were observed between zero and 15% strategy change

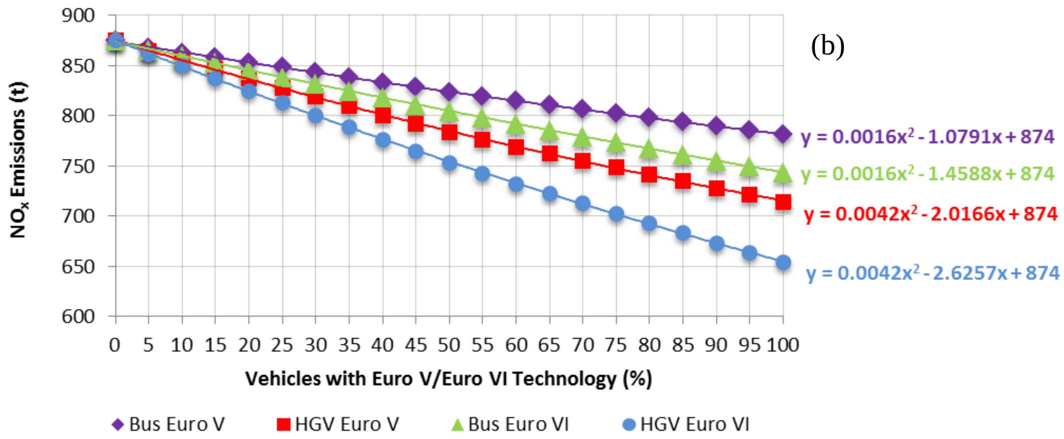
The scatter plots of e_i versus $\widehat{Y_i}$ of those models that had SEE (and therefore SS(Res)) values 0> were visually assessed for non-random patterns in the data. The CO_2 plots for the low emissions vehicle strategies showed random scatter suggesting model fit was appropriate. Clear non-random scatter was observed in the NO_x emissions plots for HGV Euro V and Euro VI technology strategies. Those strategies marked with a * in Figure 37 were observed to have higher residuals in absolute terms when predicting the base-case emissions value (zero % strategy change). In some cases (HGV to Euro V/VI CO_2 and Car to Euro 6 NO_x) relatively higher residuals were observed when predicting emissions from 0%, 5%, 10% and 15% strategy changes. However, given that the SEE values of all of these strategies were relatively small, all other regression assumptions were met and the polynomials visually appeared to describe the data trends well, the models were deemed to be a good fit.

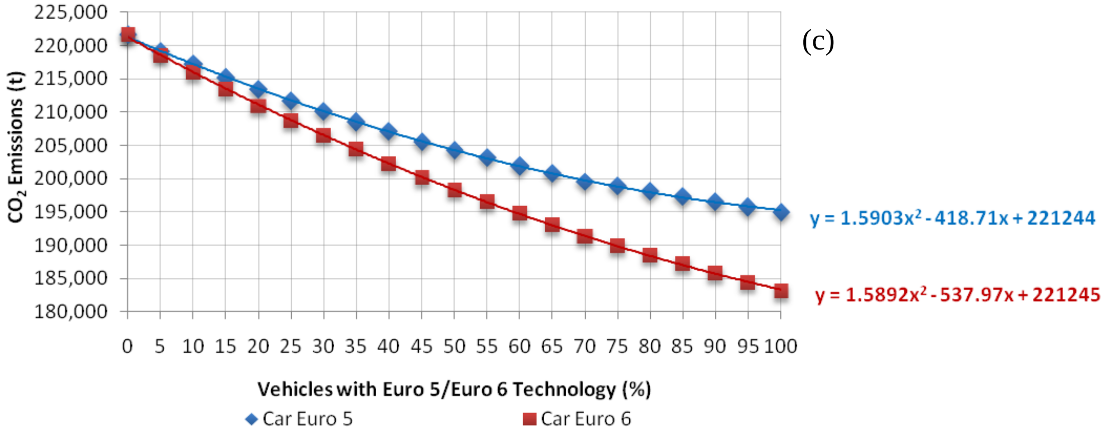
7.3.1 Emissions Abatement Technology Strategies

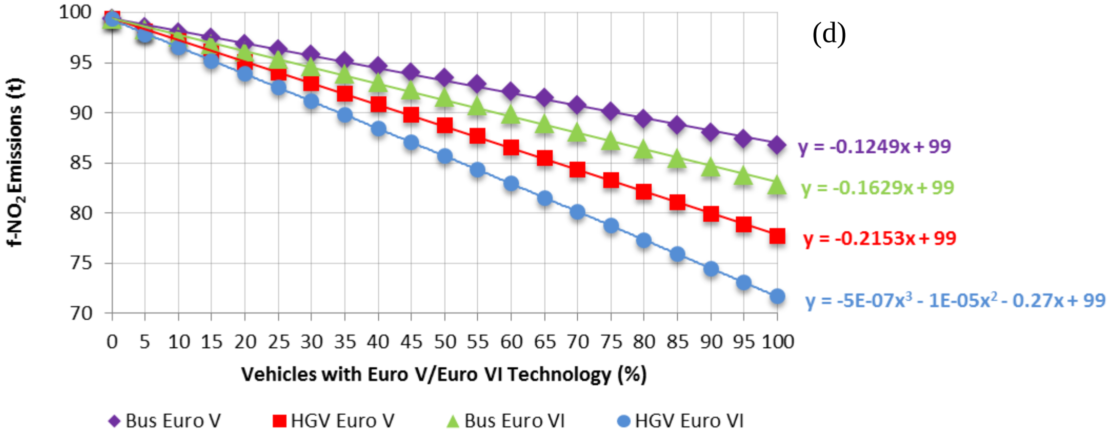
Figure 38(a) to Figure 38(g) show the change in emissions relative to the base-case as a result of changes to the vehicle fleet composition in favour of Euro 5/V and Euro 6/VI equipped vehicles. The highest reductions in NO_x emissions modelled were observed with the introduction of new technology into the car fleet (Figure 38(a)). The replacement of all the cars with Euro 5 and Euro 6 vehicles showed reductions of 308t (35%) and 330t (38%) respectively. The second highest reductions in NO_x were observed with the introduction of new abatement technology into the HGV fleet (Euro V 161t [18%] and Euro VI 221t [25%]). In contrast, the smallest reductions in NO_x emissions were observed for technology changes made to the LGV vehicle stock (figure 38(b)). The removal of 10% of the oldest cars in favour of Euro 6 equipped vehicles showed a 10% reduction in NO_x, which is comparable to that of 100% technology change for LGV vehicles (98t [11%] Euro 5 and 113t [13%] Euro 6; Figure 38(b)). A 100% change in the bus fleet to Euro V and Euro VI showed NO_x reductions of 94t (~11%) and 132t (15%) respectively relative to the base-case.

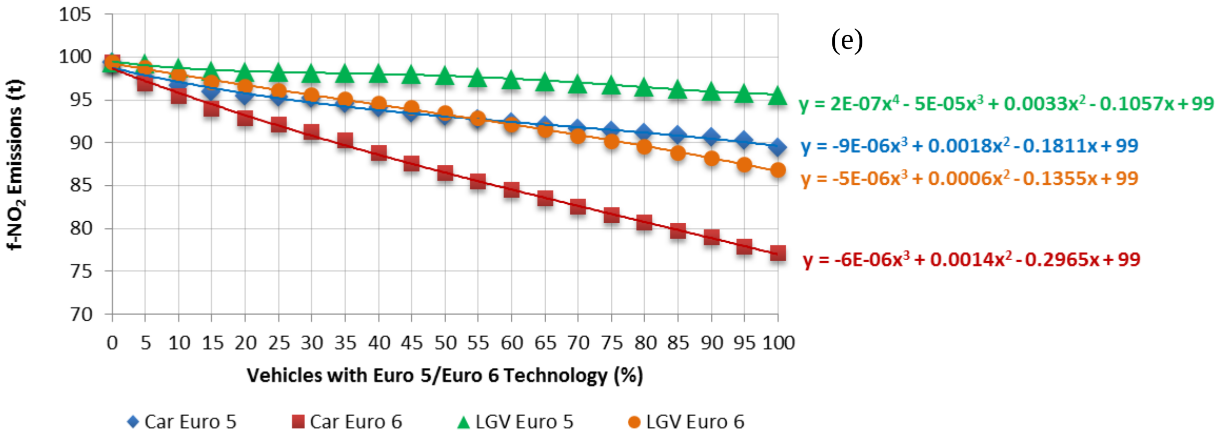
Figure 38(a) to Figure 38(g) Change in emissions (t) relative to the base-case as a result of changes to the vehicle fleet composition in favour of Euro 5/V and Euro 6/VI equipped vehicles

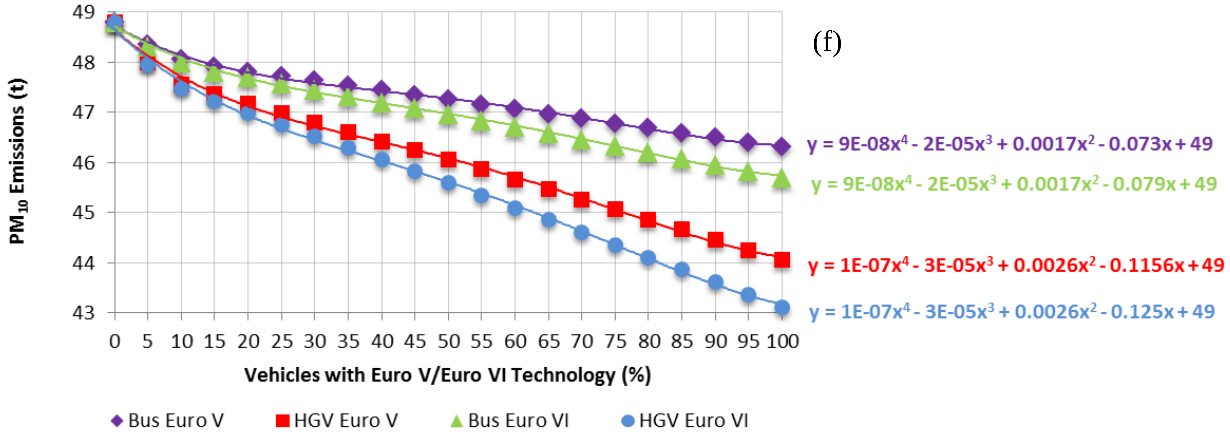


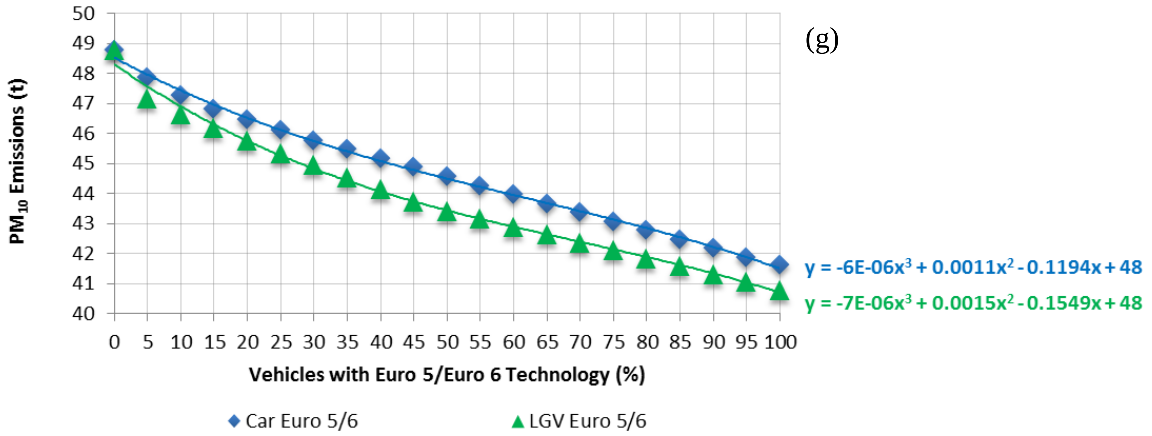



(c)
CO2 Emissions (t)
225,000
220,000
215,000
210,000
205,000
200,000
195,000
190,000
185,000
180,000
0 5 10 15 20 25 30 35 40 45 50 55 60 65 70 75 80 85 90 95 100
Vehicles with Euro 5/Euro 6 Technology (%)
Car Euro 5
Car Euro 6
y = 1.5903x2 - 418.71x + 221244
y = 1.5892x2 - 537.97x + 221245


(d)
f-NO2 Emissions (t)
100
95
90
85
80
75
70
0 5 10 15 20 25 30 35 40 45 50 55 60 65 70 75 80 85 90 95 100
Vehicles with Euro V/Euro VI Technology (%)
Bus Euro V
HGV Euro V
Bus Euro VI
HGV Euro VI
y = -0.1249x + 99
y = -0.1629x + 99
y = -0.2153x + 99
y = -5E-07x3 - 1E-05x2 - 0.27x + 99


(e)
f-NO2 Emissions (t)
105
100
95
90
85
80
75
70
0 5 10 15 20 25 30 35 40 45 50 55 60 65 70 75 80 85 90 95 100
Vehicles with Euro 5/Euro 6 Technology (%)
Car Euro 5
Car Euro 6
LGV Euro 5
LGV Euro 6
y = 2E-07x4 - 5E-05x3 + 0.0033x2 - 0.1057x + 99
y = -9E-06x3 + 0.0018x2 - 0.1811x + 99
y = -5E-06x3 + 0.0006x2 - 0.1355x + 99
y = -6E-06x3 + 0.0014x2 - 0.2965x + 99





Reductions in CO_2 emissions of <1% were observed with the introduction of new emissions abatement technology to the HGV, LGV and bus vehicle stocks. The introduction of new abatement technology to the car fleet had a substantial impact on CO_2 emissions with maximum reductions of 26,556t (12%) and 38,492t (17%) observed for Euro 5 and Euro 6 strategies respectively (Figure 38(c)).

The highest reductions in f-NO_2 emissions modelled were observed with the introduction of new technology into the HGV fleet (Figure 38(d)). The total replacement of the HGV stock with vehicles equipped with Euro V/VI technology showed f-NO_2 emissions reductions of 22t (22%) and 28t (28%) respectively. Comparable reductions in f-NO_2 were observed with the replacement of all cars with Euro 6 technology (22t [22%]). However, the introduction of Euro 5 technology to the car fleet was observed to have considerably lower f-NO_2 emissions reductions (10t [10%]) which were similar to those seen for the replacement of LGV vehicles with Euro 6 technology (13t [13%]) (Figure 38(e)). The introduction of Euro 5 technology to the LGV vehicle stock resulted in the smallest reduction in f-NO_2 emissions (maximum 4t [4%]). Introduction of Euro V and Euro VI technology to the bus fleet was found to have maximum emissions reductions of 13t (13%) and 17t (17%) respectively.

All of the new abatement technology strategies, with the exception of the bus to Euro V/VI strategies, resulted in PM_{10} emissions reductions that were of a similar magnitude with maximum reductions (100% change to Euro 6/VI) observed to be between 5t (10%) and 8t (16%). However, the introduction of Euro V and VI equipped technology to the bus fleet was found to result in the smallest reductions in PM_{10} (2t [5%] and 3t [6%] respectively for 100% change; Figure 38(f)). The largest reductions in PM_{10} emissions were observed with changes in technology to the car and LGV fleets (7t [15%] and 8t [16%] respectively Figure 38(g)). It should be noted that car Euro 5 and Euro 6 and LGV Euro 5 and Euro 6 strategies respectively showed the same reductions in PM_{10} emissions.

7.3.2 Low Emissions Vehicle Strategies

Figure 39 shows the % change in CO_2 emissions relative to the base-case as a result of changes to the vehicle fleet composition in favour of low emissions vehicles, namely PHEVs operating in charge sustaining mode and ZEVs. The highest CO_2 reductions were observed when cars were substituted for ZEVs. A 20% change in the car fleet to ZEVs resulted in a reduction of 31,014t (14%) of CO_2 which is comparable to the reductions observed for the Euro 5/6 strategies for cars. A maximum reduction in CO_2 emissions of 155,067t (70%) was shown for the removal of all cars in favour of ZEVs. Maximum CO_2 emissions reductions observed for PHEVs (80,231 [36%]) were significantly greater than CO_2 reductions observed for any of the technology or fuel strategies.

Figure 39 Change in CO_2 emissions (t) relative to the base-case as a result of a change in car with PHEVs or ZEVs

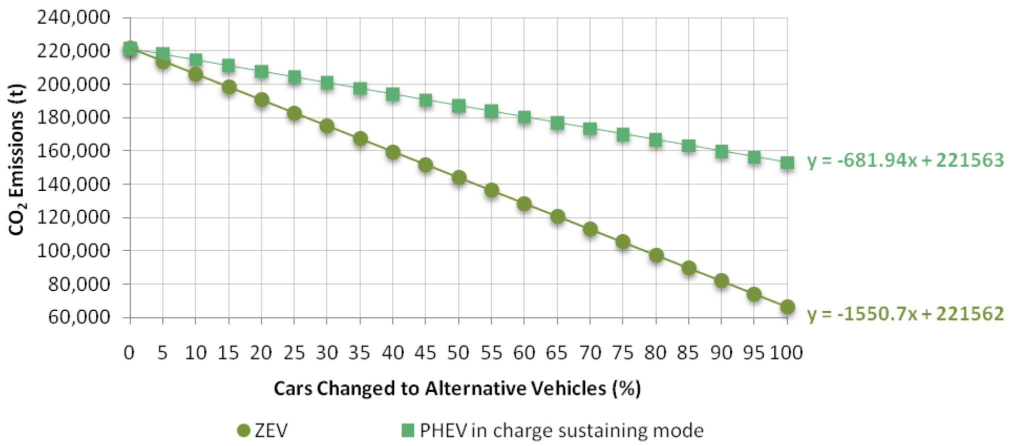
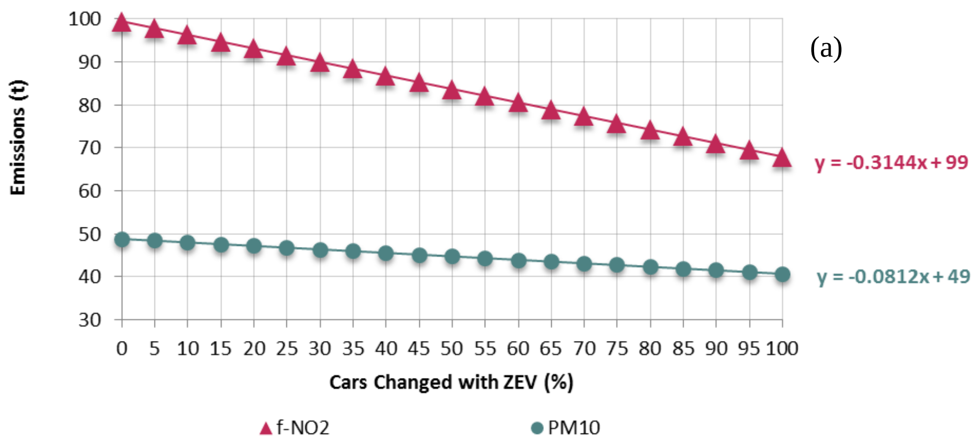
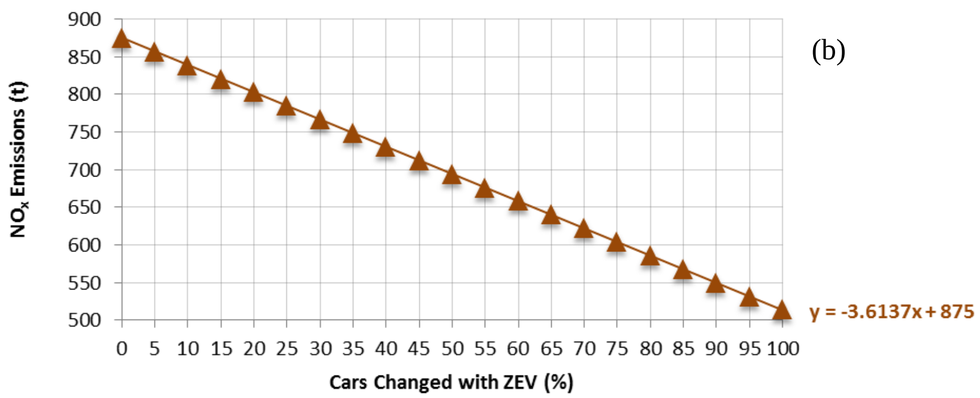


Figure 40(a) and Figure 40(b) show the % change in PM_{10} and f-NO_2 and the % change in NO_x emissions respectively relative to the base-case as a result of changes to the vehicle fleet composition in favour of ZEVs. Maximum reductions of 361t (41%) and 31t (32%) were observed for NO_x and f-NO_2 respectively. A reduction in PM_{10} of 8t (16%) was observed when all of the cars were replaced with ZEVs which is comparable to the maximum reductions achieved from the new emissions abatement technology strategies. Statistical comparison between NO_x emissions resulting from an introduction from ZEVs and PHEVs to the car fleet revealed that there was no significant difference (p-value 0.05>) between the two data sets.

Figure 40(a) and Figure 40(b) Change in PM_{10} and f-NO_2 and NO_x emissions (t) relative to the base-case as a result of a change in car to zero emssions vehicles (ZEVs)



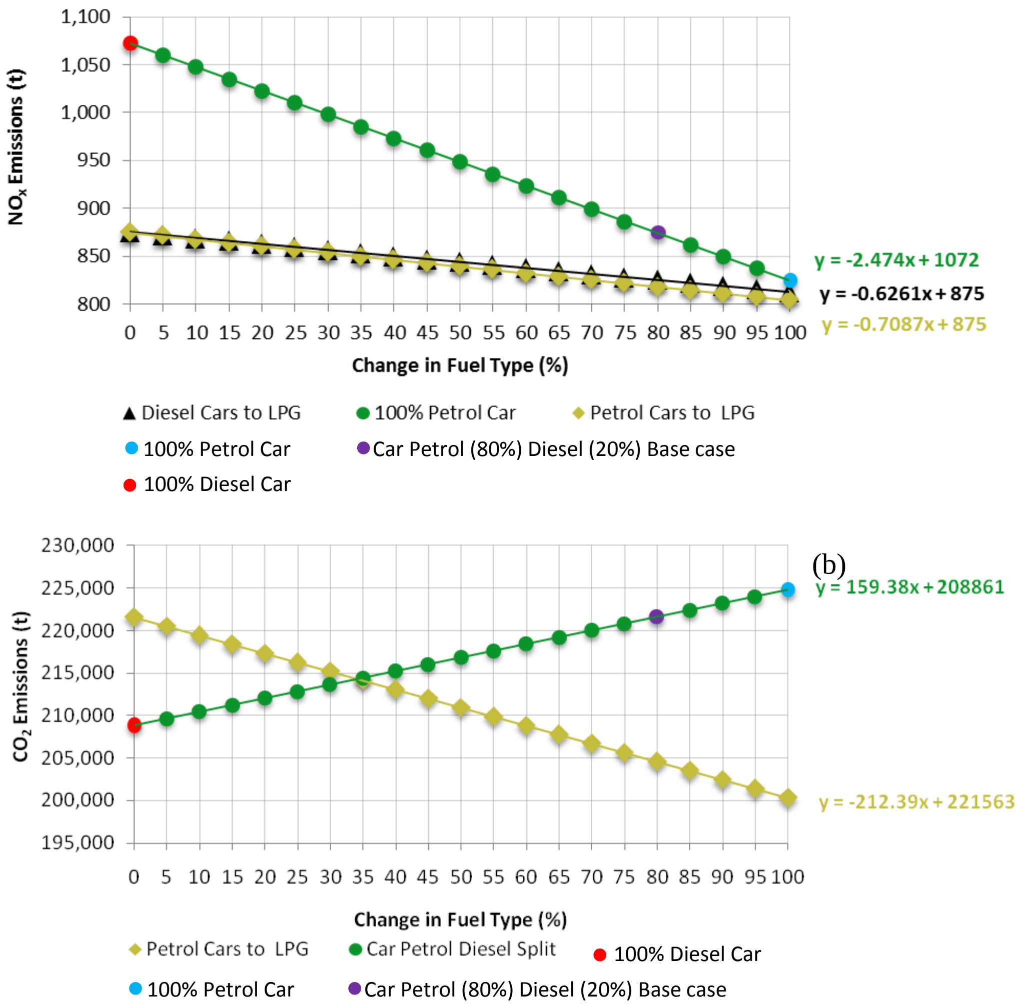


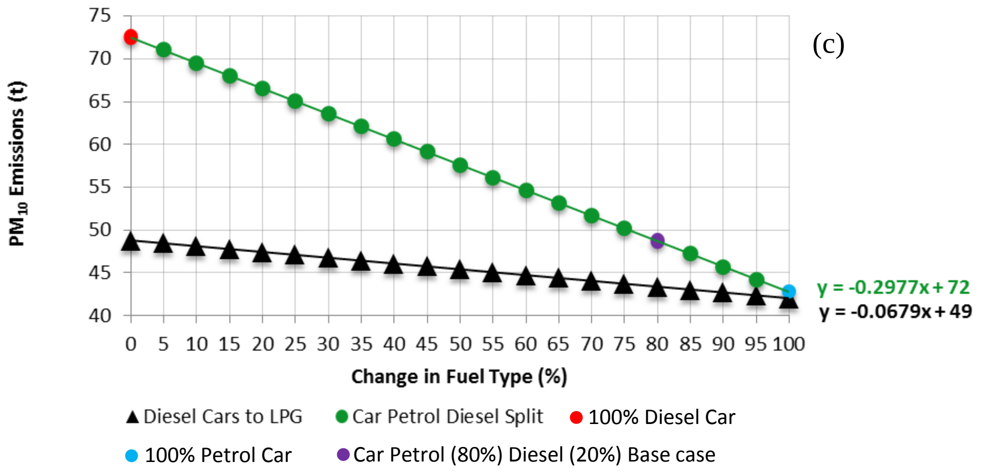
7.3.3 Fuel Strategies

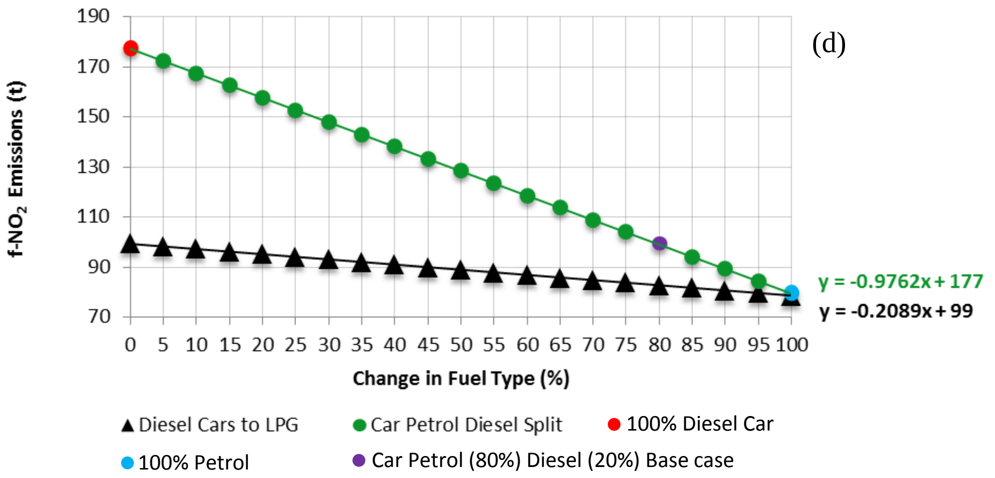
Figure 41(a) to Figure 41(d) show the % change in NO_x, CO_2, PM_{10} and f-NO_2 emissions relative to the base-case as a result of changes to car fuel type, namely a switch in petrol or diesel to LPG or a change in the petrol diesel fuel split. Very small changes (<1%) in PM_{10} and f-NO_2 emissions were found for petrol to LPG strategies and a less than 1% change in CO_2 emissions similarly was found for the diesel to LPG strategy.

NO_x emissions reductions of 49t (6%), 62t (7%) and 71t (8%) were observed when 100% of the car stock was fuelled with petrol, 100% of diesel cars were replaced with cars fuelled by LPG and when all of the petrol cars were changed to cars fuelled by LPG respectively (Figure 41(a)). An increase in NO_x emissions was observed when the number of petrol (diesel) cars in the fleet was decreased (increased). A car fleet fuelled completely by diesel showed 198t (23%) increase in NO_x emissions.

Figure 41(a) to Figure 41(d) Change in NO_x, CO_2, PM_{10} and f-NO_2 emissions (t) relative to the base-case as a result of changes to car fuel type, namely a switch from petrol or diesel to LPG or a change in the petrol-diesel split







A switch from petrol to LPG within the car fleet showed the highest reductions in CO_2 emissions out of all the fuel strategies (maximum of 21,239t [10%]) (Figure 41(b)). An increase (decrease) in the % of cars fuelled by petrol (diesel) in the fleet showed CO_2 emissions to increase by 3,188t (<2%) for the maximum change. In contrast, a decrease (increase) in the number of petrol (diesel) cars showed a reduction in CO_2 emissions of 12,750t (6%) in the extreme case.

The PM_{10} emissions reductions observed for the fuel strategies showed similar trends to those observed for NO_x, with the petrol to LPG strategy showing reductions of <1%. Maximum reductions in PM_{10} emissions of 7t (14%) were observed for the diesel to LPG strategy (Figure 41(c)). A decrease (increase) in the number of petrol (diesel) cars in the fleet was shown to significantly increase PM_{10} emissions. A 60-40 petrol diesel split in the car fleet showed an increase in PM_{10} emissions of 6t (11%) and a fleet with cars fuelled completely by diesel showed an increase in PM_{10} of 24t (33%). Similarly, a fleet with cars fuelled completely by diesel fuel showed an increase in f-NO_2 emissions of 78t (44%) (Figure 41(d)). A change of petrol cars in favour of LPG fuelled vehicles had a very small (<1% reduction) impact on f-NO_2 emissions. A maximum reduction in f-NO_2 emissions of 21t (21%) was observed for the diesel car to LPG strategy.

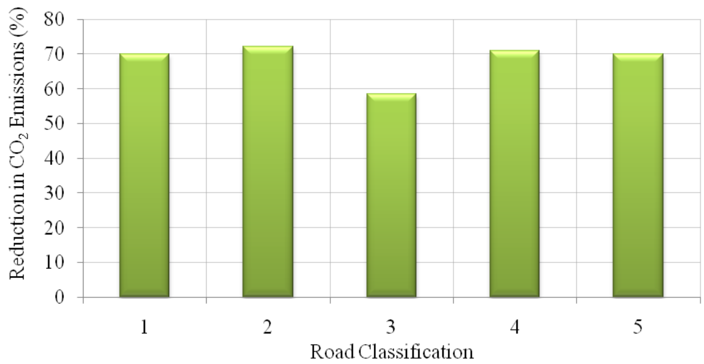
7.3.4 Change in Emissions by Road Classification

Figure 7 in Chapter 5 (section 5.4) shows the spatial locations of the five road classifications over the entire Leicester road network. The base-case emissions for the five road classifications for the LCC LA area can be seen in Appendix H. The highest reduction in CO_2 emissions resulted from a 100% change in cars to ZEVs (Table 27). These reductions were relatively uniform for all road classifications (Figure 42). However, the reduction in emissions (58%) on links belonging to road classification 3 were lower than those observed (70% to 72%) for the other road classifications relative to the base-case. In addition, links grouped in road classification 3 were observed to have the smallest reduction in emissions out of all the classifications for the PHEV strategies. In contrast, the highest reductions in PM_{10} and f-NO_2 emissions were observed with the introduction of Euro VI technology to the bus fleet on roads belonging to classification 3. In general, the highest reductions were found for roads belonging to classification 2 and classification 3.

Table 27 Strategies resulting in the highest (1st) and second highest (2nd) emissions reductions by road classification

Pollutant	**Rank Reduction (1st /2nd)**	**Strategy**	**Classification**
NO_x	1st	ZEV	2
	2nd	Car Euro 6	2
CO_2	1st	ZEV	2
	2nd	Car Euro 6	2 and 5
PM_{10}	1st	BUS Euro VI	3
	2nd	LGV Euro VI	1
f-NO_2	1st	BUS Euro VI	3
	2nd	HGV Euro 6	5

Figure 42 Reduction in CO_2 emissions for each of the five road classifications resulting from 100% change in cars to ZEVs



The changes in NO_x and f-NO_2 emissions observed as a result of 100% change in petrol fuelled cars to LPG fuelled cars over the entire network were not uniform across the five road classifications with some links increasing in emissions and others showing a reduction (Table 28). Links grouped in road classifications 2, 3 and 5 were found to decrease in NO_x emissions and emissions from classifications 1 and 4 were observed to increase. A similar trend was observed for f-NO_2 emissions with the exception of links belonging to road classifications 3 and 4 which showed an increase in f-NO_2.

Table 28 Change in NO_x and f-NO_2 emissions (%) as a result of 100% switch from all cars in the Leicester road network fuelled by petrol to cars fuelled by LPG

Road Classification	**Change in NO_x Emissions (%)**	**Change in f-NO_2 Emissions (%)**
1	5	4
2	-11	-1
3	-3	1
4	1	3
5	-14	-3

7.3.5 Achieving a 38% Reduction in CO_2

The only strategy that resulted in a 38% reduction in CO_2 was a 53% change in cars to ZEVs. The same strategy was observed to reduce NO_x, f-NO_2 and PM_{10} emissions by 22% (192t), 17% (17t) and 9% (4t) respectively.

It should be noted that the data tables used in this work are not presented here but can easily be reproduced using the regression equations documented above.

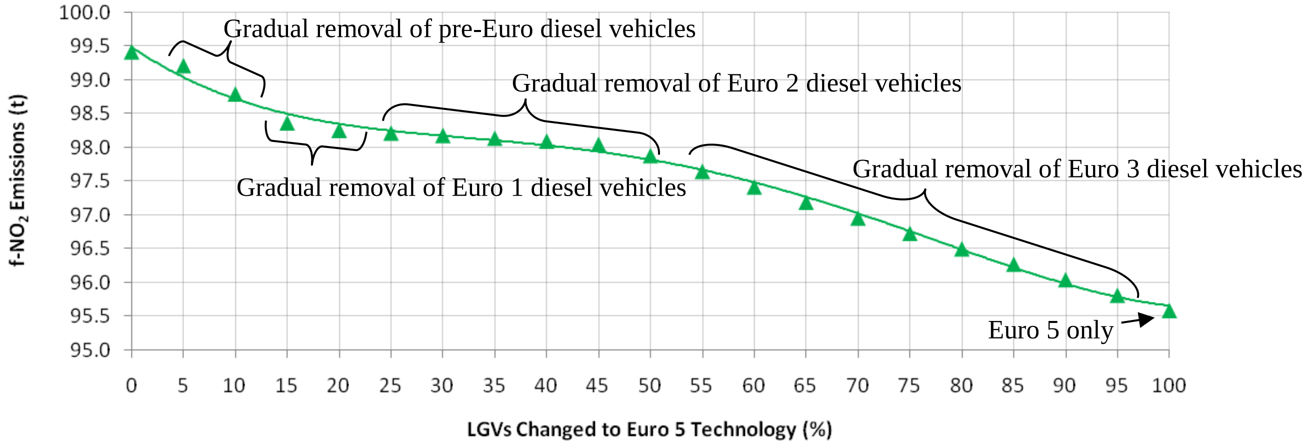
7.4 Discussion

The results showed substantial reductions in vehicle pollutant and or CO_2 emissions from the introduction of improved abatement technologies, fuels and low emissions vehicles into the Leicester fleet. In some cases a 'win-win' for air quality improvement and carbon reduction was observed. However, in other cases a trade-off was found where a win-win was achieved but higher reductions in pollutant or CO_2 emissions were observed from other strategies. These findings are discussed in more detail below and the impact of strategies on emissions relative to road characteristics is discussed. However, first an evaluation of the statistical relationships observed between strategy and change in emissions is documented.

7.4.1 Relationships between Strategies and Emissions

Linear trend lines were fitted to 20 of the strategies. These changes reflected the linear change in emissions factors that were modelled. As a result of the linear relationships R^2 values of one were observed and the residuals averaged zero. In contrast, the emissions abatement technology strategies were fitted with polynomial regressions models. These non-linear relationships were observed because changes were made to the fleet at the Euro class level. Therefore, as the successive removal of each Euro class type took place the value of $\widehat{\beta_1}$ changed and hence a polynomial relationship was observed. In addition, as each Euro class was reduced so too was the number of failed catalyst vehicles of the class. These vehicles are gross polluters (Boulter *et al.,* 2009a, 2009b, 2009d). Therefore, the gradual reduction in these vehicles further contributed to the fluctuations in $\widehat{\beta_1}$ observed. This was perhaps best illustrated when emissions from a change in LGV to vehicles equipped with Euro 5 technology were plotted (Figure 43). The gradual removal of each diesel Euro class (pre-Euro to Euro 3) resulted in four major changes in $\widehat{\beta_1}$ and subsequently a quartic regression model was fit to the data set. However, changes in $\widehat{\beta_1}$ can also be seen between 0% and 5% and between 95% and 100% strategies in this case. A sixth degree polynomial could have been fit to reflect these changes but the residuals of the quartic model were very small (<0.1t) and all of the regression assumptions were met. As such the fitting of a sixth degree polynomial was considered over fitting. Those models that had SEE values of 1t> typically had the highest residuals when predicting the base-case value as the change in $\widehat{\beta_1}$ between 0% and 5% was not reflected in the model as is the case in Figure 43. Subsequently the difference between Y_i and $\hat{Y}$ was greatest at these points. A greater number of strategies modelled in PITHEM at the lower end of the strategy % range (e.g. 1%, 2%, 3%, 4%) may have provided more confidence in fitting a higher degree polynomial. Future work should look to investigate whether such an approach would significantly improve the predictive power of the model.

Figure 43 Change in f-NO_2 emissions as a result of the introduction of Euro 5 technology to the LGV fleet



The sequential changes in the non-linear models resulted in clear patterns in the data which allowed polynomial curves to be fitted easily with little data point variance around the best fit line (e.g. Figure 43). Therefore, R^2 values of one were observed and the residuals averaged zero for these models.

The changes in $\widehat{\beta_1}$ observed for the new abatement technology strategies highlighted that emissions reductions achieved will fluctuate over time as the vehicle fleet evolves. Therefore, it is necessary for policy makers to continually track the impact of such strategies on toxic pollutant and CO_2 emissions. As a result the equations output from this research become valuable to a policy maker as they allow for the rapid assessment of changes to the vehicle fleet and the subsequent analysis of emissions.

7.4.2 Win-Win for Air Quality and Climate Change?

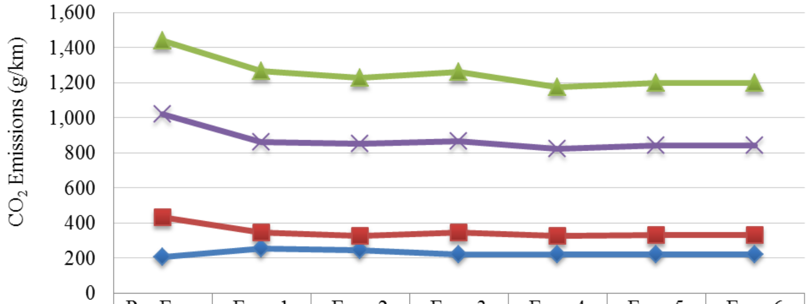
Table 29 shows the rank effectiveness (1st, 2nd, 3rd and 4th) in emissions reductions (relative to the base-case) as a result of implementing Euro 6/VI technology changes by vehicle type. In terms of NO_x and CO_2 reductions the introduction of emissions abatement technology to the car fleet was best. In addition, cars equipped with Euro 6 technology were found to substantially reduce PM_{10} and f-NO_2 emissions. Therefore, the replacement of cars with cars equipped with new emissions abatement technology offered a 'win-win' for air quality improvement and CO_2 reduction. However, greater PM_{10} and f-NO_2 emissions reductions were observed with the introduction of Euro VI technology to the LGV and HGV vehicle stock respectively. Consequently a trade-off was observed where a 'win-win' was achieved through changes to the car fleet but at the cost of higher emissions reductions from other strategies.

Table 29 The rank effectiveness (1st, 2nd, 3rd and 4th) in emissions reductions (relative to the 2005 base-case) as a result of implementing technological changes by vehicle type

	Car	**LGV**	**HGV**	**Bus**
NO_x	1st	4th	2nd	3rd
CO_2	1st	-	-	-
PM_{10}	2nd	1st	3rd	4th
f-NO_2	2nd	4th	1st	3rd

The introduction of new abatement technology into the LGV, HGV and bus fleets was observed to have little impact (<1% reduction) on CO_2 emissions. This is because Euro 5/V and Euro 6/VI standards, like all other Euro standards for these vehicle types do not have limit values for CO_2 (Boulter *et al.,* 2009a). Therefore, the UK emissions factors used in this research show little change in CO_2 with the introduction of successive Euro technology (Figure 44). For example, the emissions factors for LGV Euro 3 to Euro 6 vehicles are 219gCO_2/km based on an average-speed of 30km/h. In some cases Euro 5/V and Euro 6/VI emissions factors increase relative to early standards due to the occurrence of a fuel debt incurred by the addition of the technology (Boulter *et al.*, 2009a; USEPA, 2003; Dong *et al.,* 2008). For example, Euro V and Euro VI emissions factors for rigid HGVs (3.5t-7.5t) (332gCO_2/km based on an average-speed of 30km/h) are marginally higher than those of rigid HGVs equipped with either Euro IV (326gCO_2/km based on an average-speed of 30km/h) or Euro II (325gCO_2/km based on an average-speed of 30km/h) technology. This is due to a slight increase in fuel usage due to the assumed requirement of a DPF or SCR catalyst (Boulter *et al.*, 2009a; USEPA, 2003; Dong *et al.,* 2008). Therefore, in this research any minor reductions in CO_2 observed as a result of the removal of Euro II rigid HGVs were offset by the introduction of HGVs with Euro V/VI technology. Subsequently, arguably negligible changes in CO_2 emissions were observed. The 2009 emissions factors for buses and artic HGVs show a slight reduction in CO_2 emissions with each successive Euro class. However, in this research they accounted for a relatively small proportion of the vehicle stock and as such changes in CO_2 from these vehicles had little impact on total network emissions.

Figure 44 CO_2 emissions factors from the 2009 UK database for various vehicles travelling at an average-speed of 30 km/h

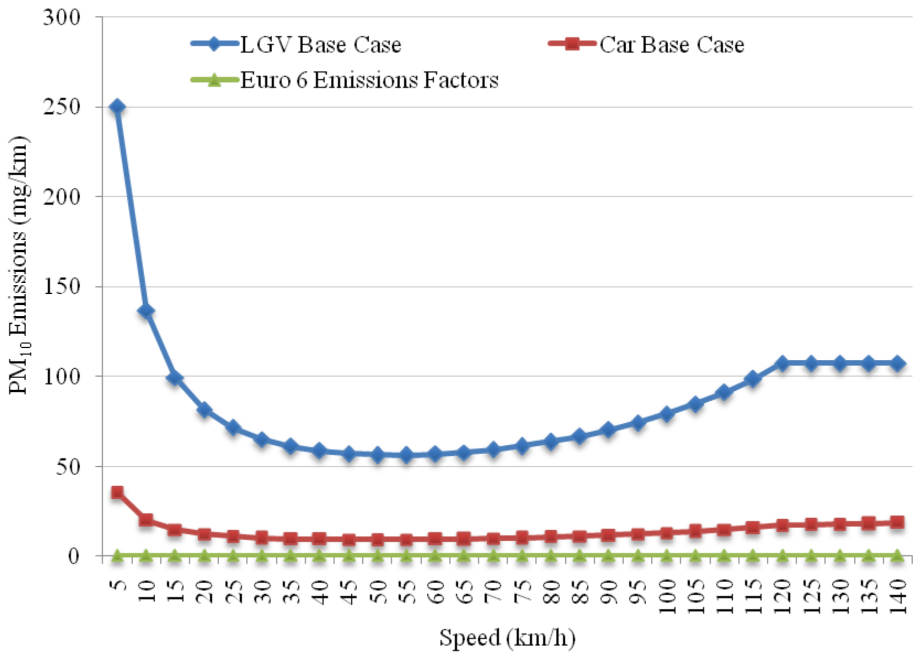


	Pre Euro	Euro 1	Euro 2	Euro 3	Euro 4	Euro 5	Euro 6
Van (N1 (III))	205	252	243	219	219	219	219
Rigid HGV (3.5t-7.5t)	432	344	325	346	326	332	332
Aritc HGV (34t-40t)	1,440	1,265	1,227	1,263	1,175	1,196	1,196
Bus (15t-18t)	1,019	862	854	866	823	842	842

In contrast to the emissions factors for LGVs, HGVs and buses the 2009 CO_2 emissions factors for cars were developed to take into consideration the average fleet CO_2 legislation introduced for all new cars in Europe (Boulter *et al.*, 2009d). Therefore, in this research substantial reductions in CO_2 were found with a change in cars to vehicles equipped with Euro 5 and Euro 6 technology.

Despite the number of cars being significantly greater than the number of LGVs within the Leicester fleet the introduction of Euro 6 technology to the LGV stock was found to reduce PM_{10} emissions the most. Both LGV and car Euro 6 (and Euro 5) vehicles are assigned an emissions rate of 0.5mg/km in the UK 2009 emissions database due to the assumption that these vehicles require DPFs to comply with type approval standards (Boulter *et al.*, 2009a). However, the base-case emissions rates for LGVs were substantially higher than those for cars (Figure 45). A switch from the LGV base fleet to an LGV fleet comprised entirely of Euro 6 vehicles resulted in PM_{10} emissions that were on average 85mg/km lower, whereas the introduction of Euro 6 technology to the car fleet reduced emission rates by only 13mg/km on average. Therefore, the introduction of Euro 6 technology to the LGV fleet had a larger impact on PM_{10} emissions than Euro 6 equipped cars. High base-case emissions were also the reason why reductions in NO_x and f-NO_2, as a result of the introduction of Euro 6 technology to the HGV fleet, were comparable to those observed from the Euro 6 car strategies.

Figure 45 Fleet weighted light goods vehicles (LGVs), fleet weighted passenger car and Euro 6 light duty vehicle (LDV) PM_{10} emissions factors for the year 2005



A change from diesel fuelled cars to LPG fuelled cars showed the greatest reductions in pollutant emissions relative to the other LPG strategies. However, the same strategy was shown to reduce CO_2 emissions by less than 1%. In contrast, a change in fuel type from petrol cars to LPG cars showed substantial CO_2 emissions reductions (maximum 21,239t [10%]) but had an arguably negligible (<1%) impact on PM_{10} and f-NO_2 emissions. These findings suggest a lack of synergy between those LPG strategies that reduce CO_2 emissions and those that improve air quality. The LPG strategies showed the greatest reductions in CO_2 emissions of all fuel strategies. Initially it was hypothesised that this was primarily due to the replacement of pre-Euro cars with Euro VI cars in the LPG strategy. However, closer inspection of the emissions factors revealed that the inclusion of Euro VI technology had little impact on the LPG strategy CO_2 emissions. Furthermore, fleet weighted car LPG CO_2 emissions rates were observed to be on average 7000mg/km lower than fleet weighted petrol car CO_2 emissions rates suggesting that the emissions reductions found were not caused by the inclusion of Euro VI vehicles.

The car petrol diesel fuel split strategies failed to show a win-win for a reduction in CO_2 and pollutant emissions. Changes to fuel use by the car fleet were shown to increase CO_2 emissions when an increase in petrol vehicles was implemented but the same strategy was shown to decrease pollutant emissions. Therefore, it can be argued that any change in the car diesel petrol fuel split would work against aligning climate change and air quality policy. However, this research has shown Euro 5 and Euro 6 technology to substantially reduce pollutant emissions. Therefore, a shift towards Euro 5/Euro

6 diesel cars could yield a significant win-win for air quality and climate change. The success of such a strategy is dependent on the technology introduced being adequate to meet the Euro 5/Euro 6 diesel emissions limit values in the 'real world' and not just on a dynamometer.

The greatest reductions in toxic pollutant and CO_2 emissions out of all of the strategies modelled were found for the introduction of ZEVs to the car fleet. Furthermore, an introduction of ZEVs was the only strategy for which a 38% reduction in CO_2 was observed. ZEVs can be considered representative of EVs under current legislation or PHEVs operating in charge depleting mode. Furthermore, ZEVs by definition have zero emissions. In this respect the introduction of ZEVs can be observed as the removal of cars (and subsequently a reduction in car VKT) from the fleet without a change in the Leicester road network dynamics (i.e. vehicle speed and flow). Therefore, this research suggests that further VKT restriction in the car fleet would result in substantial emissions reductions and a win-win for air quality and climate change. Moreover, it indicates that policy options that limit VKT are likely to achieve greater emissions reductions than a change in technology, vehicle (other than ZEV) or fuel.

Maximum CO_2 emissions reductions achieved for the introduction of PHEVs were higher than CO_2 reductions found for any of the technology or fuel strategies. In addition, the NO_x emissions reductions found for PHEVs were not significantly different from those observed for ZEVs, which suggested that the introduction of PHEVs would result in a win-win for air quality and climate change in Leicester. This was not surprising given the small emissions rate (0.01gNO_x/km) specified in PITHEM based on the research of Fontaras *et al.* (2008). PHEVs, such as the Plug-in Toyota Prius, typically have a range of ~20km in charge depleting mode after which the ICE is switched on and the vehicle is operated in charge sustaining mode (JEC 2011). The average trip length in the UK is 11km (DfT, 2011d) which further supports the findings of Fontaras *et al.* (2008) and Hagman and Assum (2012) that PHEVs operate predominately in charge depleting mode in urban environments and subsequently have very low pollutant emissions rates. Therefore, strategies that encourage the uptake of PHEVs whilst providing sufficient charging facilities, for example at places of work, would enable substantial pollutant emissions reductions to be achieved. Such reductions would depend on driver charging behaviour. Therefore, from an air quality perspective, strategies that encourage regular PHEV charging are beneficial. From a climate change perspective, such a strategy may lead to an increase in WTT CO_2 emissions but these emissions are typically out of the control of local authorities. However, given the UK governments plans to decarbonise the electricity grid by 2030 (DECC, 2010), WTT CO_2 emissions for electric vehicles may become of less concern.

When considering the road classifications, both increases and decreases in NO_x and f-NO_2 emissions were observed when 100% change in petrol cars to LPG fuelled vehicles was modelled. This was because of the sensitivity of Euro 1 LPG cars to changes in average-speed. At speeds lower than ~22 km/h NO_x emissions from these vehicles are higher than those from an equivalent petrol fuelled car (Figure 46(a)). At speeds above ~22 km/h emissions from these vehicles are lower than those from an equivalent petrol fuelled car. Therefore, links belonging to road classifications 2, 3 and 5, which had average-speeds of 35km/h, 27km/h and 39km/h respectively, were observed to have a decrease in NO_x emissions (Table 30). Whereas links grouped in road classifications 1 and 4 increased as their average-speeds were 13km/h and 18km/h respectively. Similar observations were made for Euro 1 LPG cars and f-NO_2 with LPG vehicles having higher (lower) emissions than petrol cars at speeds below (above) ~28km/h (Figure 46(b)).

Figure 46(a) and Figure 46(b) Speed dependent NO_x and f-NO_2 emissions rates (g/km) for LPG, petrol and diesel fuelled cars

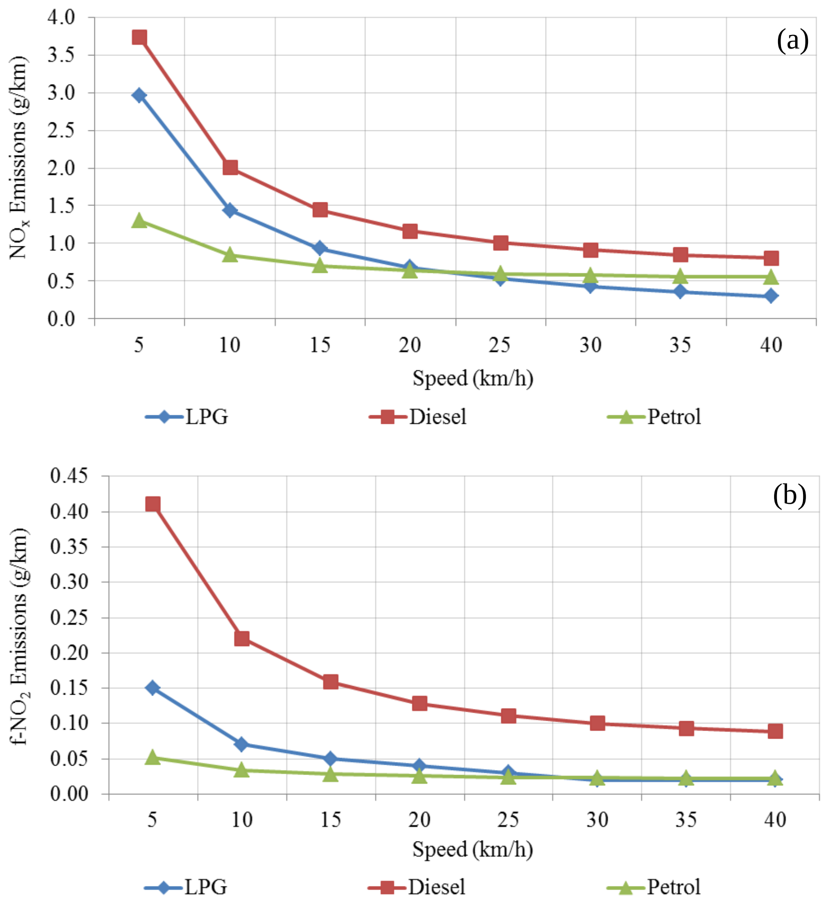


Table 30 Average-speed of the five road classifications and change in NO_x and f-NO_2 emissions (%) as a result of 100% switch from all cars in the Leicester road network fuelled by petrol to cars fuelled by LPG

Road Classification	Average-speed (km/h)	Change in NO_x Emissions (%)	Change in f-NO_2 Emissions (%)
1	13	3	3
2	35	-8	-1
3	27	-2	0
4	18	0	2
5	39	-10	-2

When considering emissions changes by road classification, the highest reductions in NO_x and CO_2 emissions were observed for a change in the car fleet to ZEVs and vehicles equipped with Euro VI technology on roads grouped in classification 2. This was expected given the relatively high LDV flows of, and large proportion of roads belonging to, classification 2. Spatially roads assigned to this classification were spread throughout the city exhibiting no geographical trend. Therefore, policy options involving the promotion of ZEVs and Euro 6 technology would have to target the Leicester road network as a whole and not just the AQMA. This may be considered a disadvantage compared to other strategies which can be targeted at more spatially invariant road classifications. Such a policy option was observed in this research. The introduction of Euro VI technology to the bus fleet on roads belonging to classification 3 was found to have the highest reductions in PM_{10} and f-NO_2 emissions compared to all other classifications. This was not expected given that when considering the network as a whole the introduction of new abatement technology into the car fleet was observed to have the highest pollutant emissions reductions. As a result classifying roads not only for air quality modelling but for evaluation of strategies and policies is beneficial as it has allowed for the identification of significant emissions reductions that would otherwise have gone unnoticed. Links grouped in classification 3 are predominately city centre feeder roads which are located within the LCC AQMA (Appendix H). In addition, they are characterised by high bus flows (average of 11% of classification 3 vehicle fleet composition) and relatively low HGV flows. Therefore, this research suggests a technology upgrade for the bus fleet in Leicester to Euro V/VI would have significant air quality benefits. Given the location of the bus roots on city centre feeder roads within the AQMA, such a change would help limit NO_2 emissions exceedences. However, a technology change to the bus fleet has been shown in this research to have negligible impacts on CO_2 emissions. Euro V/VI equipped HGV vehicles were observed to substantially reduce pollutant emissions and this strategy was found to be particularly successful on roads belonging to classification 5. Classification 5 comprised roads that were typically on the city ring road or on city centre feeder roads, which further highlights the importance of targeting these key traffic routes with emissions reduction strategies.

7.4.3 Policy Options for Leicester

The LCC's LTP 3 primarily aims to increase the quality and quantity of bus services operating within the LA area (LCC, 2011b). This research has shown that substantial reductions in pollutant emissions can be achieved through the upgrade of the Leicester bus fleet to Euro V/VI technology. Currently, bus operators in Leicester work within an overall emissions allowance with a year on year reduction (LCC, 2011b). However, the allowance is likely to be increased given the plans for greater bus services. Therefore, it is advised that prior to expansion the existing bus fleet must be improved to meet higher levels of environmental regulation. Furthermore, it is suggested that any additional vehicles must comply with Euro V/VI standards or better still electric buses should be considered. If funding permits, the LCC should look to subsidise the acquisition of electric buses for use in the city.

Improved vehicle abatement technology has been shown in this research to have little impact on CO_2 emissions from the Leicester bus fleet. Therefore, in order for an increase in bus frequency to be beneficial in terms of CO_2 emissions reduction, bus patronage must be increased and private car use simultaneously decreased. The LCC LTP 3 documented that new and improved bus facilities and infrastructure will encourage the use of public transport together with smart ticketing and subsidised fares as a result of Quality Bus Contracts with First and Arriva bus companies (the two main bus providers in Leicester) (LCC, 2011b). Whilst this is likely to encourage greater bus use it is advised that a stronger emphasis is placed on reducing passenger car VKT. Strategies that aggressively limit private car VKT and simultaneously provide high quality and reliable public transport have been shown to be very effective in reducing emissions from vehicles e.g. Hong Kong (see Cameron *et al.*, 2004). In this research total fleet VKT was limited to 2005 levels and only one strategy was found to meet Leicester's target of a 38% reduction in CO_2 emissions. This research subsequently indicated that a greater decrease in passenger car VKT would offer maximum improvements in air quality and reductions in CO_2 emissions. Therefore, this work provides evidence and support for policies and strategies that aggressively reduce VKT. However, the LCC should be aware that strategies that aim to reduce VKT should be coupled with policies that limit the induced demand and the rebound effect (e.g. reduce the capacity of roads for traffic such as bus only lanes, widening pavements and introduce speed restrictions) caused by a decrease in VKT and the subsequent surplus of road capacity.

The LTP 3 does not make direct reference to reducing VKT and in fact makes reference to allocating additional network capacity (through maximising the current network capacity by improving traffic signalling and making physical changes to junctions) to the increased demand for passenger trips (LCC, 2011b). It is suggested that the network capacity is not maximised as this will only encourage more traffic and will have little impact on already heavily congested and polluted areas of the city. Instead, financial penalties or incentives should be introduced that discourage private car use particularly in the city centre and on city centre feeder roads. The LTP 3 already suggests stricter parking measures will come into force (LCC, 2011b). However, many car parks in the city centre are privately owned and are beyond the control of the LCC. Although road pricing has been put on hold in Leicester due to questions of financial feasibility (income from the scheme not sufficient to sustain its operation), it is advised that it should be revisited with particular focus on the city centre feeder roads and outer ring road. For example, a toll system similar to that implemented in Singapore (see Santos *et al.,* 2004), which enforces a charge per entry may provide financial sustainability whilst aggressively discouraging private car use during certain times of the day. Such a scheme could be a 'polluter pays' based policy to encourage bus and HGV companies to upgrade their fleets. This research has shown substantial pollutant emissions can be achieved if this were the case particularly on key traffic routes in the city. However, road pricing is likely only to encourage public transport use if toll costs were higher than bus fares. Therefore, if road pricing is reconsidered the LCC must work with the Bus Quality Partnership to ensure that fares remain competitive so that toll costs can remain low enough so to not damage the local economy.

A 25% increase in the number of houses in central Leicester has been forecast by the LCC. In addition, plans for 3 new Greenfield housing developments comprising 3,000 to 5,000 new homes each have been laid down by the council (LCC, 2011b). These developments provide a perfect opportunity to encourage the uptake of low emissions vehicles. For example, electric vehicle charging facilities could be installed on all of these sites or even on every plot. The introduction of low emissions vehicles to the Leicester fleet has been shown in this research to greatly improve local air quality and reduce tailpipe CO_2 emissions. Therefore, it is advised that the LCC look favourably upon planning applications that incorporate electric vehicle charging infrastructure. Similarly, the LCC should look to install a greater number of charging facilities in the city and suburbs ensuring that the posts are evenly spread throughout the LCC LA area (classification 2 roads). Government funding, such as that available from the Sustainable Transport Fund, could be used to pay for some or the entire EV infrastructure. The LCC should continue to actively market, promote and encourage the uptake of low emissions vehicles. Marketing and promotional material should focus heavily on the government funding plug-in car grant scheme which provides financial incentive for the uptake of PHEVs and EVs. As a way of leading by example a greater proportion of the LCC's own vehicle fleet could be replaced with EVs. Furthermore, given that 50% of all journeys to work in Leicester are less than 5km (LCC, 2011b) the introduction of EV and PHEV company car schemes for local businesses could help reduce emissions and improve air quality in Leicester. The LCC should work with local businesses to encourage such a scheme and where possible offer financial support. In connection this research has shown the introduction of new abatement technology to the LGV fleet to have substantial benefits for air quality. Therefore, policies that encourage local businesses to retrofit or upgrade their

LGV fleet would be beneficial. Road pricing would act as a financial incentive to encourage such a change.

The current LTP 3 strategies for reducing emissions from HGVs include re-routing of heavy traffic away from sensitive receptors, encouraging the use of cleaner vehicles and encouraging the use of HGV distribution hubs (LCC, 2011b). The latter involves HGV hubs where goods are unloaded into cleaner vehicles and subsequently transported to locations throughout the city. The re-routing of HGVs is not advised as traffic management of this kind only shifts air quality problems to another area of the city and does not in any way alleviate pollution issues (Huang and Huang, 2003). Encouraging the use of HGV hubs and cleaner vehicles should continue but HGVs are owned by private companies and are out of direct control of the LCC. However, if road pricing was to be reconsidered with strict financial penalties for older HGVs, then greater pollutant emissions reductions are likely. This research has shown that HGV fleet renewal with Euro V/VI vehicles can significantly improve air quality in Leicester. Furthermore, although this research has shown that improving the emissions abatement technology within the Leicester HGV fleet will not result in a reduction in CO_2 emissions, a road pricing scheme may further encourage the use of HGV hubs or reduce HGV VKT (through logistics optimisation) thereby offering a win-win.

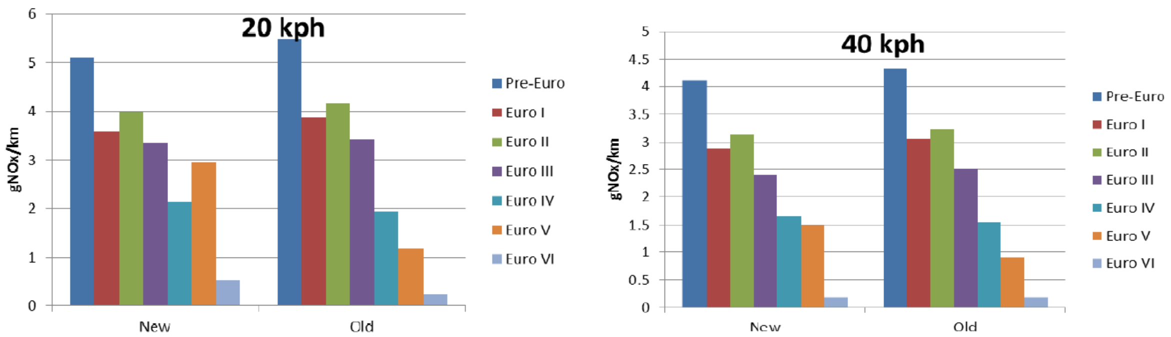
In the more extreme case the LCC could enforce mandatory fleet renewal once vehicles reach a certain age. This research has shown that the removal of the oldest vehicles in a fleet can result in significant local air quality benefits and CO_2 reductions. The mandatory removal of vehicles of a certain age could be enforced in Leicester but such a scheme is more likely to be enforced at a national level. The UK government funded ‘scrappage scheme’ ran between May 2009 and April 2010 and provided financial incentive towards the purchase of a new car if a vehicle greater than 10 years old was scrapped (Maer, 2012). The LCC could implement a strategy similar to the scrappage scheme which would encourage fleet renewal. However, a scheme that offered greater financial incentive (e.g. subsidised or free bus travel) for those who scrap an old car and do not buy another vehicle would likely result in greater reductions in CO_2 and toxic pollutant emissions.

Finally, it is suggested that the LCC use the regression equations and data tables output in this research when assessing the impact of planned or implemented strategies on air quality and CO_2 emissions in Leicester. The tables can be rapidly used meaning they are a cost effective way to carry out initial investigations.

7.4.4 Limitations

Issues surrounding the emissions factors used in this research have been partly described in Chapter 6, section 6.7.2. Fleet weighted PM_{10} and NO_x emissions factors from COPERT 4 where documented to have increased relative to 2009 DfT factors. The DfT guidance note concerning the interim COPERT 4 factors (DEFRA, 2012d) highlighted that the HGV and bus fleet standards for NO_x differ significantly between the 2009 DfT emissions factors (old) and the COPERT 4 v8.1 (new) interim emissions factors (e.g. Figure 47(a) and Figure 47(b)). The Euro V COPERT NO_x emissions factors for HGVs and buses at 20km/h are more than double those of the old factors and are significantly higher than Euro IV factors at the same speed. These differences occur because the new factors have separate functions for HGVs and buses equipped with SCR and for those equipped with EGR, whilst the old factors made no such distinction (DEFRA, 2012d). Subsequently the new factors reflect the poor performance of SCR at urban speeds. A total of 849 roads (22%) in this research had speeds less than or equal to 20km/h. Furthermore, the average-speed of the network was 31km/h. Therefore, it is likely that the NO_x and f-NO_2 emissions savings documented in this research concerning the introduction of new emissions abatement technology into the HGV and bus fleets are overestimated. However, according to the DfT the new factors are to be considered interim as uncertainties still remain in the Euro V/VI factors because too few vehicles have been tested under real world conditions (NCL, 2012).

Figure 47(a) and Figure 47(b) The UK 2009 DfT emissions factors (old) and the COPERT 4 v8.1 emissions factors (new) for rigid HGVs <7.5t at 20 km/h (kph) and 40km/h (kph) (DEFRA 2012d)



A lack of information on the data used for the development of the emissions rate for PHEVs in the low carbon tool was a major limitation of this work. Sales and vehicle characteristics (types of Prius) information would not be released by the DfT and subsequently estimates of TTW CO_2 emissions were made using the DEFRA (2012c) conversion factors for company reporting. To this author's knowledge the JEC (2011) fuel life cycle analysis on which the DEFRA (2012c) WTT emissions rates are based is the most comprehensive to date. Therefore, the ratio used in this research to derived PHEV TTW CO_2 emissions was considered the most appropriate at time of use. However, as PHEVs gain a greater market share in the UK fleet more information regarding TTW emissions will likely become available allowing the accuracy of the emissions factor used in this research to be assessed. Furthermore, such information would allow for the estimation of PM_{10} and f-NO_2 emissions from PHEVs operating in charge sustaining mode.

The regression equations produced in this research had R^2 values of one. Therefore, it was clear that there was a systematic change in the emissions created by the systematic change in the penetration. In reality a systematic change is unlikely. However, this research has provided valuable insight into the impacts of a change in technology, fuel or vehicle on emissions from road transport. In future a method to generate greater variation in the values could be explored.

7.5 Chapter 7 Summary

The 2005 emissions base-case compiled in Chapter 6 was edited to reflect a change in emissions abatement technology, vehicle or fuel. In addition, a VKT restriction was imposed on the vehicle fleet that did not allow any increase in VKT from the base year. Strategies were modelled in 5% increments until 100% was reached and emissions changes relative to the base-case were calculated. Regression analysis allowed for the interpolation between the 5% increment. The changes in emissions relative to the base-case for each strategy were plotted and regression was used to interpolate between the 5% increments. This provided a flexible approach to strategy modelling as the regression equations allowed any % strategy change to be modelled and subsequent emissions analysed.

A reduction in both CO_2 and toxic air pollutant emissions (‘win-win’) was found when cars were changed to diesel cars equipped with Euro 6 technology. However, greater PM_{10} and f-NO_2 emissions reductions were observed with the introduction of Euro VI technology to the LGV and HGV stocks respectively. These strategies were found to have negligible impacts on CO_2 emissions. Consequently a trade-off was found where a ‘win-win’ was achieved through changes to the car fleet but at the cost of higher pollutant emissions reductions from other strategies. The introduction of Euro VI technology to the bus fleet on roads located predominantly on key traffic corridors within the AQMA resulted in substantial air quality benefits. Therefore, zonal based strategies (e.g. pay per entry road user charging) could be introduced in Leicester to reduce emissions from the bus fleet. A win-win from the introduction of LPG to the car fleet was not found. Therefore, strategy options that promote the uptake of LPG should be avoided if climate change and air quality policy is to be aligned. A switch from cars to ZEVs resulted in the highest CO_2 and pollutant emissions reductions out of all the strategies modelled. ZEVs can be considered representative of EVs under current legislation. This strategy was found to be particularly effective on roads characterised by relatively high LDV flows and low bus and HDV flows that were located across the entire LCC LA area. A 53% penetration of ZEVs into the Leicester fleet was the only strategy found to reduce CO_2 emissions by 50% relative to a 1990 base. Therefore, this research indicates that substantial and arguably extreme changes will be required in order for compliance with air quality and climate change limit values and targets to be achieved. Furthermore, given that a change in emissions abatement technology, fuel and vehicle was modelled in an exhaustive way (i.e. 100% change was modelled), the findings of this research suggested that a more aggressive VKT restriction is necessary in order for targets to be met.

Based on the strategy modelling findings four main policy options were developed for Leicester; 1) the bus fleet should be upgraded to included Euro V/VI technology and the quality and quantity of public transport services should be increased; 2) a pay per entry road user charging scheme should be considered as this has the potential to reduce private car VKT, 'clean' the Leicester vehicle stock (particularly the HGV fleet) and encourage the use of public transport; 3) provisions should be made by the council for the widespread installation of electric vehicle charging infrastructure and to encourage the uptake of low emissions vehicles by local businesses and; 4) a quality bus contract should be set up in Leicester that provides free public transport for a period of time for those who scrap a vehicle greater than ten years old and do not purchase another vehicle.

Finally, the regression equations and data tables produced in this research present to the decision maker valuable insights into the relative impact of improved vehicle abatement technology, fuels and low emissions vehicles penetration into the current vehicle fleet. In essence, these enable informed decisions on how to best invest scarce resources (e.g. limited budgets), perhaps to replace particular vehicle fleets (Euro VI buses); or incentivise third parties to take action (e.g. green travel plans) or to justify to the public that road user charging is fair, making sure the polluter pays (e.g. a higher charge for HGVs).

8. Summary, Conclusions and Future Work

In this chapter a summary of the research carried out is presented. A number of conclusions are drawn from the work described and future research is documented.

8.1 Summary

A clear research gap was identified by the UK government in their document entitled ‘Air Pollution: action in a changing climate,’ which stated that ‘further work is needed to facilitate comparison of air quality and climate change impacts.’ Therefore, the research presented in this thesis aimed to contribute to this knowledge gap by investigating the impact of road transport strategies on air quality and CO_2 emissions. Three main findings from the literature influenced the approach taken to investigate these impacts; 1) a more aggressive VKT restriction has the potential to result in substantial reductions in both toxic air pollutants and CO_2 emissions; 2) the introduction of new emissions abatement technology, fuels and low emissions vehicles to the road transport sector are considered important if climate change targets and air quality limit values are to be met and; 3) current strategy modelling approaches are relatively inflexible and often do not allow substantive conclusions to be made about whether a strategy does or does not have the potential to meet air quality and climate change targets. Therefore, this research aimed to assess the impact of a vehicle VKT restraint and a change in emissions abatement technology, fuel or vehicle on CO_2 emissions and toxic air pollutants derived from road transport. The Leicester city road network for the year 2005 was used as a case study in this research. A base-case emissions inventory for CO_2, PM_{10}, NO_x and f-NO_2 for the LCC LA area was compiled and evaluated using an air quality model. A statistical method was presented that applied factor and cluster analysis to assign roads into groups (classifications) so that diurnal profiles could be assigned to roads with similar characteristics prior to air quality modelling. This provided a useful tool to local authority officers to set up air quality models which is less labour intensive. In addition, this enabled the typical characteristics of the road network in Leicester to be identified. A Gaussian air quality model, ADMS-Urban, was used to evaluate the emissions inventory compiled. The model was found to significantly over-predict and under-predict NO_2 and PM_{10} concentrations at seven and five monitoring locations across the city of Leicester respectively. The error attributed to the emissions inventory was estimated to be between 11% and 57% of the total error found depending on location and pollutant considered. A large proportion of the emissions inventory error was attributed to the use of unrepresentative emissions factors. In addition, the classification specific diurnal profiles developed were found to underestimate the length of peak traffic flows, which further contributed to error in the predictions.

The base-case was edited to reflect a change in emissions abatement technology, vehicle or fuel and emissions were recalculated. In addition, a VKT restriction was imposed on the vehicle fleet that did not allow any increase in VKT from the base year. The changes to the base-case were made in increments of 5% until 100% was reached (e.g. 5%, 10%, 15% etc. of cars were changed to ZEVs). The changes in emissions relative to the base-case for each strategy were plotted and regression was used to interpolate between the 5% increments. This provided a flexible approach to strategy modelling and can be considered an advantage over previous approaches documented in the literature as the regression equations output in this work allowed any % strategy change to be modelled and consequential emissions change to be estimated. In addition, the emissions per road classification were calculated for the base-case and for each of the 100% change strategies (e.g. 100% cars changed to ZEVs). This allowed the effectiveness of each of the strategies to be analysed spatially and for the relationship between emissions change and road characteristics to be assessed.

A reduction in both CO_2 and toxic air pollutant emissions ('win-win') was found when the penetration of ZEVs and PHEVs to the car fleet was modelled. A switch from cars to ZEVs resulted in the highest emissions reductions out of all the strategies modelled. ZEVs can be considered representative of EVs under current legislation. The ZEV strategy was found to be particularly effective on roads characterised by relatively high LDV flows and low bus and HDV flows that were located across the entire LCC LA area. A 53% penetration of ZEVs into the Leicester fleet was the only strategy found to reduce CO_2 emissions by 50% relative to a 1990 base. Therefore, this research indicated that substantial and arguably radical changes will be required in order for compliance with air quality and climate change limit values and targets to be achieved. Furthermore, given that a change in emissions abatement technology, fuel and vehicle was modelled in an exhaustive way (i.e. 100% change was modelled), the findings of this research suggested that a more aggressive VKT restriction is necessary in order for targets to be met.

A win-win for air quality and climate change was found when cars were changed to cars equipped with Euro 6 technology. This research indicated that a switch to diesel Euro 6 cars would be the most beneficial. However, greater PM_{10} and f-NO_2 emissions reductions were observed with the introduction of Euro VI technology to the LGV and HGV stocks respectively. These strategies were found to have negligible impacts on CO_2 emissions. Consequently a trade-off was found where a 'win-win' was achieved through changes to the car fleet but at the cost of higher pollutant emissions reductions from other strategies. The introduction of Euro VI technology to the bus fleet on roads located predominantly on key traffic corridors within the AQMA resulted in substantial air quality benefits. Therefore, zonal based strategies (e.g. pay per entry road user charging) could be introduced in Leicester to reduce emissions from the bus fleet.

Substantial pollutant emissions reductions were found as a result of the introduction of new emissions abatement technology into the HGV and LGV fleets. However, these strategies were found to have negligible CO_2 emissions reductions and therefore did not provide a win-win for air quality and climate change. Similarly, a win-win from the introduction of LPG to the car fleet was not found. Therefore, the uptake of LPG or investment in the introduction of new emissions abatement technology to the LGV or HGV fleets should only be considered as a part of a sustainable policy package that comprises other measures, such as logistics optimisation or a reduction in VKT.

Based on the strategy modelling carried out, four main policy options were developed for the Leicester road network that have the potential to reduce both CO_2 emissions and toxic air pollution. These involve upgrading the bus fleet with new emissions abatement technology, implementing a pay per entry road user charging scheme, the widespread installation of electric vehicle charging infrastructure and offering financial incentive for scrapping vehicles and using public transport. Finally, it was advised that the LCC use the regression equations and data tables produced in this research as they provide valuable insights into the relative impact of improved vehicle abatement technology, fuels and low emissions vehicles on CO_2 emissions and toxic air pollution. They enable the rapid assessment to be made of potential strategy options and allow informed decisions on how to best invest scarce resources (e.g. limited budgets).

8.2 Conclusions

The following main conclusions can be drawn from the research carried out:

1) The requirement of further comparison of air quality and climate change impacts documented by the UK government highlighted an opportunity for research to be under taken that investigated the impact of road transport strategies on carbon dioxide emissions and toxic air pollution.

2) The capability of modern air quality models to allow a finite number of diurnal traffic profiles to be used in dispersion calculations provided an opportunity to explore a method by which roads could be grouped to allow diurnal traffic profiles to be specified for links with similar characteristics.

3) Factor and cluster analysis can be combined to classify roads to enable traffic profiles to be assigned to roads with similar attributes and to allow road vehicle characteristics to be explored.

4) The method of factor and cluster analysis used to classify roads in this research has an advantage over other methods documented in the literature as it allows the classification process to be driven by the data, requires no a priori information about the road network and ensures that variables containing a large proportion of shared common variance (e.g. bias resulting from limitations and assumptions intrinsic to traffic models) are not included in the classification process.

5) Gaussian air quality models are extremely sensitive to meteorological, background and emissions data used for dispersion calculations. Therefore, the use of ADMS-Urban in this research provided a quality check on the emissions resulting from the LCC traffic model.

6) The use of interpolation factors to calculate hourly traffic flows can result in an underestimate of peak traffic periods and resulting congestion. This issue was found to result in air quality model under-prediction in this research. Therefore, the strategy modelling carried out reflected this shortfall.

7) The introduction of Euro VI technology to the bus fleet on roads located predominantly on key traffic corridors within the AQMA resulted in substantial air quality benefits. However, the introduction of new emissions abatement technology to the bus fleet did not result in CO_2 emissions reductions.

8) Classifying roads not only for air quality modelling but for the evaluation of strategies and policies was found to be beneficial as it allowed significant emissions reductions to be identified that other strategy modelling approaches documented in the literature would have missed. Furthermore, it allowed for the spatial impacts of the strategies modelled to be assessed which provided insight into how such strategies could be implemented.

9) Substantial pollutant emissions reductions were found as a result of the introduction of new emissions abatement technology into the HGV and LGV fleets. However, these strategies were found to have negligible CO_2 emissions reductions and therefore did not provide a win-win for air quality and climate change. Similarly, a win-win from the introduction of LPG to the car fleet was not found. Therefore, the uptake of LPG or investment in the introduction of new emissions abatement technology to the LGV or HGV fleets should only be considered as a part of a sustainable policy package that comprises other measures, such as logistics optimisation or a reduction in VKT.

10) The car petrol diesel fuel split strategies failed to show a win-win for a reduction in CO_2 and pollutant emissions. Changes to fuel use by the car fleet were shown to increase CO_2 emissions when an increase in petrol vehicles was implemented but the same strategy was shown to decrease pollutant emissions. Therefore, it can be argued that any change in the car diesel petrol fuel split would work against aligning climate change and air quality policy.

11) However, a reduction in both CO_2 and toxic air pollutant emissions (‘win-win’) was found when cars were changed to diesel cars equipped with Euro 6 technology.

12) The introduction of Euro VI technology to the LGV and HGV stocks respectively resulted in greater PM_{10} and f-NO_2 emissions reductions than when new emissions abatement technology was introduced to the car fleet. Consequently a trade-off was observed where a ‘win-win’ was achieved through changes to the car fleet but at the cost of higher emissions reductions from other strategies.

13) A win-win for air quality and climate change was found with the penetration of ZEVs and PHEVs to the car fleet. The highest reductions in toxic pollutant and CO_2 emissions out of all of the strategies modelled were found for the introduction of ZEVs, which can be considered representative of EVs under current legislation.

14) A 53% (or greater) penetration of ZEVs to the car fleet was the only strategy for which a 50% reduction in CO_2 for a 1990 base was found. Therefore, this research indicates that substantial and arguably radical changes will be required in order for compliance with air quality and climate change limit values and targets to be achieved.

15) ZEVs by definition have zero emissions. In this respect the introduction of ZEVs can be observed as the removal of cars (and subsequently a reduction in private car VKT) from the fleet without a change in the Leicester road network dynamics (i.e. vehicle speed and flow). Therefore, this research suggested that further VKT restriction in the car fleet would result in substantial emissions reductions and a win-win for air quality and climate change. Moreover, it indicated that policy options that aggressively limit VKT are likely to achieve higher emissions reductions than a change in technology, vehicle or fuel.

16) The regression equations produced in this research provide a flexible tool for the policy maker to support decision making. In contrast to previous strategy modelling approaches documented in the literature the equations and data tables developed enable the rapid

assessment to be made of potential strategy options and allow informed decisions on how to best invest scarce resources (e.g. limited budgets).

17) Leicester was chosen as a case study because it shares many characteristics of other cities in the UK (see Chapter 4) and national vehicle fleet composition data in was used in this study. These methodological approaches allow the regression equations and data tables output to be transferred to other cities in the UK. Furthermore, the findings of this research can be used by local authorities throughout the UK to make informed decisions enabling money to be spent more wisely."

18) In the past, a policy maker may have had to consider the outputs of a number of different strategy modelling studies in order to draw conclusions as to whether a strategy could or could not result in a win-win for air quality and climate change. However, strategy modelling studies are not directly comparable due to assumptions made (see section 2.4). In contrast to previous strategy modelling studies, this research adopted a flexible approach to strategy modelling and can be used as a single point of reference from which substantive conclusions can be drawn.

8.3 Suggestions for Future Research

1) The methodology presented for classifying roads involved the use of specific predictor variables and it is recommended that the technique is tested further using different data inputs.

2) The NO_x and PM_{10} emissions factors used in this research have recently been updated as they were considered not to be representative of real world emissions. The new factors released are to be considered interim by the UK government as they still comprise a number of uncertainties. Therefore, in future, when a more comprehensive and complete set of emissions factors is available, the representativeness of the outputs from this work should be reassessed and adjusted as appropriate. This could be done through the addition of a simple correction factor to the regression equations allowing the models to capture the changes in emissions factors.

3) The use of simulated traffic data was considered a significant limitation to the research carried out. Unrepresentative traffic flows, speeds and vehicle fleet compositions were estimated to have been a cause of error in the emissions inventory compiled and may have influenced the road classification process presented. However, in reality automatic traffic recorders (ATRs) and manual count data exist for only on a relatively small proportion of

roads meaning that the spatial coverage of real world traffic data does not meet the requirement of regional scale emissions inventories and air quality models. Therefore, transport and air quality professionals have no choice but to use simulated data in modelling studies. In the future, if greater spatial coverage of real world traffic data becomes available then the strategy modelling carried out in this research could be recalculated.

4) The use of national data to define vehicle fleet composition in this research was, on the one hand, considered a limitation as it may not have been representative of the vehicle mix in Leicester. On the other hand the use of average vehicle fleet composition data has the advantage of making the outputs from this research more applicable nationally. Therefore, in the future the application of the regression equations and data tables produced in this research to other road networks in the UK could be explored.

5) The regression equations produced in this research had R^2 values of one. Therefore, it was clear that there was a systematic change in the emissions created by the systematic change in the penetration. In reality a systematic change is unlikely. Away round this would be to generate random variation in the values and repeat the PITHEM analysis. This could provide greater insight into the impacts of a change in technology, fuel or vehicle on emissions from road transport.

8.4 Contribution to Academic Research and Practice

1) This work highlights the short fall of Chen et *al.*'s (2008) road classification research. Having identified the problems with Chen et *al.*'s (2008) work it then explores a novel method for classifying roads that is data driven and not restricted by the subsequent application of the number of clusters output. The factor and cluster analysis method used is unique to this research. It provides a robust and statistical method for classifying roads where previously there was none.

2) The research presented is the first piece of work that has tackled the balance between CO_2 and toxic emissions in great detail at the local authority level. It considers both climate change and air quality impacts in the context of the local authority policy maker. Unlike previous strategy modelling studies it does not include or confuse WTW emissions as these are typically outside of the remit of control of a local authority. Furthermore, the findings of this research are combined to make a set of policy actions for Leicester local authority based on their LTP. Previous studies have failed to consider the implications of win-win strategies

being implemented at the local authority level. In this research these implications are quite clearly addressed.

3) The strategy modelling method developed (incremental changes followed by regression) is unique to this research. A flexible and exhaustive approach was adopted that allowed for the identification of either those strategies that could meet the target or those that under maximum change could not. Previous strategy modelling studies typically inform of those fixed changes that are not able to bring about the required emissions reductions and subsequently this research can be considered at an advantage over previous work.

4) The flexible strategy modelling approach adopted in this research allowed substantive conclusions to be drawn from the research. The findings of this study clearly expose the fact under the current CO_2 emissions reduction road map targets will not be achieved by 2050. They provide an evidence base that previously did not exist and are a point of reference on which to build new and more aggressive emissions reductions strategies.

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GLOSSARY OF TERMS

Term	Definition
AADT	Annual Average Daily Traffic
AAGE	Average Absolute Gross Error
AQMA	Air Quality Management Area
ATR	Automatic Traffic Recorder
AURN	Automatic Urban Rural Network
CAFE	Clean Air For Europe
CDF	Cumulative Distribution Function
CFD	Computation Fluid Dynamics
CLTM	Central Leicestershire Transport Model
CNG	Compressed Natural Gas
CRST	Chemical Reaction Scheme with Trajectory
CV(s)	Conventional Vehicle(s)
DECC	Department of Energy and Climate Change
DEFRA	Department for Environment, Food and Rural Affairs
DfT	Department for Transport
DNA	Deoxyribonucleic acid
EFA	Exploratory Factor Analysis
ERG	Exhaust Gas Recirculation
EU	European Union
Euro Standard'	Refers to the emissions standards enforced in the European Union
EV(s)	Electric Vehicle(s)
FA	Factor Analysis
FAC2	Factor of 2
FAC5	Factor of 5
FB	Fractional Bias
FOEX	Fraction of over-prediction
FSD	Fractional Standard Deviation
FTP	Federal Test Procedure
GDP	Gross Domestic Product
GHG(s)	Greenhouse Gas(es)
GRS	Generic Reaction Set
HDV(s)	Heavy Duty Vehicle(s)
HEV(s)	Hybrid Electric Vehicle(s)

Term	Definition
HFCV(s)	Hydrogen Fuel Cell Vehicle(s)
HGV(s)	Heavy Goods Vehicle(s)
hr	Hour
ICE	Internal Combustion Engine
IP	Inter Peak
KMO	Kaiser-Meyer-Olkin
LA	Local Authority
LCC	Leicester City Council
LDV(s)	Light Duty Vehicle(s)
LEZ	Low Emissions Zone
LGV(s)	Light Goods Vehicle(s)
Link'	Section road
LPG	Liquid Petroleum Gas
LTP	Local Transport Plan
MG	Geometric mean bias
MRB	Mean Relative Bias
MRSE	Mean Relative Square Error
MSA	Measure of Sampling Adequacy
MSE	Mean Square Error
NAAQS	National Ambient Air Quality Standards
NAEI	National Atmospheric Emissions Inventory
NEDC	New European Driving Cycle
NGHGI	National Greenhouse Gas Inventory
NMSE	Normalised Mean Square Error
NSD	Normalised Standard Deviation
NTM	National Transport Model
PAF	Principal Axis Factoring
PCA	Principal Component Analysis
PHEV(s)	Plug-in Hybrid Electric Vehicle(s)
PITHEM	Platform Integrated for Transport, Health and Emissions Modelling
ppb	Parts per billion
ppmv	Parts per million volume
RMS	Root Mean Square
ROS	Reactive Oxygen Species
RSD	Remote Sensing Detector
SACTRA	Standing Advisory Committee for Trunk Road Assessment
SCR	Selective Catalyst Reduction
SEE	Standard Error of the Estimate
TTW	Tank-To-Wheel
USA	United States of America
VG	Geometric mean variance
VKT	Vehicle Kilometres Travelled

Term	Definition
WTT	Well-To-Tank
WTW	Well-To-Wheel
ZEV(s)	Zero Emissions Vehicle(s)

Mathematical Term	Definition
C	Pollutant Concentration
U	Wind Speed
Q	Emissions Rate
σ_y and σ_z	Horizontal (y) and vertical dispersion (z) coefficients
L_{MO}	Monin-Obukhov Length
$u.$	Friction velocity at the Earth's surface
k	von Karman constant (0.4)
g	Acceleration due to gravity
F_{θ_0}	Surface heat flux
p	Density of air
c_p	Specific heat capacity of air
T_0	Surface temperature
Q_S	Source Strength
Z	Height of receptor above ground
y	Lateral distance from plume centreline
z_p	Height of the plume above ground
$\mathrm{L_s}$	Source length
t	Time to travel to source
b	Constant (0.3)
τ	Constant (0.1)
N_H and N_L	Number of heavy and light vehicles per second respectively
$U_H U_L$ and $U_H U_L$	Speeds of the heavy and light vehicles respectively
A_H and A_L	Areas covered by heavy and light duty vehicles respectively
w	Road width
q_{jk}^2	Square of the off-diagonal elements of the anti-image correlation matrix
r_{jk}^2	Square of the off-diagonal elements of the original correlations
AIC	Anti Image Correlation
F	Dry deposition
F_{wet}	Wet deposition
$\mathrm{V_d}$	Deposition velocity
v_s	Terminal velocity
v_d'	Deposition velocity as a function of diffusion
Λ	Washout Coefficient
dz	Deposition height
$\mathrm{C_p}$	Predicted concentration
$\mathrm{C_o}$	Observed concentration
$\mathrm{T_a}$	Averaging Time
$\bar{\mathrm{C}}$	Average of data set

Mathematical Term	Definition
N	Number
i	Observational unit
β_0	Intercept
β_1	Slope
Y	Dependent variable
X	Independent variable
E	Residual
$\hat{Y}$	Value of Y that is estimated by X using the regression equation
$\widehat{\beta_0}$	Value of β_0 that is estimated by X using the regression equation
$\widehat{\beta_1}$	Value of β_1 that is estimated by X using the regression equation
$ss(Res)$	Sum of squares of the residuals
$\bar{Y}$	Mean of Y

APPENDIX A

A.1 Road Transport's Contribution to Global and Regional Air Pollution

Developing regions of the world, such as those in Asia, have only recently experienced economic growth which has in turn led to increased development of road transport infrastructure and a rapid increase in the number and use of motor vehicles on the road (OEDC, 2010a). Consequently, pollutant emissions from road transport have increased in these regions. For example, road transport in India's major cities is now estimated to account for 70% of total CO, 50% of total HC, 30-40% of total NO_x, 30% of total PM_{10} and 10% of total SO_2 emissions (Sharma *et al.*, 2005) and in Malaysia private cars are responsible for 75% of total CO and PM_{10} emissions and 76% to 79% of total SO_2 and NO_2 emissions (Afroz *et al.*, 2003). In 2009, over 120, 000 km of new highway increased vehicle emissions in China and air quality in these areas significantly deteriorated (NBS, 2010). Similarly, in 2009, 164 air quality monitoring sites in India recorded annual mean PM concentrations in excess of 90μg/m^3 (with the average for Delhi being 150 μg/m^3) and 41 sites recorded annual average NO_2 concentrations greater than 41μg/m^3 (CPCB, 2011). A study by Azim *et al.* (2010) revealed that between 1997 and 2006 average PM_{10} pollution concentrations in Kuala Lumpur (Malaysia) were 58μg/m^3 and as a result failed to comply with EU air quality limit values. Similarly maximum annual mean NO_2 concentrations were found to exceed EU limits having reached 67μg/m^3. The exceedences observed by Azim *et al.* (2010) were attributed to heavy traffic flows and congested road networks. Similarly, in 2005 only 31% of major cities in China met national air quality standards (Smyth *et al.* 2008) with annual average PM_{10} and NO_2 concentrations of 121μg/m^3 and 38μg/m^3 respectively recorded in the previous year (Kan *et al.*, 2009). Moreover, it is well documented that China's mega cities (Beijing, Shanghai and the PRD; Guangzhou, Shenzhen and Hong Kong) have some of the worst air pollution in the world (Kan *et al.,* 2009; Chan and Yao, 2008; Smyth *et al.*, 2008; World Bank, 2007).

In contrast to developing regions, developed regions of the world, which by definition have already experienced substantial economic growth, have recently observed a general decline in emissions from road vehicles despite a continued increase in demand for road transport (EEA, 2011). This has primarily come about due to stringent legislation and the introduction of stringent emissions abatement technology (OEDC, 2010). However, these areas of the globe still have poor air quality as a result of road transport activities. For example, 119.5 million people in the USA in 2008 lived in counties that exceeded the national ambient air quality standards (NAAQS) for ozone (100 μg/m^3 hour average) and 36.9 million people lived in areas that exceeded standards for PM (15μg/m^3 $PM_{2.5}$ annual average, 35μg/m^3 $PM_{2.5}$ 24-hour average; 150μg/m^3 PM_{10} 24-hour average) (USEPA, 2008). In the same year emissions from road transport contributed around 60%, 20%, 30% and 10% of total CO, VOCs, NO_x and PM emissions in the USA (USEPA, 2008). In the EU, road transportation contributed to 39% of NO_x and 36% of CO emissions in 2006 (EEA, 2008). In 2009 20% of the European urban population lived in areas where the EU 24-hour air quality limit value for PM_{10} was exceeded, 12% of the population were exposed to levels of NO_2 that exceeded limit values and exceedences in NO_x due to traffic hot spots were observed across Europe (EEA, 2011). Furthermore, Austria, Belgium, Denmark, Greece, France, Hungary and Slovakia all failed to comply with the EU air quality legislation for PM_{10} (40µg/m^3 annual average) in 2008 (EC, 2009). In 2010 the UK road transport was responsible for 37%, 43% and 24% of total NO_x, CO and PM_{10} emissions respectively (NAEI, 2012a). The UK is currently failing to meet EU air quality limit values for NO_2 (40µg/m^3 annual average) and PM_{10} (EC, 2010; DEFRA, 2011).

Common to both developed and developing countries is road traffic congestion. Congestion occurs when the demand for travel becomes higher than the road network capacity (Hassan *et al.,* 2011). It results in traffic delay, queuing, stop-and-go conditions, low average-speeds and frequent acceleration and deceleration episodes (Stopher, 2004). These traffic characteristics in turn result in greater fuel use and higher tailpipe emissions. Sjodin *et al.* (1998) found 4, 3 and 2 fold-increases in CO, HC and NO_x during congestion conditions relative to non-congested conditions in Goteborg, Sweden. Zhang *et al.* (2011) documented emissions and fuel consumption under rush hour congestion to have increased by 11-31% compared to free flow conditions in Michigan (USA) and De Vliger *et al.* (2000) found increases in emissions and fuel consumption of between 10% and 200% during rush hour congestion relative to off-peak traffic conditions in Brussels and Antwerpen (Belgium). In the UK in 2012 ~15% of all trips were delayed due to congestion (DfT, 2012a) and recently congestion has contributed to some of the most damaging pollution episodes ever recorded in the UK and in Europe in terms of loss of life (Anderson, 2009b; Voutard *et al.*, 2007; Wichmann, 2004; Stedman, 2004; Fischer *et al.,* 2004; Vautard *et al.,* 2005). Such health impacts as a result of congestion and poor air quality have come at great financial cost to governing bodies. Estimates suggest that in Europe congestion every year results in financial losses equivalent to nearly 1% of the EU gross domestic product (GDP) (de Coensel *et al.*, 2012) and in the UK excess delay results in financial penalties of £11 billion per year, carbon emissions impose a cost of £4 billion per year and health issues associated with poor air quality, noise from traffic and inactivity cost £25 billion (DfT, 2011a).

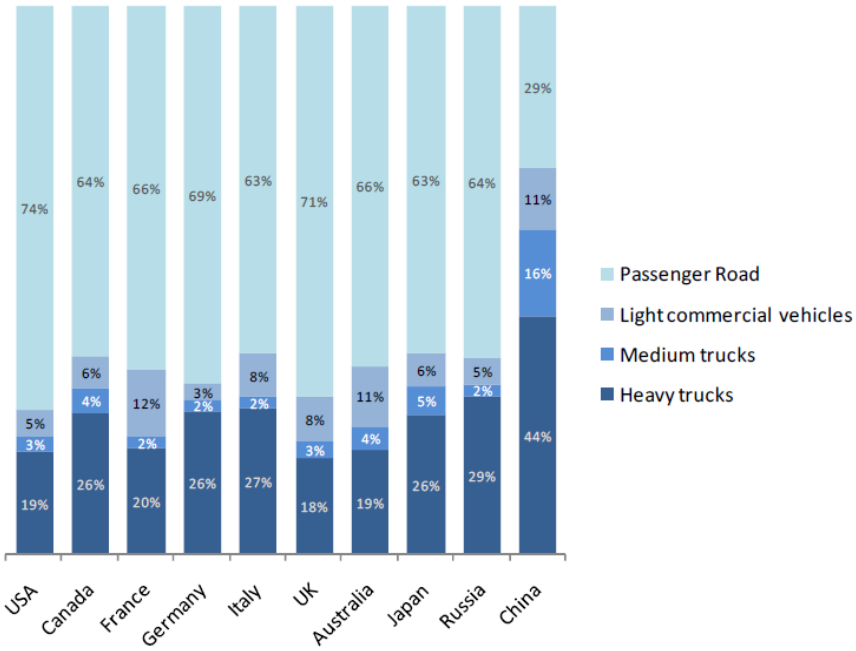
A.2 Road Transport's Contribution to Global and Regional CO_2 Emissions

The amount of CO_2 emitted from vehicle distance travelled is directly proportional to fuel consumption (Ong *et al.*, 2011). Therefore, as global road VKT increased so have CO_2 emissions from transport. Between 1995 and 2005 global levels of CO_2 increased by 1.9 ppmv/year and in 2007 two sectors, electricity generation and transport produced nearly two-thirds of the world's CO_2 emissions (transport 21% and electricity and heat 41%) (IEA, 2009). In total 26% of global CO_2 emissions are sourced from transport (Chapman, 2007). In 2011 the top six emitters of CO_2 were China (29%), US (16%), EU27 (11%), India (6%), the Russian Federation (5%) and Japan (4%) (Olivier *et al.,* 2012).

Historically, as with toxic air pollutants, global CO_2 emissions from transport were dominated by developed regions of the world (Vallero, 2008). However, emerging economies are rapidly increasing their share of global CO_2 emissions and in 2006 China replaced the USA as the highest emitter of CO_2 in the world accounting for 25% of total global carbon emissions (Pao *et al.*, 2012). Collectively China and India are responsible for 80% of Asia's CO_2 emissions (Timilsina and Shrestha, 2009). Emissions of CO_2 from China's road transport sector increased from 66 Mt to 334 Mt between 1990 to 2008 (ITF, 2011) and in India road transport CO_2 increased from 27 Mt in 1980 to 105 Mt in 2000 (Singh *et al.,* 2008). Although the transport sector in these regions of the world has a low (~ 10%) contribution to total CO_2 emissions relative to the combustion of fossil fuels for energy generation it is predicted that road transport's share will rapidly increase as dramatic economic and population growth continue (Timilsina and Shrestha, 2009). For example, passenger traffic in India has been predicted to grow at 8% per year and freight has been estimated to increase by more than 5% by 2021 relative to a 1990 base (Ramanathan and Parikh, 1999) and in China road transport has been predicted to become the dominant oil consumer by 2020 (He *et al.,* 2005). Similar trends have been predicted for central and eastern European emerging economies with the demand for road transport estimated to double and CO_2 emissions from transport estimated to increase by 70% by 2030 relative to a 2000 base (Zachariadis and Kouvaritakis, 2003).

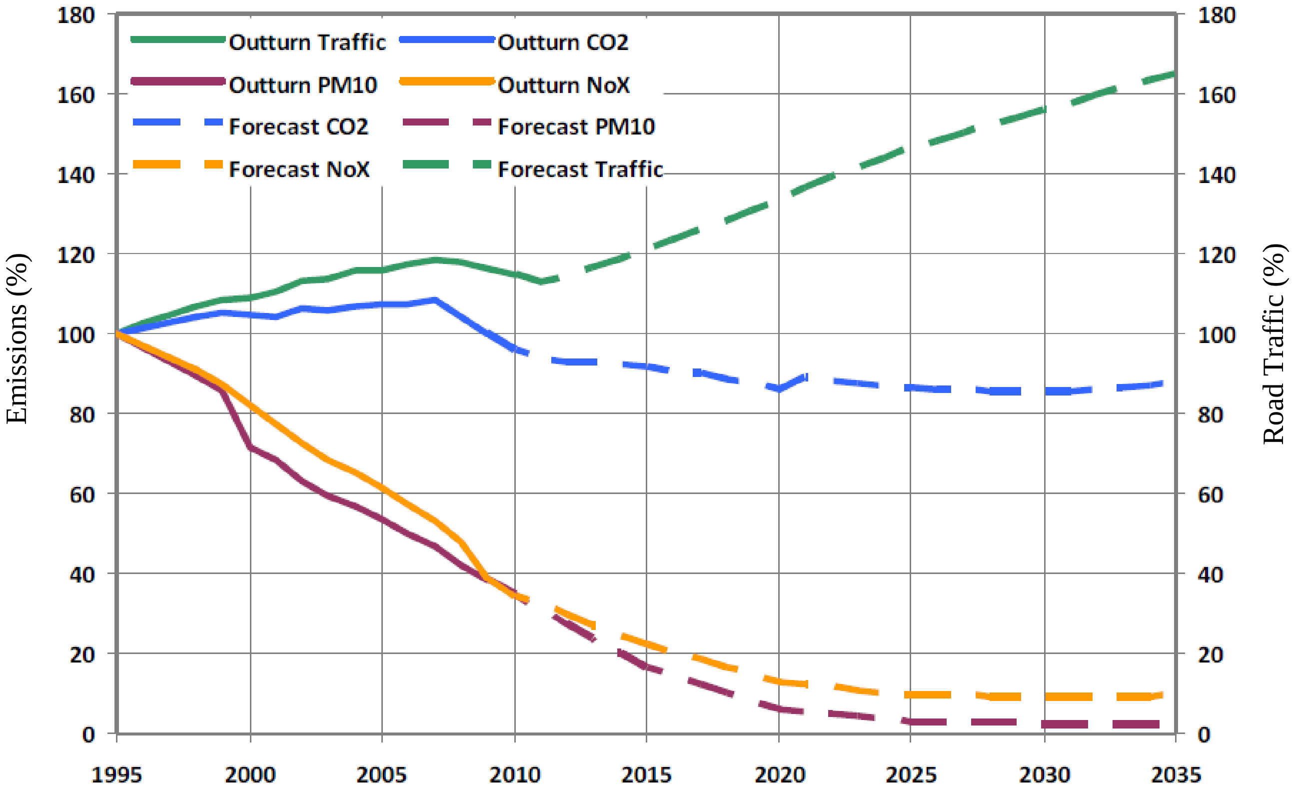
Figure A.1 shows the estimated breakdown of freight versus non-freight road CO_2 emissions in selected countries for 2005 (ITF, 2010a). Whilst passenger cars (road) dominate CO_2 emissions from road transport, in China the majority (44%) of CO_2 emissions from road transport was attributed to heavy trucks. This was primarily due to the increased number of heavy goods vehicles (HGVs) and miles travelled because of the reopening of the border between China and Kazakhstan and increased trade with Russia (OEDC, 2010). In contrast, in the USA 74% of total CO_2 emissions were from passenger cars and it was documented by the IEA (2009) that in 2007 the USA had the highest level of travel per capita in the world (more than 25, 000km/per person/year).

Figure A.1 Estimated breakdown of freight versus non-freight road CO_2 emissions in selected countries for 2005 (ITF, 2010a)



In developed regions of the world 81% of transport CO_2 comes from road traffic (Chapman, 2007). In the US between 1990 and 2010 there was an 18% increase in CO_2 emissions from transport and total CO_2 emissions increased from 1486 million tonnes to 1746 million tonnes during the same time period (USEPA, 2012a). In the UK between 1990 and 2007 CO_2 emissions reductions of 3.5%, 11.5%, 15% and 17% were documented for the domestic, power generation, industry and agriculture and forestry sectors respectively (BERR, 2008). However, the transport sector did not mirror such reductions as emissions from transport increased by 18% between 1992 and 2004 (DEFRA, 2008). Moreover, emissions from privately owned vehicles were estimated to have increased by 4% between 1990 and 2006 (Woodcock *et al.*, 2009). Research has found UK CO_2 emissions from road transport to show no real reduction in emissions between 1990 and 2010 despite an increase in the energy efficiency of vehicles (NAEI, 2012b). A slight decrease in CO_2 emissions from road transport in the UK was observed between 2007 and 2008 as a result of a reduction in travel due to the economic crisis (ITF, 2010; IEA, 2009). However, despite the recent downturn in emissions traffic volume is predicted to increase. The road transport forecasts presented in Figure A.2 show the latest results from the Department for Transport's National Transport Model (NTM) (DfT, 2012b), which produced forecasts of road traffic growth, vehicle tailpipe emissions, congestion and journey times up to 2035. By 2035 CO_2 emissions will have declined by ~10% relative to 1995 levels. Substantial reductions in NO_x (72%) and PM_{10} emissions (92%) have also been predicted by 2035. However, it was predicted that congestion will increase in line with traffic demand and the seconds per mile lost due to congestion was forecast to increase from 19 seconds in 2010 to 32 seconds in 2035 (DfT, 2012a). This indicates an increase in air pollution in some heavily trafficked areas.

Figure A.2 The historical and forecast traffic and emissions for England between 1995 and 2035 produced by Department for Transport's National Transport Model (DfT, 2012b)



APPENDIX B

B.1 Health Impacts of Traffic Related Air Pollution

It is well documented that a significantly large portion of traffic related air pollutants are harmful to human health (Anderson *et al.,* 2009a; Balmes *et al.,* 2010; Donaldson *et al.,* 2005; Kangtip *et al.,* 2006; Novaes *et al.,* 2010; OECD, 2010a; Prockop and Chichkova, 2007; Raub *et al.,* 2000; Raub,1999; Tsai *et al.,* 2010), with many pollutant species categorised as known carcinogens (Arayasiri *et al.,* 2010; Burgaz *et al.,* 2002; Guerra *et al.,* 1995; Paz *et al.,* 2009). Exposure to such pollutants can occur over a long period of time and cause severe health effects (see COMEAP, 2010, 2009). Similarly, an abnormally high concentration of these air pollutants over a short period of time, often caused by low winds and temperature inversion, can cause illness and death. Such an occurrence is known as a pollution episode (USEPA, 2012b). The impacts of pollution episodes on human health in the UK and across Europe have been well documented (Anderson, 2009b; Voutard *et al.,* 2007; Wichmann, 2004), with perhaps the most significant pollution episode in recent times documented during the summer heat wave in 2003. Stedman (2004) estimated that there were 2000 excess deaths in the UK caused by air pollution during the first two weeks of the 2003 June-August heat wave. Fischer *et al.* (2004) documents 1000 to 1400 excess deaths in the Netherlands and Vautard *et al.* (2005) estimated 3100 excess deaths in Italy during the same time period. More generally, in 2009 air pollution was estimated to reduce the life expectancy of every person in the UK by an average of 7-8 months and as many as 50, 000 premature deaths are attributed to poor air quality annually (House of Commons, 2010).

The primary health effects from exposure to toxic pollutants include the onset of lung disease, heart disease and reduced oxygen supply to the heart which can lead to heart attack (Table B.1). Children and those people with existing cardiovascular or respiratory disease (e.g. asthma) are often the most sensitive to toxic air pollution exposure (COMEAP, 2009; Li *et al.,* 2003). In the UK and in Europe O_3 and PM are the greatest concern with regards to human health as pollution episodes involving these pollutants are the most common (Anderson, 2009b; Voutard *et al.,* 2007; Wichmann, 2004; Stedman, 2004; Fischer *et al.,* 2004; Vautard *et al.,* 2005). Furthermore, there is no known safe level of exposure to O_3 and PM, although strong evidence suggests that the reduction of such pollutants will have health benefits (EC, 2005; COMEAP, 2009). Coughing, tightness of chest, nausea, difficulty breathing and decreased ability to exercise are all symptoms of O_3 exposure (Bree *et al.,* 1995). These symptoms come about due to decrements in lung function, airway inflammation and tissue damage and airway hyperresponsiveness (Inoue *et al.,* 2008). In addition, O_3 can form reactive oxygen species (ROS) in the body which can attack DNA and ultimately lead to lung cancer (Jorge *et al.,* 2002).

From their research Cheng *et al.* (2003) concluded that ozone levels below current ambient standards may induce DNA breaks suggesting a greater risk to those exposed.

Table B.1 Major Health Effects from Exposure to Toxic Air Pollutants (DEFRA, 2012a)

Pollutants	**Health effects**
Nitrogen Dioxide, Sulphur Dioxide, Ozone	These gases irritate the airways of the lungs, increasing the symptoms of those suffering from lung diseases.
Particles	Fine particles can be carried deep into the lungs where they can cause inflammation and a worsening of heart and lung diseases.
Carbon Monoxide	This gas prevents the uptake of oxygen by the blood. This can lead to a significant reduction in the supply of oxygen to the heart, particularly in people suffering from heart disease.

Particles can cause severe health effects, including respiratory disease, cardiovascular disease and lung cancer (Anderson *et al.,* 2009; Sanchez-Perez *et al.,* 2009; Gilli *et al.,* 2007; Palli *et al.,* 2008; Wise *et al.,* 2006; Brown *et al.,* 2005). It has been identified that the finer fraction of PM, $PM_{2.5}$ shows the greatest association with mortality (COMEAP, 2010, 2009). Exposure to high concentrations of PM can cause lung inflammation, an abnormal heart rate, reduced ability to remove clots, degeneration of the arteries, the formation of blood clots, reduced blood supply and ultimately death or hospitalisation (Donaldson *et al.,* 2005). Epidemiological studies indicate that acute exposure to PM increases the number of hospital admissions for arrhythmia, myocardial infarction and congestive heart failure (Rhoden *et al.,* 2005). In addition, ROS are induced by PM and can cause an allergic inflammation and trigger an asthmatic episode (Li *et al.*, 2003).

APPENDIX C

C.1 Typical Characteristics of Emissions Model Validation Techniques

Table C.1 Typical characteristics of emissions model validation techniques (Smit *et al.*, 2010)

Measurement technique	Subject of comparison	Input data[a]	Spatial features	Temporal features	Driving conditions
Laboratory	Emission factor [g veh km^{-1}]	Measured (100%)	Urban journey, no gradient effects included.	Resolution: typically 10 minutes (representing urban journey for one vehicle), with total sampling time of about 35 hours.	Both urban and motorway traffic conditions.
On-board	Emission factor [g veh km^{-1}]	Measured (100%)	Urban journey, road gradients of −4% to +5% included in the driving patterns (Silva et al., 2006).	Resolution: typically 4–14 minutes (representing urban journey), with total sampling time of several days.	Both urban and motorway traffic conditions.
Tunnel	Emission factor [g veh km^{-1}]	Measured (100%)	Section of road with lengths varying from a few hundred meters (Ingalls, 1989) to 10 km (Hausberger et al., 2003). Several studies done in tunnels with significant road gradients up to 4.2% (Kirchstetter et al., 1996).	Resolution: typically one hour averages, but total sampling times vary from 10 hours (Hwa et al., 2002) to a month (Colberg et al., 2005a).	Mainly high-speed, free-flowing traffic.
Remote sensing	Emission factor, Total Emissions [g veh km^{-1}, g kg^{-1} fuel]	Measured (100%)	Several locations, varying from 3 (Ekström et al., 2004) to 35 (Singer and Harley, 2000). Locations typically with slight or significant road gradients (up to 5%) (e.g. Singer and Harley, 1996)	Resolution: typically less than one second, and sampling times vary from 36 days (Singer and Harley, 2000) to 7 months (Guo et al., 2007).	Both urban and motorway traffic conditions.
Ambient concentration	Concentration [μg m^{-3}]	Measured (50%), Modelled (50%)	Typically one location only, but a few studies used more locations (2–3) up to 12 (Peace et al., 2004) and 31 locations (Mensink et al., 2001).	Resolution: typically one-hour averaged values, but total sampling times vary from a few hours (Negrenti, 1998; Vogel et al., 2000) to a full year (Namdeo et al., 2002; Peace et al., 2004).	Mainly urban locations.
Mass-balance	Emission flux [kg h]	Modelled (100%)	Urban areas of 10 × 10 km^2 (Panitz et al., 2002) to 20 × 20 km^2 (Mensink, 2000).	Resolution: typically 1 hour with total sampling time of a few hours.	Both urban and motorway traffic conditions.

[a] Traffic volume, speeds, fleet composition.

[a]Traffic volume, speeds, fleet composition

APPENDIX D

D.1 Data Provided by Leicester City Council

Figure D.1 Location of point sources within the Leicester City Council (LCC) Local Authority (LA)Area

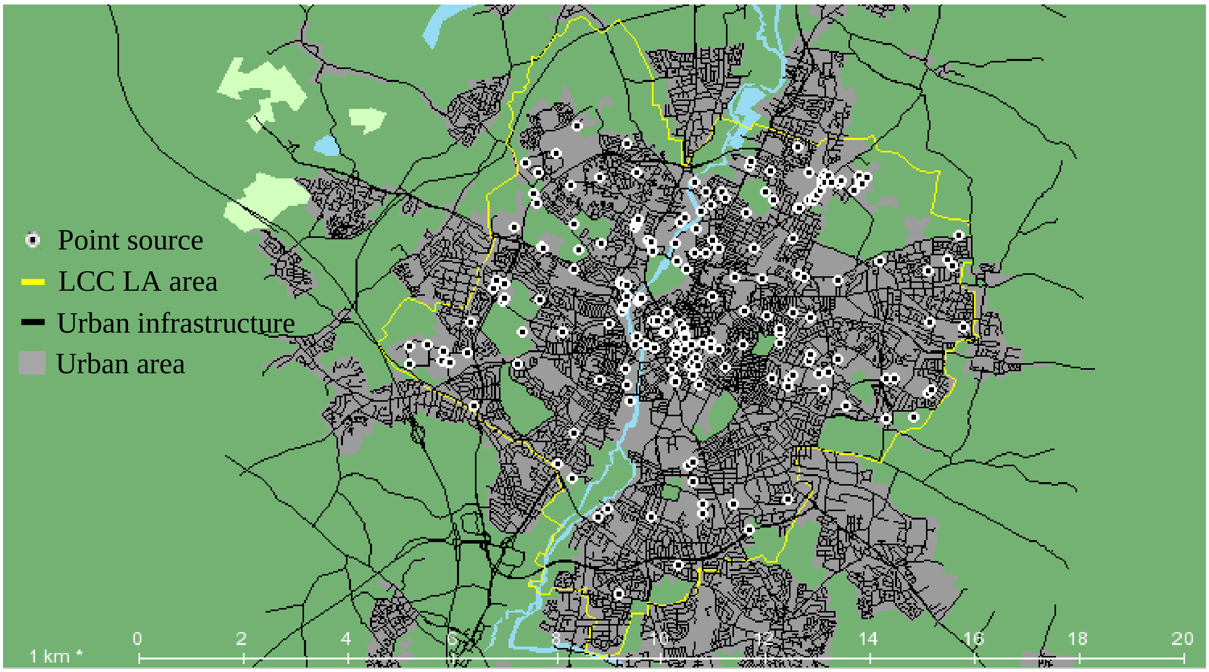
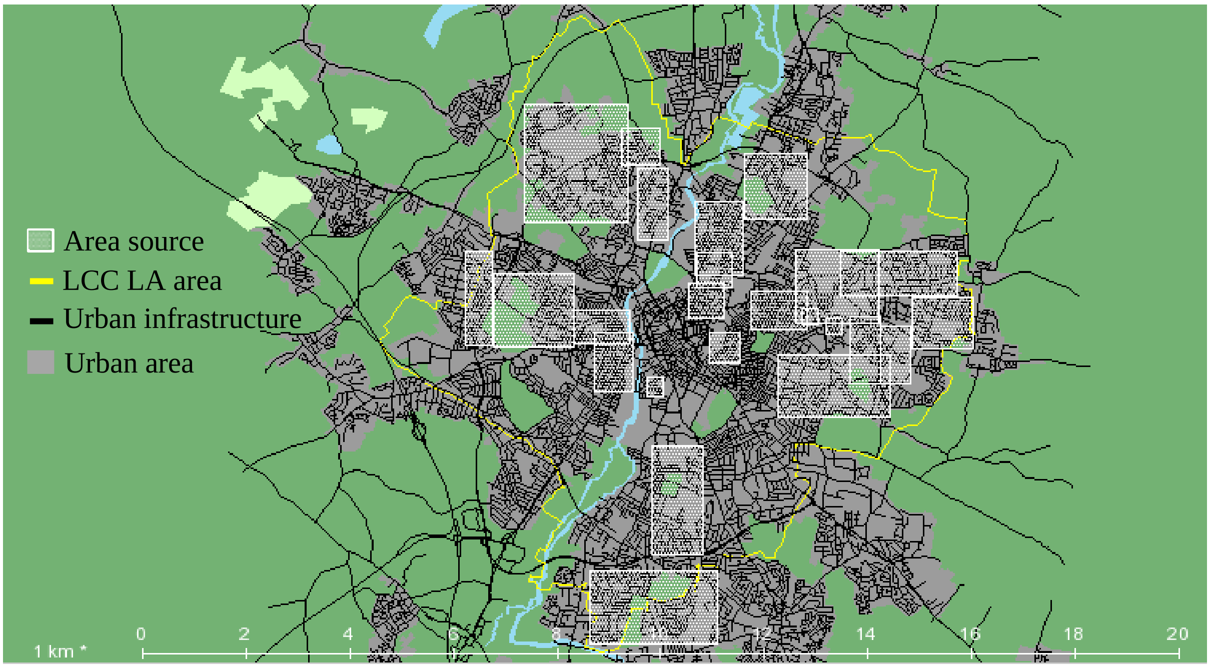


Figure D.2 Location of area sources within the Leicester City Council (LCC) Local Authority (LA)Area



*Note area sources overlap but are not double counted as emissions included in one are not included in the other.

Figure D.3 Month by month profile of Leicester's traffic flow

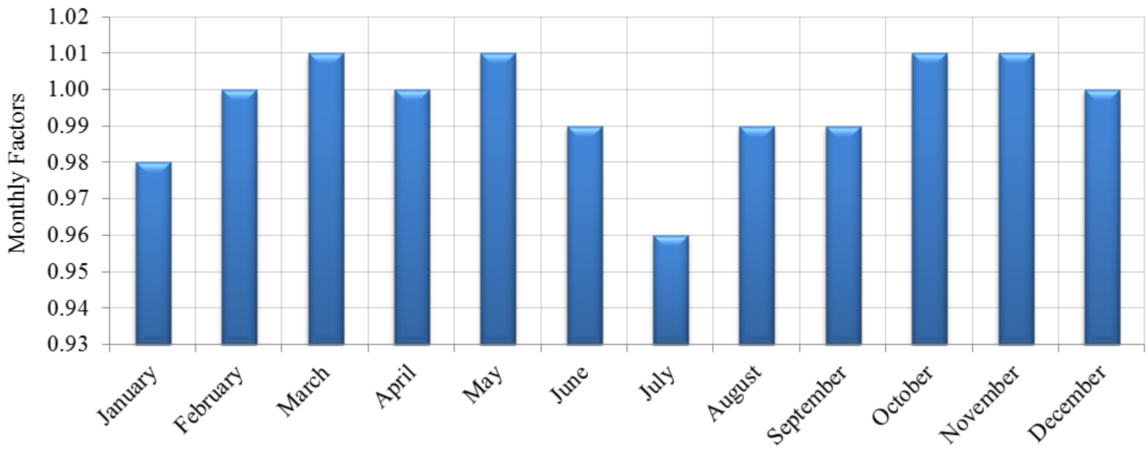


Table D.1 Traffic data output from SATURN

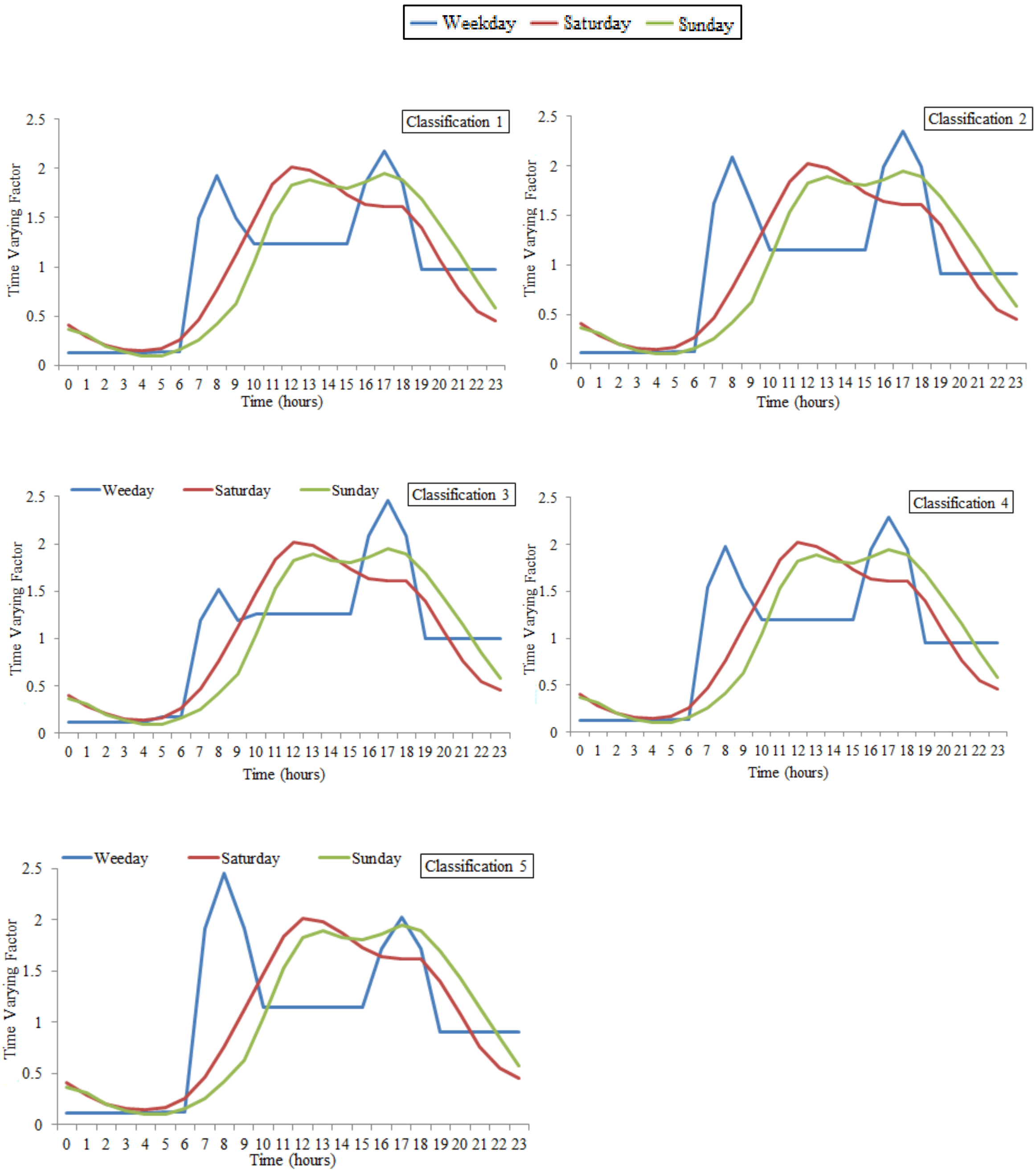
Variable	Description	Units
Link ID*	Unique Identifier for the road link	N/A
No. Lanes*	Number of lanes on link	N/A
Total	Total traffic flow	PCU/h
Lights	Light duty vehicle traffic flow	PCU/h
Heavies	Heavy duty vehicle traffic flow	PCU/h
Bus	Bus vehicle traffic flow	PCU/h
Cruise Speed	Speed from stop line to stop line allowing for speeds to decrease according to speed-flow delays	km/h
Free Flow Speed	Speed based on free flow conditions; value does not comprise a change in speed to account for approaching a stop line	km/h
Q Average	Average link vehicle queue	PCU/h
Junction Delay	Link junction delay	s
QUE FLOW	Average difference between demand flow to arrive at the downstream stop-line and 'actual' flow which arrives at the stop line	PCU/h
Green T	Average time that traffic signals remain on green over period	s
Bus NEAR	Demand bus flows in a near side bus lane	PCU/h
Bus MID	Bus flows on 'middle' link as opposed to bus lane	PCU/h
Bus OFF	Demand bus flows in a off side bus lane	PCU/h
Bus Q	Average link bus queue	PCU/h
Bus EN U	Bus entry flow which enters link upstream	PCU/h
StopL D	Link delay at stop-line	s
Network Speed	link speed based on simulation travel time which takes into consideration transient delays, queuing delays and speed-flow delays	km/h

*Variables from SATURN not output for AM (08.00h), inter-peak (average hour between 10.00h to 15.00h) or PM (17.00h) periods. All other variables were output for these three periods.

APPENDIX E

E.1 Diurnal Traffic Profiles

Figure E.1 Five diurnal profiles developed based on factor and cluster analysis in Chapter 5



APPENDIX F

F.1 Time Series Analysis of Observed and Predicted Pollutant Concentrations

Figure F.1(a) Time series graph of predicted and observed NO_2 concentrations ($\mu g/m^3$) and Figure F.1(b) observed vs predicted NO_2 concentrations ($\mu g/m^3$) at Abbey Lane from 1st January 2005

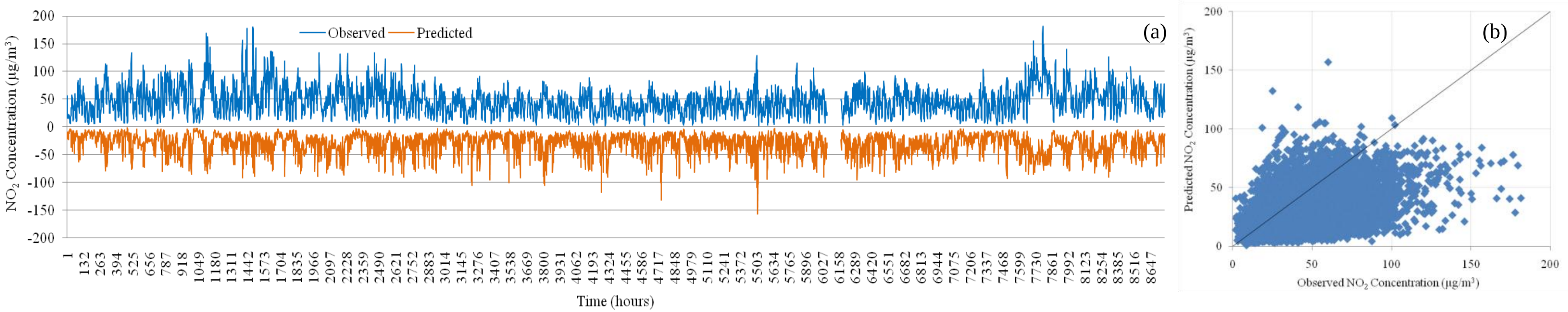


Figure F.2(a) Time series graph of predicted and observed NO_2 concentrations ($\mu g/m^3$) and Figure F.2(b) observed vs predicted NO_2 concentrations ($\mu g/m^3$) at Imperial Avenue from 1st January 2005

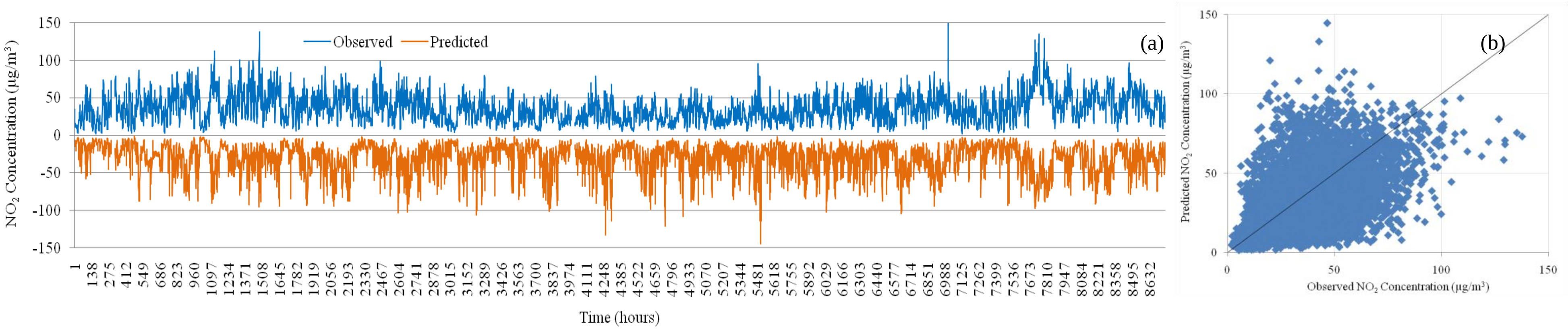


Figure F.3(a) Time series graph of predicted and observed NO_2 concentrations (µg/m^3) and Figure F.3(b) observed vs predicted NO_2 concentrations (µg/m^3) at Melton Road from 1st January 2005

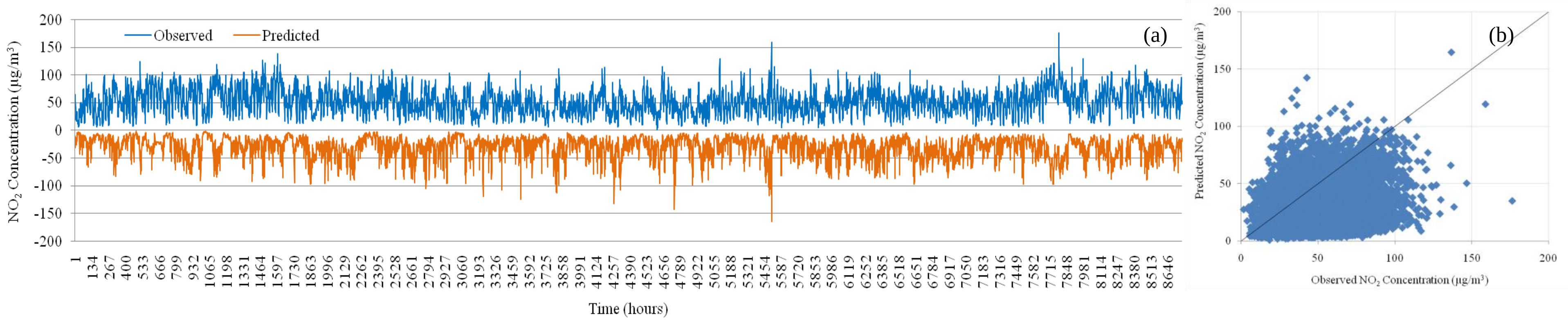


Figure F.4 Time series graph of predicted and observed NO_2 concentrations (µg/m^3) and Figure F.4(b) observed vs predicted NO_2 concentrations (µg/m^3) at Uppingham Road from 1st January 2005

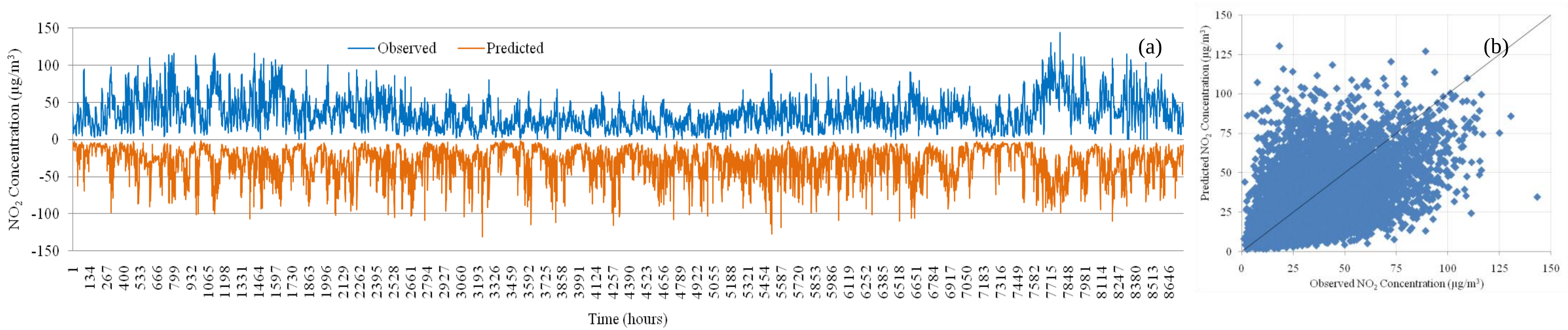


Figure F.5(a) Time series of background and predicted PM_{10} concentrations ($\mu g/m^3$); Figure F.5(b) predcited vs background PM_{10} concentrations; Figure F.5(c) observed and predicted PM_{10} concentrations ($\mu g/m^3$) and; Figure F.5(d) observed vs predicted PM_{10} concentrations at Abbey Lane from 1st January 2005

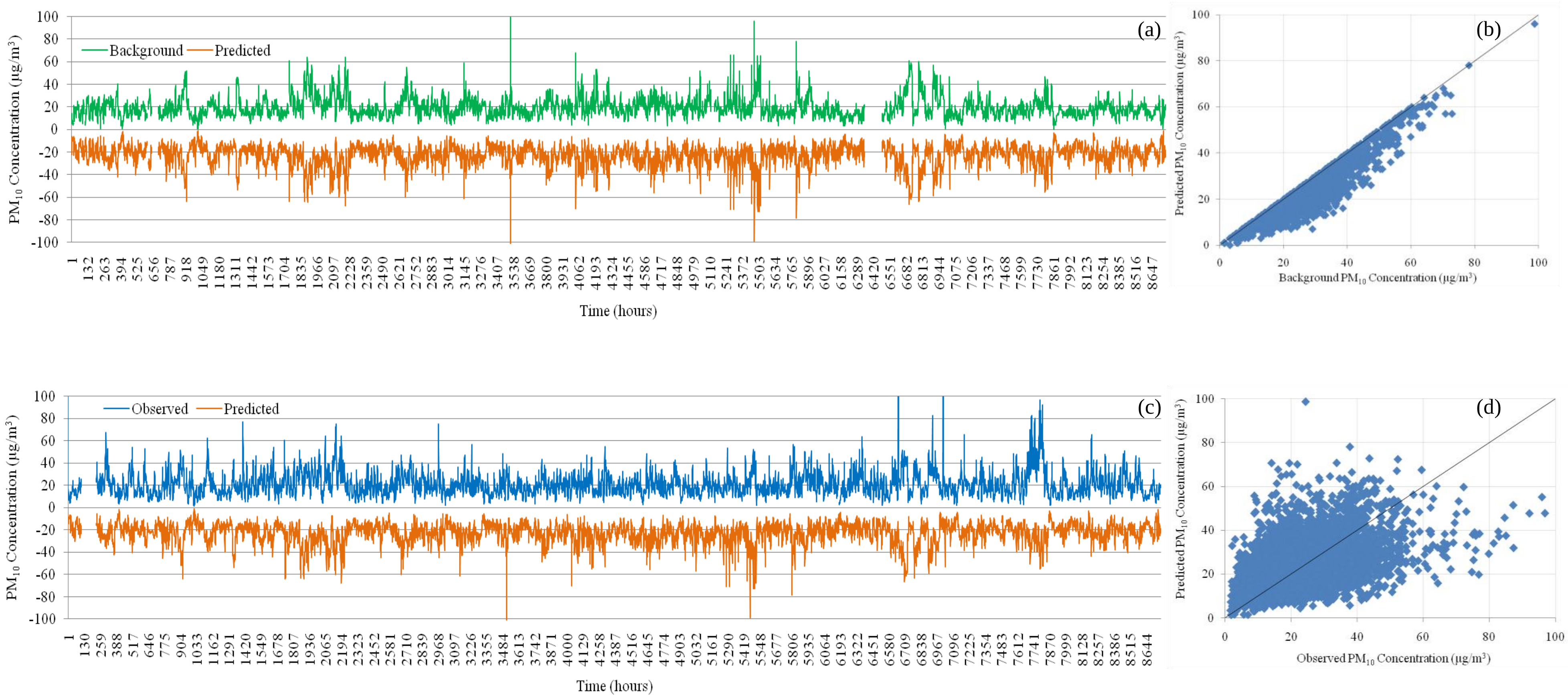


Figure F.6(a) Time series of background and predicted PM_{10} concentrations (µg/m^3); Figure F.6(b) predcited vs background PM_{10} concentrations; Figure F.6(c) observed and predicted PM_{10} concentrations (µg/m^3) and; Figure F.6(d) observed vs predicted PM_{10} concentrations at the New Walk Centre (NWC) from 1st January 2005

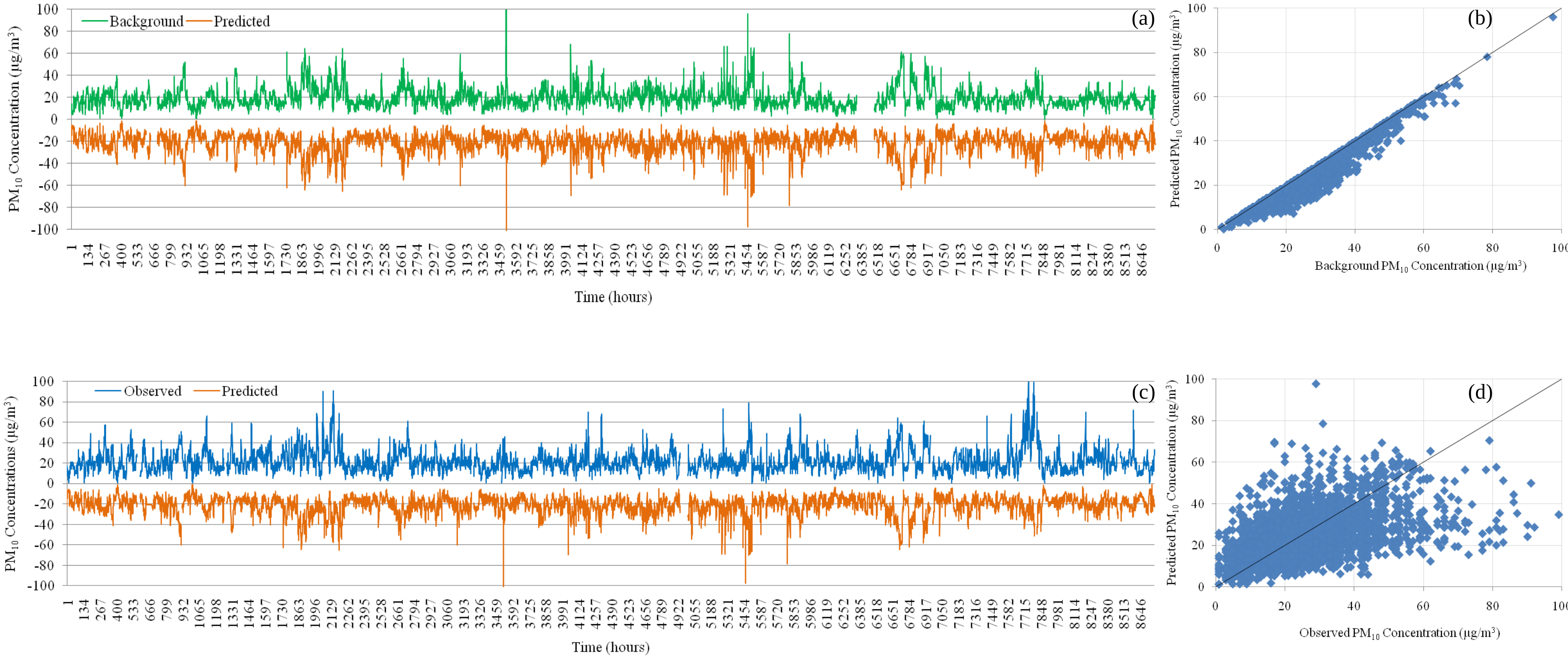
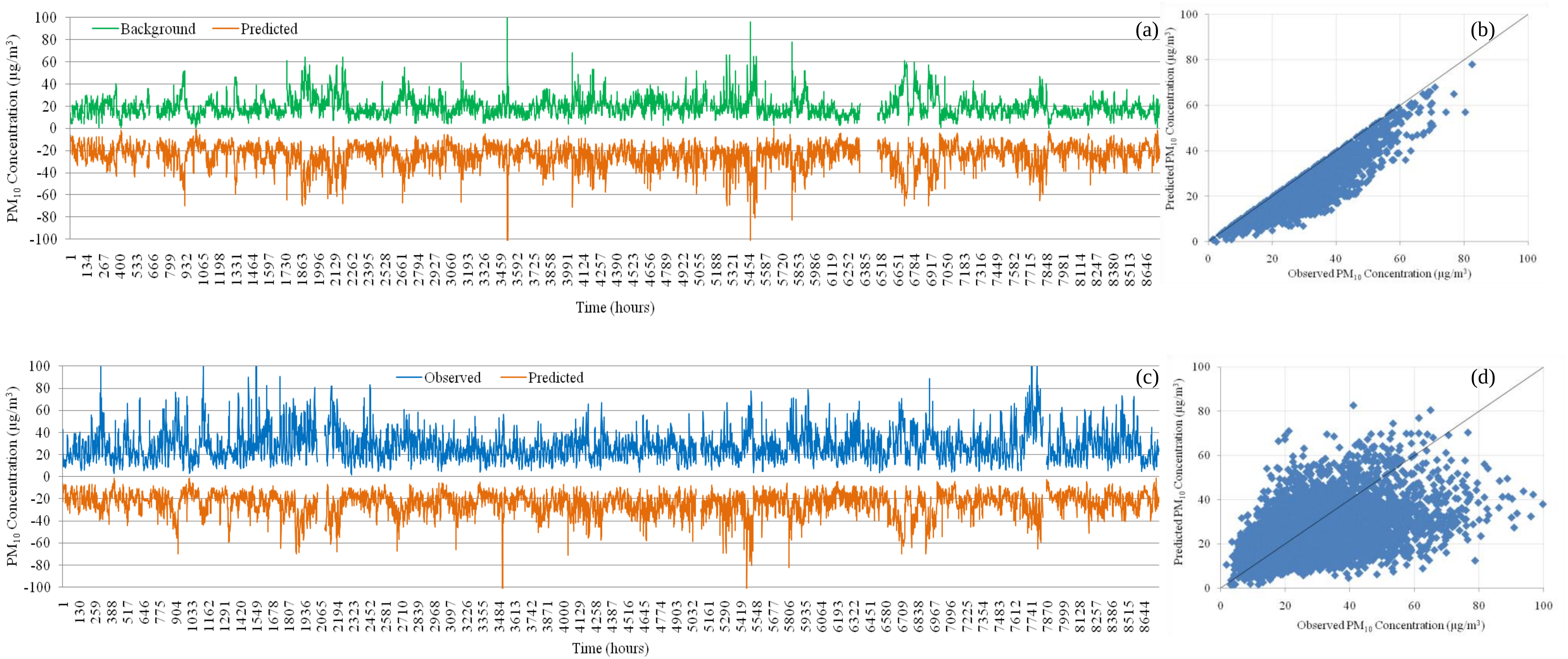


Figure F.7(a) Time series of background and predicted PM_{10} concentrations (µg/m^3); Figure F.7(b) predcited vs background PM_{10} concentrations; Figure F.7(c) observed and predicted PM_{10} concentrations (µg/m^3) and; Figure F.7(d) observed vs predicted PM_{10} concentrations at Glenhills Way from 1st January 2005



APPENDIX G

G.1 Box Plot Analysis of Pollutant Concentrations by Wind Direction, Wind Speed and Time of Day

Figure G.1 Ratio of predicted to observed NO_2 concentrations by wind direction (degrees), wind speed (m/s) and time of day (hours) at Abbey Lane

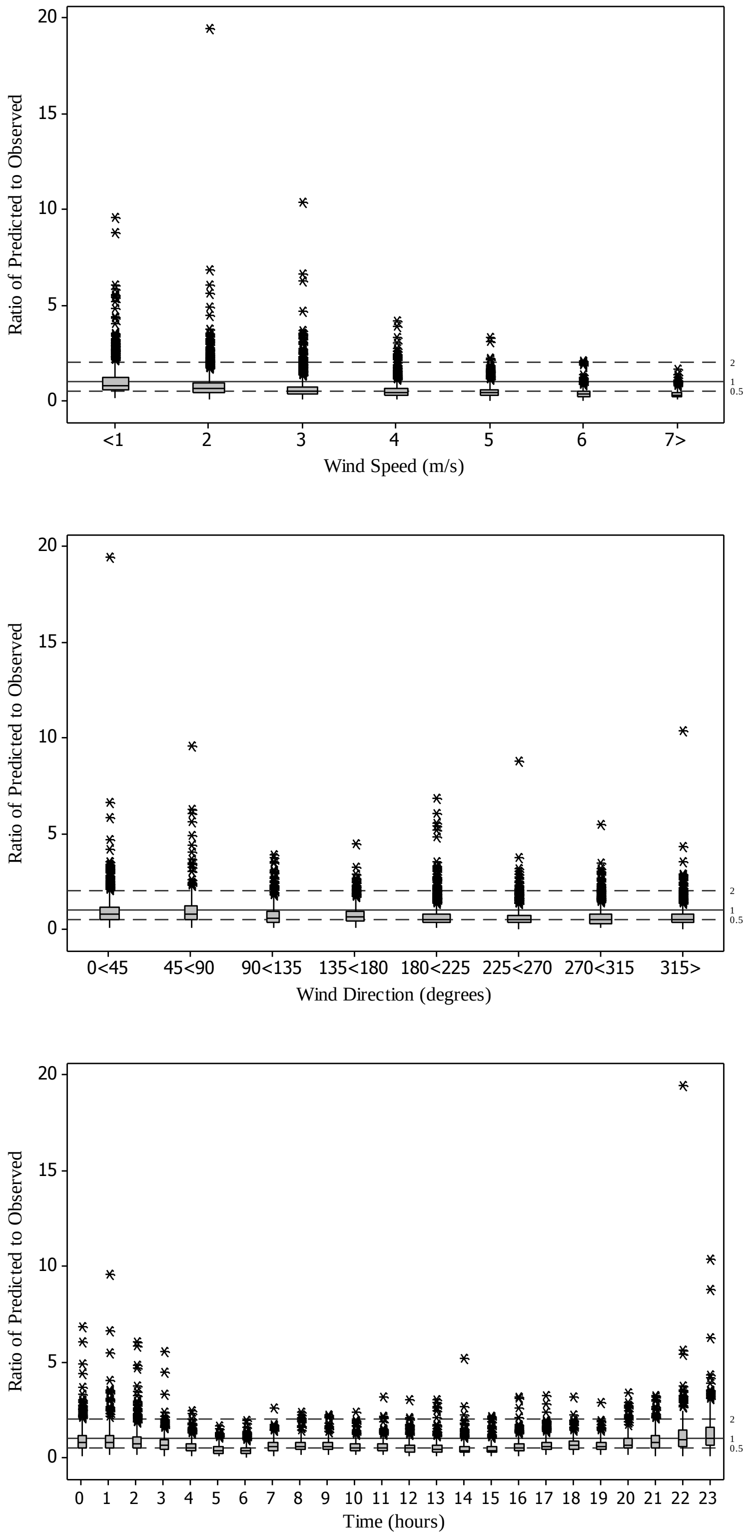


Figure G.2 Ratio of predicted to observed NO_2 concentrations by wind direction (degrees), wind speed (m/s) and time of day (hours) at Glenhills Way

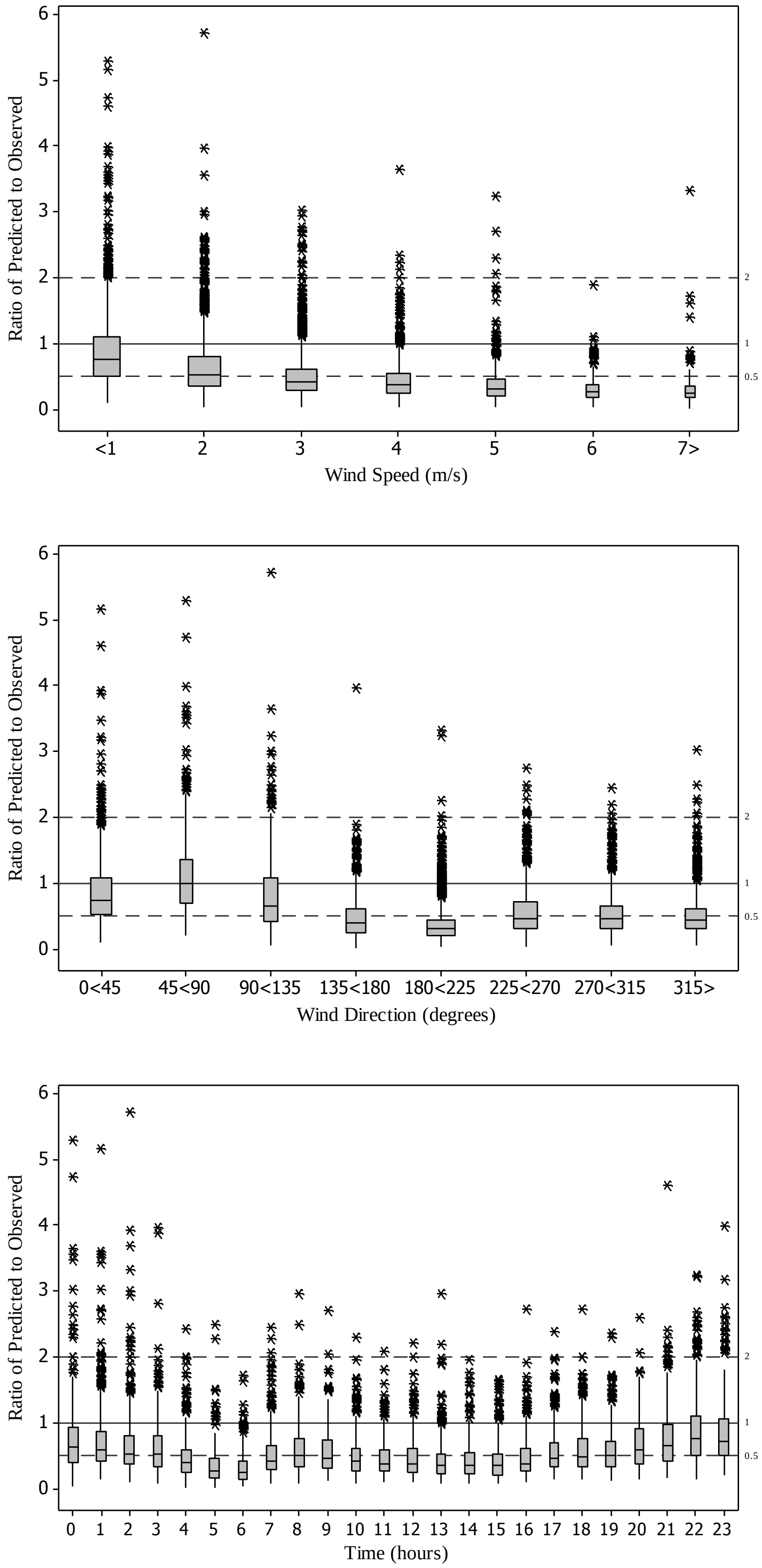


Figure G.3 Ratio of predicted to observed NO_2 concentrations by wind direction (degrees), wind speed (m/s) and time of day (hours) at Imperial Avenue

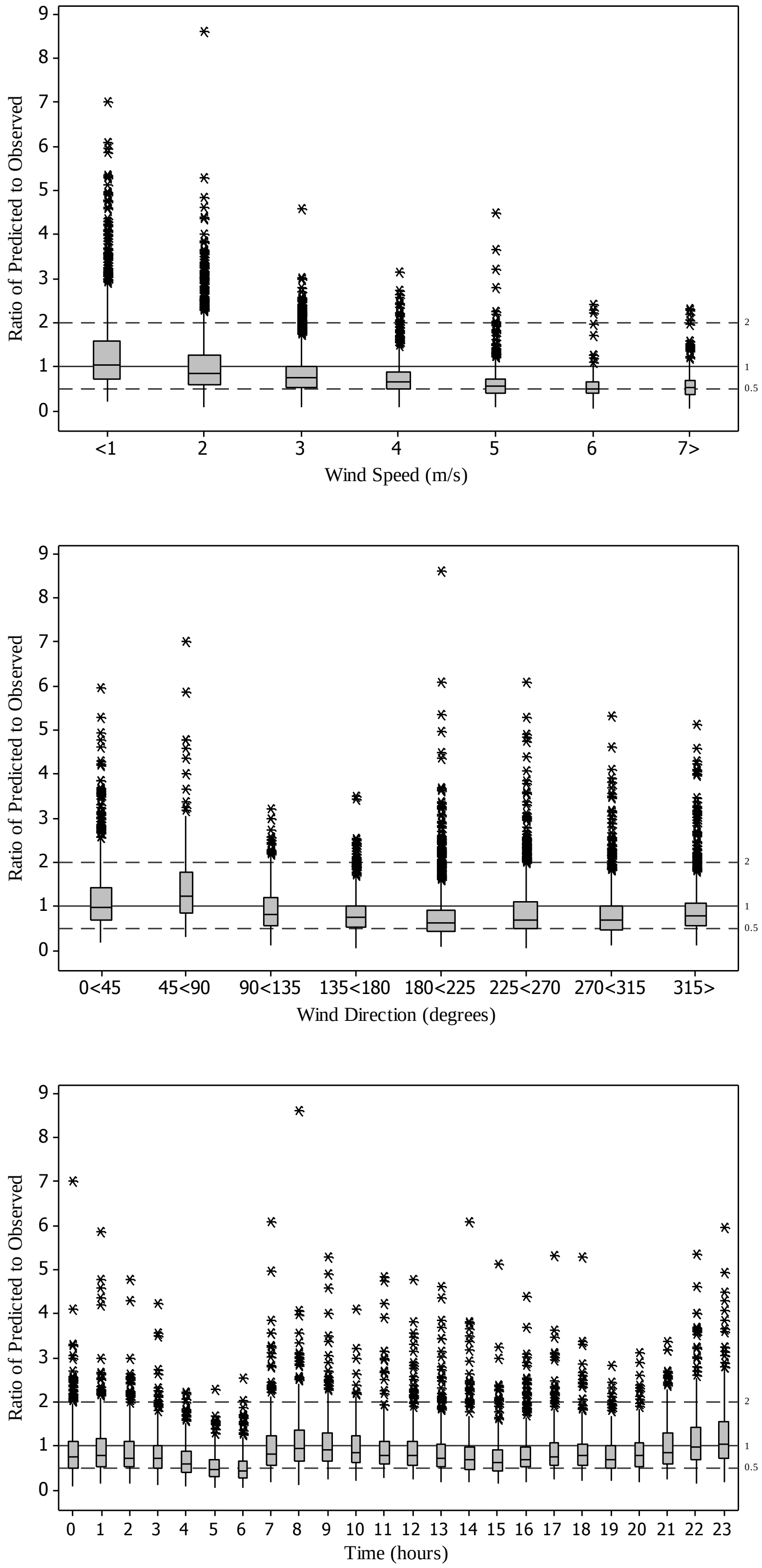
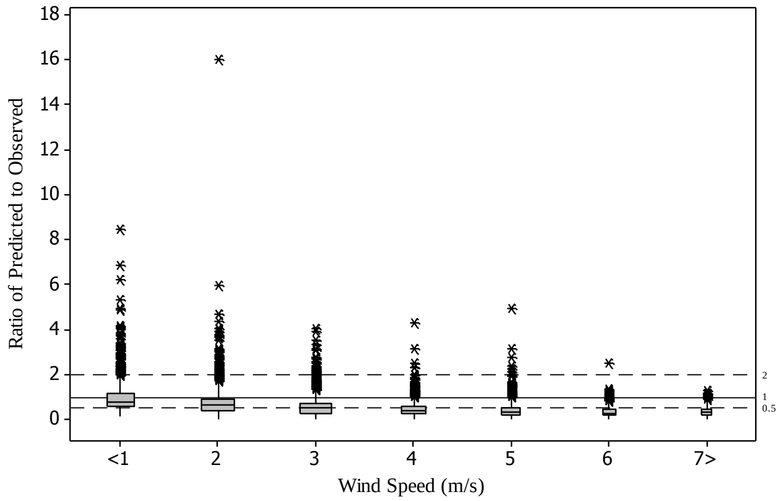
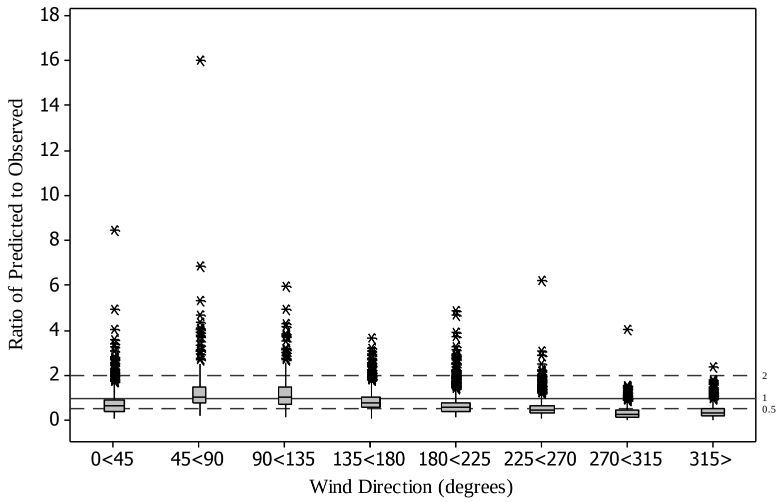


Figure G.4 Ratio of predicted to observed NO_2 concentrations by wind direction (degrees), wind speed (m/s) and time of day (hours) at Melton Road





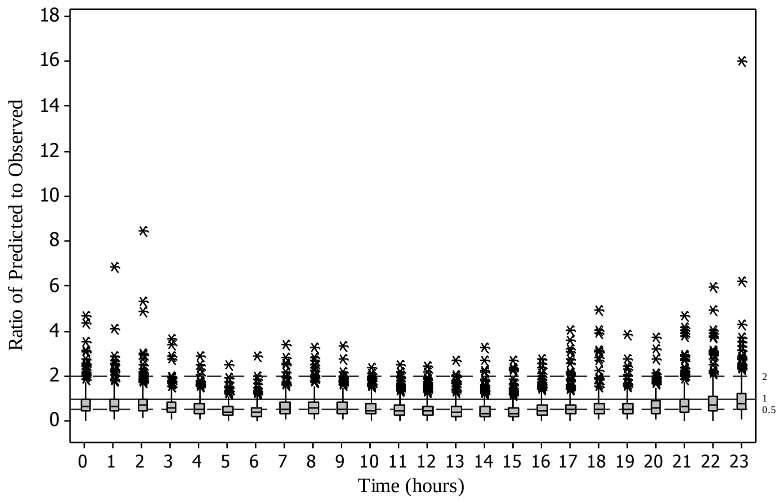


Figure G.5 Ratio of predicted to observed NO_2 concentrations by wind direction (degrees), wind speed (m/s) and time of day (hours) at the New Walk Centre (NWC)

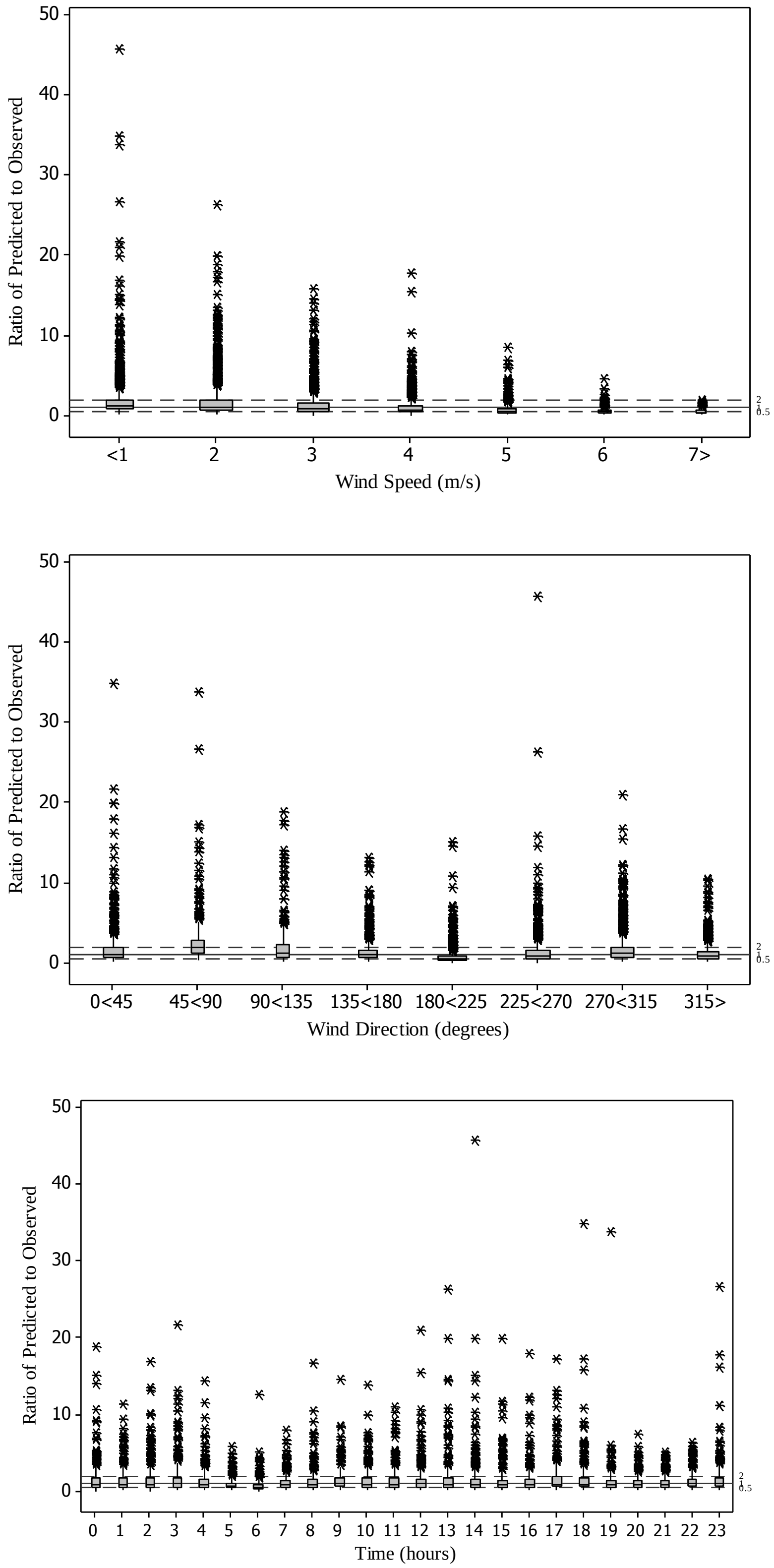
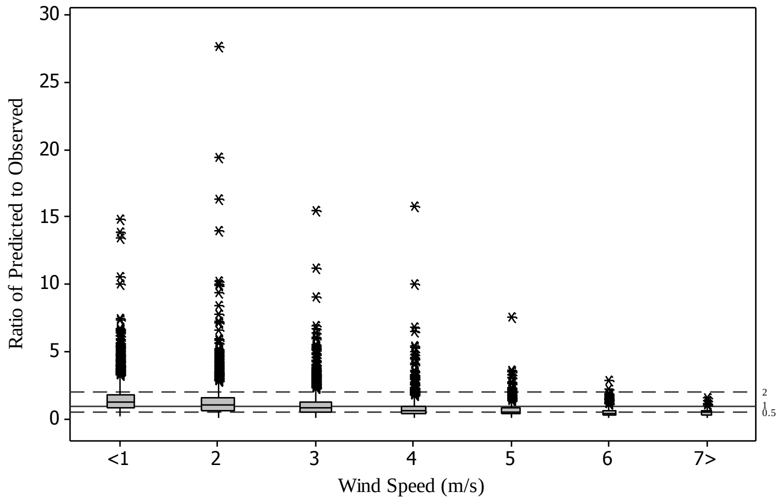
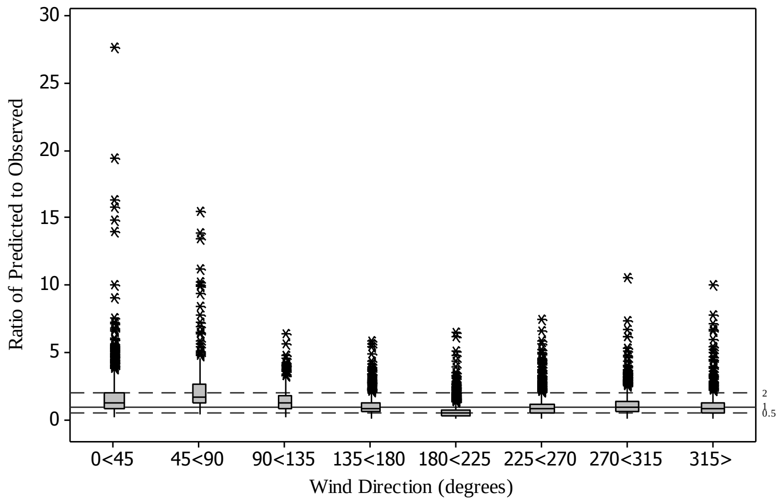


Figure G.6 Ratio of predicted to observed NO_2 concentrations by wind direction (degrees), wind speed (m/s) and time of day (hours) at Bassett Street





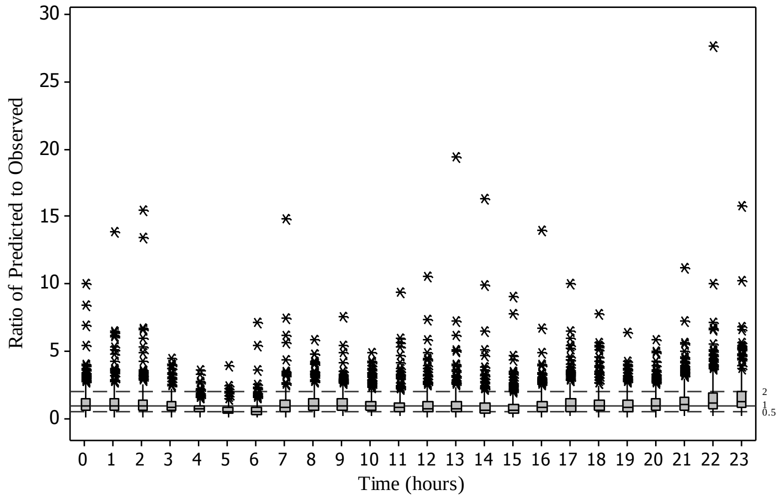
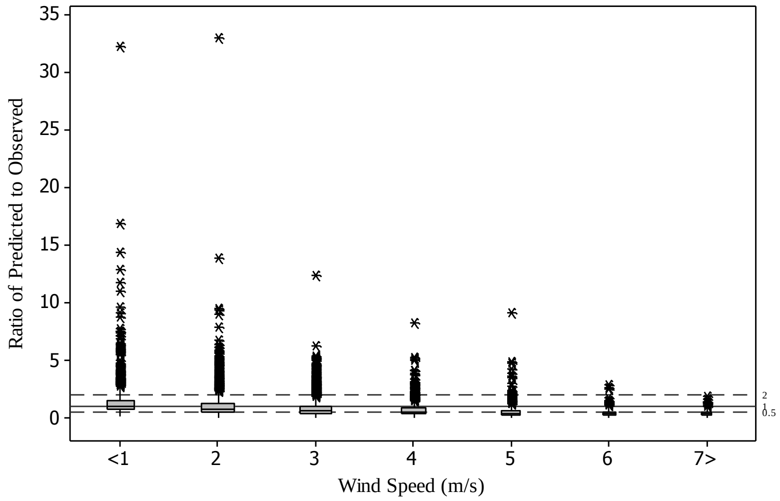
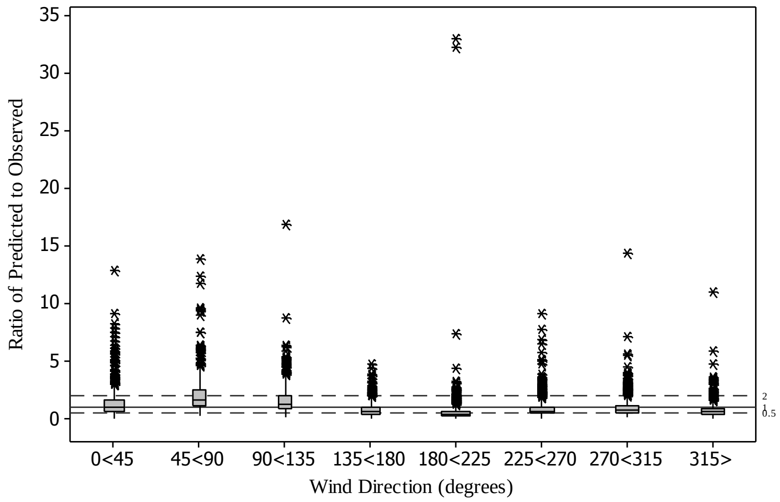


Figure G.7 Ratio of predicted to observed NO_2 concentrations by wind direction (degrees), wind speed (m/s) and time of day (hours) at Uppingham Road





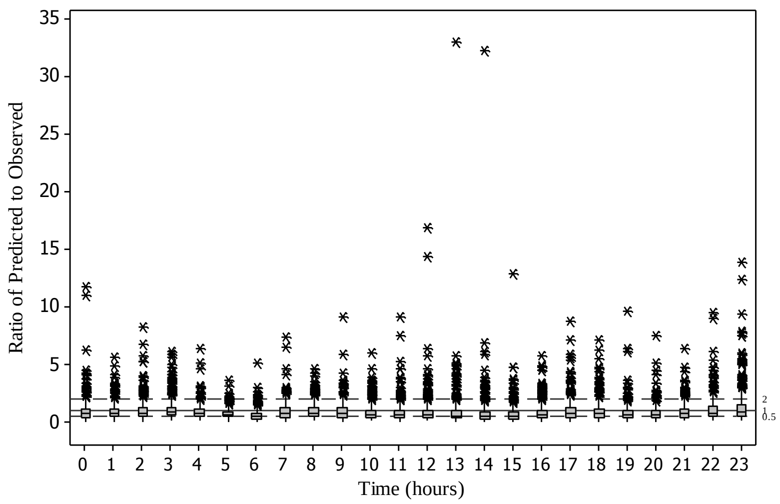


Figure G.8 Ratio of predicted to observed PM_{10} concentrations by wind direction (degrees), wind speed (m/s) and time of day (hours) at the New Walk Centre (NWC)

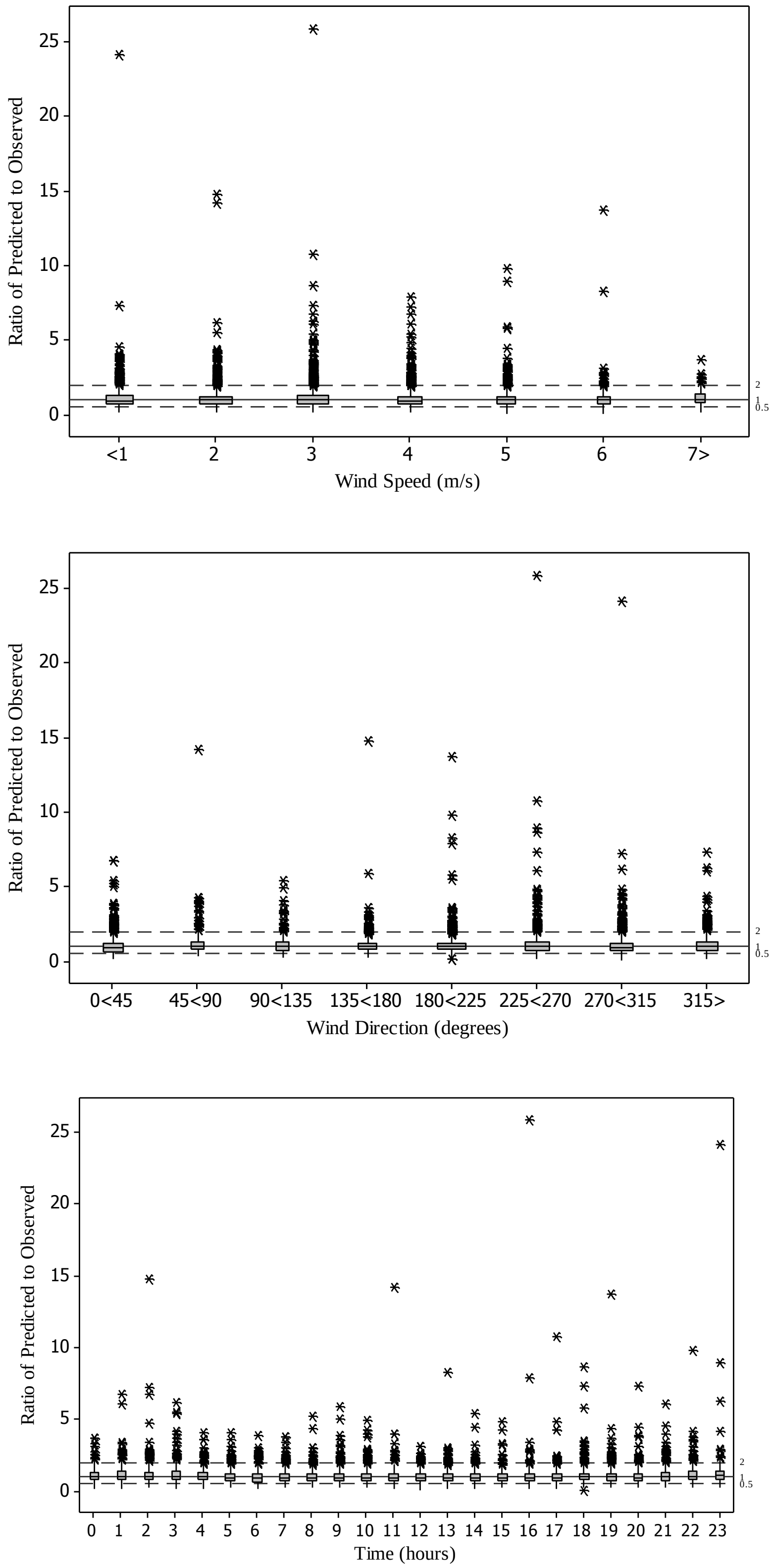


Figure G.9 Ratio of predicted to observed PM_{10} concentrations by wind direction (degrees), wind speed (m/s) and time of day (hours) at the Abbey Lane

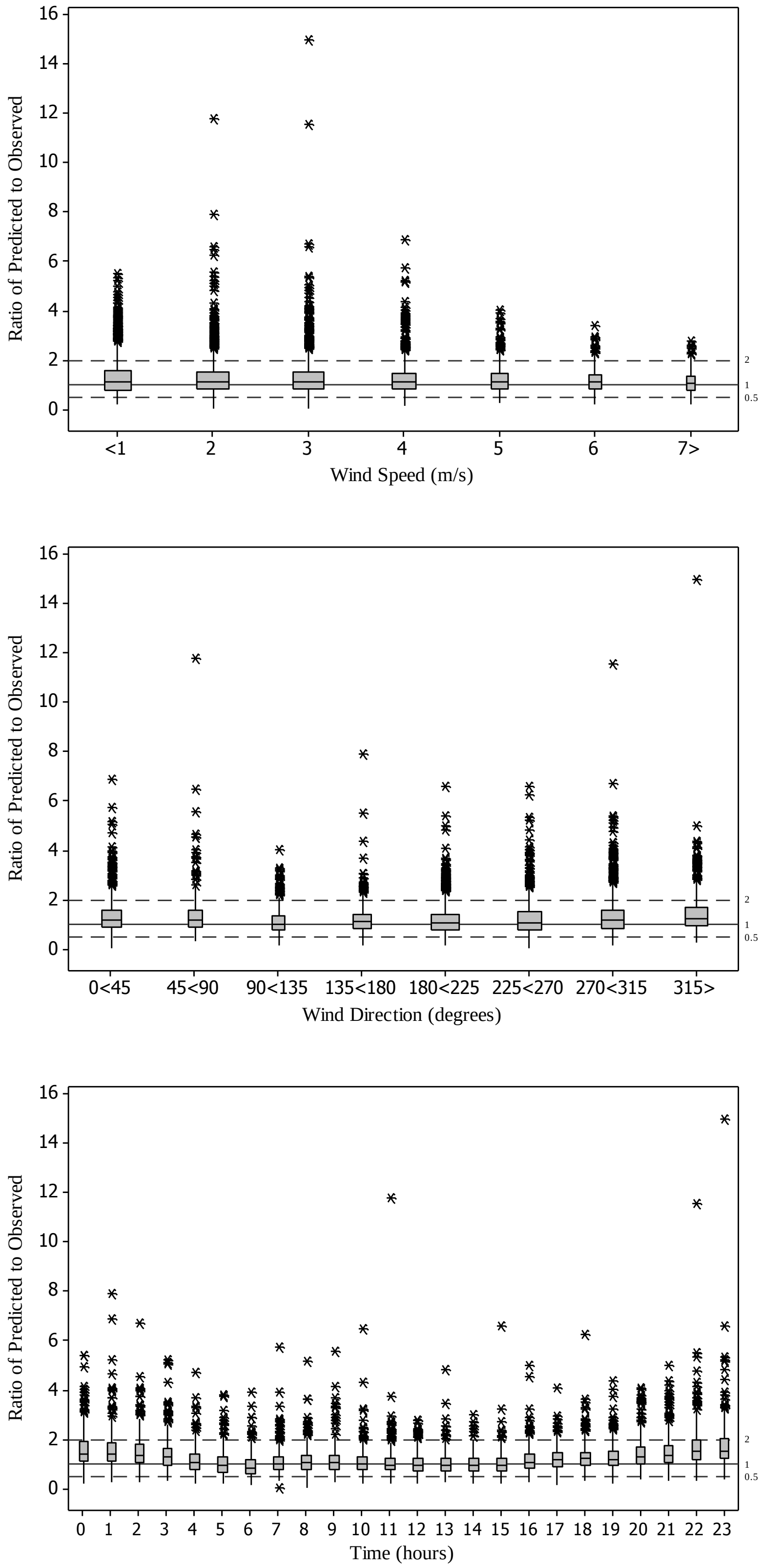


Figure G.10 Ratio of predicted to observed PM_{10} concentrations by wind direction (degrees), wind speed (m/s) and time of day (hours) at the Glenhills Way

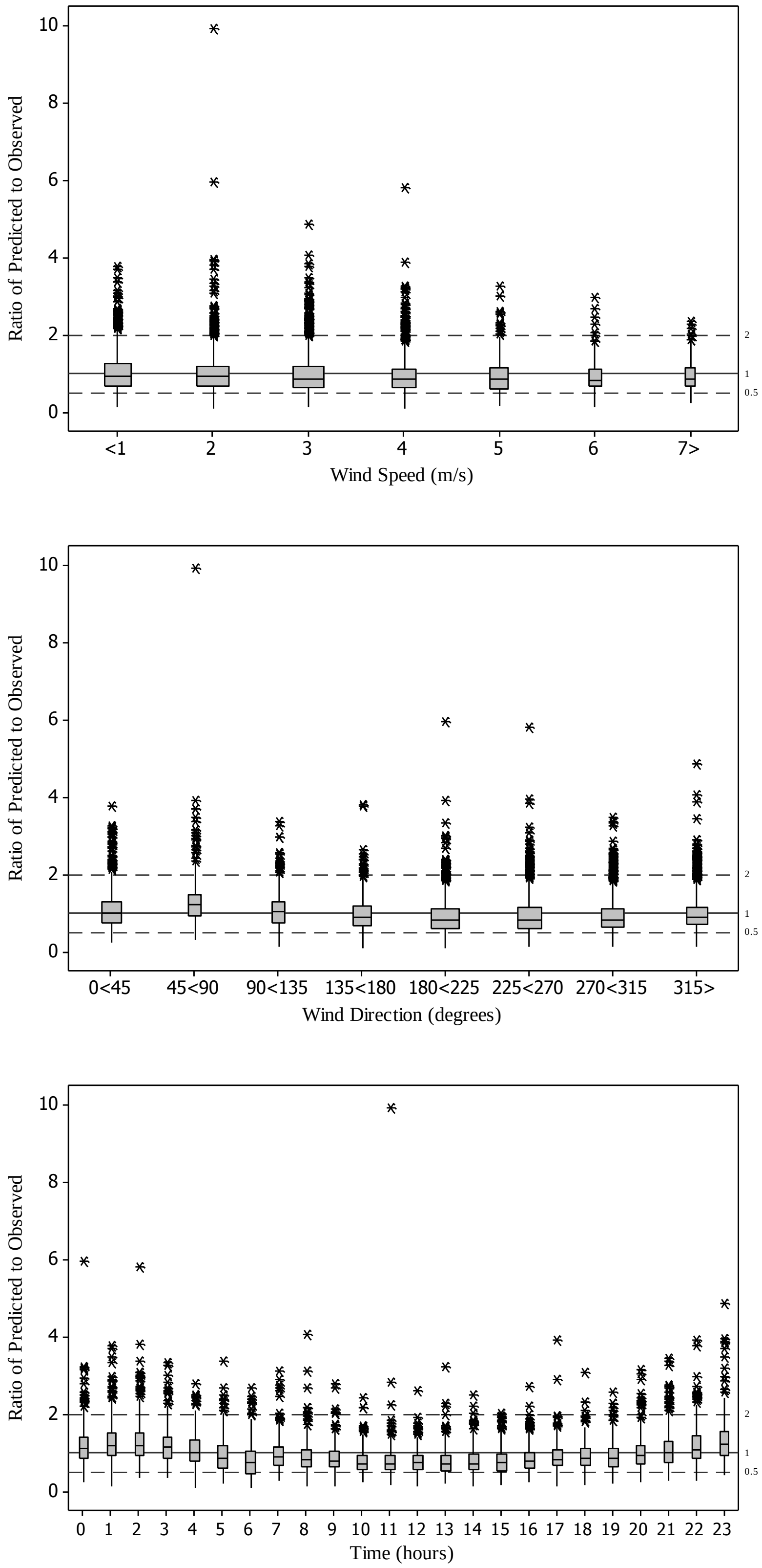


Figure G.11 Ratio of predicted to observed PM_{10} concentrations by wind direction (degrees), wind speed (m/s) and time of day (hours) at the Imperial Avenue

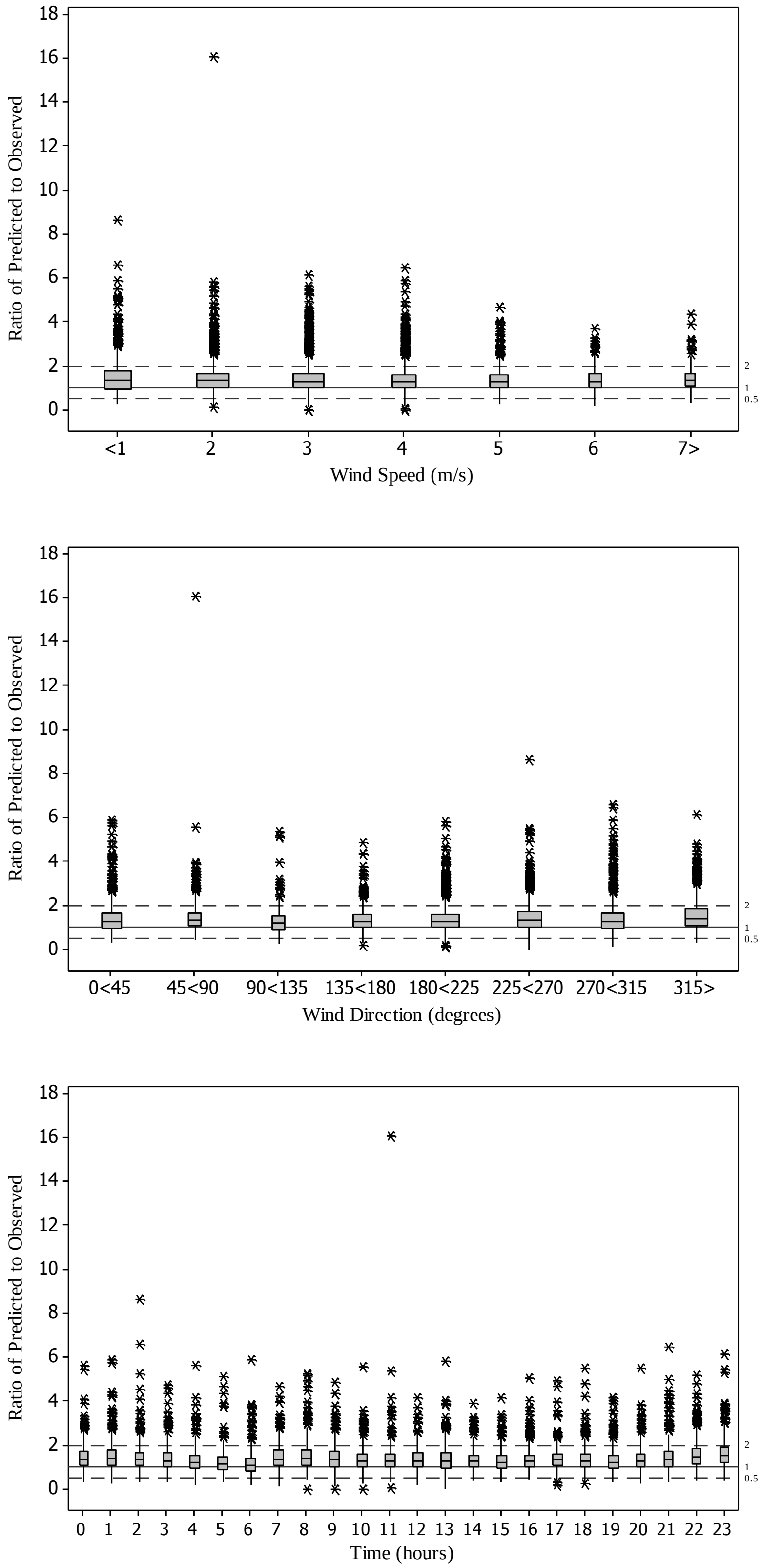
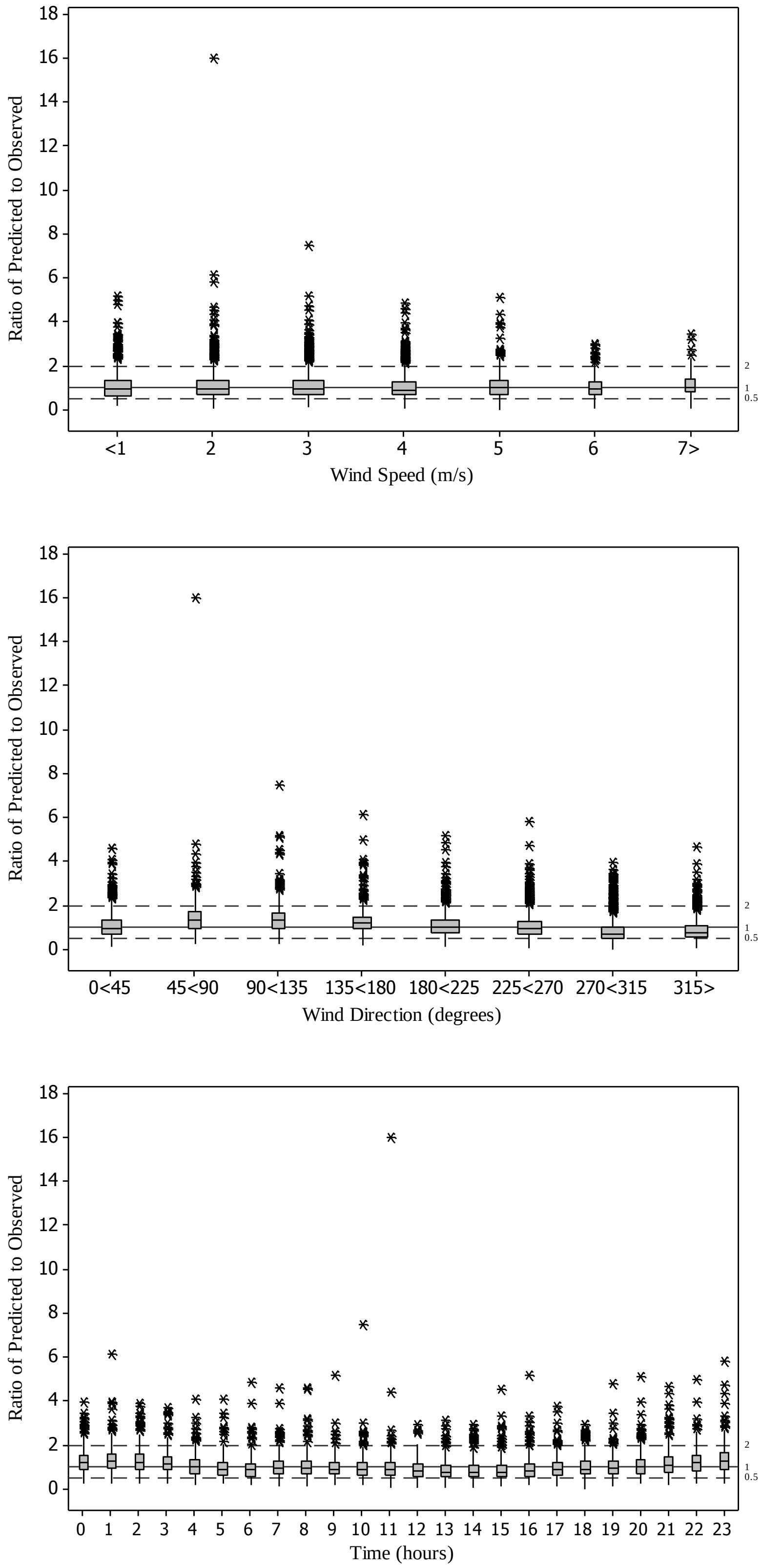


Figure G.12 Ratio of predicted to observed PM_{10} concentrations by wind direction (degrees), wind speed (m/s) and time of day (hours) at the Melton Road



APPENDIX H

H.1 Emissions and Locations of the Five Road Classifications

Table H.1 Base-case emissions (t) per road classification for the entire Leicester road network

Road Classification	NO_x (t)	CO_2 (t)	PM_{10} (t)	f-NO_2 (t)
1	95	25,334	5	11
2	261	69,269	16	29
3	76	15,350	4	9
4	130	35,075	7	15
5	313	76,536	18	34
Total	875	221,563	49	99

Figure H.1 Map of Leicester road network, road classifications and air quality management area