PhD in Engineering

An Investigation of Smarter Driving: Emission & Exposure Modelling and Micro Simulation

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Declaration

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Dedicated To

Md. Shah Alam and Shamsun Nahar Begum, my beloved parents, who sacrificed most of their joys for my well-being, who taught me ethics, unconditional love, kindness, sincerity, and respect for others.

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Abstract

Promoting smarter driving may be a useful initiative to reduce the negative environmental impacts of travel in the present car dominated era. Smarter driving may include efficient driving and route choice which reduces fuel consumption, CO_2 emissions (Eco-Routing) as well as personal exposure to harmful pollutants. However, efficient driving and Eco-Route choice techniques possess some practical as well as technological limitations, primarily because of the real-time nature of their application. Efficient driving that refers to controlling/limiting acceleration and speed of vehicles may have a network wide impact of increased overall network travel time. Although, many investigations of such Eco-Driving have reported potential reductions in fuel consumption and CO_2 emissions ranging from 5% to 40% across various jurisdictions and initiatives, a review of the literature revealed contradictory impacts of Eco-Driving that required further investigated.

In congested city centre traffic, many conflicting views exist in the literature, resulting in some doubt over the effectiveness of the policy in such circumstances. Micro-simulation of the environmental and traffic performance of Eco-Driving has been conducted for the Dublin city road network, to assess its network level impacts. The results of this investigation showed that increasing levels of Eco-Driving in a road network resulted in significant environmental and traffic congestion detriments at the road network level in the presence of heavy traffic. In addition, the impacts of the intersections replacement by roundabouts were also evaluated. Negligible transport impacts were found from Eco-Driving in the presence of low traffic congestion for all scenarios. But, large negative impacts were observed for high traffic volume scenarios with the increase level of Eco-car penetration. Increases in CO_2 emissions of up to 18% were found from these studies. However, with the addition of vehicle to vehicle or vehicle to infrastructure communication technology, which facilitates dynamic driving control on speed and acceleration/deceleration in vehicles, improvements in CO_2 emissions and traffic congestion could be possible using Eco-Driving.

On the other hand, the literature review also revealed that the actual range of saving from Eco-Routing was 0.35 –42% fuel and the extent of the variation depended heavily of the level of congestion present. However, no serious issues were identified for Eco-Routing impact. Nonetheless, technological advancement of real time information system was not found to be connected with emission based Eco-Routing systems in practical use, and this may become a

serious flaw of this strategy if the practice becomes widespread. A solution for this has been outlined from an extensive literature review, and a model was developed that is sensitive to vehicle characteristics such as speed, temperature and occupancy. The model is suitable for deployment in any city and effectiveness was evaluated after a field trial in Dublin and Vienna. Several lessons were learned from the developed model, including the importance of real-time data integration, vehicle registration data integration and further modification of the model.

Analogous information that can be useful for the drivers for route choice is exposure information. Such information was required to investigate a comparison to the conventional route choice cost factors before deployment. Thus, the level of exposure to a particular pollutant, or dose of pollutant that a person inhales during travel were compared against choice factors such as: time, distance, generalised cost, CO_2, value of time, and running cost. At first the particular challenge was to estimate the exposure concentration of a pollutant along each road in a network. A possible low cost, yet effective approach to estimation of average daily exposure concentration at city scale is the Land Use Regression (LUR) method. Some methodological modifications have been conducted within the LUR framework and the daily level of air pollution concentration has been estimated in the presence of limited available input data. Concentrations estimated from the model were transferred to the road network level to estimate the exposure concentration along the roads. Hourly fluctuations of NO_x concentrations were applied further for the hourly prediction of the concentrations.

A series of 16 models were developed for PM_{10} air quality in Dublin, which included models for validation of the modified LUR methodology developed in this study. It was found that using a non-parametric regression model could out-perform linear regression based models, however to a lesser extent than that of Artificial Neural Networks. Some dynamic predictors such as a predictor representing trans-boundary air pollution, and vehicle count from loop detectors were assessed which open scope for future research. The final route level analysis revealed that a reduction of dose caused a small increase in travel time and large increase in distance. For different origin and destination pairs the magnitude might be changed drastically, but the pattern will be similar. The local setting was the primary reason for variation in the lowest dose based routes compared to the conventional cost factors of route choice. Such findings may pose a limit of the widespread use of routing based on exposure. However, dose could still be placed as an option in route choice modules for people with priority health issues.

List of Publications

Journal Publication:

-ALAM, M.S., & MCNABOLA, A. (2014). A Critical Review and Assessment of Eco-Driving policy & Technology: Benefits & Limitations, *Transport Policy*, Volume 35, September 2014, Pages 42–49

-ALAM, M.S., & MCNABOLA, A. (2015). Exploring the modelling of Spatio-temporal variations in air pollution within the land use regression framework: Estimation of PM_{10} concentrations on a daily basis, *Journal of the Air & Waste Management Association, January 2015,* DOI:10.1080/10962247.2015.1006377

Conference Publications:

- ALAM, M.S., & MCNABOLA, A. (2013). Eco-Driving policy & Technology: Benefits, Limitations & Future Research, *Environ Conference*, Galway. January 2013.

- ALAM, M.S., & MCNABOLA, A. (2013). An Assessment of a New Determinant for Smarter Route Choice, *Proceedings of the Irish Transport Research Network*, September 5-6th.

- ALAM, M.S., & MCNABOLA, A. (2013). Eco-Driving Policy & Technology: A Review of Benefits & Limitations in CO_2 Emissions Reduction, *9th ITS European Congress*, Dublin, June 4.

- ALAM, M.S., & MCNABOLA, A. (2012). A critical review of Eco-Driving and proposal for CO_2 Emissions modelling to facilitate Eco-Routing, *Proceedings of the Irish Transport Research Network*, Belfast, August, 2012, pp1-8.

Glossary of terms

AADT:	Annual average daily traffic.
Air Pollutant:	Anything emitted to the air which could have a detrimental effect on human health or the environment.
Air quality:	A measure of the level of pollution in the air.
Ambient Air:	The air located outside of buildings/ Outdoor air.
Atmosphere:	The mass of air surrounding the Earth.
Artificial Neural networks/ANN:	It is often called as statistical black box; is composed of interconnecting artificial neurons that build mathematical models mimicking the properties of biological neurons.
Carbon footprint:	Carbon footprint is a measure of the impact of fossil energy use.
Carbon tax:	A tax on fuels according to their carbon content.
Catalytic converter:	A vehicle emissions control device that converts toxic by-products of combustion in the exhaust of an internal-combustion engine to fewer toxic substances by way of catalysed chemical reactions.
Cold start emission:	Higher emission rates occurs often for a few minutes while starting a vehicle engine after a long time. This happens during the time difference between cooling state and lighting up the catalyst convertor (until the temperature reaches 300-350°C).
Dose:	Dose is the amount of pollutant that someone inhaled. Dose is the function of travel time, pollutant concentration and breathing rate.
DTM:	Digital Terrain Model.
Eco-Driving:	A smart and safe way of driving, in terms of avoidance of sudden acceleration and breaking, and choosing of an eco-friendly route that offers low emission compared to other best possible routes (*e.g.* time priority route, shortest distance route) for that origin-destination pair.
Eco-Routing:	Choosing a route that offers low emission compared to other best possible options like time priority route, shortest distance route.
Emissions:	Gases or particles released into the air that may have harmful effect on global warming or air quality.
Euro emission standard category:	European emission standards define the acceptable limits for exhaust emissions of the vehicles sold in the EU member states.
Exposure:	The amount of contact that a person has with the pollutant.
FSM:	Fixed site monitor, a collection of air monitoring equipment spread across an area whose readings are used to understand the Air Quality in that area.
FCD:	Floating car data, normally obtained through Global Positioning System Device in relation to satellite.
GC:	Generalised cost (GC) is the sum of monetary and non-monetary cost of a journey.

GIS: Geographic Information System.

GPS device: The Global Positioning System (GPS) device is a space-based satellite navigation system that provides location and time information.

Greenhouse gases: Gases that trap heat radiating from the Earth's surface, such as: carbon dioxide (CO_2), methane (CH_4) and nitrous oxide (NO_2).

Headway: Headway is a measurement of elapsed time or distance between every two consecutive vehicles.

Intelligent Transport System (ITS): Here, it refers to traffic signalling systems: SCOOT, SCATES or UTOPIA (see below).

Land use: The total of arrangements, activities and inputs undertaken in a certain land cover type.

LUR: Land use regression.

Mode: Method of travel.

MLR: Multiple linear regression.

NPR: Non parametric regression.

Occupancy: Number of occupants using a vehicle/transport.

Parking time: The idle time of a vehicle which represents the degree of a catalytic convertor's coolness/temperature.

Particulate Matter$_{10}$/PM$_{10}$: Particulate matter is made up of many different compounds that has an aerodynamic diameter of 10µm or less.

Peak and off peak hour: Usually in peak hours the transport demand is high and streets become congested whereas the opposite happens during an off-peak hour.

Personal Exposure: The amount of pollutant inhaled by a commuter during a trip.

RC: Running cost.

Regression: In statistics, regression analysis is a technique for estimating the relationships among response and explanatory variables.

Real-Time Traffic: Real-time traffic means the actual condition of the traffic in a particular network in the real time sense. This traffic information can be obtained from GPS device, mobile devices, satellite images or analysing data from ITS infrastructure.

Road grades: The grade/slope of a road refers to the amount of inclination of that road to the horizontal.

Saturation flow rate: The saturation flow rate crossing a signalized stop line is defined as the number of vehicles per hour that could cross the line if the signal remained green all of the time.

SCATS: Sydney Coordinated Adaptive Traffic System; Intelligent Transportation infrastructures that obtain traffic volume/occupancy information from the road.

SCOOT: Split, Cycle, Offset Optimisation Technique.

Solar radiation: Radiation emitted by the Sun.

UTOPIA: Urban Traffic OPtimisation by Integrated Automation.

VKT: Vehicle kilometre travelled.

VOT: Value of time.

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Introduction

Chapter 1

1.1 Background

Air pollutants include gaseous substances, liquid droplets or solid particles released into the atmosphere that have an adverse effect on human health (Ye *et al.*, 1999), climate change and/or the environment (Strawa *et al.*, 2010; Uherek *et al.*, 2010). Greenhouse gases (GHG) such as carbon dioxide (CO_2), methane (CH_4) and nitrous oxide (N_2O) are naturally present in the atmosphere as part of the Earth's carbon and nitrogen cycles. These gases build the atmosphere around the earth that traps heat inside. CO_2 is the primary GHG as the amounts of CH_4 and N_2O released by anthropogenic activities are not as high (US EPA, 2014). The IPCC (2014) reported that CO_2 contributed at least 78% of the total greenhouse gas emissions from 1970 to 2010. Aside from the GHGs, some of the most common air pollutant from a human health perspective include: sulphur oxides (SO_x), particulate matter (PM_x), nitrogen oxides (NO_x), carbon monoxide (CO) and volatile organic compounds (VOCs). These pollutants are also present in the atmosphere in trace amounts, but may cause negative impacts on the human health and eco-systems when exceeding certain concentration levels in a specific timeframe.

The IPCC (2014) reported that the GHG level is at its highest now in the last 800,000 years and its gradual increase in the last 30-years (1983 to 2012) separate this period is probably the warmest of the last 1400 years. A global warming of 0.65 to 1.06°C for land and ocean surface temperature together increased over the period of 1880 to 2012 and caused a loss of arctic sea-ice from 3.5 to 4.1% per decade (IPCC 2014). With the increase in population, economic and human activities in the 21st century, GHG emissions are rising and Stocker *et al.* (2013) projected that the global surface temperature is likely to rise as a result. These predictions include a further 0.3 to 1.7^{o}C for their lowest emissions scenario using stringent mitigation and 2.6 to 4.8^{o}C for their worst case emissions scenario.

Air Pollution is ranked as the 8th most important risk factor in premature death worldwide (WHO 2005a). In the European Union, air pollution has been shown to be responsible for 500,000 premature deaths per annum (EuroActiv, 2013). The WHO (2014) estimated that some 80% of air pollution related premature deaths were due to ischaemic heart disease and strokes, while 14% of deaths were due to chronic obstructive pulmonary disease or acute lower respiratory infections; and 6% of deaths were due to lung cancer. Lim *et al.* (2012) reported outdoor PM_{10} was the 9th highest global risk factor for health loss. According to the exposure risk of citizens, PM_x has been identified as one of the most important pollutants in the European Union (EEA, 2013a). PM_x are the particles having a diameter of x (Commonly assessed range for x are 1 micron or less, 2.5 microns or less and 10 microns or less), and usually are a complex mixture of organic and inorganic substances such as ammonia, black carbon, mineral dust, nitrates, sodium chloride, sulphate, and water either in a liquid or in a solid form. It has been reported that approximately 90% of the European urban population are exposed to levels above the World Health Organization (WHO) guidelines for PM_{10} (Schneider *et al.*, 2014). In Dublin Ireland, almost all the fixed site monitoring stations (FSMs) had daily mean values > 50 μg/m^3 on several days during 2013 (see Table 1.1).

Table 1.1: Summary statistics for daily PM_{10} concentrations in Dublin Area in 2013

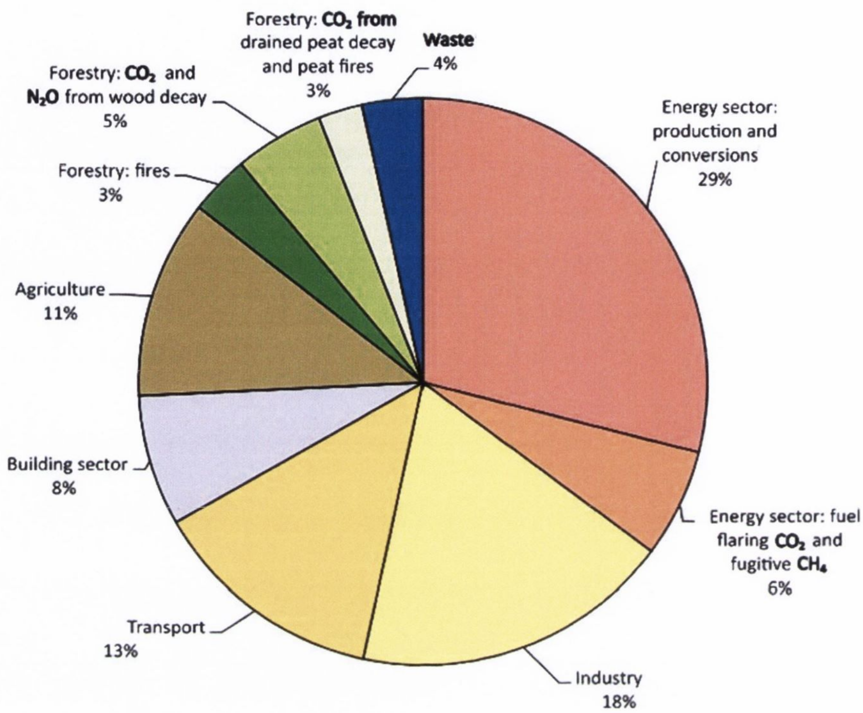
Statistics	Winetavern	Rathmines	Phoenix Park	Blanchardstown	Dun Laoghaire	Ballyfermot	Balbriggan	Davitt Road	Finglas	St Anne's Park	Tallaght
	μg/m^3										
Annual mean	14	17	14	20	17	12	25	13	15	19	17
Median	12	14	11	17	14	10	21	11	13	18	13
% data capture	93	99	94	100	84	93	93	94	92	99	100
Values >50*	3	8	3	11	5	2	15	1	3	0	5
Daily Max	60	76	72	89	82	62	100	59	64	50	77

*PM_{10} daily limit for the protection of human health: No more than 35 days in a year can be >50 μg/m^3 for an area from 2005. *Source: O'Dwyer (2013)*

In addition, annual PM values are also close to the WHO 20 μg/m^3 limit value. Exposure to PM can cause damage to the central nervous system, cardiovascular disease, irritation to eye, ear, nose, and throat, difficulty in breathing, respiratory irritation, inflammation, infections, asthma, influenza, reduced lung function, low birth weight, premature birth, impaired lung development, possible birth defects, and possibly autism (Katsouyanni *et al.*, 2010; US EPA, 2012; Dabney, 2013). Katsouyanni *et al.* (2010) predicted a decrease of 15 premature deaths per 100 000 inhabitants if PM concentrations were reduced to 20 μg/m^3 on all days in Europe.

Anthropogenic activities are the primary sources of these pollutants. The United Nations Environment Programme - UNEP, (2012) noted that the energy sector (35%), industry sector (18%), and transport sector (13%) were the top three sources of GHGs in 2010 (see Figure 1.1). In the EU, CO_2 emissions from transport increased by 25% in 2007 compared to 1990 and had a share of 23.1% of the EU27 CO_2 emissions (EC, 2010). More than 71% of these emissions in 2007 originated from road transport (EU, 2012). In other words, road transport is responsible for approximately one-fifth of the EU's total CO_2 emissions (Hill *et al.*, 2012). Passenger cars alone are responsible for about 12% of EU CO_2 emissions. This is a cause for concern due to the present and predicted passenger transport growth rate, which was estimated to increase by 35% between 2000 and 2020 (DGET, 2006). In addition, important precursor compounds to tropospheric ozone (O_3) and secondary organic aerosol formation, such as VOCs, CO and NO_x are predominantly emitted from such transport vehicles (Bradley *et al.*, 1999; Warneke *et al.*, 2007; Baker *et al.*, 2008; Parrish *et al.* 2009; Schneidemesser *et al.*, 2010).

Similar to CO_2, the release proportions of air pollutants that cause adverse impact on human health vary across different sectors. For instance, commercial, institutional, and household emissions were the highest contributory source of PM_{10} in the EU, followed by the industrial and road transport sectors in second and third position respectively. The first position remained unchanged for $PM_{2.5}$, however second and third positions were reversed (EEA- European Environmental Agency, 2014).



Source: UNEP (2012)

Figure 1.1: Global GHGs emissions in 2010

Transport sector is one of the top three polluting sources from both climate change and human health impact perspectives in the EU. The Transportation Research Board-TRB, (2002) also noted that vehicle emissions have become the dominant source of air pollutants, including CO_2 and PM in many areas. These pollutants are a result of the burning of fossil fuel inside internal combustion engines, however these can also be emitted as a non-exhaust pollutant, *e.g.* PM from brake and tyre wear during vehicle movement (Grigoratos and Martini, 2014). Zhang and Batterman (2013) noted that traffic congestion increased vehicle emissions and degraded ambient air quality, and caused excess morbidity and mortality for drivers, commuters and individuals living near major roadways. As daily human activity patterns are highly related to the transport sector, it is necessary to reduce population exposure to PM_{10} while in contact with traffic along with reducing the contribution of the transport sector to climate change through its CO_2 emissions.

1.2 Combating the release of air pollution emissions

The national, regional or international governments are setting policies and initiatives to combat climate change and improve air quality following framework conventions, guidelines and commitments.

As a result of the environmental impacts of air pollution emissions, global leaders at the 15th United Nations Framework Convention on Climate Change (UNFCCC) Conference of the Parties, held in 2009 at Copenhagen, aimed to limit the future increase in global mean temperature to below 2°C (UNFCCC, 2010). For the road transport sector this means the average vehicle fleet emissions rate to be achieved by all new cars is 130 g/km CO_2 by 2015 and 95 g/km CO_2 by 2021. These targets represent reductions of 18% and 40% respectively compared with the 2007 average fleet emission rate of 158.7 g/km CO_2 (EU, 2014a). In order to achieve these, policies target many initiatives and technologies are being introduced in the transport sector. These cover a wide range of areas in road transport such as direct interventions on vehicle movement, *e.g.* fuel tax (Sterner, 2007), congestion pricing (De Palma and Lindsey, 2011), parking pricing policies (Jansson, 2010), overall system management (Michaelis and Davidson, 1996); shifting to cleaner modes of power generation and low-emissions vehicles (Oltra and Jean, 2009; Thiel *et al.*, 2010; Ogden and Anderson, 2011); shifting to alternative fuels (EC,2007) and fuels with reduced sulphur content (Minjares *et al.*,2013); improvements in public and sustainable transport (Lautso, *et al.*, 2004); carbon tax systems (Giblin and McNabola, 2009; Hennessy and Toi, 2011) and soft policies to raise public awareness of carbon footprints and to encourage the sustainable movement of people *e.g.* car sharing, information and education, research and development (Santos *et al.*, 2010) and Eco-Driving (Santos *et al.*, 2010; IEA, 2012).

The WHO updated its guidelines on thresholds and limits for air pollutants in 2005. These air quality guidelines were the most important scientific reference point for EU guidelines (Oberthür and Gehring, 2006). The European Commission's Air Quality Framework Directive of 1996 was superceded by the Ambient Air Quality and Cleaner Air for Europe (CAFE) Directive (2008/50/EC) in May 2008. The CAFE Directive was transposed into Irish legislation by the Air Quality Standards Regulations 2011:S.I. No. 180 of 2011 (EPA, 2014a). In order to reduce PM exposure, the WHO (2013) concluded that policy makers should consider regulatory measures (*e.g.* limits for emissions from various sources), structural changes (such as changing modes of transport) as well as encouraging behavioural changes by individuals (*e.g.* using cleaner modes of transport, driving more efficiently).

From the wide range of policies and interventions which have been proposed or enacted, it can be seen that individuals may play a role in order to reduce CO_2 as well as reducing their personal exposure to air pollution in transport.

1.3 Smarter-driving: a car user's strategy?

A strategy which utilises the role of individuals and encourages the reduction of vehicle emissions intensity at end user level is Eco-Driving, a driver behaviour based method which has begun to receive more focused attention in literature (Beusen *et al.*, 2009; Barkenbus, 2010; Sivak & Schoettle 2012, Alam & McNabola, 2013a, b). Eco-Driving has been defined as a decision making process which influences the fuel economy and emissions intensity of a vehicle to reduce its environmental impact (Sivak and Schoettle, 2012). These decisions include: vehicle maintenance, route selection (Eco-Routing), vehicle loading and on-road driving control. However, only dynamic aspects of this definition (*i.e.* route selection, and on-road drive) have been considered as a part of smarter driving in this thesis. Route selection in the Eco-Driving concept refers to driving on a route that offers lowest fuel consumption and CO_2 emission. As a part of a smarter driving routing decision, the route with the lowest exposure may also be considered. Research has indicated that traffic and congestion drive poor air quality and contribute to increased risks of morbidity and mortality for commuters and individuals living near roadways (WHO, 2005a; HEI, 2010; Zhang and Batterman 2013). Zhang and Batterman (2013) further noted that exposure risk associated with congestion must consider travel time, the duration of rush-hour, and congestion-specific emission estimates. Tasi *et al.* (2008) reported lower travel time causes lower exposure to PM in comparison to bus and MRT. Karanasioua *et al.* (2014) reported from a European study that personal exposure to PM_{10} during car commuting is highly dependent on traffic intensity, speed and the type of ventilation inside the car. Zhang and Batterman, (2009) reported that a 30 min/day travel delay accounted for 14 ±8% of $PM_{2.5}$ for a typical working adult on weekdays. In short, congestion lowers the average speed, which increases travel time and exposure on a per vehicle basis (Zhang and Batterman, 2013). In addition, significant spatial variation in PM_{10} concentrations in cities was also reported in many studies (Eeftens *et al.*, 2011; Chen *et al.*, 2010a, Dons *et al.*, 2013a). Thus, avoiding high traffic intensity areas, congestion and highly polluted areas may offer a smarter routing solution.

Several recent research projects *e.g.* Eco-Drive (ecoDriver factsheet, 2012) and PEACOX (EU, 2014b) under the Framework Programme 7 of European Union may provide a useful indication of the importance given to Eco-Driving and Eco-Routing as potential policy options for lowering emissions and exposure. A number of Eco-Driving field trials outlined significant benefits from Eco-Driving (Boriboonsomsin *et al.*, 2010; Strömberg and Karlsson, 2013; Wang *et al.*, 2011; Ho *et al.*, 2015). However, many scientific experiments have provided conflicting views on the emission reduction, network performance as well as the accident potential of Eco-Driving, where negative impacts have been reported in several cases (Ando and Nishihori, 2011; Qian and Chung, 2011).

Luo *et al.* (2013) reported a significant amount of reduction of population exposure to air pollution that could be achieved with the implementation of intelligent routing algorithms which result in an increase of about 10% in travel time. However, the impact is unknown If routing is based on minimising personal exposure of the driver. Personal exposure of driver/commuter can be defined as the amount of particular pollutant inhaled during a travel; thus, personal exposure is a function of air pollution concentrations in the roadway, the contact time with the pollutant during travel/travel time and breathing rate of the driver/commuter. If routing is based on lowest CO_2, or fuel consumption, which is highly related to vehicle speed (and thus travel time) it is predicted that this may also lower personal exposure. Similarly, Eco-Routing, or choice of a route that causes lower emissions among a set of alternatives has also been reported for its potential to reduce emission in many experiments (Ericsson *et al.*, 2006; Ahn and Rakha, 2008), but may have some logical drawbacks of shifting congestion elsewhere, increasing travel distance and time (Stren, *et al.*, 1996; Boyle and Mannering, 2004). In addition, the emission factors that are applied at present for Eco-Routing may not be adequate for vehicle routing information (Kang, *et al.*, 2011).

Given the many conflicting views and limitations which are present in literature a need exists to examine in detail the environmental impacts of Eco-Driving and vehicle routing. This proposed research for submission for Ph.D investigates these conflicting aspects of this smarter driving policy and technology.

1.4 Objectives of PhD research

The overall research question to be addressed in this thesis is: Can smarter driving, using Eco-Driving and/or Eco-Routing, reduce personal exposure to air pollution and reduce the climate change impacts of car travel? In order to investigate this question the following objectives will be addressed in this thesis. In addition, several sub-questions will also be developed and answered in the coming chapters of this thesis in order to address the overarching question:

- A review of the literature on the environmental and human health impacts of Eco-Driving and Eco-Routing policy and technology.
- An investigation of the impacts of Eco-Driving on CO_2 emissions, fuel consumption and traffic congestion at fleet level and in -congested urban road networks.
- An assessment of the impact of Eco-Routing on CO_2 emissions.
- An assessment of the impact of Eco-Routing on personal exposure.

Several aspects of smarter driving policy have been shown to be questionable, or to have scope for improvement in the literature. Thus, those issues associated with smarter driving have been assessed under this research in relation to their impact on the environment and human health. The results of this research will refine the idea of smarter driving for commuters into a more effective policy. For this, usage of modern research techniques, modelling and simulation of the environment, and real world field trials have been deployed. This research investigation deals within the domain of environmental engineering and intelligent transport systems engineering.

Contributions to both concepts for policy formulation and model development have been considered as the novel aspects of this Ph.D research. The following publications were aimed to achieve this.

- ALAM, M.S., & MCNABOLA, A. (2014). A Critical Review and Assessment of Eco-Driving policy & Technology: Benefits & Limitations, Transport policy, 2014, vol. 35, issue C, pp 42-49.
- ALAM, M.S., & MCNABOLA, A. (2015). Exploring the modelling of Spatio-temporal variations in air pollution within the land use regression framework: Estimation of PM_{10} concentrations on a daily basis, Journal of the Air & Waste Management Association, Published in January, 2015.

- ALAM, M.S., & MCNABOLA, A. (2014). Network wide Impact of acceleration and deceleration operation of the Eco-Vehicles in different network configurations.. (Under Preparation).

1.5 Context of this research

This research was carried out as part of the Persuasive Advisor for CO_2-reducing cross-modal Trip Planning (PEACOX) project (2011-10-01 to 2014-09-30) funded by the European Union Framework 7 programme (EU, 2014b). The PEACOX project was designed to develop a persuasive multi-modal mobile trip planner for reducing the CO_2 consumption of travel in Dublin and Vienna. As a part of the project, emission and exposure models were developed and applied to both cities. The project was also restricted to the available data in both cities in certain aspects of this research.

Literature Review

Chapter 2

This chapter has been partially published in: ALAM, M.S. & MCNABOLA A. A Critical Review and Assessment of Eco-Driving policy & Technology: Benefits & Limitations, Transport Policy, 35, 2014, p42 - 49

2.1 Introduction

Eco-Driving as a part of the smarter driving was reviewed critically. All the aspects of the Eco-Driving, starting from the concept were discussed in this chapter. Policy, field trials, and micro-simulation results regarding Eco-Driving were analysed. Eco-Routing was also discussed from the perspective of economic, transport and environmental impact. The latter impact of Eco-Driving is the main focus of this research, and thus the literature review focuses on the environmental impacts. Micro simulation of Eco-Driving and modelling of emissions were thus also required as part of the review. To understand the modelling exercise and carry out the research ahead, modelling platforms that were applied in previous research were also reviewed.

The Eco-Routing concept involves the selection of a route from a set of alternatives that offers either lowest CO_2 or fuel consumption. Similar to this, healthy routing may involve lowest exposure to pollutants while driving. Unlike fuel consumption or emissions level from vehicles which remains within a certain range, pollutant concentration in a roadway is unpredictable. Thus, an air quality model may be required to carry out the healthy routing exercise. The final part of the literature review on routing based on minimum exposure, includes a review of air quality models.

2.2 Eco-Driving: a critical review of the concept

Eco-Driving is a fuel efficient way of driving and, according to Sivak and Schoettle, (2012) Eco-Driving may be classified as: strategic decisions (vehicle selection and maintenance), tactical decisions (route selection and vehicle load), and operational decisions (driver behaviour). Several different strategies have been developed to date to promote Eco-Driving, including training courses, driving contests, and driving assistance tools (*e.g.* displays communicating suggestions (Kim and Kim, 2012) on vehicle speed or route choice).

2.2.1 Strategic decisions

Strategic decisions may aid in the reduction of the environmental impact of travel. Eco-Driving in this context includes the regular maintenance of vehicles (Sivak and Schoettle, 2012). Vehicle maintenance keeps vehicles emitting within their desired limits. Optimal tyre pressure and regular maintenance of the engine and emission control system are the two additional key strategic decisions. Tyres with increased rolling resistance can cause a significant drop in fuel economy (Sivak and Schoettle, 2012), while it has been reported that up to 40-50% of excess total emissions can be attributed to the deterioration of vehicle emission control systems over time (An and Ross, 1996). Borken-Kleefeld & Chen (2015) reported that CO, NO_X and Hydro-carbon (HC) emissions increases as a factor of 1.15 to 2.25, 1.2 to 3.4, and 0.1-9.6 respectively deepening on the vehicle size, emissions band and mileage of the vehicle use. Recent studies showed that fixing a faulty oxygen sensor can provide lower emissions by providing a better fuel economy, for instance accurate signals of air fuel ratio to the engine can provide up to 40% extra mileage (EPA, 2011).

2.2.2 Tactical decisions

Tactical decisions can also be made to limit the negative environmental impact of travel as part of Eco-Driving. These could include issues such as the optimum choice of route to limit CO_2 emissions or choices on vehicle loading to reduce fuel consumption and CO_2 emissions. It has been noted that an extra 45 kg of load in a vehicle was found to cause a 2% increase in fuel consumption (EPA, 2011). This increase in fuel consumption is also clearly dependent on the size of the vehicle, the length/time of travel, and the driving style of the driver.

Smaller engine vehicles would result in a higher increase in fuel consumption for the same increase in vehicle load, compared to vehicles with larger engines (EPA, 2011). However, the load factor is sometimes misleading, for instance, carrying an extra 45kg reduces fuel economy by <=2%, but an increase in load factor (*e.g.* for a 45kg additional passenger) reduces the per capita CO_2 consumption (Walsh *et al.*, 2008). This point also highlights the importance of how the environmental impact of Eco-Driving is quantified *i.e.* per person or per vehicle in this case. As will be seen later in this section, similar problems are highlighted by this research when considering the per vehicle impact of Eco-Driving versus the road network level impacts.

Numerous investigations have reported that a 15– 40% increase in fuel economy can be achieved (subject to road grade and congestion) through the selection of Eco-Routes, *i.e.* the optimum route choice limiting CO_2 emissions and fuel consumption (Sivak and Schoettle, 2012). It has been estimated that the choice of route using a fuel consumption and emission model can result in energy savings of up to 23% if motorists choose lower emissions routes (Ahn and Rakha, 2008). An investigation was conducted in Sweden to analyse fuel consumption and CO_2 emission using a navigation system where the optimisation of route choice was based on the lowest total fuel consumption. It was found that 46% of trips, which were the result of drivers' spontaneous choice of route, were not the most fuel-efficient. These trips could save, on average, 8.2% of fuel by using a fuel-optimized navigation system. This corresponded to a 4% fuel reduction in fuel consumption for all journeys (Ericsson *et al.*, 2006). While such positive results are encouraging, as discussed further in Section 2.5, there is a notably wide range in the claimed benefits of Eco-Routing.

In order to facilitate the Eco-Routing decision making process, driver assistance tools are required, such as on-board or online Eco-Routing navigation systems, disseminating the optimum route choice to drivers. However, existing driver assistance devices for Eco-Routing commonly use road-link based information to suggest eco-friendly routes (Barth *et al.*, 2007a). Some of the models determine the total emissions from a certain route based on either historical traffic data or fleet-wide average emission factors. Such models fail to take account of real world driving conditions, for example, if all drivers were to use such technology in a particular area and take the suggested Eco-Route, then this route would very quickly become congested, resulting in increased emissions. At present such an eventuality is not a problem as the penetration of Eco-Routing navigation systems among the population of drivers in most countries is low. If, however, Eco-Routing was to become widespread, current driver assistance technology would not operate satisfactorily in congested traffic networks. To avoid this limitation, it is necessary to connect such models with real time traffic information sources.

2.2.3 Operational decisions

Any vehicle is capable of producing much more emissions in real on-road driving conditions than its respective emission standard due to inefficient driving styles, traffic congestion, road grade, heavy winds, *etc.* Changes in driving style can be incorporated into an individual's operational decisions as part of Eco-Driving, reducing the emissions from a trip. This operational decision can either be developed by practice, or can be aided by tools enabling acceleration control *e.g.* an active acceleration pedal (Vlassenroot *et al.*, 2007), Intelligent Speed Adaptation (Vlassenroot *et al.*, 2011) and optimal gear change (Beckx *et al.*, 2007). Aggressive driving behaviour such as hard acceleration and braking, excessive speed, open windows, *etc.* results in higher emissions rates from a vehicle compared with a more gradual, smooth driving style. OECD/IEA, 2005 noted an increase of 25-48% fuel consumption due to aggressive driving. De Vlieger (1997) reported aggressive driving caused up to four times higher emissions than that of from normal driving. Such changes in driving behaviour have been shown to result in significantly higher reductions in emissions and energy consumption compared to other Eco-Driving decisions such as better maintenance practices (Shaheen *et al.*, 2011). Numerous investigations have reported that maintaining an Eco-Driving style can reduce fuel consumption by 5–30% (OECD/IEA, 2005; Zarkadoula *et al.*, 2007; Barkenbus, 2010; Boriboonsomsin *et al.*, 2010; Sivak and Schoettle, 2012). Such savings in fuel have subsequently resulted in monetary savings, for example, an estimation of 10.2% in fuel saving during an Eco-Driving training session of bus drivers in Athens subsequently estimated savings of over €6million per annum (Boriboonsomsin *et al.*, 2010). OECD/IEA, 2005 reported a 3.5% saving of fuel in Europe from national total by Eco-Driving. Again, as discussed further in Section 2.5, a notably wide range of potential savings has been reported in the literature.

Investigations have suggested that Eco-Driving with the aid of driver assistance devices can play a significant role in reducing emission and fuel consumption (Yang *et al.*, 2012). Eco-Driving indicative devices are designed to provide instantaneous fuel rate and CO_2 emissions information, also advising on acceleration/braking rates (Beusen *et al.*, 2009; Ando *et al.*, 2010). In these devices, engine data in real time and/or GPS data are used for emissions calculations. However the models working behind these existing devices are also subject to limitations from an emission modelling perspective and have scope for improvement. Similar to existing Eco-Routing models, many of the available Eco-Driving models are limited by their use of average emission factors to predict CO_2 emissions over a specific travel distance. Such models fail to take account of the smooth or aggressive driving style of a driver and therefore do not give an accurate representation of the environmental impact of operational Eco-Driving decisions. Future developments in models of this nature should account for detailed vehicle trajectories (*e.g.* Beckx *et al.*, 2010) in real time in order to capture periods of hard acceleration and increases in engine load.

Eco-Driving models with similar limitations have also been developed based on the average emission for a particular road link (*e.g.* link average speed or average emission factor) or based on normal driving cycles (Manzoni *et al.*, 2011; Kang *et al.*, 2011; CarbonDiem, 2012) Static Eco-Driving cycle (Mensing, *et al.*, 2014) has the same limitation of normal driving cycle of averaging of emissions during estimation. Other important methodological limitations of existing Eco-Driving models in practice are the omission of road grade information, wind impact, and hot/cold emission factors. Future research should also focus on the development of Eco-Driving models which includes the aforementioned factors to provide a more reliable estimate of its impact to users.

2.3 Eco-Driving policy

Based to a certain extent on the positive scientific evidence outlined in the previous section many national governments have adopted Eco-Driving policies as a means of reducing energy consumption and CO_2 emissions in the transport sector. Historical evidence for Eco-Driving was first found from an audience training background study by Department of Energy (DoE) in US in 1976. Other landmark training examples in this field included an effort by Wisconsin Clean Cities (US), a non-profit environmental group in 1994 and Eco-Driving training by the Swedish National Association of Driving Schools in 1998 (Quille *et al.*, 2012).

In 2001, the European Climate Change Programme (ECCP) estimated the potential for a significant reduction of CO_2 from the implementation of Eco-Driving training and education (SenterNovem, 2005). Also in 2001, 'Eco-Driving Europe' began to accelerate the establishment of Eco-Driving by providing guidance to the drivers (Eco-Driving Europe, 2004). Several European countries such as Finland, the Netherlands, Spain, Ireland and Germany have incorporated Eco-Driving policy within their national CO_2 reduction or climate change strategies (Hoed *et al.*, 2006, IEA, 2008 and Miller *et al.*, 2011). National policy in Ireland, for example, has been developed which recognises that driving style can significantly affect the amount of energy and emissions from a single vehicle (DTTS, 2009). In the Netherlands an Eco-Driving government programme forms part of national policy documents targeting CO_2 emission reductions from transport. In 2006, a CO_2 emission reduction of 0.3 Mega ton (Mton) and 0.6 Mton were found to be directly and indirectly related to these Eco-

Driving activities (Berg, 2007). A subsidy for the promotion of Eco-Driving has been provided since 2007 as part of the Swiss Energy Action Plan in order to promote fuel savings of between 10% and 15%, as well as fewer accidents, less wear and tear of vehicles, and greater protection of the environment (IEA, 2012). The European Union has also mandated the fitting of Gear Shift Indicators (GSI), which display shifting up or down signs on the instrument panel of all new cars from 2012, to ensure optimal gear changing and thereby improved fuel efficiency (Kojima and Ryan, 2010).

Eco-Driving is also a subject of transport policy interest in many Asian countries like China (Cheng *et al.*, 2012), Japan (IEA, 2008), and Korea (Kojima and Ryan, 2010). Eco-Driving as a government policy has also been in place in Japan since 2003 and government grants are available to subsidise Eco-Driving Management Systems. Recently, Korea, New Zealand and Australia have also commenced Eco-Driving policies (Symmons *et al.*, 2009; Kojima and Ryan, 2010) and the initiative has also been reported in North America (Shaheen *et al.*, 2011).

It is therefore clear that Eco-Driving is an initiative which has seen widespread adoption over the past decade. However, as discussed in the following sections, some limitations may exist for the claimed benefits arising from previous Eco-Driving investigations. In addition, research also exists which highlights the possible negative impacts of Eco-Driving on the environment. These negative impacts may have been overlooked by policy makers in many countries.

2.4 Network level impact

2.4.1 Eco-Driving style

Individual driver benefits from fuel savings through Eco-Driving have been reported in many studies (Sivak and Schoettle, 2012). In addition, Eco-Driving has been considered as a low-cost policy option that aids in achieving Kyoto and other climate change targets and improvements in air quality (OECD/IEA, 2005; SenterNovem, 2005). However, some research investigations have recently reported potentially negative issues that lower the credibility of the Eco-Driving initiatives.

An investigation was conducted at a signalised road junction where vehicles were equipped with dynamic Eco-Driving technology. It was found that there were indirect network-wide energy and emissions benefits to overall traffic, even at low Eco-Driving penetration rates (5–20%) among drivers if Eco-Driving was co-ordinated with traffic signals (Xia *et al.*, 2011). However, this investigation was based on car following theory with no turning movements incorporated in the network, which may not accurately represent real world practice. In contrast, another group of researchers used micro-simulation at intersections, and found that Eco-Driving based on moderate and smooth acceleration can cause negative environmental impacts with higher total emissions (Qian & Chung, 2011).

The relationship between vehicle speed, flow and traffic density is complex. Reducing the speed and acceleration of an individual driver may cause that individual's carbon footprint to reduce; however, overall CO_2 emission of vehicles on a section of roadway may increase at the traffic network level, as vehicles spend more time on a particular road. In congested traffic situations such low speed may cause a higher total link CO_2 due to higher numbers of traffic staying on a particular link for a longer time.

Wang *et al.* (2012) reported from simulation results that higher levels of CO_2 are emitted considering the entire network, as a result of Eco-Driving during moderate congestion. In addition, the introduction of speed/acceleration based Eco-Driving behaviour may reduce the signalised intersection capacity by allowing fewer numbers of vehicles to pass at an intersection for a given period of time. An investigation using micro-simulation on a ring road found that travel time was higher with a decrease in the level of service when Eco-Driving was incorporated in the model a free-flow condition (Wang *et al.*, 2012).

Kobayashi *et al.* (2007) reported that intersection travel time increases as a result of increased Eco-Driving vehicles in low and congested flow conditions. Such an increase in travel time on a road may cause a general limitation in the Eco-Driving concept for congested urban driving conditions. However, Eco-Driving on longer distance journeys (*i.e.* rural or highway) in the absence of a number of intersections and heavy traffic congestion may still achieve the claimed benefits of previous vehicle-based investigations. Furthermore, Eco-Driving in congested traffic for some public transport systems, such as buses with bus-only lanes may also not suffer from this potential limitation.

2.4.2 Eco-Routing

Eco-Routing strategy may also cause significant negative impacts at the network level, if fully implemented. A micro-simulation showed that increasing information (while an individual is at home before taking a trip) reduces total network trip duration (Stern *et al.*, 1996). However, research findings have also been reported which highlight that Eco-Routing does not necessarily reduce travel time (Ahn *et al.*, 2012). In such cases, drivers may offset the benefit of a less congested route by travelling at a higher speed. It has also been revealed that if drivers receive information on route changes to avoid adverse traffic conditions, they tried to minimise their travel time further by increasing speeds down-stream of congestion (Boyle and Mannering, 2004). An investigation of two large traffic networks confirmed that the Eco-Routed vehicles do not always save fuel compared to the standard user, and the fuel saving from Eco-Routing is sensitive to the network configuration, congestion levels, and the penetration of Eco-Routing vehicles (Ahn *et al.*, 2012).

2.5 Cross-comparison of research findings

As noted above, the reported benefits of Eco-Driving in the literature varies from 5 – 30%, which has made it an attractive option for policy makers to address national and international climate change mitigation targets. Table 2.1 and 2.2 presents a summary of a number of investigations examining the impacts of Eco-Driving on fuel and CO_2 emission. These investigations have been grouped into field trial investigations, reviews / reports, and modelling investigations.

It can be noted that the results of Eco-Driving investigations based on actual field trial data in real world driving conditions are typically at the lower end of the scale of claimed benefits, ranging from 4.8% to 6.8%. An exception to this is can be seen in Qian *et al.* (2013), where a range of savings from 2.9 to 18.7% were reported. This study was conducted at a 1 km straight racetrack with 3 temporary traffic signals installed. The variation in savings in this study was reported to be associated with the variation in the behaviour of individual drivers. In addition, Barth and Boriboonsomsin (2009a) also reported a savings of 13% based on a limited field trial experiment. This study compared several runs of an Eco-Driving vehicle with a non-Eco-Driving vehicle in freeway conditions which were unaffected by traffic intersections. Monetary savings and CO_2 emissions reductions based on these measured fuel savings are also reported in a number of studies. No study reported a negative impact from Eco-Driving based on field investigations. However, this is due to the fact that field trial investigations have focused exclusively on measuring the impact of Eco-Driving on individual vehicles, neglecting the impact on the entire fleet or network. Such an investigation would be more difficult to carry out in practice, and therefore this objective has only been addressed by modelling investigations to date.

Table 2.1: Summary of Eco-Driving Research Findings[+]

Authors	Type of Study/Objective	Methodology	Fuel Savings	CO_2 Emissions Saving
Rolim *et al.*, 2014	Field Trial; Eco-Driving training with feedback and no feedback	20 Drivers (11 were in control Group); 1364 days; 8137 trips	EDT: 4.8% fuel saving	6.56 g/km
Boriboonsomin *et al.*, 2010	Field Trial; instant feedback EDA device; tests without Eco-Driving training + Questionnaire	20 Drivers; 2 Weeks	EDA: City street 6%; Highways 1%.	---
Zarkadoula *et al.*, 2007	Field Trial; Training on a route, followed by real world driving.	3 drivers; Training on a 15 km route	EDT: 10.2% ED: 4.35% at actual traffic.	---
Qian *et al.*, 2013	Field Trial; Various positions of two Eco-Drivers on the platoon of 15 cars.	15 drivers; 1km straight road with three intersections.	ED: 2.9 to 18.7%	---
Beusen *et al.*, 2009 & Beusen & Degraeuwe 2013	Field Trial; Before and after training analysis.	10 drivers; 10 months	EDA: 6.7% overall; (20% of drivers achieved no fuel saving)	---
Ando *et al.*, 2011	Field Trial; A group of test runs in normal traffic condition.	15 vehicles run in sequence for 16 round trips on a 6.4km route over 2 days.	Improvement of 0.9km/l	---
Strömberg & Karlsson 2013	Field Trial: Group 1: EDA, Group 2: EDA+EDT, Group 3: Control.	54 Drivers; 16 km route, 6 week period	6.8%; No difference between group 1 & 2.	---
Rutty *et al.*, 2013	Field Trial: 3 phase study; ED course; monitoring and feedback; training.	Concluded result from final phase. one month for each phase	---	1.7 kg per vehicle per day
Barth & Boriboonsomsin, '09a	Simulation^^ and a limited field trial with EDA.	Freeway, Typical passenger vehicles	Simulation: 37% Experiment:13%	Simulation: 35% Experiment: 12%
Barkenbus, 2010	Review	Concluded from various researches.	ED: 10%; 42.8 billion litres at national level*	Optimal: 100 & Conservative scenario: 33 million metric tones

[+]Note: estimations were based on year *2005; ED= Eco-Driving in general; EDT= Eco-Driving training/coaching; EDA= Eco-Driving assistance device; ^^ 20% penetration of Eco-Driving car.

Table 2.2: Summary of Eco-Driving Research Findings (Continued)[+]

Authors	Type of Study/Objective	Methodology	Fuel Savings	CO_2 Emissions Saving
Sivak & Schoettle, 2012	Review	Analysing data from different sources.	ED: Speed control-7-30%; ED: Aggressive driving: 20-30%.	---
Berg, 2007	Policy Research	Concluded from programme data^.	---	ED": 0.3 Mtons directly ED": 0.6 Mtons indirectly
Wilbers & Wardenaar, 2007	Report	Concluded from various researches.	ED": 10% saving	---
Mensing *et al.*, 2011	Model developed for potential fuel gain.	Algorithm tested for free-flow urban setting	34% maximum saving,	---
Kobayashi, *et al.*, 2007	Model comparison between no, all and 50% eco driving.	1 km straight road with two traffic signals	---	Increase total CO_2 in near capacity condition.
Saboohi & Farzaneh 2009	Algorithm development using micro-economic theory.	Tested for five scenarios considering the traffic level and accidents.	1.5l/ 100km	---
Qian & Chung, 2011	Model; Moderate/smooth acceleration (at different Eco-Driving penetration rates).	One multi-lane intersection	---	-Reduce individual CO_2 -Increase intersection level CO_2
Miller at al., 2011	Report	Concluded from various researches.	EDA/ Moderate ED: 15% savings.	---
Klunder *et al.*, 2009	Report	Concluded from various researches.	EDT-5-15%; EDA-10%	---

[+]Note: estimations were based on year ^2006; ED= Eco-Driving in general; EDT= Eco-Driving training/coaching; EDA= Eco-Driving assistance device; "ED includes Driving school curriculums; Re-educating licensed drivers; Fuel saving in-car devices, Tyre pressures and Purchasing behaviour.

The claimed benefits of Eco-Driving investigations based on reviews and reports can be seen to be typically higher than the reported benefits claimed during field trials. Figures are reported typically in the range of 10 – 15% fuel savings, with some investigators claiming benefits of up to 30%. While in certain instances Eco-Driving has been shown to result in fuel savings of this level the majority of the evidence would suggest that on balance across the spectrum of drivers, vehicle types and traffic conditions, the individual benefits of Eco-Driving have been found to be closer to a value of 5%. In addition, it was also reported that this effect of Eco-Driving is gradually lost (e.g. +0.21%/week) in the months after the course (Beusen & Degraeuwe, 2013). As such, these review and reports, some of which have been compiled to make recommendations to the EU and various other governments appear to give an inflated impression of the benefits of Eco-Driving compared to the majority of reported field studies. In addition, as no field study has attempted to quantify the network level impact of Eco-Driving during urban congestion, recommendations on the implementation of the concept as a policy are not based on a complete picture.

Table 2.3 presents a cross comparison of published literature on the benefits of Eco-Routing on CO_2 emissions and fuel consumption. Again, these are grouped according to the type of investigations carried out; modelling and reviews. While a number of the modelling investigations did use measured traffic data to make predictions on Eco-Routing no investigation could be described as purely a field trial. As such investigations have yet to measure in real world driving conditions, the effects of Eco-Routing on fuel consumption or emissions. Modelling investigations which used measured traffic data did so as a comparison of predicted fuel consumption and/or CO_2 emission from alternative 'Eco-Routes '. In addition to the use of measured traffic data, the modelling investigations used

Table 2.3: Summary of Eco-Routing Research Findings

Authors	Type of study, Objective	Methodology	Fuel Savings	CO_2 Emissions Saving
Ericsson *et al.*, 2006	Model: real world data and model application.	Most fuel economic routes were compared against original route	8.2% for 109 journeys > 5 min 4% prediction for all routes	---
Ahn & Rakha, 2008	Model: real world data and model application.	Route choice (Arterial Vs. Highways) behaviour was investigated using GPS data.	18-23% (Peak hour comparison) 19% (identical travel time)	20%(Peak hour comparison) 18% (Identical travel time)
Scora *et al.*, 2013	Model: Eco-Routing algorithm using meso-scale data	Road grade and vehicle weight have been considered for the shortest route.	12.7% reduction of fuel consumption, considering the road grade between empty and loaded vehicle.	---
Ahn & Rakha, 2013	Model: city wide micro simulation & single sample case study	Tested with different Eco-Driver penetration rates and network configuration	3.3% - 9.3% in comparison to travel time minimising algorithm.	(Reduce travel distance, but not necessarily travel time, depends on network configuration).
Kang *et al.*,2011	Model: Development of a link based driving pattern classifier for Eco-Routing & single sample for illustration	Tested Eco-Routing against time priority and shortest path routes for one trip	---	Eco route vs. Time priority: 23%* Eco route Vs. Distance priority: 1%*
Andersen *et al.*, 2013	Model: Development of Eco-rating system & single example for illustration	Calculate eco-weight for links in a network based on GPS and fuel consumption data during morning peak.	Eco route Vs. Time priority: 28%* Eco route Vs. Distance priority: 1.7% *.	---
Boriboonsomin *et al.*, 2010	Model: Eco-Routing navigation system vs. shortest time and path routes; One example for illustration.	Random origin- destination; Airport to Los Angles city centre during evening peak hour.	Eco route Vs. Time priority: 32%* Eco route Vs. Distance priority: 1.4%*.	Eco route Vs. Time priority: 33%* Eco route Vs. Distance priority*: 1.8%.
Barth *et al.*, 2007	Model: Eco-navigation technique and 4 case studies	Two freeway routes having approximate 44 kilometres considered different congestion scenario	0.35-42% saving depending on congestion level*.	0.60-42% saving depending on congestion level*.
Sivak & Schoettle, 2012	Review	Analysed data from different sources.	15-40% considering congestion and road grade.	---
Klunder *et al.*, 2009	Report	Analysed from past research data.	---	2.1% considering route choice and congestion avoidance.

* time and distance may vary while considering fuel saving between an Origin-Destination pairs

methodologies such as micro-simulation and routing algorithms to estimate the impact of Eco-Routing on fuel consumption and CO_2 emissions. The reported fuel savings arising from Eco-Routing for these investigations shows a considerable range from as low as 0.35% up to 42%. Savings achieved from the choice of route can be seen to be heavily affected by the level of congestion and by road grade across the reported investigations. In the case of Scora *et al.* (2013) account was taken of road gradient and vehicle weight and the 12.7% reduction in fuel consumption reported is a comparison of a hilly versus flat route with reduced vehicle load.

Results from many of the studies presented were obtained comparing route choices with one origin and one destination (Barth *et al.*, 2007; Ahn and Rakha, 2008; Boriboonsomsin in *et al.*, 2010; Kang *et al.*, 2011; Andersen *et al.*, 2013).The higher potential for fuel consumption and CO_2 savings reported in these studies was strongly related to the level of traffic congestion present. Where non-peak hour traffic and/or low traffic intensity roads were concerned, fuel savings potential were of the order of less than 10% (Ericsson *et al.*, 2006; Ahn and Rakha, 2013). It should also be noted that Eco-Routes were not typically found to be the shortest distance route or the shortest time route (Ahn and Rakha, 2008; Boriboonsomsin *et al.*, 2010).

The two reviews/reports which dealt with Eco-Routing found during this study gave entirely conflicting summaries of its potential. 15 –40% and 2.1% are reported as the potential fuel and CO_2 emissions savings by Sivak and Schoettle (2012) and Klunder *et al.* (2009), respectively. As can be seen from Table 2.3, the reported literature would suggest that the actual range is 0.35 –42% and the extent of the variation depends heavily of the level of congestion present, with low congested levels limiting the impact of Eco-Routing.

In summary, the benefits of the various Eco-Driving initiatives described thus far for individual vehicles and at road network level are presented in Table 2.4, based on the evidence provided in the literature. It is clear that CO_2 emission and fuel consumption savings can be made by more efficient driving styles, route choice and other environmentally friendly decisions. However, conflicting views on the traffic network level impact of a number of Eco-Driving techniques in congested urban traffic conditions have also been highlighted, where the weight of evidence would suggest a negative impact.

Table 2.4: Eco Driving Initiative, system effects vs. individual impacts.

Eco Driving Initiative	Reported Individual Impacts	Reported System Effects
Eco-Routing	• Reduced travel time • Reduced fuel consumption • Reduced CO_2 emissions • Longer trip in comparison to shortest path.	• Speeding downstream of congestion • Based on network configuration, reduction of vehicle travelled distance, but not necessarily travel time.
Tyre Pressure/ Vehicle Load	• Reduced fuel consumption. • Reduced CO_2 emissions.	• No Impact.
Eco-Driving Training/Assistance Devices	• Reduced fuel consumption. • Reduced CO_2 emissions. • Improved driver behaviour • Not always reduce travel time.	• Effect on vehicle headway thus, reduced intersection capacity. • Increased congestion, fuel consumption and CO_2 emission at road network level.

The available evidence also suggests that fuel and CO_2 emissions savings could be achieved through the adoption of Eco-Routing behaviours and technologies in single trips in both congested and non-congested traffic situations.

2.6 Application of micro-simulation software for Eco-Driving impact assessment

As highlighted above conflicting views are in evidence across the literature on the road network level impacts of Eco-Driving and much of this work has been carried out using micro-simulation as the measurement of this impact in the field would be difficult to execute. Thus micro-simulation and its application to Eco-Driving assessment warrant further investigation.

Micro-simulation for the purpose of assessment of Eco-Driving has only been applied in a few studies as mentioned in section 2.5. These studies were either designed to assess the impact of changes in general driving behaviour, or assessment of new technology that places a limit on driver behaviour (conforming to Eco-Driving). Qian and Chung (2011) applied the microscopic traffic simulator AIMSUN and assessed how the variation of acceleration rate adopted by drivers directly affects traffic performance. Eco-Driving in this study was defined as vehicles having acceleration profiles with a 10% and 20% reduction in maximum acceleration rate. However, the simulated network in this study consisted of a single through lane and a signalised intersection where traffic volumes were 300 veh/h, 600 veh/h and 1000 veh/h for different scenarios. The later traffic volume was slightly over the capacity regarding signal timings. The traffic signal design included a 30 second green light followed by a 20 second red light. Results were taken from five random simulations for each scenario for one hour, and results from before-and-after comparisons indicated potentially negative impacts when using Eco-Driving. However the road network in this study was very simplistic and the results could not necessarily be applied to a large network of significantly different intersections.

Kobayashi *et al.* (2007) trained 28 drivers with Eco-Driving education (*i.e.* No unnecessary idling, avoiding sudden, sharp acceleration, and the use engine brakes efficiently) and subsequently obtained acceleration, deceleration curves from field measurements. These curves from the field data were used for an Eco-Driving evaluation using VISSIM. Ten simulations were conducted (one hour for each scenario) using different random-number seeds in a 1000m straight two-lane road where two traffic signals were kept at 300m and 600m apart. These signals consisted of 30-second green followed by 3-second yellow and 27-second red light. The offset of consecutive signals was not considered for simplicity. The simulations were executed for different traffic volumes from 100 veh/h to 1800 veh/h. Results showed that the emissions from of Eco-Driving showed improvement in comparison to normal driving until the traffic volume reached 1700 veh/h where a negative impact from Eco-Driving was observed for emissions. In addition, in-order to avoid such a negative impact, this investigation assessed the effect of switching traffic flow from Eco-Driving to normal driving at this critical point. In reality this was assumed to simulate the use of a variable-message board in traffic.

Xia *et al.* (2011) defined Eco-Driving as adjustment of driving trajectory in relation to traffic signals and carried out a micro-simulation investigation to assess the impact of this definition of Eco-Driving on network level CO_2 emission. PARAMICS was used to simulate a two-way single lane arterial road with 11-signalized intersections which were 500m to 650m apart. However, no turning movements were designed or tested. Once a technology-equipped vehicle came within 300 m of a traffic signal, the model replaced its default velocity profile with one based on a dynamic Eco-Driving algorithm. Each intersection was equipped with a fixed-time traffic light with three signal phases. The speed limit was set to 40 mph for the entire corridor. In the experiment, the maximum fuel saving and emission reduction were found during medium congestion (corresponding to traffic volume of 300 veh/lane/h) and with low penetration rates of Eco-Driving cars (5%, 10% and 20%).

Wang *et al.* (2012) studied the impact of two algorithms of adapted cruise control (*i.e.* efficient driving considering with and without minimising CO_2 emissions) that leads to improvement in traffic flow by restricting deviations from the desired speed profile and/or the desired distance to a proceeding vehicle. These algorithms were simulated to represent the use of Vehicle-to-Vehicle (V2V) and Vehicle-to Infrastructure (V2I) communications technology, whereby the movement of vehicles may be controlled to improve the efficiency of driving in relation to the road network and in relation to other vehicles. This simulation was on a 1 km single lane ring road and the result from 5 minutes runs concluded that the CO_2 emissions rate per vehicle at free flow conditions were lower (5.2g/km/veh) when using algorithms considering the minimisation of CO_2 emissions than that of algorithms without a CO_2 consideration. In addition, the traffic flow (veh/h) was also found to be lower for the algorithm with CO_2 consideration, and difference in total CO_2 was 26.7% due to the lower flow. However, under congested conditions, the CO_2 emissions rate was 10.5 g/km/veh for the algorithm with CO_2 consideration and the traffic flow is also 25% higher than that of the algorithm without CO_2 consideration. Under congested conditions higher traffic flow caused more CO_2 emissions which were a contradiction with the common expectation that more CO_2 may result from congestion induced by slow driving. This exception to the more common finding has been occurred in this study due to the improvement of traffic speed in the network as a result of the simulation of V2V communication among vehicles. In addition, it is also noted that increase in average density (veh/km) increases vehicle flow (veh/h) for eco-algorithm which eventually increases CO_2 emissions rate (0.75%).

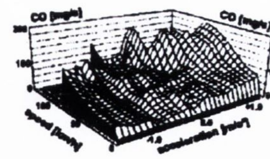
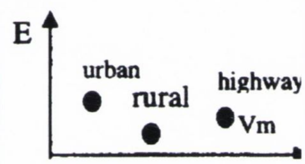
In short, it has been noted that a number of research investigations were conducted for Eco-Driving which is mostly focused on field trial using individual or a small number of vehicles, probably due to resource limitations. For the fleet level such analysis is only feasible by simulation or modelling and the weight of evidence would suggest a potential negative environmental impact with increasing numbers of Eco-Driving vehicles under heavy traffic. However conflicting views were present and these often had a number of methodological limitations such as the use of very small road networks with one intersection or a small number of intersections and with many restrictions on vehicle movement. Some studies showed the potential to overcome these negative impacts with the use of V2V or V2I technology Thus, actual Eco-Driving that comprises gentle acceleration and deceleration by Eco-Drivers on a large network for different car penetration rates in a different congestion levels requires further research. In addition, it is also unknown how supporting technology equipped vehicles in large networks may contribute to environmental impact.

2.7 Emissions modelling at different scales of application

Emission modelling may be carried out at different scales ranging from the level of individual trips to road links to city-wide road networks and national level models (Smit *et al.*, 2008a). These models also require different amounts and resolution of data *e.g.* average vs. instantaneous speed, road categories, road grade, *etc.* Strum *et al.* (1996) classified models with basic data requirements for different scale of models as shown in Table 2.5.

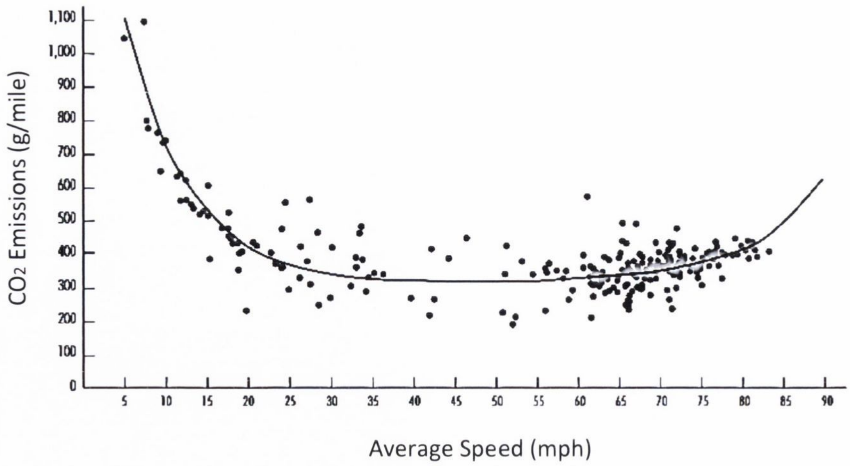
Models acting at different levels generally show similar trend, or result. However, sometimes trip level models are more accurate, and may show different trends than that of meso level models. Int Panis *et al.* (2011) estimated the relative change in emissions for 5 pollutants for a reduction of speed limit from 50 to 30 km/h in urban traffic, and found that trip level models showed a decrease for PM while the macroscopic approach predicted an increase.

Table 2.5: Emissions model at different scales.

Driving behaviour	**Emission Factors**	**Source**
Significant for each road* Emission calculation based on actual driving behaviour	To be defined for each driving pattern	Emission maps 
To be grouped into the streets with the same driving characteristics (fine classification)** Emission calculation based on specific road categories	Predefined function for different street categories	Emission functions 
To be grouped in some main street classes (coarse classification)*** Emission calculation based on vehicle kilometres travelled	Predefined factors for different street categories	Emission factors 

Note:* Related to trip level emissions modelling;**city or regional level; *** meso scale; *Source: modified after Strum et al. (1996).*

However, the general trend for CO_2 and three other pollutants were similar between the two models. Uncertainty associated with CO_2, and CO estimation is lower and generally follows a U shaped curve for steady driving condition for all the vehicles (Figure 2.1). Barth and Boriboonsomsin, (2009b) developed the following CO_2 emissions curve using CO_2 emissions from average speed in trip segments representing speeds in different category of roads (e.g. Freeways). OECD, (2006) noted that, in steady driving conditions, CO and CO_2 emissions, in terms of g/km travelled, are highest at very low travel speed (15 km/h or, 9.3mph or less).



Source: Barth and Boriboonsomsin (2009b)

Figure 2.1: Emission-speed plot of individual trips or segment of trips.

Emission models based on average vehicle speeds (second and third row of Table 2.5 or Figure 2.1) do not explicitly account for congestion since they do not incorporate input parameters that describe the presence or nature of congestion (Smit *et al.*, 2008a). Models based on average speed counts associated with specific traffic conditions are derived by accounting for differences between a desired average traffic speed and other environmental parameters, and those associated with the standardised driving cycle. Since emission rates are based on an average speed in fixed driving cycles, there is only a limited ability to consider alternate driving patterns, such as Eco-Driving. While different driving cycles can produce identical average speeds, emissions depend strongly on the specific acceleration and deceleration patterns of the vehicle fleet. Thus, actual emissions can be significantly underestimated by such models since acceleration, deceleration and aggressive driving patterns are not fully represented (Joumard *et al.*, 2000).

Manzie *et al.* (2007) demonstrated that mitigating stop-and-go motions by anticipating downstream traffic conditions could generate a fuel saving of up to 33% for vehicles equipped with intelligent drivetrains. Stop-and-go behaviour in congestion may provide a different driving profile with the same average speed (*e.g.* two routes might provide same average speed of 30km/h, but one might have congestion in several links and higher speed limit in others whereas, the other route might provide constant 30km/h speed in all the links). In addition, hard acceleration may also change the fuel burning pattern such as inducing fuel rich conditions which may increase HC and CO emissions even with the presence of a catalytic converter. On the other hand, excess NO_x emissions can occur in lean fuel mode coupled with high temperature (Zhang *et al.*, 2011), and the presence of unburned fuel may increase PM and HC emissions (Cappiello, 2002).

Information on second by second vehicle trajectories is important for modelling vehicle emissions in detail because during a hard acceleration period the engine load increases significantly. Investigations have indicated that during periods of high engine loading CO is the main output as fuel to air ratio is not sufficient to produce CO_2 (Marsden *et al.*, 2001).

Other important methodological limitation of existing real-time emissions modelling applications are the omission of road gradient and hot and cold emission factors. A number of studies reported that the CO emission rate increases as road grade increases for light-duty gasoline vehicles (Kelly and Groblicki, 1993; Kean *et al.*, 2003; Zhang and Frey, 2006). Therefore emission factors vary for CO and CO_2 significantly in these cases. In addition, wind speed may also be a significant factor which affects the aerodynamic drag on a car, increasing or decreasing emissions.

In short, average speed based models inaccurately estimate emissions for specific road segments and traffic conditions (Smit *et al.*, 2008b). Joumard *et al.* (1995) presented a model to calculate emissions as a function of the vehicle type and its instantaneous speed and acceleration in the form of a two-dimensional function for all vehicle types.

Many improvements have been developed to date with this and similar concepts, including application of a multi-dimensional engine map, or models based on actual driving patterns, using instantaneous speed and acceleration/deceleration profiles as inputs. These models are often labelled as instantaneous or modal models.

2.7.1 Emissions modelling at the meso-scale

Emissions models that were developed at the meso-scale are often used in the preparation of an emission inventory for GHG emissions compliance at national level. As this research is more focused on the prediction of emissions at the trip level only a short overview of existing meso-scale models are discussed here.

The MOBILE model was developed by the US Environmental Protection Agency to estimate the emission rates from on-road motor vehicles at national level. However, this model is now almost replaced by the MOtor Vehicle Emissions Simulator (MOVES). The MOVES model takes into consideration recent advances in on-road measurement technology as opposed to solely using dynamometer data along with some other improvements. The California EMission FACtor (EMFAC) Model performs a similar function as the MOBILE model, but predicts emissions from on-road vehicles operating specifically in California (EPA, 2003, 2009).

Another model, the COmputer Programme to calculate Emissions from Road Transport (COPERT) was financed by the European Environment Agency (EEA) (Ntziachristos & Samaras , 2000) in order to a calculate air pollutant emissions from road transport. In EU area, another methodology, the Handbook of Emission Factors for Road Transport (HBEFA) was developed in 1995 on behalf of the Environmental Protection Agencies of Germany, Switzerland and Austria. HBEFA provides emission factors, *i.e.* the specific emissions in g/km for various vehicle categories at different level of disaggregation and traffic situations.

2.7.2 Link based emissions modelling and Eco-Routing: method and practices

Unlike speed, acceleration is not well correlated with road properties and traffic conditions (Nie and Li, 2013). So, link based emission estimations require different sophisticated approaches. The simplistic form of emissions estimation from a link for an individual vehicle is to multiply an emission factor either by distance travelled or by travel time. To calculate the aggregated level of emissions for a certain time at this link requires further multiplication of that product with the link traffic volume. However, if emissions factors are generated from a trip based method (*i.e.* using average emission factors over an entire trip) and compared with link level estimation, there will be a mismatch and the link-based method will provide a higher emissions estimate than the trip based method. This is because the link-based approach is likely to be more sensitive in measuring emissions effects due to specific changes in traffic conditions, particularly those conditions with low speeds (Bai *et al.*, 2007). Link based emissions models were developed to assess the impact of changes in signal timing, or infrastructure on CO_2 emission in a network. These methods can also be used to assess new modelling methodologies (*e.g.* the inclusion of road gradient in models), or modelling of vehicle routing options such as lowest CO_2 emissions.

For Eco-Routing, emissions models are typically used to predict the emission associated with different routes and an optimal route is then selected. Alternatively, emissions can be considered as a cost component of route choice to find the optimal one as carried out by Kang *et al.* (2011). For the prediction of emission, the main factor affecting the accuracy of the prediction is the resolution and temporal characteristics of inputs such as speed. Maden *et al.* (2010) modelled emissions as a function of link speed in a vehicle routing assessment which included variations in traffic according to the time of day. Heuristic algorithms where used to predict the optimum route taking into account link speed variations and the results showed a 7% emission reduction could be saved from a trip.

Kang *et al.* (2011) outlined the development of a model that characterized six primary driving patterns for links which were subsequently applied to estimate the fuel consumption and emissions for theses links. Boriboonsomsin and Barth (2009) evaluated an advanced navigation system capable of evaluating the effect of road grade on vehicle fuel consumption and carbon dioxide. Real world experimental results showed that road grade had significant effects on the fuel economy for light-duty vehicles both at the roadway link level and at the route level. Mensing *et al.* (2011) developed an eco-friendly route model using Eco-Driving cycles through the use of the dynamic programming optimization method for a vehicle in an off-line simulation, which was not suitable for real time driver assistance due to the high computational cost and the use of driving cycles.

Ryu *et al.* (2013) utilized real-time traffic data and developed a methodology for estimating CO_2 emissions per link unit. Because of recent developments in V2I communication technology, and in real time data from probe vehicles (PVs), real-time speed per link unit can be calculated. Nie and Li (2013) developed an Eco-Routing model where many of the criticism of driving cycles have been accounted for. The model, however, assumes values for gear ratio and acceleration behaviour, and no stop-go behaviour and also considers a probabilistic distribution to describe the waiting time associated with each turning movement in the intersection. Andersen *et al.* (2013) developed an Eco-Routing model (the EcoTour System) that assigns eco-weights to a road in network to assign eco-friendliness based on GPS and fuel consumption data collected from vehicles. In this method, vehicle engine and GPS based data collection from the network is necessary, and segments missing with such data were handled by statistical modelling. Bandeira *et al.* (2013) developed emissions factors for Eco-Routing. For this, GPS second-by-second trajectory data, travel distance, cost, travel time, infrastructure quality, occurrence of incidents, and road grade were analysed. Boriboonsomsin *et al.* (2010, 2012) and Scora *et al.* (2013) focused on vehicle mass and road grade for Eco-Routing. Scora *et al.* (2013) developed a model (Eq. 2.1) for Heavy-Duty trucks that provided a more accurate projection of energy use than the standard average speed based estimation by accounting for two important parameters that affect power: vehicle mass and road grade. Boriboonsomsin *et al.* (2010, 2012) developed a method to estimate link-based energy/emission factors (g/mile) for Eco-Routing (Eq. 2.2 & Eq. 2.3). Except this following study, detailed vehicle characteristics were not focused on in many Eco-Routing studies.

$$Fuel = Intercept + a_1 m + a_2 g + a_3 gm + a_4 g^2 m + a_5 v + a_6 v^2 \quad \text{Eq. (2.1)}$$

Where, m = vehicle mass; g = road grade; v = vehicle velocity; a_1, ..., a_6 = modelling coefficients

$$EOPS \propto f(V, R, T, O) \quad \text{Eq. (2.2)}$$

Where, *EOPS* = fuel consumption (in grams per mile) for link; *V* = vector of vehicle characteristics, *e.g.*, vehicle type, model year, and loaded weight; *R* = vector of roadway characteristics, *e.g.*, roadway type, vertical grade, and type of intersection at link ends (stop-sign, signalized, or none); *T* = vector of traffic characteristics, *e.g.*, speed, density, or congestion level; *O* = vector of other explanatory variables, *e.g.*, driver characteristics and the environment.

$$ln(f_k) = \beta_0 + \beta_1 v_k + \beta_2 {v_k}^2 + \beta_3 {v_k}^3 + \beta_4 {v_k}^4 + \beta_5 gk \quad \text{Eq. (2.3)}$$

Where, f_k = Log transformed fuel consumption (in grams per mile) for link 'k'; β_0= modelling coefficient; v = Speed; g = Road grade.

Bandeira *et al.* (2013) analysed real world vehicle trajectory data from two different vehicles and drivers traversed several urban and intercity routes, and found that an average slope of 3% may increase CO_2 and fuel use by about 30%. Thus, the importance of inclusion of road grade is understandable. However, the above models (Boriboonsomsin *et al.*, 2010, 2012; Scora *et al.*, 2013) applied a Dynamic Roadway Network (DynaNet), which has grade data on links from 25 feet to 1.2 miles in length. This grade data was approximated from GPS data for every second (Scora *et al.*, 2013). The road grade for all the links in a city or large area is usually not available (Barth *et al.*, 2007) and such GPS trajectory based method for grade definition is costly. In addition, Zhang and Fery (2006) noted that multiple runs on the same roadway may be required to obtain a stable estimate of road grade at specific locations; data correlation, and receivers with sufficient accuracy and precision are required. Other methods such as aggregating design drawing data, obtaining direct on-road measurements, and LIDAR (surveying from aircraft) may not be feasible because of cost effectiveness for a large area, or citywide scale. Similarly, Bandeira *et al.* (2014) suggested innovative approaches integrating link-based functional relationships between historical speed micro scale patterns data of individual vehicles and real time macro scale traffic measurements into eco routing algorithms which is data demanding and may not be feasible for a citywide scale.

Ahn and Rakha (2008) investigated the impacts of route choice decisions on vehicle energy consumption and emission rates using microscopic and macroscopic emission estimation tools and concluded that ignoring acceleration impact on fuel consumption and emissions estimation would reverse the rank of two alternative routes (a highway and an arterial). Nie and Li (2013) and Bandeira *et al.* (2014) noted the importance of vehicle characteristics in Eco-Routing. Nie and Li, (2013) included many microscopic characteristics, *e.g.* acceleration events associated with link changes and intersection idling, in vehicle routing decision by using assumptions and statistical distribution. To obtain values for these events from statistical distribution may not be feasible for a city-wide scale model. However, such efforts are also in vain if models are not connected with real time data sources.

It could be also argued that if Eco-Routing information was disseminated widely to road users, where it is based on historical or link average data; this may make the suggested route no longer the eco-friendly choice if all drivers choose that route. Thus for Eco-Routing to work effectively in widespread practice then it is crucial that Eco-Routing models incorporate real time traffic speed data in their prediction of emissions and subsequent route choice suggestions.

Many previous investigations have developed Eco-Routing models based on historic data/route suggestion based on past data and it is clear from the literature that Eco-Routing based on real time traffic data is not well established (Manzoni *et al.*, 2011). It must also be recognised that the widespread adoption of Eco-Routing would ideally result in an equilibrium state in terms of CO_2 emissions between available route choices. Therefore, the fuel and emissions savings found in previous investigations (see section 2.5), which were based on controlled experiments may overestimate the ultimate savings achievable using this technique *i.e.* the impacts of Eco-Routing on fuel consumption of individual vehicles were Eco-Routing is not widespread in the network may be significantly different to the impact of Eco-Routing on fuel consumption at road network level were most vehicles in the network using Eco-Routing technology.

In addition to the limitations of existing Eco-Routing emissions models based on historical data or average speeds, other simplifications of the modelling process are also regularly present in previous investigations which further reduces the accuracy of CO_2 emission predictions and thus the proposed route choice. For example, cold start emissions elevate the emission for a trip as the catalyst requires some time after a vehicle is started to reach its optimum temperature. Incorporation of factors which account for cold start emissions is important especially for short trips, where the component of emissions associated with cold start may outweigh the emission from the remaining portion of a journey.. In addition, wind impact on modal emission estimation, or routing has not yet been evaluated. Wind can play a vital role on routing in open space up vs. city areas.

In summary, existing models of CO_2 emission for Eco-Routing often do not include real time traffic parameters, road grade information, detailed vehicle characteristics or cold emission factors, and underestimate emissions rates as a result. It was discussed that incorporation of road grade for a model suitable for any city or area may not be feasible according to the current state of resources, however, the rest of the parameters could be included in any model for an Eco-Routing application in any city.

2.7.3 Micro-level emissions modelling: Instantaneous or Modal emission models

Velocity-acceleration matrices derived from driving cycles and short driving cycles, and emissions engine maps (*e.g.* engine power-speed-emission relationship) can be applied for emissions estimation at the most disaggregated (trip) level (Barth *et al.*, 1996). At this disaggregated level, models can be 'instantaneous' *e.g.* emissions rate is predicted at the second by second level, or 'modal' in the sense that the model estimates emissions for different smaller segments of a trip, *e.g.* idling, acceleration, deceleration, cruising, fuel enrichment, lean and stochastic mode. Hallmark and Guensler (1999) also mentioned that to implement instantaneous models, statistical distributions of vehicle activity corresponding to the amount of the time vehicles spend at different speeds, and corresponding acceleration is necessary. The primary parameters are speed and acceleration and lately grade and air-conditioning operation can also be included. In order to work with the 'modal' concept a few parameters are necessary to model as well, such as the combined efficiency of the transmission as a function of engine speed and tractive power demand, gear ratio using any simple statistical specification of shift scheduling, engine speed, and the equivalence ratio according to driving characteristics. Based on the characteristics of the methodology models under these categories could be grouped as:

- Power based Models (Modelling methodology uses engine power based parameters)
- Velocity-acceleration based models (Modelling methodology uses vehicle trajectory based parameters)

2.8 Integration of traffic simulation/GPS data and modal/ instantaneous emissions models

Conducting Eco-Driving experiments either in the field or by micro-simulation requires integration of output data to a fuel consumption model and/or emissions model, and thus a review regarding previous studies were included here. Zhang *et al.* (2011) obtained real world second-by-second vehicle speed and acceleration data and used this in Comprehensive Modal Emission Model (CMEM) to produce emissions estimations. Micro simulation software is also capable of predicting such speed and acceleration data for numerous scenarios. Thus, the characteristics of the simulated vehicle trajectories should be similar to input of the instantaneous/modal emissions model in order to get emissions for a micro simulated scenario. Temporal and vehicular aggregations are necessary (Scora and Barth, 2006), and such integration can be applied to both conventional and greenhouse pollutants, and have been used to model the impacts of traffic congestion (Barth and Boriboonsomsin, 2008).

The simulation model usually assesses future scenarios such as the impact policy change on air quality, environmental impact of new vehicle technology, estimate of emissions from past congested conditions (Cappiello, 2002; Int Panis *et al.*, 2006; Lee *et al.*, 2009; Hao *et al.*, 2010), *etc.* Micro simulation and emissions models are integrated using an add-on interface, third party software, or manually formatting one output to feed inputs for other models (Abou-Senna and Radwan, 2013; Kun and Lei, 2007). On the downside, microscopic models tend to be data and computationally intensive when modelling large areas with complex road networks (Zhang *et al.*, 2011), and such integration of large amounts of data may create further complexity in the emission modelling step. Different micro-simulation and modal/instantaneous model pairs have been integrated in different previous studies. These included micro simulation software VISSIM, PARAMICS and AISUM, pair with emissions modelling software MODEM, PHEM, CMEM, and VERSIT (Boulter and McCrae, 2007; Kun and Lei, 2007; Chamberlin *et al.*, 2011). These model pairs, application in previous research and their selection for use in the current research project are further discussed in Chapter 3 and also in Appendix A. Few of these pairs have been mentioned below:

- VISSIM - MODEM,
- VISSIM-PHEM,
- VISSIM-CMEM,
- PARAMICS-CMEM,
- PARAMICS-MODEM
- AISUM-VERSIT^{+micro},
- VISSIM-VERSIT,
- VISSIM-PHEM

2.9 Air quality modelling and personal exposure

Typically, exposure models rely upon ambient air concentration inputs from a sparse network of monitoring stations (Isakov *et al.*, 2009). Air quality models are first developed and usually connect to population or personal exposure assessment (Isakov *et al.*, 2009; Dons *et al.*, 2011a,b; Pilla 2012; Dons *et al.*, 2013a; Luo *et al.*, 2013; Su *et al.*, 2015). Developing an air quality model requires resources and efforts as the transport and transformation of air pollution in the atmosphere is complex, involving many chemical and physical processes. As a result difficulties often arise in the development of deterministic models that can accurately predict air pollution concentrations which include both temporal and spatial variations over large areas. However, many statistical models have been successfully developed to predict air pollution over large areas, including temporal and spatial variation. Such statistical modelling techniques have included approaches such as: multiple linear regression (MLR), land use regression (LUR), principal component analysis, non-parametric regression (NPR), artificial neural networks (ANN), time series analysis, *etc.* in various studies (Comrie, 1997; Abdul-Wahab *et al.*, 2005; Arian *et al.*, 2007; McNabola *et al.*, 2009; Chen *et al.*, 2010a, b; Donnelly *et al.*, 2011a; Dons *et al.*, 2013b).

There are many air quality modelling concepts developed to date around the world. Based on these concepts many software packages, *e.g.* AERSCREEN, CALPUFF, ADMS-SCREEN, AERMOD, ADMS 4, CALQ3HCR, BLP, OCD, OSPM, EPA-CMBv8.2 were developed (US EPA, 2010; Pilla, 2012; BC, 2014). These air quality models use mathematical and numerical techniques to simulate the physical and chemical processes that affect air pollutants as they disperse and react in the atmosphere. Based on inputs of meteorological data and source information like emission rates and stack height, these models are designed to characterize primary pollutants that are emitted directly into the atmosphere and, in some cases, secondary pollutants that are formed as a result of complex chemical reactions within the atmosphere (US EPA, 2010). Modelling concepts that are commonly applied (US EPA, 2010; BC, 2014; Briggs, 1997) have been mentioned below:

- Dispersion Modelling- These models use equations to represent the physical dispersion of air pollutants travelling in the atmosphere, and to estimate the concentration of pollutants at specified ground-level receptors surrounding an emissions source.
- Photochemical Modelling- These models are applied to simulate the impacts of pollution from all sources by estimating pollutant concentrations and deposition of both inactive and photo-chemically reactive pollutants over large spatial scales.
- Statistical models-These models are developed based on observed data from fixed site monitors (FSMs), or other monitors and define historical trends over time, or correlate pollutant concentrations with the receptors, receptor characteristics, or other properties around the receptor *e.g.* time series analysis, Kalman filters (Milionis and Devis, 1994a,b; Finzi and Nunnari, 2005). Other statistical modelling techniques include approaches such as: MLR, principal component analysis, NPR, time series analysis, *etc.* in various studies (Comrie, 1997; Abdul-Wahab *et al.*, 2005; Arian *et al.*, 2007; Chen *et al.*, 2010a, b; Dons *et al.*, 2013b).
- Geographical information systems (GIS) based Models -These models usually apply different statistical concepts in relation to spatial location. These models are usually capable of mapping the concentration of air pollutants over the area.
- Receptor Modelling–based on the chemical and physical characteristics of gases and particles measured at the source and receptor, receptor models estimate the contribution of the sources to the receptors using mathematical or statistical procedures.
- Meteorological models- these models do not directly estimate air pollution, however, can assist forecasting air quality by predicting the location and concentrations of pollutants that result from emission sources. Usually, the output from these models can be a critical input into dispersion models.

In this research, however, only air quality models that can be applied for routing algorithms and city-wide prediction of air quality have been discussed.

2.10 Personal exposure and route choice modelling

The impact of transport related air pollution on health has been noted in chapter 1. These negative impacts are related to various factors in the transport sector. Dons *et al.* (2013a) highlighted that traffic intensity is a major explanatory variable for in-vehicle black carbon exposure, together with the timing of the trip and the degree of urbanization. Karanasiou *et al.* (2014) noted that levels of PM and black carbon to which bus passengers are exposed very much depended on the selected route, as highly busy streets contained higher ambient levels of exhaust emissions from neighbouring vehicles. Intermodal differences in exposure concentrations have also been widely reported (McNabola *et al.*, 2008; Int Panis *et al.*, 2010). Dekoninck *et al.* (2014) noted that personal exposure can be sensitive to modal choice or larger scale evaluations on OD matrices and/or modified traffic networks. Dons *et al.* (2012) emphasised that exposure in transport is not straightforward to relate a simple metric such as travel time to integrated personal exposure or inhaled dose, rather it is dependent on multiple factors such as transport modes used, the timing of trips (time-of-day, day of the week), and possibly the geographical location of the trip where further research was highlighted as required. Jarjour *et al.* (2013) reported that fine and ultra-fine PM, CO, and black carbon were all elevated on a high-traffic route compared to the low-traffic route. Dons *et al.* (2013a) reported that average Black Carbon concentrations on highways (10.7 $\mu g/m^3$) are comparable to concentrations on urban roads (9.6 $\mu g/m^3$), but levels are significantly higher than concentrations on rural roads (6.1 $\mu g/m^3$). Route level studies of personal exposure showed that different routes offered different levels of PM concentration in the cities (McNabola *et al.*, 2008; Adams *et al.*, 2001). Thus, it could be noted that personal exposure in traffic situations is sensitive to trip time, mode choice, route choice, and origin and destination of the trips.

Regression based models were the most common form of personal exposure modelling. Dons *et al.* (2013a) noted that people tend to move from one place to another during the day, their exposure to air pollution will be determined by the concentration at each location combined with the exposure encountered in transport. For black carbon exposure assessment, Dons *et al.* (2013a) developed a land use regression model, combined with a fixed indoor/outdoor factor for exposure in indoor environments/micro-environments and a separate regression model taking into account transport mode, timing of the trip and degree of urbanization. This regression model for communities is capable of estimating exposure in different transport modes using information on timing of the trips (peak, off-peak and weekend), degree of urbanization (highway, urban, suburban and rural), and instantaneous traffic intensity (veh/h). Timing of trips and urbanization were significant predictors for active modes in the model.

However, the development of these models requires a significant amount of monitoring data which is a limitation in the development of a city-wide model. For instance, McCreddin *et al.* (2014) applied 255 samples of 24-h personal exposure in real time over a 28 month period for model development. Dons *et al.* (2013a) developed a model based on data from 62 individuals who simultaneously measured pollutant concentrations, GPS positions, and transport mode in an electronic diary. Such data is not readily available in many cases and thus the development of air quality models based on readily available data would be of benefit to the use of Eco-Routing for lowest exposure.

Pilla (2012) and Pilla & Broderick (2015) developed a personal exposure model for commuter route choice in Dublin based on point, line and area source modelling. Luo *et al.* (2013) developed a Vehicle Navigator to minimize pollutant exposure and found that exposure to PM among 5-14 year-old school children could be reduced significantly higher margin on a typical school day with the implementation of intelligent routing algorithms with a cost of less than 10% increase in travel time. Luo *et al.* (2013) applied a Gaussian dispersion model and applied many modelled traffic measurements data, such as traffic speed, traffic flow, fleet composition, emission rate, or an emission inventory for a specific vehicle activity for estimation of pollutant concentrations.

Based on a number of assumptions and using the pollutant concentrations, the exposure intake fraction was included in this model, as shown in Eq.2.4:

$$iF = \frac{ppl*BR*C}{Q} \quad \text{Eq. (2.4)}$$

Where, *ppl* is the population, and *t* is the exposure duration; *BR* is the breathing rate for the target population (m^3/h/capita); *C* is the concentration over the population (g/m^3); *Q* is the emissions (g/h).

The final routing was implemented using ArcMap, in which the underlying least-cost algorithm is Dijkstra's algorithm (ESRI, 2013). The cost function for routing is shown in Eq. 2.5:

$$Cost_i = w * iF_i + (1\text{-w})*t_i \quad \text{Eq. (2.5)}$$

Where, *w* = weight factor that determines the trade-off between time'*t*' and intake fraction 'iF ' in a route 'i'. In some studies Intake (*I*) or dose as shown in Eq.2.6 has been estimated in place of intake fraction for assessing the level of exposure. Dose is the amount of pollutant absorbed or deposited in the body in a certain period of time.

$$I = \int \int_{T_1}^{T_2} Q_B\left(a(t)\right) C_{amb}(x, y, t) \gamma_{\mu(t)} dt \qquad \text{Eq.(2.6)}$$

Where, I is the mass of pollutant inhaled (mg) by an individual integrated over time t from T_1 to T_2 (h); $Q_B(a(t))$ is the individual's volumetric breathing rate (m^3/h), which depends on that person's time varying activity level, $a(t)$; $C_{amb}(x,y,t)$ is the ambient pollutant concentration (mg/m^3) near the individual, which is a function of location (x, y) and time; and $\gamma_{\mu(t)}$ is a dimensionless factor for each microenvironment, that accounts for differences between the ambient concentration and the exposure concentration (attributable to ambient sources) in that microenvironment.

The study by Luo *et al.* (2013) was the only research found in the literature to date which has dealt with routing based on minimum exposure. However, the aim of that research was to minimise exposure among population groups external to the vehicle. On the other hand, route choice based on minimum exposure of the driver has not been evaluated to date in detail. In short, it could be noted that a model could be developed using any of the concepts above to develop healthier routing choices for travellers. Dispersion (Marshall *et al.*, 2006) or GIS based regression models (Mölter *et al.*, 2012) were previously used to estimate exposure while traveling. However, minimising route choice criteria in relation to other route choice criteria have yet came under scrutiny.

Usually, the primary target for route choice of the travellers is to minimise travel time, or travel cost. Route choice for the travellers may also be governed by many criteria, such as reliability, avoiding congestion, maximizing comfort, and optimizing fastest routes (Golledge, and Garling, 2002; Tilahun and Levinson, 2010; Bandeira *et al.*, 2013). Since the last decade, CO_2 emission from vehicles has also been studied as a determinant for choice of routes. Integration of CO_2 at traffic assignment stage in transport models (Sugawara and Niemeier, 2002; Ahn and Rakha 2008); CO_2 as a component of the generalized travel cost factor (Yu-qin, *et al.*, 2013), field trial and experiments using navigation systems (Ericsson, *et al.*, 2006, Kang, *et al.*, 2011), *etc.*

provided evidence that individuals may reduce their carbon footprint choosing Eco-Routes. Recently, intelligent transportation systems (ITS) based methods and devices for Eco-Routing were discussed in many studies to facilitate the drivers' route choice decision-making process (Alam and McNabola, 2013a, b; Yao and Song, 2013). Healthier routes based on the lowest exposure to pollutant concentration can also be presented to travellers through these ITS facilities, however the impact of that is required to be evaluated. Ahn *et al.* (2012) showed that Eco-Routing based on CO_2 did not necessarily reduce vehicle travel distance or travel time; thus, there may be similar effects if PM_{10} concentration was chosen as a route choice cost factor.

2.11 Summary

Following this review of literature the following observations could be used to summarise the main findings:

- *Eco-Driving Network Impacts*

Eco-Driving Policy has the potential to reduce CO_2 emission and fuel consumption in certain circumstances, but in congested city centre traffic many conflicting views exist in the literature, resulting in some doubt over the effectiveness of the policy in such circumstances.

- *Eco- Routing*

Existing models of CO_2 emission for Eco-Routing that has been placed for public uses often do not in include real time traffic parameters, detailed vehicle characteristics, cold start emission factors, road grade and underestimate emissions rates as a result. Existing advanced models did include some of these parameters, however these required advanced database systems. Due to recent development of ITS, some real-time parameters are now available for big cities and thus, a model can be develop that can be applied to these cities.

- *Healthier Routing*

Previous investigation reported that different routes in the cities offer different level of pollutant concentration. Thus, healthier routing might minimise the exposure among drivers. However, the impact of such routing on other route choice criteria is as yet unknown.

Methodology of the Research

Chapter 3

3.1 Introduction

This chapter of the thesis provides an outline of the reasoning behind the development of this research programme by highlighting findings from the literature and connecting these with the gaps in knowledge, available tools, and strategies for carrying out the research.

3.2 Definition of the research boundary

This research is focused purely on the transport and environmental impact aspects of the Eco-Driving. Int Panis *et al.* (2006) suggested that the analysis of the environmental impacts of any traffic management and control policies is a complex issue and requires detailed analysis of not only their impact on average speeds but also on other aspects of vehicle operation such as acceleration and deceleration. The conflicting views on these transport and environmental impacts that exist in the literature can be further investigated using either field trials or micro-simulation. Due to the resource limitations, micro-simulation has been identified as an appropriate tool for this investigation.

Micro-simulation has been deployed for scenario based analysis. This study was designed to explain the impact of Eco-Driving on a congested large urban network and in realistic settings which has not been carried out by previous investigations. The investigation incorporated a congested network in terms of traffic signal that restricts drivers to operate suggested Eco-driving operations e.g. limited scope for maintaining cruse speed. This investigation has also focused on the use of different strategies of Eco-Driving, the level of Eco-Driving penetration, the influence of road geometry, and the influence of different levels of traffic volume. Acceleration/deceleration aspects and speed improvement as a result of ITS based communicative strategies only considered for Eco-Driving definition in Micro-simulation. Acceleration/deceleration is the major aspect of fuel saving and one the major aspects of Eco-driving (Sivak and

Schoettle, 2012). Deceleration which indicates well anticipation of the traffic situation as avoidance of sharp deceleration reduces unnecessary fuel burn. On the other hand, Ericsson (2001) identified 9 major factors of driving pattern, out of 62 that has effect on instantaneous emissions four of which are related to power demand and acceleration. For CO_2 emissions acceleration with strong power demand was identified as the most important factor. Thus, acceleration pattern was considered major focus of the micro-simulation study.

As part of the literature review, Eco-Routing based on lowest personal exposure was also highlighted as an area of smarter driving requiring further research. Assessment of vehicle routing based on lowest exposure requires micro-environment based air quality modelling (Wu *et al.*, 2005; Zhao *et al.*, 2007; Burke *et al.*, 2001; Kousa *et al.*, 2002; Jensen, 2006). In other approaches, an air quality model was required to be developed first followed by route level analysis as a second step (Luo *et al.*, 2013). In the current research, the Dublin and Vienna city areas have been considered as part of this study owing to the needs of the PEACOX project which funded this research and the availability of data for both. As such an Eco-Routing model based on lowest exposure was developed for Dublin and Vienna using the aforementioned two-step process.

For Eco-Routing based on lowest emissions, two models were also developed; a simplified model representing the most common models available in practice, and another as an advanced model that considered the disaggregated level of vehicle class, fuel technology, dynamic emissions factors, cold start emission factors, and peak/off-peak emission factors. The results of these models were compared against each other by evaluating field trial data available in Dublin as part of the PEACOX project. The models were designed to function in an online system using real time data. However, road grade factor has not been included in the modelling approaches due to limited information of actual road slope data for an entire city.

3.3 Research framework

The research framework in Figure 3.1 presents the different steps and inter-connectivity of the various element of this research project. Information regarding data sources and software applied in this research have been incorporated in this Chapter. However, more detailed information about the methods, modelling strategies, and data management are also discussed in the relevant chapters.

3.3.1 Data collection

For the study of Eco-Driving impacts at road network level using micro-simulation, annual average daily traffic (AADT) data were obtained from the Traffic Noise & Air Quality Unit of Dublin City Council (DCC) in GIS format. In addition, existing knowledge of the Eco-Driving empirical evidence has been taken into consideration from journal articles (Kobayashi *et al.*, 2007, Ando & Nishihori, 2011; Qian & Chung, 2011; Xia, *et al.*, 2011) and general practices (Ecowill:ecodrive.org, n'd; Emission Zero, 2009;). The traffic simulation environment was developed based on the Dublin city road network, which was digitized from Google map images. In addition, traffic signal and traffic turning movement data were obtained from field observations. The rationale behind the study area and boundary conditions are described in the micro-simulation chapter.

For the modelling of vehicle routing based on lowest exposure, an air quality model was first required to be developed for Dublin and Vienna. PM_{10} and other pollutant concentrations data from fixed site monitors (FSMs) were collected from the Environmental Protection Agency, Ireland and Municipal Government of Vienna, Austria. PM_{10} data were collected using a gravimetric instrument, or analysed gravimetrically from sampled volumes of air in the Dublin area, whereas fine dust samplers were applied in Vienna (Vienna City Administration 2006; Irish EPA 2014). In addition, daily traffic count at the nearest junction to the FSMs was obtained from real-time loop detectors (SCATS) in Dublin from Intelligent Transport Systems Ireland, Dublin City Council (DCC). Road length data for Dublin were also obtained from DCC, whereas the Open Street Map dataset was applied for Vienna (OSM, 2013).

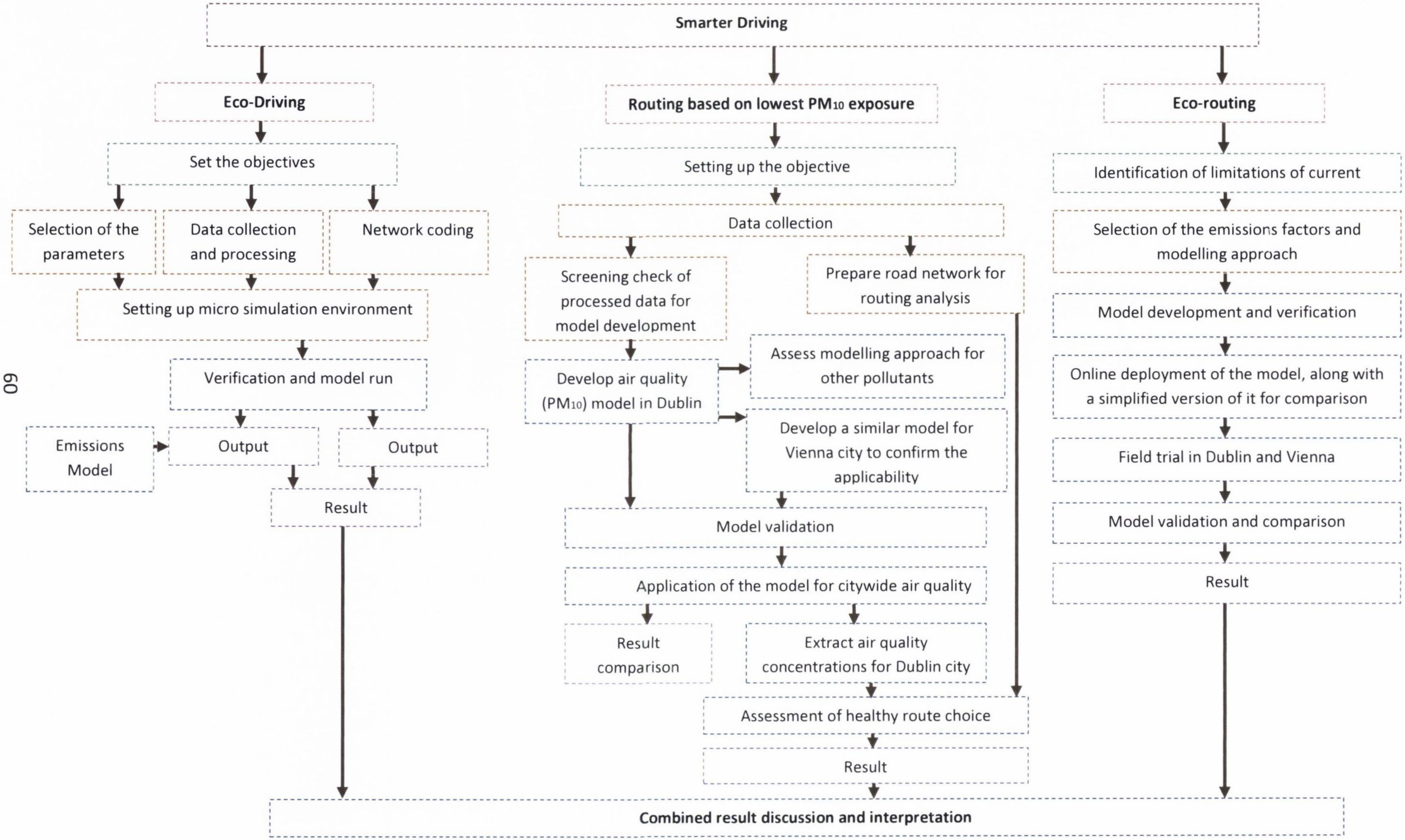


Figure 3.1: Overall framework for the Ph.D research

Land use GIS datasets were obtained from the European central database system (EEA, 2013b) and Open Street Map (OSM, 2013). Population densities for Dublin were collected from the Central Statistics Office (CSO, 2013) and from the European central database system for Vienna (EEA, 2013c). The average population density in Europe was collected from CIESIN (2013).

Dublin meteorological data were combined from both Phoenix Park and Airport stations operated by Met Éireann for modelling purposes. Vienna data were obtained from the Schwechat-Flughafen station and were validated against the 2012 dataset of Hohe Warte station (ZAMG, 2013). The air history was determined using the Hybrid-Single Particle Lagrangian Integrated Trajectory (HYSPLIT) model (ARL, 2013). For the lowest exposure routing analysis, the road network was updated with the Speed Limit By Laws, 2011 of DCC (DCC, 2013). Speed variation according to the road type was also collected (RSA, 2012). Additional data for routing analysis, such as vehicle occupancy data, and value of travel time (VOT) have been collected from the NRA (2011, 2012), actual travel time in Dublin was collected from ITS (2010) and vehicle running costs were collected from AA (2012).

Vehicle occupancy data from above sources has also been included in the Eco-Routing model development for lowest CO_2 emissions. Hot CO_2 emission factor equations were collected from Boulter *et al.* (2009). To account for the 'excess cold start emission per start' equations developed by the ARTEMIS Project have been included in the model from Boulter and Lathlam (2009).

3.3.2 Review and selection of modelling concepts and platform

3.3.2.1 Selection of micro-simulation software

In order to understand the micro-simulation studies as mentioned in section 2.5, Chapter 2, software platforms applied in those studies were reviewed. In addition, this review would provide an understanding of the modelling concepts that work behind the software platforms, and their usefulness for the planned experiments.

Micro-simulation models can be classified according to traffic conditions such as urban, motorway, combined, or others (*e.g.* roundabout). VISSIM has been chosen for the micro-simulation study after reviewing the common software packages available including: PTV VISSIM, PARAMICS, S-PARAMICS & Q-PARAMICS and AIMSUN. It is noted that each of the software packages followed some built-in principle, and no obvious benefit was noted in one over the others. Thus, among these candidate simulation platforms, VISSIM software has been chosen for modelling. Details of this review are contained in Section A1, Appendix A.

- VISSIM:

VISSIM ("Verkehr In Städten - SIMulationsmodell"; German for "Traffic in cities - simulation model) was first developed in 1992 by PTV (Planung Transport Verkehr AG) in Karlsruhe, Germany. VISSIM is a micro-simulation software suite developed for modelling urban and motorway traffic operations. A very high level of detail in simulation can be achieved in VISSIM for road geometry and positioning of road infrastructure, *e.g.* signal controllers. Traffic demand, route choice, traffic flow and emissions models are integrated in this software package. This model is based on a number of theories including psycho-physical car following theory, a rule-based lateral movement algorithm for lane selection, lane change and lateral movement, tactical driving behaviour/anticipated driving at conflict areas, cooperative merging, *etc*. The traffic demand models follow a behaviour-oriented, disaggregated approach, and the model computes the set of trip chains performed during one day in the analysis area (Boulter and McCrae, 2007).

The Wiedemann (1974) approach is followed for psycho-physical car following theory in VISSIM. Wiedemann (1974) defines the driver perception thresholds and the regimes formed by these thresholds. There is another car-following model called Wiedemann 99 car-following theory in VISSIM, which is in many ways similar to Wiedemann 74, except that some of the thresholds in the 99 model are defined differently and sometimes simpler ways to model freeway traffic (Gao, 2008).

In the lane-changing model in VISSIM by Sparmann (1978) vehicles move judging the questions: Whether there is a desire to change lane, whether the present driving situation in the neighbouring lane is favourable, and whether the movement to a neighbouring lane is possible (Kan and Bhan, 2007). Vehicles are allowed to conduct two kinds of lane changes in VISSIM: Necessary lane change and free lane change. The necessary lane change is applied when the vehicle needs to reach the connector of the next routine. The free lane change happens when the vehicle is seeking more space or higher speed (Gao, 2008).

The route choice of vehicles in VISSIM can either be static or dynamic. Traffic flow for static route choice is usually defined by the users whereas dynamic route choice is estimated by iteration. The traffic flow model in VISSIM is discrete and stochastic in the sense that the values of the parameter selection that governs the outcome are unpredictable, however these also follow a given distribution. These values are obtained from user defined desired speed distribution, desired and maximum acceleration and deceleration distribution, traffic volume and composition. Using these parameter values, the position of each vehicle is recalculated every 0.1–1 seconds in the network using above mentioned car following theory and lateral movement algorithm. Selection of these parameter values is connected with the random seed. Using a different random seed includes a stochastic variation of input flow arrival times. Simulation runs with identical input files and random seeds generate identical results. For meaningful results it is recommended to determine the arithmetic mean based on the results of multiple simulation runs with different random seed settings (PTV, 2013).

For emission estimation in VISSIM, additional information such as model, year and mileage distributions are required as well as temperature of the coolant and catalysts. However the files for engine profile and emission factors are no longer functional, and thus the emission module of VISSIM is difficult to deploy. This module is now replaced by a standalone module EnViVer (Environmental VISSIM VERSIT^{+} simulations) software.

3.3.2.2 Selection of Modal/ Instantaneous model

In order to estimate CO_2 emissions from the output of VISSIM, an instantaneous/modal model is required. The candidate models are below:

- Power based Models
  - Generic/Physical Model
  - PHEM
  - Vehicle Specific Power(VSP) based model
  - Comprehensive Modal Emission Model (CMEM)

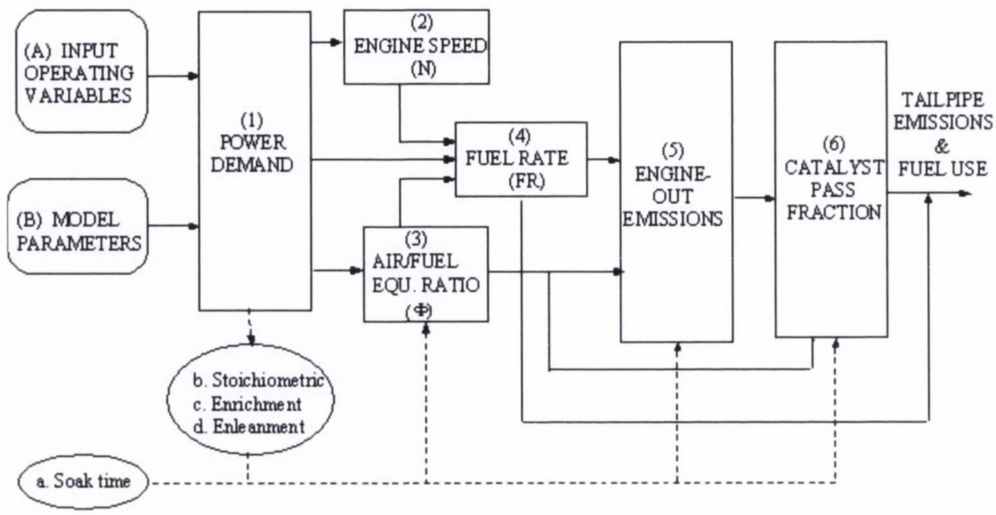
- Velocity-acceleration based models
  - MODEM
  - Nonlinear Regression
  - VT-Micro
  - VERSIT^{+micro}

A general outline of the above models has been included in Section A2, Appendix A. CMEM has been chosen for the emissions modelling platform because of its availability during the project and lower complexity of integration with VISSIM output data compared to other models.

- Comprehensive Modal Emission Model (CMEM):

CMEM was first developed in the late 1990's with sponsorship from the National Cooperative Highway Research Program (NCHRP) and the U.S. Environmental Protection Agency (EPA). This model can be used at a micro-scale and macro-scale level, meaning that emissions can be modelled from a specific vehicle to aggregated vehicle fleets from various categories. The specific feature of the model is that the model does not predict emissions for specific makes and models of vehicles, but rather estimates emissions for vehicle categories. This model follows a physical/power-demand modelling approach (Figure 3.2). The physical operating conditions in the model are: a) variable soak time start/cold start; b) stoichiometric operation; c) enrichment (High Fuel); and d) enleanment (High oxygen). As this model is sensitive to power demand, such as enrichment, that may be caused by hard acceleration, the estimation of the emissions using CMEM would be of benefit for the investigation of Eco-Driving.

Commanded enrichment occurs during a number of circumstances, especially acceleration from idle, which is particularly important in urban driving (Kelly and Groblicki, 1993; De Vlieger 1997; Barth *et al.*, 1996). The model is capable of such shifts from operating conditions while power demand changes, for instance the operating condition is switched from stoichiometric to enrichment when the vehicle power demand exceeds a power enrichment threshold. The power demand is determined based on specific vehicle parameters. The model was established as a physical power demand model and then must be combined with vehicle operating parameters that are characteristic of real-world driving, and these combination yield high resolution emission rates for different engine conditions.



Source: CMEM (2006)

Figure 3.2: CMEM modelling process

Parameters that can be specified for model operation are different vehicle categories and specifications according to vehicle type, condition and accessories (*e.g.* vehicle mass, number of gears, number of cylinders, *etc.*). Impact of road grade factors can also be included. Finally, vehicle tailpipe emissions, quantified on a second-by-second basis, are derived as the product of fuel rates (*FR*), engine-out emission indices ($g_{emission}/g_{fuel}$), and a time-dependent catalyst pass fraction (CPF). The formula is (Eq. 3.1):

$$Tail\ pipe\ emissions = FR * \frac{g_{emissions}}{g_{fuel}} * CPF \qquad \text{Eq. (3.1)}$$

The latest version 3.01e Beta of CMEM provides Java Graphical User Interface (GUI) runs both the light duty vehicle and heavy duty vehicle portions of the CMEM model. This provides flexibility to obtain emission data for single or multiple vehicles from a similar or various categories with different trajectories specified in the vehicle activity file. It should be noted that the CMEM model was developed for both passenger cars and small trucks under Light Duty Vehicles (LDV) category, and model parameters are needed to be calibarated in order to estimate emissions for any specific vehicle category (e.g. petrol powered passenger car).

3.3.2.3 Selection of air quality model

For modelling of vehicle routing based on lowest exposure, an air quality model was first required to be developed. All the candidate models were reviewed in section A3, Appendix A. Gulliver *et al.* (2011a) compared the performance of four modelling approaches: based on the nearest monitoring site, Kriging, dispersion modelling and LUR, and concluded that only LUR reached acceptable levels of performance for the city area. De Hoogh *et al.* (2014) applied LUR and dispersion models and concluded that both methods may be useful for epidemiological studies of small scale variations of outdoor combustion-related air pollution, typically from road traffic. Besides, referencing may published papers Dons *et al.* (2013b) noted that account of exposure at various location using atmospheric dispersion model calls for large cost due to data collection, model setup and computational time. In addition, dispersion models are better when only a specific source related concentrations are driven. IEHIAS (2013) recommended that both LUR and Kriging can be applied to extrapolate city-wide pollution maps in order to reduce computational time. In short, the predictive performance of the LUR model is no less than that of alternatives such as dispersion modelling and this model can be applied in conjunction with the Kriging method to produce city-wide maps of air quality. Such maps would facilitate an Eco-Routing assessment based on lowest exposure.

- Land use regression

Land use regression (LUR) utilises monitored levels of the pollutant of interest as the dependent variable, and variables such as traffic, topography, and other geographic variables are considered as independent variables in a multivariate linear regression model (Gilliland *et al.*, 2005; Ryan and LeMasters, 2008). The LUR model is suitable for this research for following reasons: 1) The incorporation of site-specific variables into this method detects small area variations more effectively than other methods of interpolation (Briggs *et al.*, 1997; Gilliland *et al.*, 2005); and 2) the levels of pollution may then be predicted for any location using a regression model (Ryan and LeMasters, 2008). The landuse regression will be in the form of Eq. (3.2).

$$E = C_0 + A_1X_1 + A_2X_2 + A_2X_3 + \epsilon \qquad \text{Eq. (3.2)}$$

Where, E = Exposure Concentration; X_1 = Traffic data; X_2 = Land use data; X_3 = Weather data; ϵ = Error; A_n= regression coefficient where n=1,2, 3.....n.

LUR based models have been developed relating a variety of factors to air pollution concentration. The methodology combines air pollution monitoring data at a number of locations with the development of statistical models using predictor variables usually obtained through geographic information systems (Hoek *et al.*, 2008). Such predictor variables have included representations of demographics and land use. Predictor variables have also included meteorological conditions such as wind speed, wind direction and temperature (Arian *et al.*, 2007; Chen *et al.*, 2010a; Sahsuvaroglu *et al.*, 2012).

Different forms of variables, as well as modelling approaches have been evaluated to improve the performance of this technique, and the stability of the model predictions year on year. In many studies, temporal stability of the spatial contrast of the landuse regression was found (Chen *et al.*, 2010b; Eeftens *et al.*, 2011; Madsen *et al.*, 2011; Gonzales *et al.*, 2012; Gulliver *et al.*, 2011b,2013). The modelling development process has also been facilitated through testing conceptual and methodological changes in LUR. This testing involved the development of models for different pollutants and for differing cities. This testing also provides scope to develop air quality models that are required for practitioners and policy makers which can make reliable predictions without the need for significant amounts of additional monitoring data.

Measurement of air quality is a resource intensive process, thus this attempt as part of this research might be beneficial. Typically only limited networks of monitoring stations are available in cities due to resource limitations. At the end of model development, Kriging has been deployed to develop citywide PM_{10} concentration maps in Dublin and Vienna.

- Kriging

Kriging or Gaussian process regression is a method of interpolation. The Kriging technique interpolates the value of a random field at an unobserved location from observations of its value at nearby locations. In this method a Gaussian process is employed that is governed by prior covariances. Under suitable assumptions on the priors, Kriging gives the best linear unbiased prediction of the intermediate values.

3.3.3 Software packages for data management, analysis and modelling

VISSIM (PTV Vissim 6) and CMEM (CMEM, version 3.01e Beta) modelling platforms have been chosen for the micro-simulation study. The development of the standard LUR models was performed using R – statistical software. Data for model development were also processed using the Statistical Package for the Social Sciences (SPSS 17) in some cases. Alternative LUR modelling techniques were developed using XLSTAT 2013 for Non-parametric Regression and MATLAB (R2009b) for Neural Networks. For citywide PM_{10} concentrations, ordinary Kriging was carried out using ArcMap 10.1 software. The final Eco-Routing model for lowest exposure has also been assessed using ArcMap 10.1 software.

Eco-Routing model based on CO_2 has been developed initially in MATLAB and then transformed into a Java platform for server uploads. This Java version has been integrated with other multi-modal emission models for the PEACOX project and used in field trials in Dublin and Vienna. Field trial comprised the deployment of the emissions model on a smartphone application for a number of users in each case. The route results were presented to android smartphone users, and final field trial results were extracted from server using pgadmin3-1.20.0-beta2 software.

Eco-Driving Micro-simulation

Chapter 4

This chapter is under preparation for publication as: ALAM M.S. & MCNABOL A. Network wide Impact of acceleration and deceleration operation of the Eco-Vehicles in different network configurations.

4.1 Introduction

The objective of this chapter is to evaluate the impact of Eco-Driving on CO_2 emissions and congestion at the level of a road network, and for different traffic scenarios using a micro-simulation traffic model.

As outlined in Section 2 numerous investigations have estimated that reductions in CO_2 emissions and fuel consumption of the order of 10% are achievable for individual vehicles through Eco-Driving. However, investigations have also suggested that at the level of an intersection or road network, Eco-Driving vehicles may cause a delay in the progression of general traffic, increasing congestion and fleet-wide CO_2 emissions as a result. Therefore, a need exists to examine the impact of Eco-Driving in a congested urban traffic network, on the CO_2 emissions and levels of congestion present in the fleet or network.

Traffic simulation is a tool for the evaluation of concepts or scenarios, where considerable doubts are present in future outcomes due to changes in policy or the behaviour of certain components in the traffic system. In traffic engineering, traffic simulation is used as a tool for road design, safety analysis, and for prediction of the behaviour of the flow of vehicles. Therefore, Micro-simulation is a useful tool to enable the prediction of the impacts of increasing numbers of Eco-Driving vehicles in a road network. A complex portion of the Dublin road network with many traffic signals was selected on purpose for Micro-simulation in order assess the impact of Eco-driving. The complex setting of the roads and traffic signals along with higher traffic volume was expected to develop a required (as per objective) congested traffic situation.

In Micro-simulation studies usually different alternative scenarios are developed where traffic flows are created allowing merging and diverging activities in complex geometric road conditions to assess the impact of scenario changes. As noted in the Section A1, Appendix A, different micro-simulation software require different forms of data sets. Here, based on the conditions specified by the simulation software, Eco-Driving was evaluated using a realistic road network in a speed restricted urban centre, together with a number of differing traffic input scenarios. Following the summary of the sections 2.4 & 2.5, the research questions that are being addressed here include:

- How do different Eco-Driving car penetration rates in the different traffic flows affect the environmental and traffic performance of a large urban road network?
- How does the network configuration affect the Eco-Driving scenarios with the increasing numbers of Eco-Drivers under different volumes of traffic?
- What is the impact of different Eco-Driving strategies/technology (*e.g.* V2V communication) on the environmental and traffic performance of an urban road network?

4.2 Methodology

To address the aforementioned research questions, four experiments were conducted which differed according to either road network configuration, traffic composition, or both:

i) *Experiment 1:* A small road network containing four intersections (3 major, 1 minor).
ii) *Experiment 2:* A small road network containing 3 major roundabouts and 1 minor intersection.
iii) *Experiment 3:* A large, real-world, urban road network based on the 30 km/h speed zone of central Dublin, Ireland. (containing cars only).
iv) *Experiment 4:* A large, real-world, urban road network based on the 30 km/h speed zone of central Dublin, Ireland. (containing multimodal transport).

For the purpose of experiments, eco-cars have been defined as vehicles having relatively low average acceleration and deceleration profiles as well as having a lower standard deviation about these average values, in comparison to non Eco-Driving vehicles. Along with these characteristics, Eco-cars were also defined as being without (ECO-I: Acceleration and Deceleration) or with an overall improved speed of the vehicle fleet (ECO-II: Acceleration, Deceleration and Speed Improvement) in-comparison to the non-Eco driving vehicles.

During experiments 1 and 2 Eco-Driving vehicles in these networks were defined according to the ECO-I criteria. In an attempt to improve the environmental and traffic impacts of Eco-Driving at road network level, ECO-II cars were subsequently introduced into experiments 3 and 4. The rationale behind ECO-II is that vehicle-to-vehicle (V2V), or vehicle to infrastructure (V2I) communication technology capable of facilitating smart or intelligent Eco-Driving may introduce a better flow of traffic with an optimal speed for the road network as happened with Eco-Driving in higher traffic volume (Wang *et al.*, 2012). This was carried out in VISSIM by applying improved vehicle speed profiles to the network simulating a better flow of traffic and higher overall average speed (*i.e.* lower congestion levels). As highlighted in section 2.6, Chapter 2 previous investigations have demonstrated a possible improvement of environmental and traffic performance where algorithms and vehicle technology are used to introduce dynamic driving involving communication between vehicles and between vehicles and traffic signals (Wang *et al.*, 2012; Xie *et al.*, 2011). In experiment 3 the impacts of ECO-I and ECO-II vehicles were compared to estimate the impacts of including such intelligent transport infrastructure in vehicles and road infrastructure. Similarly, in experiment 4 only ECO-I and ECO-II vehicles were included in the assessment in the presence of a multi-modal fleet, whereas previous scenarios included only private cars.

4.2.1 Design of simulation experiments

All the scenarios under the 4 different experiments were simulated for one hour and the results were obtained from an average of ten simulations during this period. In Experiment 1 (Figure 4.1) a small network with a small number of intersections was selected. The environmental and traffic impacts of cars with three different speed profiles were simulated for low and comparatively high traffic volumes. In order to ensure more realistic driving conditions and that more groups of vehicles were created by traffic signals (*i.e.* more platoons), three different speed profiles were introduced for normal vehicles (PTV, 2011). These vehicles were then replaced with ECO-I vehicles at 3 different penetration rates 20%, 50% and 100%.

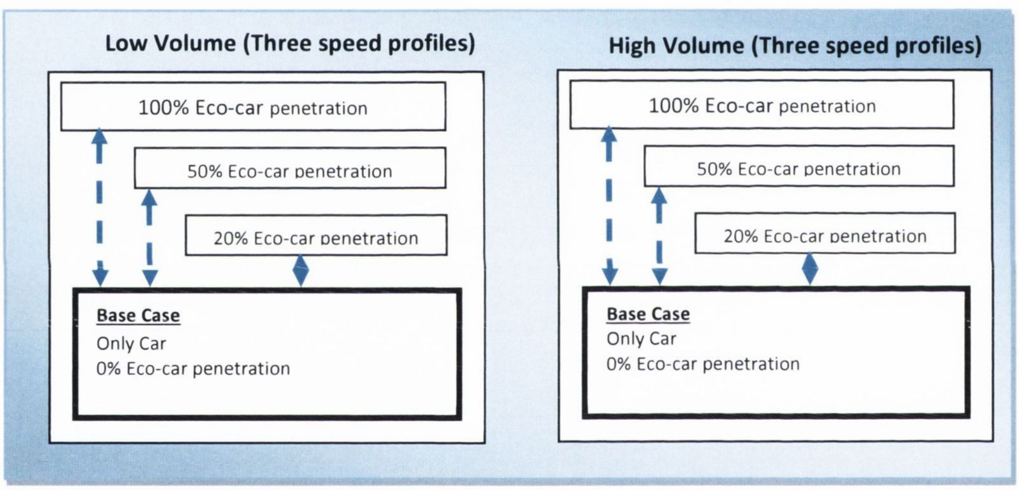


Figure 4.1: Experiment 1 in a Small Network with intersection

Using the same level of traffic volumes, Experiment 2 (Figure 4.2) was conducted on the same small road network where the major intersections were replaced with roundabouts in order to investigate the impact of road configuration on Eco-Driving environmental and traffic performance. Experiment 2 was conducted with just one speed profile following the experience from Experiment 1.

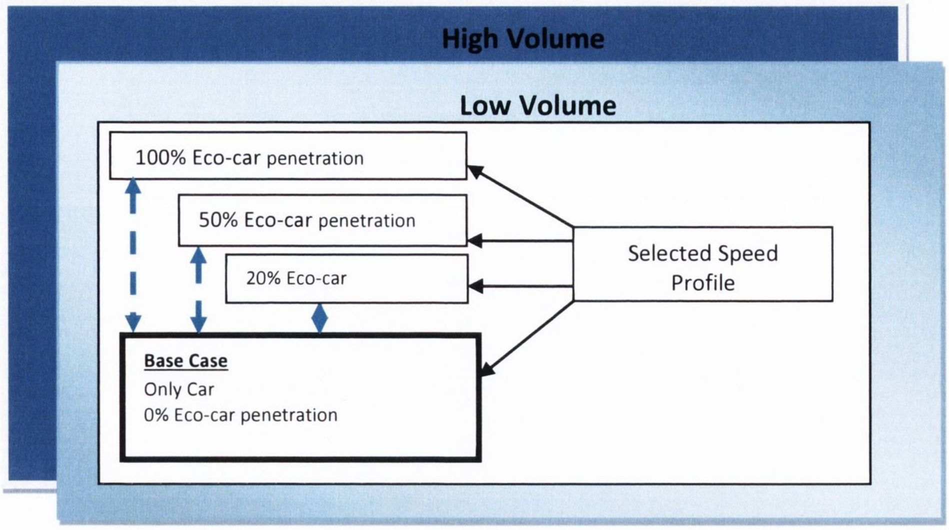


Figure 4.2: Experiment 2 in a Small Network with Roundabout

In Experiment 3 (Figure 4.3), the performance of ECO-I vehicles were compared against the same proportion of ECO-II vehicles, and the car was only the vehicle category allowed in the network. A large road network was extracted from a city road network with many intersections.

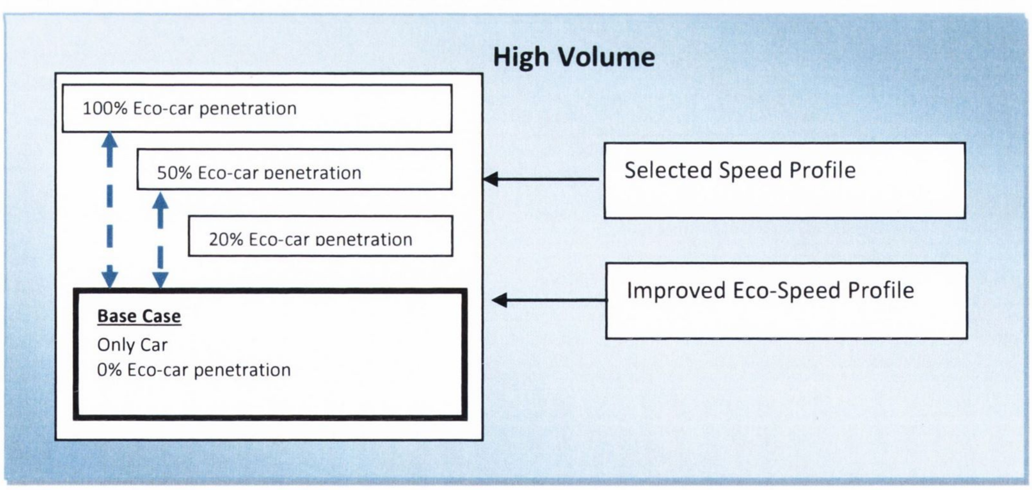


Figure 4.3: Experiment 3 in a Large Network with two definitions of Eco-Driving

For experiment 4, different levels of penetration of Eco-II vehicles have been compared using a real world traffic network and mixed traffic composition (Figure 4.4). The volume of this traffic was altered at different levels in the same large network that was applied in Experiment 3. For this experiment, peak hour traffic volume and 20% more and 20% less traffic volume were chosen.

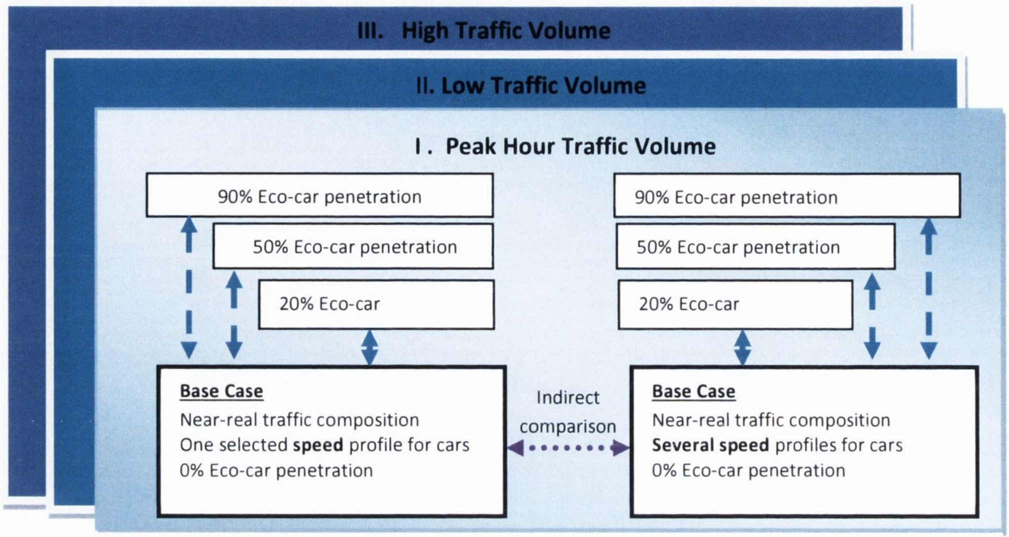


Figure 4.4: Experiment 4 in a Large Network with variation of traffic

The results of each experiment were interpreted by comparing performance criteria of alternative scenarios against that of a base scenario (Figure 4.5). Except for the base case scenario, Eco-Driven vehicles were penetrated in different proportions of the inputted total vehicles (*i.e.* 20%, 50% and 100% Eco-Driving vehicles).

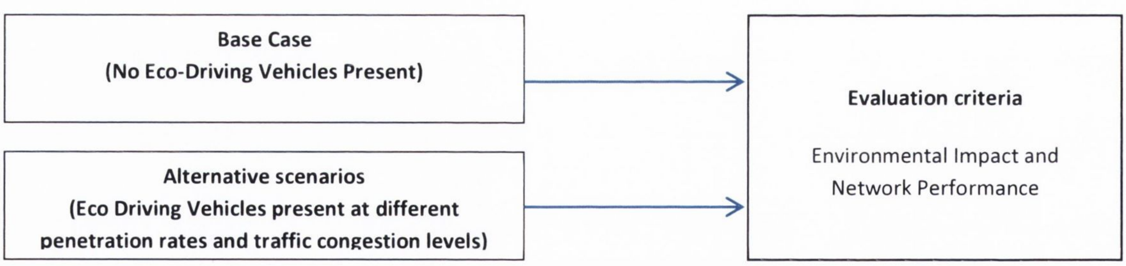


Figure 4.5: Flowchart of the Simulation plan

Each of the scenarios was also developed with variations in traffic volume in conjunction with eco-car penetration rate in order to assess their impact on the environment and the road network. The focus of this research was on the relative change of environmental and traffic performance between scenarios and the base case; not on the absolute change in any existing network. Thus arbitrary traffic input figures were used in the various scenarios. However, verification of all base scenarios was conducted in order to ensure smooth traffic flow in the complex traffic conditions.

Previous studies on impact analysis of Eco-Driving were conducted using micro-simulation for either a single or a limited number of intersections with restricted movements of traffic (See Section 2.6). In the current investigation the number of intersections was significantly greater and traffic movements were not restricted (this was applied to previous studies for simplicity).

The following criteria for environmental and traffic performance were selected to evaluate the degree of change in alternative Eco-Driving scenarios in comparison to a base scenario (no Eco-Driving vehicles present).

- Total stopped delay time (Hour)
- Travel time per vehicle-km (Minutes)
- Trip time per vehicle per km in the network (Minutes)
- Latent demand of the vehicle (Number of vehicles)
- Total CO_2 emission at the network level (Kg), or average emissions per distance (g/km)
- Total fuel consumption, CO, NO_x and HC. or average emissions per distance (g/km).

Total stopped delay is the amount of delay of all of the vehicles in the network while stopped at the intersection. Travel time is the running time of the vehicles, whereas trip time is the sum of running time and delay. These two criteria were standardised by the total number of vehicles (that were on the network, and had left the network during the simulation period), and by the corresponding total mileage travelled by all of the vehicles. The number of vehicles in the network and total mileage travelled varied between scenarios where some experiments examined the impact of Eco-Driving in low versus high levels of congestion. Sometimes simulation software does not allow mathematically calculated vehicles to enter into the modelled scenarios if the network is above capacity. These vehicles are known as latent demand.

For further analysis of the changes in impact, emissions were calculated for important segments of the simulation time. Total simulation time was not considered due to the limited computational capacity of the software/processor. In the absence of the emissions figures in some experiments, the changes in environmental impact in different scenarios were compared using network performance criteria as these parameters were directly proportional to environmental performance at network level (*i.e.* increased trip time clearly results in increased emissions and fuel consumption).

4.2.2 Experimental tool

- "Verkehr In Städten – SIMulationsmodell (VISSIM):

VISSIM was selected for micro-simulation modelling due to its availability during this research. In comparison to other modelling software some of the features of VISSIM were supportive for the selection of this software in the research, such as a very high level of detail in simulation could be achieved for road geometry and position of road infrastructure, presence of a simplified network coding system- not having node-link coding system, facility for multi-modal scenarios, and psycho-physical car modelling theory model developed by Wiedemann (1974).

At the operational level in VISSIM, each individual vehicle follows a flow model while traversing the road network. The traffic flow model of VISSIM is discrete and stochastic. It is stochastic in the sense that the values of the parameter selection that governs the outcome are unpredictable; however, these are derived from a given distribution input by as user-defined parameters. These values are obtained from user defined desired speed distribution, desired and maximum acceleration and deceleration distribution, traffic volume and composition. Using these parameter values, the position of each vehicle is recalculated every 0.1–1 seconds in the network using car following theory and a lateral movement algorithm discussed in section 3.3.2.1, Chapter 3. As outlined earlier, using these inputs it was also possible to define vehicles with significantly different speed, acceleration and deceleration profiles than the norm *i.e.* Eco-Driving vehicles.

- Comprehensive Modal Emission Model (CMEM):

A modal model CMEM was applied for the emissions calculation from VISSIM outputs. As CMEM is sensitive to power demand, such as enrichment, that may be caused by hard acceleration, the estimation of the emissions from CMEM was very useful. During enrichment, the model shifts from one operating condition while power demand changes, for instance the operating condition is switched from stoichiometric to enrichment when the vehicle power demand exceeds a power enrichment threshold. The power demand is determined based on specific vehicle parameters and vehicle operating variables (obtained from VISSIM). The latest version 3.01e Beta of CMEM provided a Java Graphical User Interface that was applied to obtain data from VISSIM.

4.3 Experimental set-up

4.3.1 The road networks

There were two kinds of data required for establishing a VISSIM network: (1) static data representing the roadway infrastructure, which included links with start and end points, link length, width, grade, lane number, and location of stop lines; (2) dynamic data required for traffic simulation applications, which included: (a) traffic volumes for all links entering the network, and traffic volume entering and for different turn directions at each intersection; (b) public transport routing, departure times and dwell times; and (c) priority rules and signal timing plans at the intersections (Kun & Lei, 2007). A large amount of time was required to code the VISSIM input data, particularly for Experiment 4 using a large urban network (Boulter & McCrae, 2007). Other inputs included traffic composition, routing decisions, vehicle movement parameter specification, *e.g.* speed, acceleration, vehicle weight distribution, *etc*.

For Experiments 3 and 4, a network for simulation was chosen from the Dublin city centre 30 km/h speed zone where a number of signalised intersections affect the flow of traffic. Ten traffic signals were situated in this 0.30 km^2 area. The latitude and longitude of that area are between (53.343963, -6.271484) and (53.342253, -6.266296). The total road length was approximately 7.26 kilometres. The networks were coded using a VISSIM graphical user interface following Figure 4.6a as well as field observations. Field observations were necessary to place the signal head and for placing the link connector according to the correct turning movements. Figure 4.6b shows signal heads as red marks, there were also conflict areas visible as yellow, other network coding requirements such as priority rules, and traffic volume input markers. A partial network was used in Experiment 1 as shown in figure 4.6c. The network shown in Figure 4.6d was applied for Experiment 2, while the network shown in the Figure 4.6b was applied in Experiment 3 and 4.

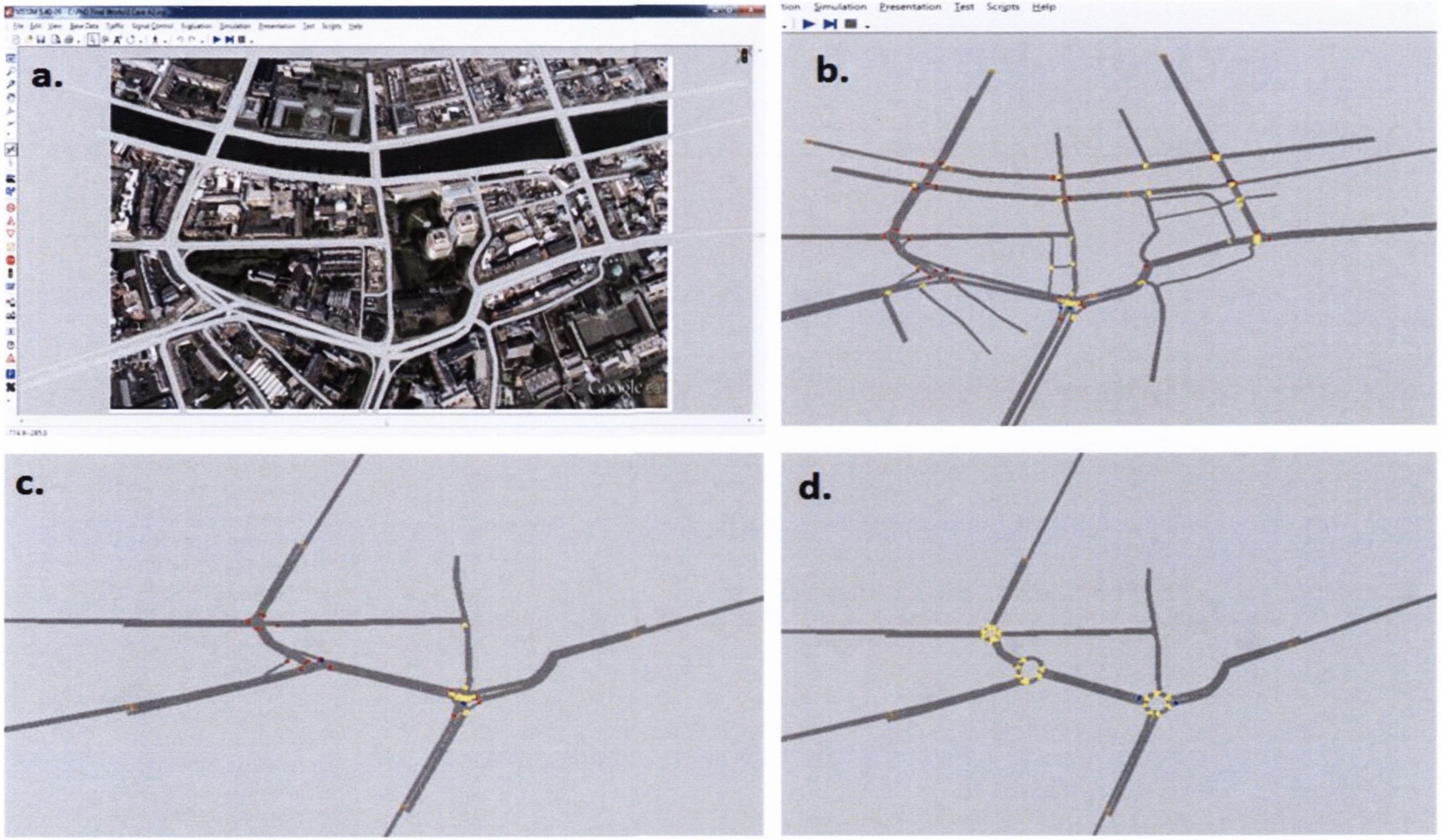


Figure 4.6: (a) network coding in the original scale in VISSIM; (b) network for experiment 3 & 4; (c) network for experiment 1; (d) network for experiment2

For signalised intersections, fixed time signal plans (see Figure 4.7) with a cycle length of 90 or 120 seconds with no offset were chosen. Times for green, amber, and red varied for different signal groups. The road grade was set to be zero for all links in the network.

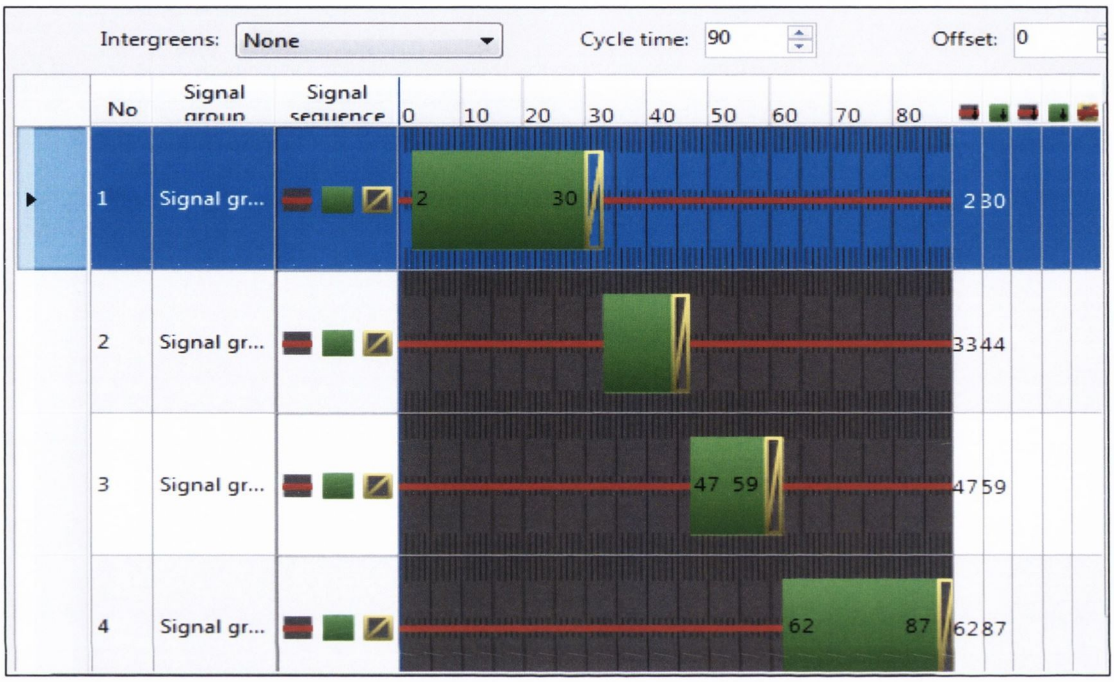


Figure 4.7: A fixed time signal plan applied in the network.

4.3.2 Traffic volume, traffic composition and routing decisions

The traffic demand data applied in Experiment 1 and 2 were the same, and traffic entered into the network from all five-entry links. The volume for low traffic scenarios were 350-600 veh/hour, whereas traffic volume was 600-950 veh/hour in the high volume scenarios. Traffic volume in the case of Experiment 3 and 4 for the links were obtained from a GIS dataset, sourced from Dublin City Council (Figure 4.8). The turning movements of the vehicles were manually calculated based on the turn allowed in the original networks, and Origin-Destinations (OD) were estimated and static routes were created.

The routing was not the same for Experiment 1 and 2; however, both of these were simple and similar for all the scenarios under the same experiment, whereas, the routing decisions for Experiment 3 and 4 were complex and required significant effort to carry out. The manual process of balancing the OD matrix was often long and tedious. VISSIM allows both static and dynamic routing, however, static routing was chosen here. Static routing is sufficient for the evaluation of comparative scenarios where there was no change in volume input. Thus, this routing decision was preferred over the more complex dynamic routing assignment. Some assumptions were considered while developing the routing decisions, such as: no vehicle stopped inside the network, the relative distribution of traffic should be the same as that given in the GIS data sets and traffic accessibility followed original site restrictions (*e.g.* Bus lane, Bus restricted roads, *etc.*).

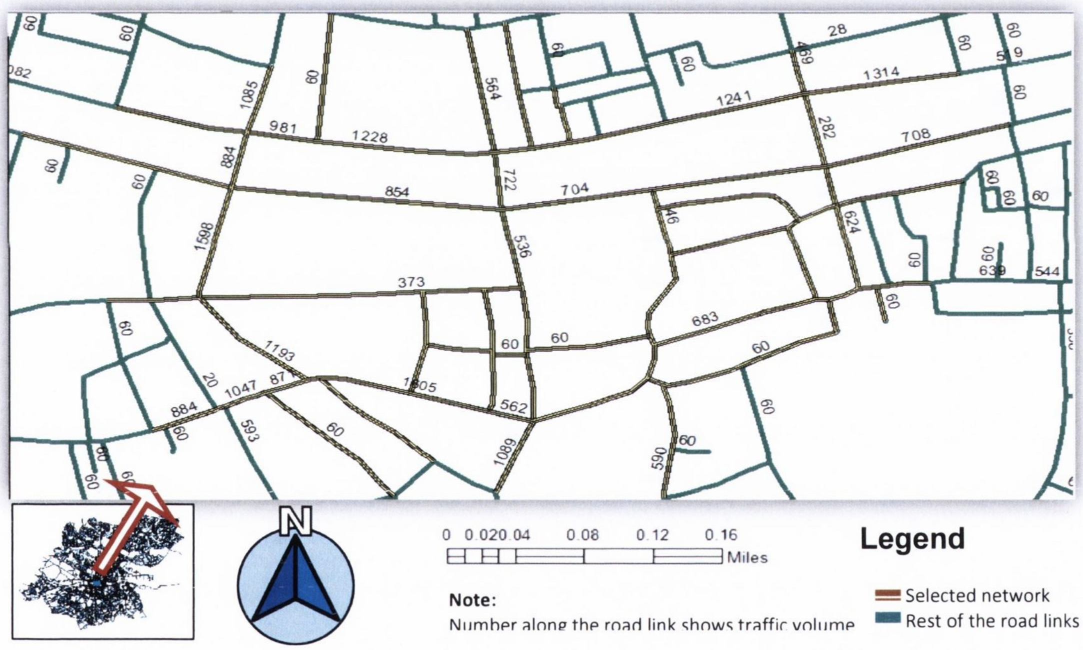


Figure 4.8: Peak hour (8-9am) traffic volume in the selected traffic links

Other traffic flow data inputted included traffic composition, and travel time. Travel time was automatically counted by VISSIM based on the speed and acceleration profiled specified in the model, other parameters for car following and lateral movement used default values, and were kept constant for all the scenarios. Traffic composition did not vary according to the category except for Experiment 4. In

Experiment 4, vehicle composition varied in both speed and category. Cars in Experiment 4 were simulated with three different speed profiles. 90% of the vehicles in this experiment were cars and the rest of the vehicle included 2% buses and 8% taxis, reflecting typical data in Dublin city centre (NRA, 2012).

4.3.3 Parameters for simulation in VISSIM

Speed, acceleration and deceleration curves were the other important parameters for examining the impact of Eco-Driving on the network.

- Speed profiles

For any vehicle type, the desired speed distribution was an important parameter that had a significant influence on road capacity and travel speeds. The desired speed in VISSIM is defined as a distribution (or, speed profile) rather than any fixed value. The first speed profile ('a' in Figure 4.9) shows a uniform desired speed distribution between a minimum and maximum allowable speed, and this was applied as a general speed profile in Experiment 1, however, it was also considered for Eco-driving vehicles (ECO-II) later in Experiment 3 and 4. This speed profile was designed to provide overall higher speed for the entire traffic flow in comparison to the other speed profiles considered in this study. As this network was obtained from a 30km/h speed zone in Dublin, the maximum allowable speed value was chosen as 30km/h (20.5mph) for this first speed profile. In addition, a 10% variation for in speed limit is recommend by VISSIM and thus the maximum speed limit was chosen as 33km/h for the next two speed profiles ('b' anf 'c' in Figure 4.9). However, minimum speed was chosen as 15km/h for all profiles as it is assumed that people will not drive below half of the speed limit in a free road under any circumstance.

The difference between the last profiles (b) and (c) lies in the difference in the percentage of the vehicles that follow the speed distribution. For speed profile (b) , the cut points were 15-20 km/h (15% percentile), 30 km/h (90% percentile) and 33 km/h (100% percentile). This means that 15% of the vehicles in the network will have a desired speed of between 15-20km/h, whereas 75% of vehicles will have a desired speed of 20-30km/h and the remaining 10% will travel at 30-33km/h. For speed profile (c), the speed cut points were: 15-20km/h (40%), 30km/h (90%), and 33 km/h (100%). Speed profile (c) tended to produce overall lower speed in the network as 40% vehicles were within 15-20 km/h.

As outlined earlier the purpose of having 3 speed profiles in the experiments was to improve the representativeness of the scenarios being modelled such that different proportions of vehicles followed differing desired speed profiles. Thus there was a variation in speed for each individual vehicle following a particular desired speed profile and also additional variation in speed as vehicles were assigned to different profiles. In Experiment 1 the impacts of Eco-Driving was assessed using all 3 speed profiles, while in Experiments 2 and 3 only the best performing speed profile was selected from Experiment 1. In Experiment 3 and Experiment 4, all 3 speed profiles were again examined to investigate their impacts on ECO-II type Eco-Driving vehicles and multi-modal traffic composition.

While travelling through a network in VISSIM, a vehicle moves at its desired speed with a small stochastic variation, or oscillation based on the driving behaviour model. VISSIM's psycho-physical driver behaviour model implies that a driver of a faster moving vehicle starts to decelerate as he reaches his individual perception threshold to a slower moving vehicle. On multi-lane links, vehicles check whether they can increase their speed by changing lanes. In a single lane, since they cannot exactly determine the speed of that vehicle, speed will fall below that vehicle's desired speed until he starts to slightly accelerate again after reaching another perception threshold (PTV, 2011).

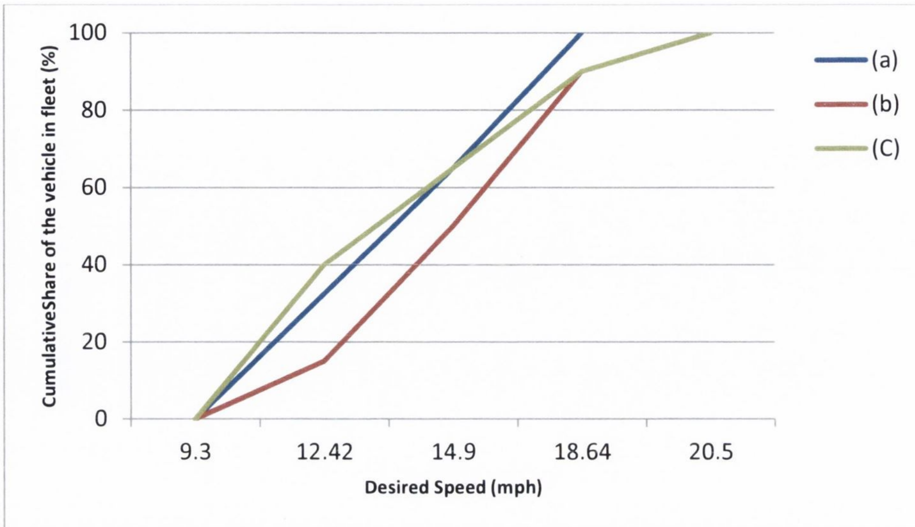


Figure 4.9: Three desired speed profiles: (a), (b) and (c).

- Acceleration and deceleration

The stochastic property of traffic flow due to variations in driver behaviour is mainly represented by acceleration and deceleration functions in VISSIM. These functions depend on the speed of the vehicles. The model assumes that drivers have preferences for different accelerations and decelerations at different speeds. For a vehicle category, a set of three acceleration and a set of three deceleration functions can be defined. In each set maximum, mean and minimum acceleration/deceleration curves are the source of variation. The software selects a value for a vehicle between the minimum and maximum acceleration/deceleration curves, assuming that the mean curve is equivalent to the mean value of a normal distribution having a value of 0.5 with standard deviation 0.15 but limited to [0.0,0.1], and that the min/max curve is 3.333 times the standard deviation (SD). These criteria ensure about 70% of vehicles is assigned with acceleration/deceleration in the inner third (±1 SD) of these random values, and 95% are inside two standard deviations. Thus by limiting the spread between the minimum and maximum curves, a lower standard deviation of acceleration and deceleration for Eco-Driving vehicles was ensured. Ando and

Nishihori, (2011) stressed that stable speed and with lower acceleration and decelerations constituted Eco-Driving behaviour for vehicles.

Usually, combustion engines reach their maximum acceleration at low speeds. Another characteristic of Eco-Driving was ensured by following lower maximum acceleration/ deceleration at low speed in comparison to the acceleration/deceleration curves of normal cars. In this study, values were adopted for normal cars (6.7 m/s^2) and Eco-Driven cars (4.9 m/s^2) from another real world experiment where entire speed acceleration profile was obtained from field experiments. Acceleration and deceleration profiles were adopted from Kobayashi *et al.* (2007) where eighteen drivers were tested who drove a Volkswagen Golf Touran GLI and Mazda Eunos 800. Significant differences in acceleration and deceleration profiles between normal and Eco-Driven cars make it an appropriate choice for this study.

The curves shown in Figure 4.10 were used which featured some changes in the spread for Eco-Driving impact analysis. Maximum acceleration curves (a) & (b) were also adopted for desired acceleration curves, and a default curve in VISSIM has been taken for the maximum deceleration curve. However, the desired deceleration curves were as shown in Figure 4.10 as (c) and (d). Buses and taxis in Experiment 4 also followed Eco-Driving acceleration/ deceleration profiles for simplicity. As these vehicles were only included to test the sensitiveness of Eco-Driving cars.

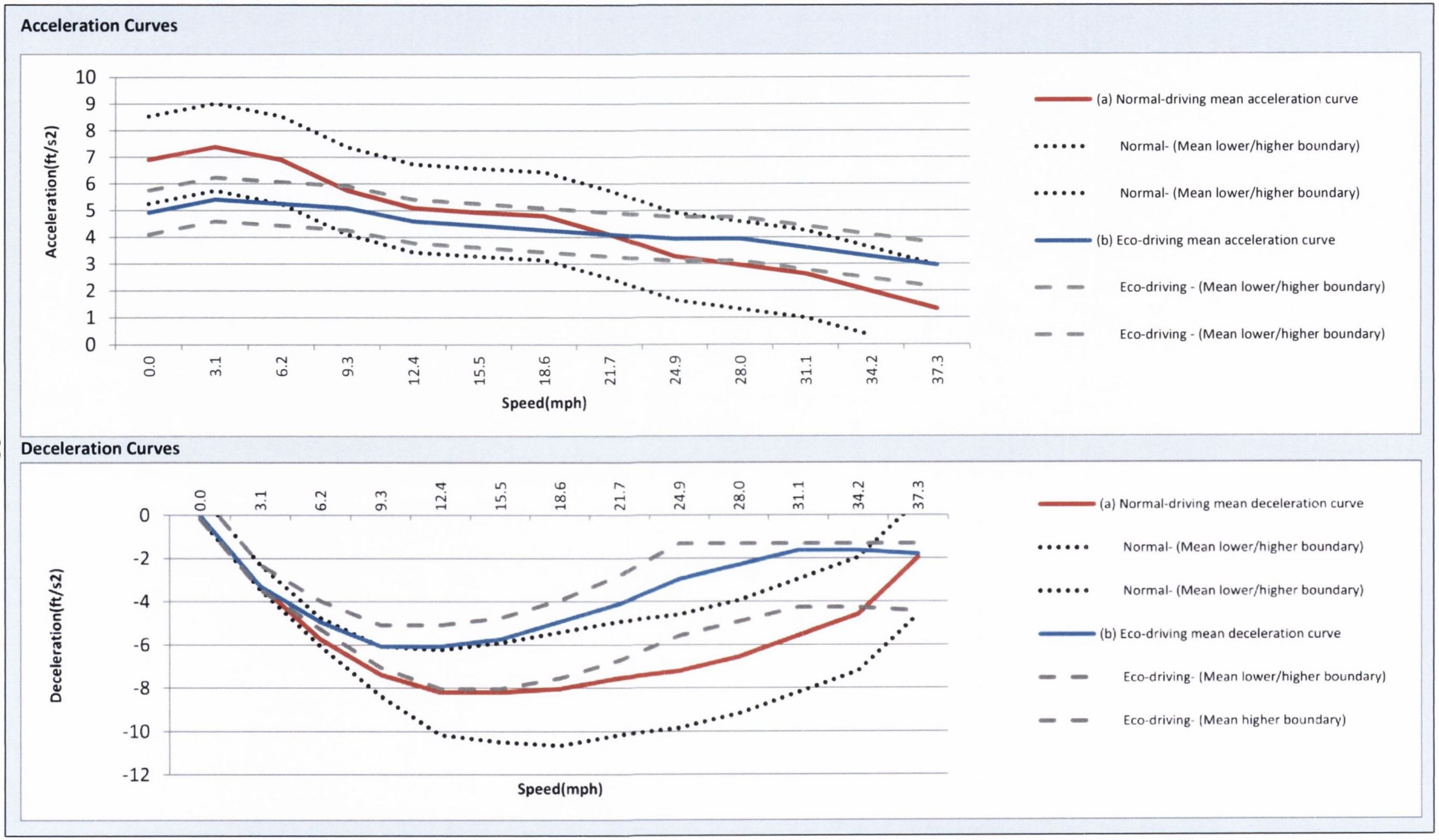


Figure 4.10: (a) Normal acceleration; (b) Eco-derived acceleration; (c) normal deceleration; and (d) Eco-derived deceleration.

• Other parameters of VISSIM

In VISSIM, parameters for calibration, specific vehicle parameters, *e.g.* vehicle mass, generic vehicle parameters, *e.g.* gear ratio and operating variables can be adjusted following the requirement of the model and situation. Except for operating variables, all default values were accepted and were kept constant throughout different the VISSIM scenario comparisons. In order to produce identical scenarios, random seed (as discussed in section 3.3.2.1, Chapter 3) 1-10 were applied. For averaging result comparison, 1-10 random seeds were used. However, for detailed acceleration and deceleration result comparison, a seed value of 9 has been chosen randomly in Experiment 1 & 2.

4.3.4 Parameters for CMEM

Like VISSIM, most of the default parameter values were applied in CMEM for emissions calculations. In CMEM, vehicle categories were derived based on groupings of vehicles with similar operating and technology characteristics. For representing all the vehicles, only one diesel vehicle category having characteristics of a three way catalyst, mileage below <50K mile, and a high power/weight ratio were chosen for emissions estimation (Figure 4.11). There was no distinguish between passenger car or small truck was made and default value of the module for the selected parameter for a diesel vehicle category was accepted for analysis. The second input that was inserted in CMEM was vehicle activity files. The data from VISSIM, such as time (in seconds), speed (mph), and acceleration (mph/s) were imported as activity files after necessary sorting and adjustment in Excel software. The estimation of emissions from the whole fleet has been carried out considering an assumption that the activity data were generated from one vehicle profile. In order to do this, each vehicle profile was added after one another for the whole fleet. There were negligible jumps in speed and acceleration between different vehicle profiles while adding speed was around 10km/h for the network. These negligible jumps were also averaged out as results were interpreted by making comparisons where the trends of changes were more important than absolute values.

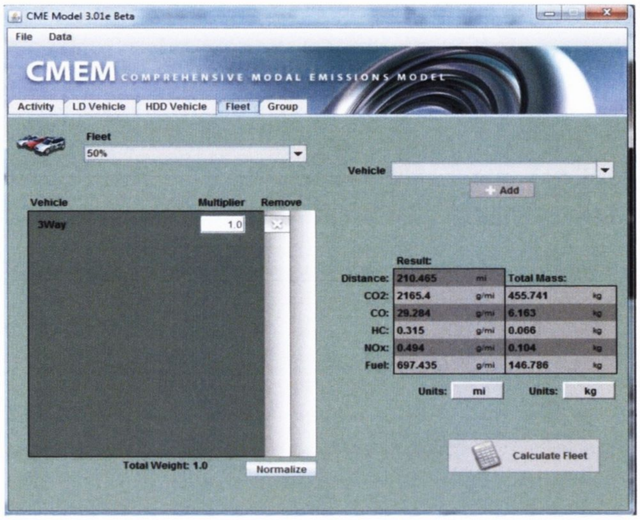


Figure 4.11: CMEM GUI shows estimated emissions

4.4 Verification

Although none of the simulations were carried out for a specific real world scenario, a verification of the model was necessary in order to produce realistic results. Verification was conducted to ensure that the computer representation implemented reflected actual driving conditions. To avoid unexpected events, such as crashing vehicles at intersections, or in roundabouts, the network was also designed with a priority rule with adjusted values (*i.e.* headway distance and gap time determined whether right turning vehicles could cross a stop line). Conflict areas were also included in the model (*i.e.* enforcing yield logic, if another vehicle moves earlier from any other direction). The signal timing was also adjusted among intersections, in order to avoid unnecessary congestion, or to ensure the smooth flow of traffic.

During simulation three types of errors may occur:

- Vehicles may be deleted from the network if a correct route is not found at the end of a link.

- Vehicles may be deleted from the network if they cannot change lane due to a rush on the desired lane.
- Vehicle input did not generate enough vehicles because the discharge rate was smaller than the input flow (Miller, 2009).

During simulation, error files were checked with discussion of Beutin (2014), and no alarming issues were observed. All of the experiments were checked in order to ensure that models produced valid and comparable results.

Miller (2009) noted that the third error category might occur while the model network (or at least the entry point in question) has a lower capacity than the actual network. This may occur while all of the traffic inputs are increased uniformly, or as an input error, or the model may be unable to process all of the vehicles set to enter the network due to the current signal timings or other circumstances that accurately reflect real world conditions. This type of error occurred only in alternative scenarios in all of the experiments. This is discussed later under latent demand criteria.

4.5 Simulation results

This section analyses the simulation results from different scenarios. Further details of the results are given in Appendix B.

4.5.1 Experiment 1: small four intersection network

Results from Experiment 1 showed the effects of differing Eco-Driving penetration rates on network level congestion and environmental impacts. Figure 4.12 shows the results of the simulations for low and high traffic volumes and for various measures of traffic congestion. At low traffic volumes, total stopped delay gradually increases with the increase of Eco-Driving car penetration rate up to 50% for all of the speed profiles examined. At 100% penetration, there is a drop in total delay, and this was most noticeable for speed profile (c). This was because 40% of the vehicles were restricted to drive less than 20km/hour and because there was less variation in the speed of the fleet, there were fewer numbers of platoons created (PTV, 2006) and smoother overall flow reduced stopped delay. The stopped delay curve for speed profile (c) was higher than that of other two. This was also because of the higher penetration of slow moving vehicles (20km/hour). However, the changes in stopped delay did not reduce the trip time (running time, and stopped delay) of the vehicles, as the increase in travel time is much higher comparison to the decrease of stopped delay.

There was no latent demand present for the low traffic volume scenarios; however, there were latent demands of vehicles in high traffic volume. Moreover, with the increase in slow moving traffic caused by increased Eco-Driving vehicles the latent demand increases as expected in the last figure of the right column in Figure 4.12. In high traffic conditions, the trip time, travel time and stopped delay increased gradually with increasing Eco-Driving vehicles. Although all the speed profiles showed a similar trend in the figures in the right hand column in Figure 4.12 in high traffic volume, the values were not same for left and right figures. At high traffic volume, travel time, trip time and stopped delay were higher in high traffic volume than that of corresponding figures in low traffic volume.

Eco-Driving vehicles were found to increase the trip time per vehicle in the network from 10.34 minutes in the base case to 11.55 minutes for 100% penetration at high traffic volume using speed profile (c). This 11.7% increase in trip time was a similar finding to that using speed profiles (a) or (b). This percentage increase in trip time was approximately linear with a 6.3% increase found at 50% penetration using speed profile (c). In the presence of low levels of traffic congestion only negligible increases in trip time per vehicle, were found (0.5-1%).

Therefore, it is clear from the analysis of this small network that Eco-Driving during heavy congestion results in an environmental detriment at fleet level and increased traffic congestion. While in the absence of traffic congestion, Eco-Driving produces no

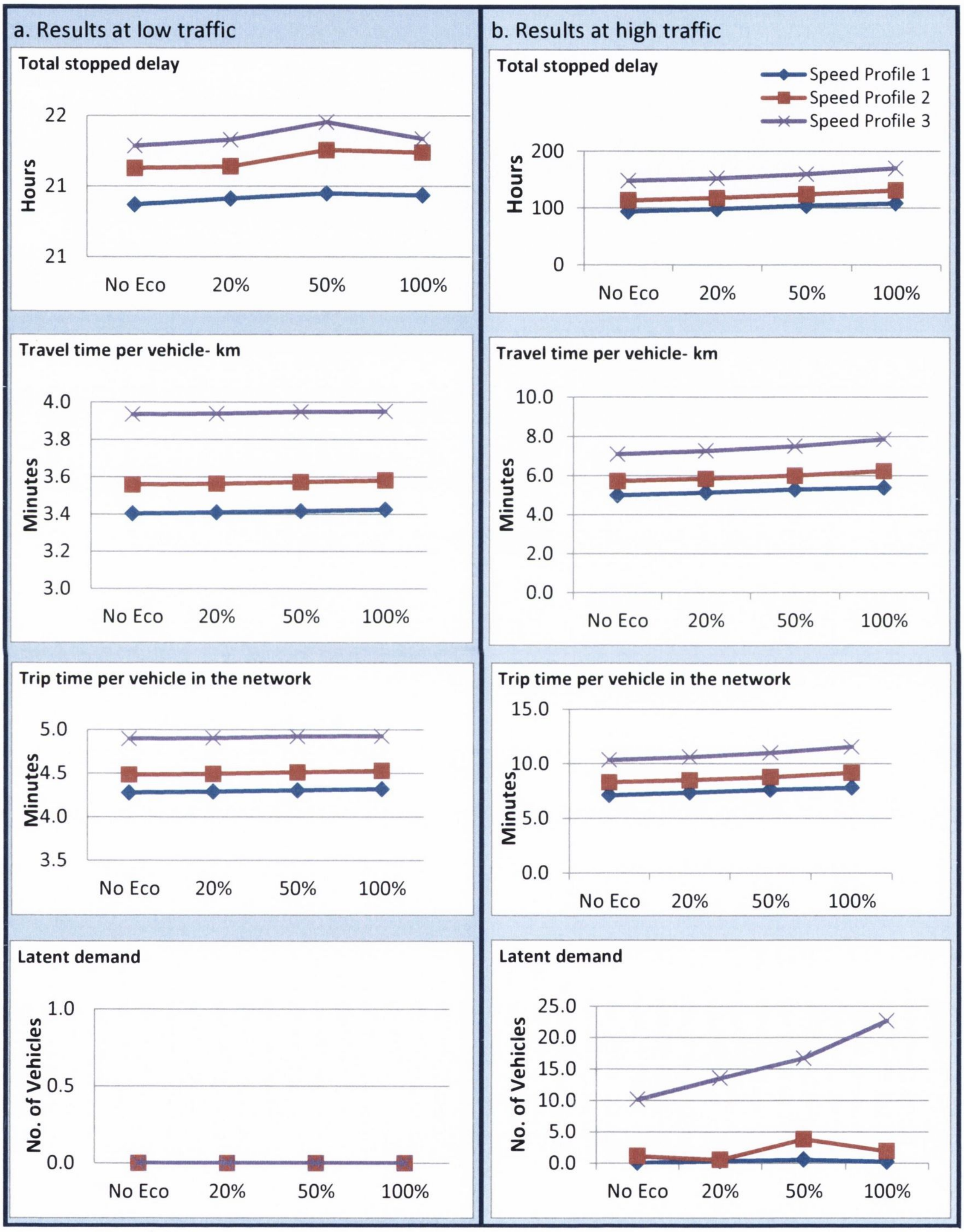


Figure 4.12: (a) shows simulation result in low traffic volume; (b) shows similar result for high traffic volume

significant impacts on fleet level travel time or congestion. Therefore, in the absence of congestion the claimed environmental benefits of Eco-Driving for individual vehicles would have a positive impact at fleet level.

Due to limitations in computational capacity available during this project, emissions data from the VISSIM outputs have been divided into four 15 minutes time segments, and only first and last two boundary segments were compared as these two segments provided better results of changes in traffic. The emissions from all the vehicles having speed profile 'b' (as an arbitrary choice as the result were similar for all profiles) that run in the network were estimated using CMEM (Table 4.1 and 4.2). The results are needed to be interpreted carefully as the CMEM model is not calibrated for any specific vehicle (Section 3.3.2.1 and 4.3.4). The unit emission values (g/km) was likely to be higher than that of the passenger car and will be close to LDV, however the result was sufficient to assess the relative change among different scenarios.

As can be seen in Tables 4.1 and 4.2 similar trends were found for emissions and fuel consumption estimations. Fuel consumption at network level increased with increasing Eco-Driving penetration rate for high traffic volumes by up to 18%. It was evident that the level of congestion increased in the network for high traffic volumes and increased Eco-Driving comparing the first and last 15 minutes of the 1-hour simulation. In the case of the low traffic volume scenarios there was little or no negative impact from Eco-Driving on fuel consumption and little or no difference between the first and last 15 minutes. Some small improvements in fuel consumption were in fact found for this scenario. CO_2 emissions in low traffic in both time segments for 100% penetration was similar to 50% penetration rate or lower and showed conformity to the reduction in stopped delay in the corresponding Figure 4.12.

Although there was no change in NO_x and HC figures, CO decreased and increased gradually in low and high traffic volumes with the increase of Eco-Driving penetration. On the other hand, the CO_2 emissions increased with the eco-car penetration rate during high traffic volume in both first and last segments (Figure 4.13), however, this trend was absent in the low traffic volume segments. Increases in CO_2 emissions for the high traffic scenarios amounted to a gradual increase of up to 18.2% at 100% penetration.

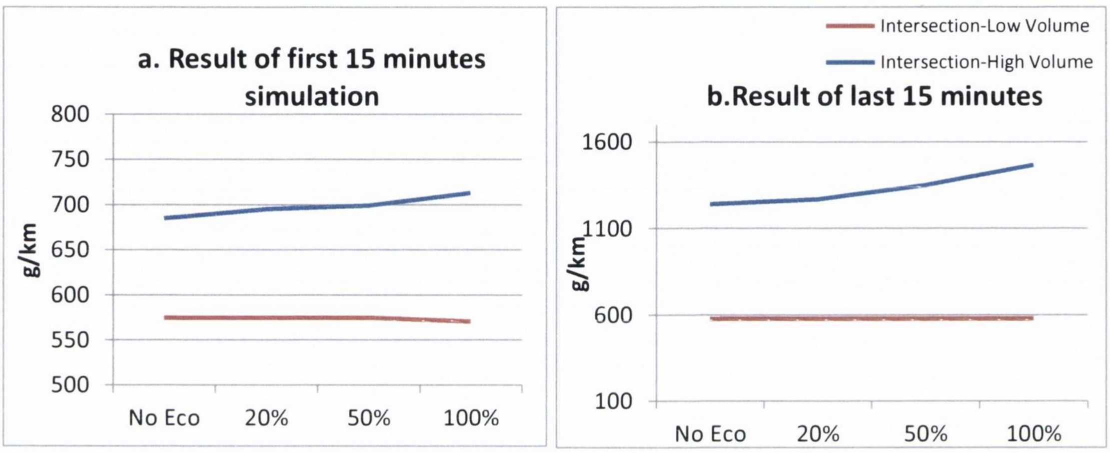


Figure 4.13: Total CO_2 emissions from vehicle in the first and last 15 minutes in high and low traffic volume

Although, the standard deviation of absolute acceleration (m/s^2) in the last 15 minutes for both high and low (Figure 4.14a) shows similarity to the SD of the first 15 minutes of absolute acceleration (m/s^2), the mean absolute acceleration (excluding zero values) was higher in the high traffic volume (Figure 4.14b) and that caused higher CO_2. In table 1, CO_2 emissions figures almost doubled in magnitude for last 15 minutes segment in comparison to the first 15 minutes segment at high traffic volume.

Table 4.1: Emissions estimation from CMEM at high traffic volume: Experiment 1,run 9

First 15 minutes (Average from all vehicles)						Last 15 minutes (Average from all vehicles)			
Unit	Pollutants	No Eco	20%	50%	100%	No Eco	20%	50%	100%
g/km	CO_2	685.1	695	699.3	713	1239.8	1269	1350.8	1466.4
g/km	CO	11.9	11.3	10.8	10.9	17.9	17.6	18.3	18.8
g/km	HC	0.1	0.1	0.1	0.1	0.2	0.2	0.2	0.2
g/km	NO_x	0.2	0.2	0.2	0.2	0.3	0.3	0.3	0.3
kg	Fuel	222	224.8	225.9	230.3	399.9	408.9	435.1	471.8

Table 4.2: Emissions estimation from CMEM at low traffic volume: Experiment 1, run 9

First 15 minutes (Average from all vehicles)						Last 15 minutes (Average From all vehicles)			
Unit	Pollutants	No Eco	20%	50%	100%	No Eco	20%	50%	100%
g/km	CO_2	574.8	574.8	574.8	570.8	577.9	579.3	578.7	578.8
g/km	CO	9.2	9	8.7	8	9.4	9.2	8.9	8.3
g/km	HC	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
g/km	NO_x	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
kg	Fuel	185.9	185.8	185.6	184	187	187.3	187	186.7

The mean of absolute acceleration/deceleration in first and last 15 minutes at low traffic volume (Figure 4.15) shows a similar trend. The changes of absolute acceleration 0.02 m/s^2 (Figure 4.14) from no-Eco to 100% eco-car penetration mean only 4 g/km CO_2 improvement (Table 4.1) in first 15 minutes. However, this benefit were overrun in last 15 by the congestion that might be triggered by lowering 0.01 of acceleration from 0.74 to 0.73 m/s^2 (right part of the Figure 4.15).

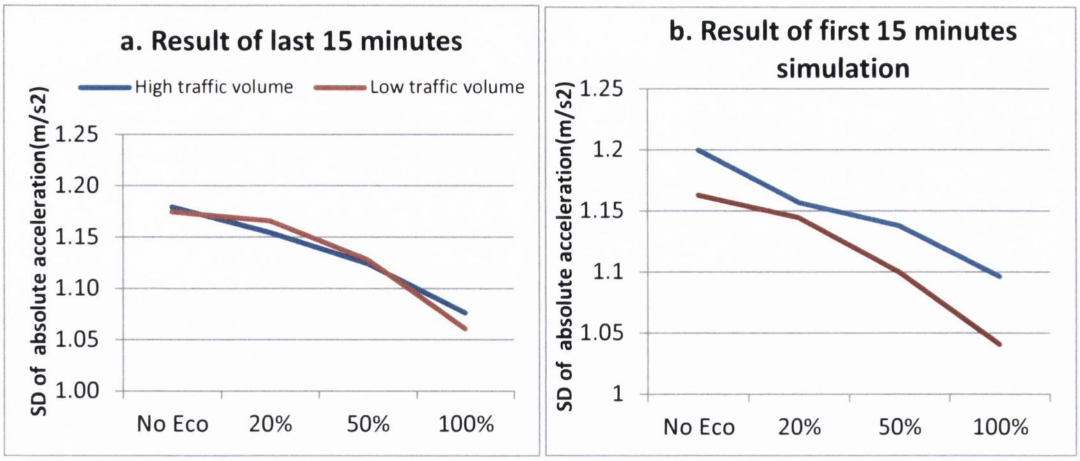


Figure 4.14: SD of absolute acceleration from vehicle in the first and last 15 minutes in high and low traffic volume

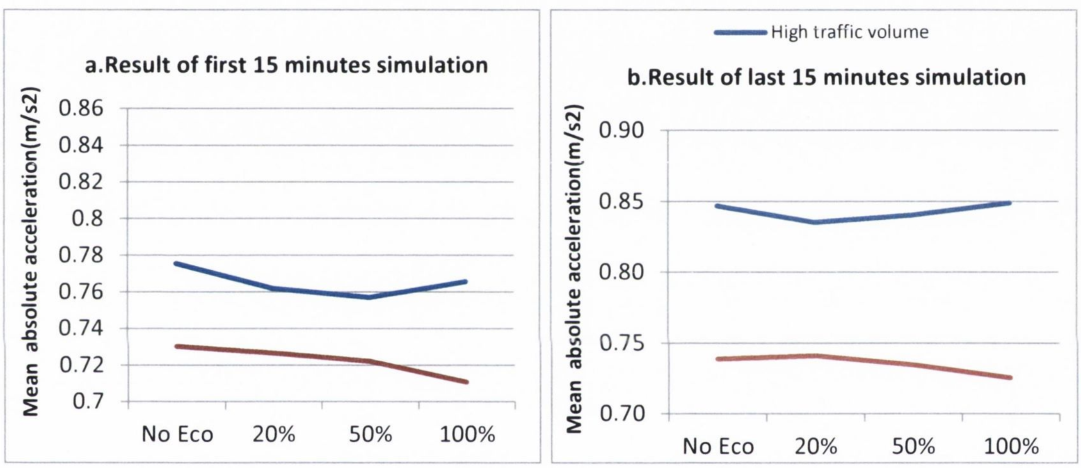


Figure 4.15: Mean absolute acceleration from vehicle in the first and last 15 minutes in high and low traffic volume.

4.5.2 Experiment 2: small network with 3 roundabouts and 1 intersection

The impact of the different Eco-Driving penetration rates on environmental and traffic performance was also assessed with three levels of input traffic flow where roundabouts replaced 3 of the 4 intersections in the road network of Experiment 1. This showed the impacts of Eco-Driving on the network performance under differing road geometry (see Figure 4.16). Again, the stopped delay, travel time and trip time all were increased with the increase of Eco-Driving vehicles. At low traffic condition, none of these values changed noticeably for increasing numbers of Eco-Driving cars. As there was no major intersection delay, the vehicles freely moved on the network and no latent demand occurred in either of the scenarios. In this case, the increase in trip time per vehicle from the base case to 100% Eco-Driving cars in high traffic volumes was 11.4%, which was very similar to the percentage increase in Experiment 1.

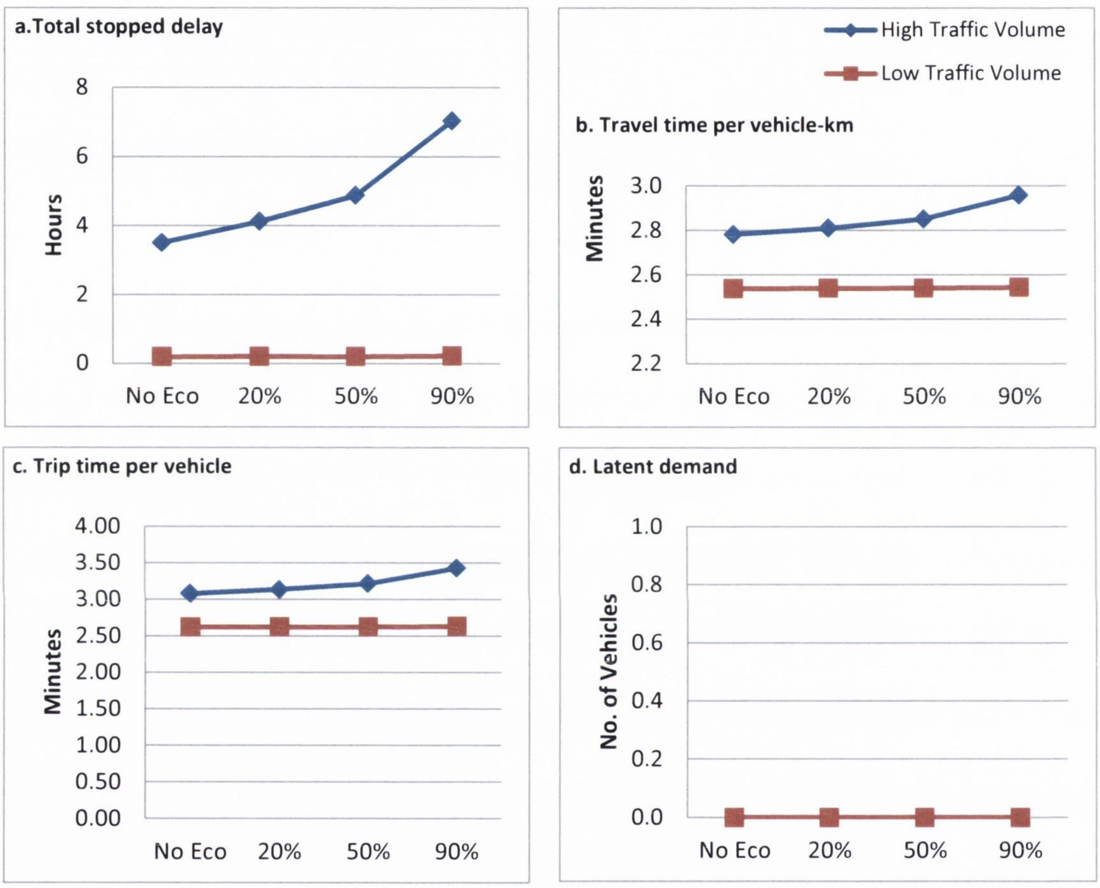


Figure 4.16: Graphical representation of simulation results from Experiment 2

As the last 15-minute segment was the most notable result in the Experiment 1, only last 15-minute segment is reported for Experiment 2. The mean and SD of the absolute acceleration/deceleration in Figure 4.17 confirmed that the driving behaviour of the fleet moves towards more an Eco-Driving nature as the level of Eco-Driving car penetration increased. As opposite to the last 15 minutes of figure 4.13, the CO_2 emissions actually reduced slightly as the Eco-Driving penetration occurred at low traffic condition (Figure 4.18). However, Eco-Driving again caused negative impacts on both traffic and environmental performance at high traffic volume.

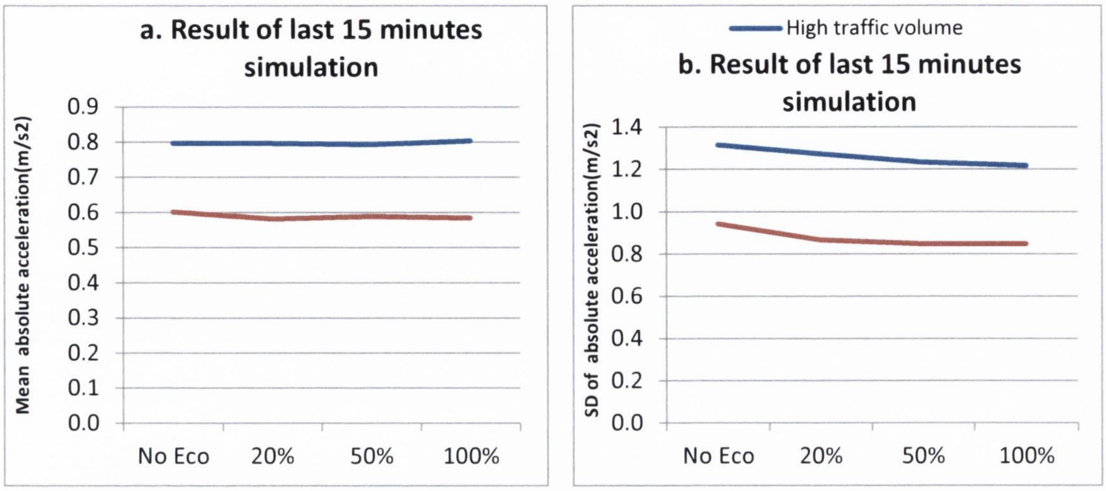


Figure 4.17: Mean and standard deviation (SD) of absolute acceleration from vehicle in the first and last 15 minutes in high and low traffic volume

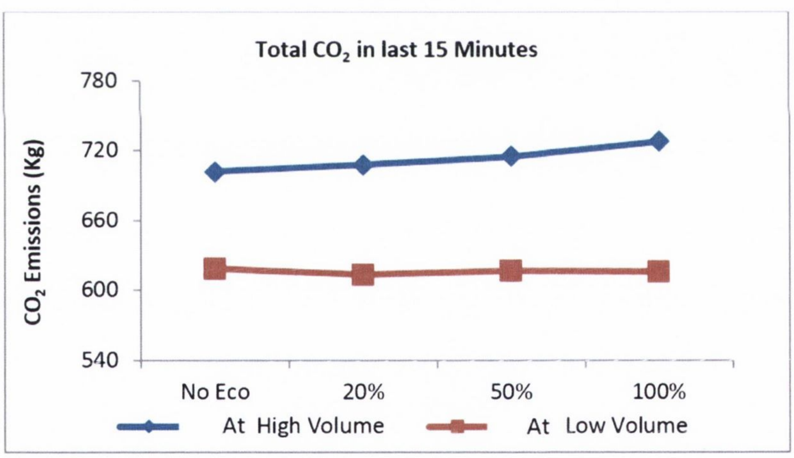


Figure 4.18: Total CO_2 emissions from vehicle in the last 15 minutes in high and low traffic volume

4.5.3 Experiment 3: large, real world, urban network including 2 approximations of Eco-Driving behaviour (cars only)

Following Experiment 1 and Experiment 2 it was clear that increases in the amount of Eco-Driving cars resulted in environmental and traffic detriments at road network level. Thus in moving the analysis forward to a larger real-world urban network, it was decided to introduce the concept of ECO-II type Eco-Driving vehicles, to assess the possibility of improving the negative impacts of Eco-Driving vehicles in future. This would be facilitated by V2V and V2I communication moderating vehicle speed and improving overall traffic flow.

In Experiment 3 (see Figure 4.19), two definitions of Eco-Driving (ECO-I: Acceleration & deceleration & ECO-II: Speed, acceleration and deceleration) were tested under high traffic volumes. As the impact of Eco-Driving at low traffic volumes was clear from the previous scenarios this was discounted here. Figure 4.20 shows that the delay, travel, trip and latent demand reduced with the increase of ECO-II Eco-Driving car penetration, and this was primarily because of improvements in the overall speed of the network (Figure 4.21), which in turn improved the capacity of the network. Thus, the flow improved (as number of vehicle completing routing/leaving network during fixed simulation duration was increased) as well as the vehicle km travelled (Figure 4.22). As emission is a function of speed, with such improvement in speed, the CO_2 emissions rate would be reduced with the increased of penetration of ECO-II type Eco-Driving.

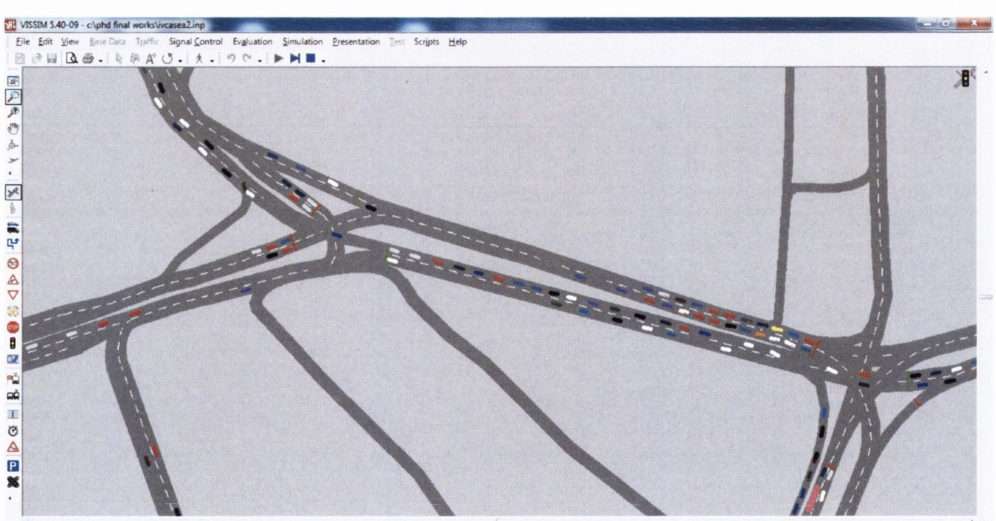


Figure 4.19: Simulated traffic in Experiment 3

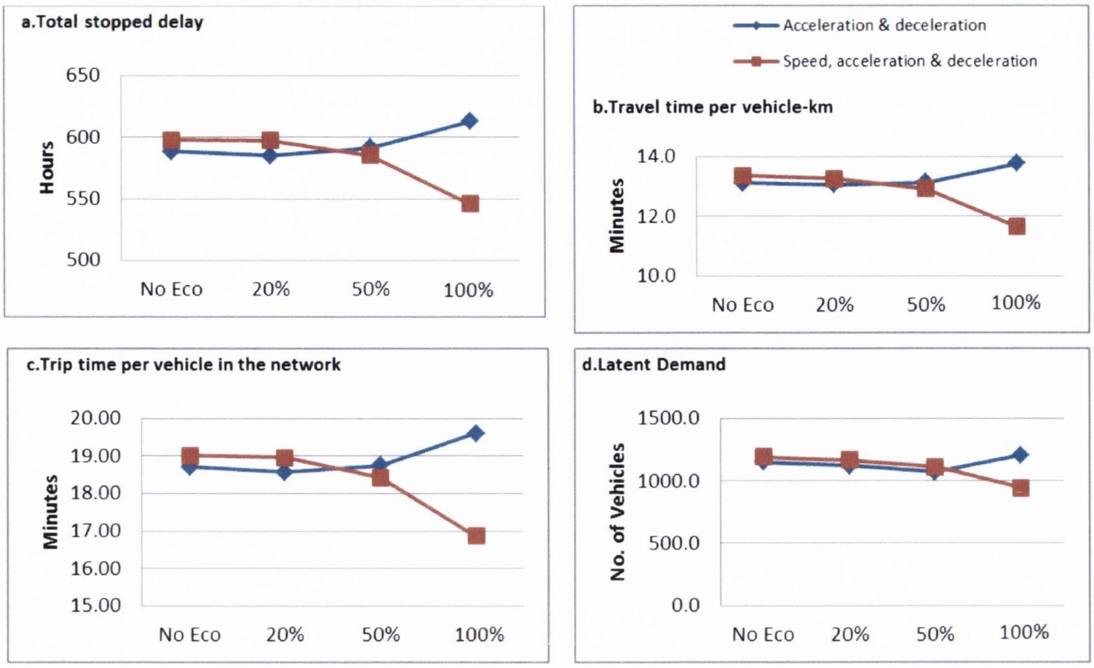


Figure 4.20: Graphical representation of simulation results from experiment 3

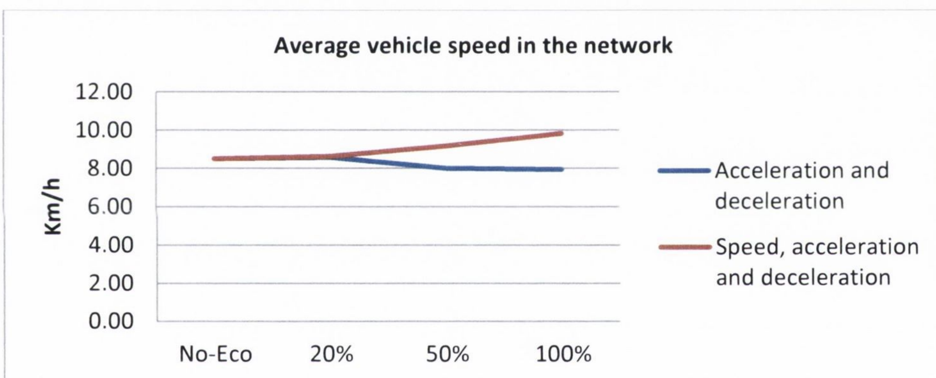


Figure 4.21: Network speed for various scenarios for two types of Eco-Driving vehicles

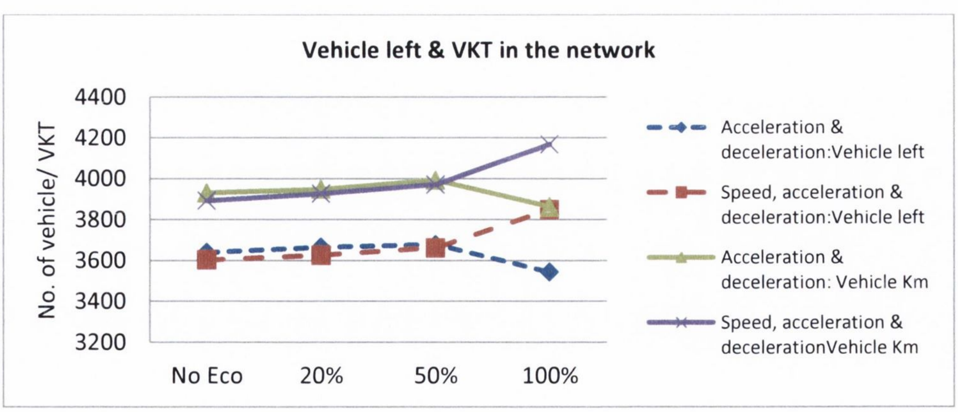


Figure 4.22: Number of vehicle left in the network, and vehicle km travelled in the network

However as can also be seen from Figure 4.21 and 4.22, in the absence of technology facilitating ECO-II type driving behaviour, Eco-Driving (ECO-I) resulted in similar negative environmental and traffic impacts with increasing penetration rate as those found in Experiment 1 and 2.

In Experiment 3, increasing the amount of ECO-I type Eco-Driving vehicles resulted in an increase in trip time per vehicle of 0.8 minutes, or 4.4% at 100% penetration. Conversely increasing the amount of ECO-II type Eco-Driving vehicles resulted in a decrease in vehicle trip time per vehicle at 2.2 minutes or, 11.5%. Therefore it is clear that Eco-Driving has a negative impact on traffic congestion and CO_2 emissions at road network level, considering a large urban network, but that with the introduction of additional intelligent transport technology in vehicles and transport infrastructure, that a positive impact is possible.

However, in the present day where many European countries have incorporated Eco-Driving into national policy without the presence of V2V or V2I communications in most cities, the impact of large increases in Eco-Driving vehicles in cities today would be negative.

4.5.4 Experiment 4: large real world urban network including multi-modal traffic compositions and ECO-II driving vehicles

In Experiment 4, ECO-II vehicles were allowed to penetrate the road network under near real traffic composition conditions. As positive impacts have been observed from ECO-II vehicles, the study further investigated this impact in a multimodal scenario. The impact of fleet speed variation was tested along with the other evaluations conducted in the previous experiments: less speed variation (first column in Figure 4.23) or more speed variation among non-Eco-Driving cars (second column in Figure

4.23). In the lower speed variation scenario, only speed profile 1 was considered and cars were replaced by different proportions of ECO-II vehicles for different scenarios. In the more speed variation scenarios, the total fleet was divided equally across all three-speed profiles, and ECO-II cars replaced cars equally from all three categories while different proportions of Eco-Driving cars entered into the network. A snapshot of the simulation representing multimodal scenario is presented in Figure 4.24.

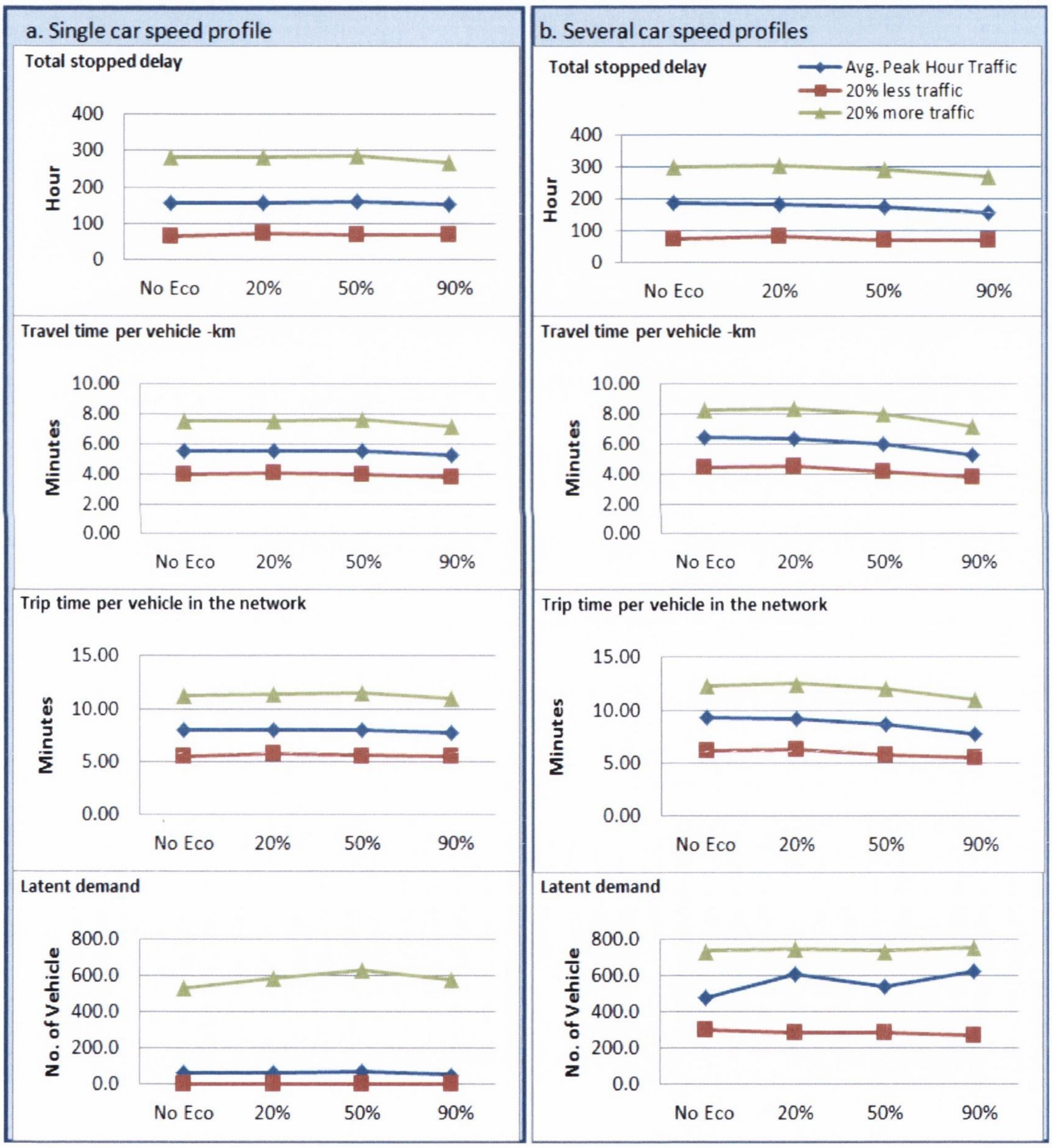


Figure 4.23: Left side figures marked by (a) shows simulation results for a single speed profile; (b) shows similar results for several speed profiles

Delay time, travel, and trip time for all three traffic scenarios provided similar results that may be compatible with the results from Experiment 3. At low traffic, stopped delay, travel time and trip time were lower than that of the other two scenarios for all levels of Eco-Driving car penetration. However, the reduction of stopping delay, travel, and trip time were not as prominent as was observed in Experiment 3.

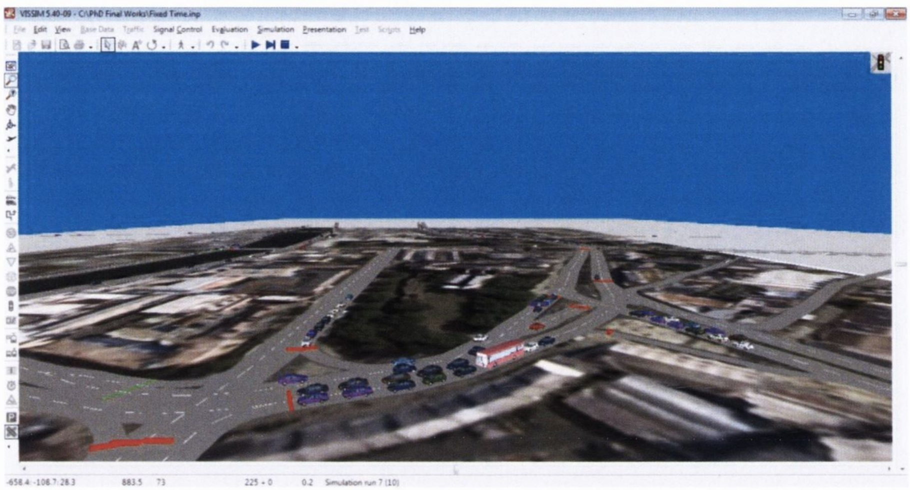


Figure 4.24: VISSIM GUI shows multi-modal traffic movement in the experiment 4

Although, a total of 10% taxis and buses travelled with the ECO-II cars, the numbers of vehicles released in these scenarios were lower than that of Experiment 3. This can be observed from the latent demand in Figure 4.20 and Figure 4.23. Even in this comparatively lower traffic volume, delay and travel time reduction in Experiment 4 was not as prominent as before. For instance, a decrease in vehicle trip time per vehicle under low traffic scenario was only between 0.57-2.71% for a single speed profile, or 10.36-16.28% for several car speed profiles), and this may be because of the multi-modal traffic composition.

For the single and several speed profiles at the high traffic volume, a 4.2%, and 13.3% benefit in travel time per vehicle kilometre was observed at the 90% ECO-II penetration rate in comparison to 0% ECO-II car penetration and this was similar to the findings of Experiment 3. Because of the traffic composition definition applied in simulations with “several speed profiles” delay and travel time is higher than that of “single speed profile”. In addition, because of the same reason, saving time in delay and travel in 90% penetration rate is comparatively higher in “several speed profiles” scenarios. In addition, such savings are lower in comparisons to low traffic volume scenarios (5.1% for the single car profile, and 18.5% in the several speed profiles) which are the result of lower level of traffic volume.

4.6 Conclusion

Eco-Driving car penetration has effects on the environmental and network performance of a road network as it results in added delays at intersection level. This effect is mostly visible during high traffic volumes. At low traffic flow, the negative impact is also visible; however, the impact primarily depends on the road network configuration. However, Eco-Driving can provide benefits if it can trigger both improvements in acceleration/deceleration and speed profile of the flow. It is highly unlikely that a driver can be a master of gentle acceleration/deceleration and cause an improvement of traffic speed, unless V2V or V2I communication technologies become widespread. Technical discussions about vehicle movements in the network in relation to the previous studies have been included in section 7.1, chapter 7.

In short, from the result of the above, it can be easily observed that the Eco-Driving policy has the worst performance in high traffic volume while there are a number of intersections present. On the other hand, it can be shown that if there is a smooth flow of traffic and an improvement of the overall speed profile of the flow due to Eco-Driving, there is a chance of improving both the traffic performance with environmental impact. Further investigation is necessary to accurately determine the effect.

Air Quality Model and Healthy Routing

Chapter 5

This chapter has been partially published as: ALAM M. S. & MCNABOLA A. Exploring the modelling of Spatio-temporal variations in ambient air pollution within the land use regression framework: Estimation of PM_{10} concentrations on a daily basis. Journal of the Air and Waste Management Association, January, 2015.

5.1 Introduction

The principle behind a route selection from a given set of the alternatives is to select a route that offers least cost. Along with many traditional cost factors of route choice (*e.g.* travel time, fuel cost, distance, and transfers), different cost factors, like emission for identifying energy efficiency, or the environmentally friendly nature of a route was applied in many recent studies (see Chapter 2). A similar attempt was conducted in this chapter with the aim of identifying healthier routes for smarter travel. From a health perspective, therefore it is necessary to select and estimate a new cost factor that is representative of the air quality of the routes. Dose of PM_{10} was selected as a generic indicator for the quality of the routes. However, a particular challenge was to estimate the air pollutant concentrations along each road in a network, and thus, the estimation of PM_{10} concentration forms a large part of the focus of this chapter.

As outlined in chapter 3, a PM_{10} air quality model was required to be developed in the first step of this analysis, followed by a comparative routing analysis, these two steps were followed in this Chapter.

The LUR modelling framework was adopted in this study due to its ability to predict the spatial and temporal variations of air quality based on readily available data in cities. As will be seen in this chapter, it can be shown that models of ambient air quality can be developed using adaptions of the original LUR concept, which produce reasonably accurate predictions based on the limited input data typically available in European cities (*i.e.* without the addition of costly measurement data in addition to that routinely recorded in the Fixed Site Monitor (FSM) network of a city).

The objective of the first step of this investigation was therefore to develop a model of ambient air quality capable of predicting daily variation and spatial variation in cities using readily available data, and later analysis of route choice based on PM_{10} concentration in relation to other route choice criteria. Dons *et al.* (2013b) developed hourly LUR models and concluded that such models are not more data-demanding than annual LUR models, however in the present study hourly PM_{10} data were not captured in the FSM air quality monitors in Dublin. Thus, temporal adjustment of modelled daily PM_{10} data was conducted using hourly NO_x data. Nethery *et al.* (2008) derived a monthly trend from six years of ambient monitoring network measurements, and applied this to land-use regression modelled annual values by either raising or lowering those values. Similar temporal adjustment was conducted by Gan *et al.* (2011) and Dons *et al.* (2013b). Dons *et al.* (2013b) noted that hourly LUR models are useful in determining long or medium term personal exposure to air pollution more accurately when combined with GPS data to estimate personal exposure. In order to achieve the overall aim of the chapter, the research questions that are being addressed here include:

- How can we develop a reliable PM_{10} air quality model for Dublin bases on limited amounts of readily available input data?
- After applying the Dublin model for PM_{10} concentrations at route level, does lowest travel time lead to the lowest exposure to PM_{10} concentration or dose for commuting?
- What conclusion can be drawn for healthy routing in comparison to the other traditional travel cost factors?

5.2 Exposure modelling: air quality model

5.2.1 Experiment design

In the first step of the LUR model development predictors were required to asses against pollutant concentration data in order to determine the empirical relationship between them. After selecting candidate variables, a PM_{10} model for Dublin was developed initially for 2009, followed by models for other pollutants in the same year. Later, PM_{10} models were developed for a larger time frame from 2007-2009 in Dublin.

In many studies, the temporal stability of landuse regression was report to be good both forward and backward in time (Chen *et al.*, 2010b; Gonzales *et al.*, 2012; Gulliver *et al.*, 2011b,2013). Chen *et al.* (2010b) and Gulliver *et al.* (2013) studied back extrapolation of LUR models, whereas Eeftens *et al.* (2011) and Madsen *et al.* (2011) proved insights of the stability of spatial contrast of LUR over the years. Gonzales *et al.* (2012) showed that the nature of the most influential predictive variables remained the same and that LUR models developed from previous years may be applicable to assess exposure conditions in subsequent years. In order to assess the transferability of the methodology between cities, the modelling steps in Dublin was also followed for data from Vienna. A PM_{10} model was first developed for Vienna in 2011, and later for the 2011-2012 time frame. The following research questions were developed to carry out the PM_{10} modelling exercise for Dublin.

- What are the predictor variables from land use, meteorological, topography and transportation sectors surrounding the FSMs that have a strong relationship with the recorded PM_{10} concentrations, and can be taken into account for LUR model development for a particular time frame?
- Are these predictors consistent for other pollutants, *e.g.* NO, NO_2, NO_x and SO_2 for that time frame?
- Is there any improvement of the models if PM_{10} data were integrated together from several consecutive years?
- Is such a model development procedure applicable to another city?
- Does the introduction of the advanced or non-linear statistical techniques for model developments lead to an improvement of model fitting?

In order to assess the above research questions, a series of 16 models (Table 5.1) were developed using a number of variations in the modelling concept for both of Vienna and Dublin. These models related the daily average pollutant concentration across Dublin or Vienna to a number of predictor variables, listed in Tables 5.2 and 5.3. Models varied in the range of predictor variables included in each; in the range of available historical input data; in the number of FSMs available; and in the statistical technique applied to relate predictor variables to PM_{10} and other pollutants concentrations. Models were first developed and refined for Dublin; the same methodology was subsequently applied to Vienna. The number of predictor variables was also limited to be no greater than the number of available FSMs to avoid over-specification of variables (Freund *et al.*, 2006).

The first model (*Dublin 1*) comprised the development of a standard LUR model for Dublin, using MLR statistical analysis technique, with the objective of establishing a baseline against which further improvements could be compared. *Dublin 1* was applied to the most recently available and reasonably complete PM_{10} dataset from the available FSM network in Dublin city during the study. *Dublin 1.1-1.4* were developed with the same dataset but for different pollutants for the year 2009. The objectives of Dublin 1.1-1.4 were to assess the ability of the methodology to predict the concentration of other pollutant types.

In regression modelling, it is possible to choose many good models (in other words, there is no single definitive "best model") from a set of data that generally yield similar overall interpretations and predictions (Pardoe, 2012). These models only differ slightly with respect to how many and which variables were included. Here *Dublin 2* is one of these models. Thus the objective of *Dublin 2* was to assess the predictive performance of this technique using a slightly different set of predictor variables (see Table 5.3).

Dublin 3 was developed using an identical approach to *Dublin 2*, using a longer period of historical input data (2007-2009). The objective of *Dublin 3* was therefore to assess any changes in the models predictive performance over a longer period of historical input data. As discussed earlier the LUR models were previously shown to be stable over time.

Table 5.1: List of the 16 models developed.

Model Name	Pollutants	Description	Number of FSMs	Input Data
Dublin 1	PM_{10}	Standard MLR approach	5	2009
Dublin 1.1	NO	Standard MLR approach for Dublin	5	2009
Dublin 1.2	NO_2	Standard MLR approach for Dublin	5	2009
Dublin 1.3	SO2	Standard MLR approach for Dublin	5	2009
Dublin 1.4	NO_x	Standard MLR approach for Dublin	5	2009
Dublin 2	PM_{10}	Alternative standard MLR approach for Dublin	5	2009
Dublin 3	PM_{10}	Standard MLR approach using a longer period of input data, but limited FSMs	5	2007-2009
Dublin 4	PM_{10}	Standard MLR a longer period of input data	7	2007-2009
Dublin 5	PM_{10}	Addition of seasonal and weekly variation *Dublin1*	7	2007-2009
Dublin 6	PM_{10}	Alternative statistical technique (NPR) using *Dublin 2* input data	7	2007-2009
Dublin 7	PM_{10}	Alternative statistical technique (ANN) using *Dublin 3* input data	7	2007-2009
Vienna 1	PM_{10}	Standard MLR approach for Vienna	13	2012
Vienna 2	PM_{10}	Standard MLR approach using a longer period of input data	13	2011-2012
Vienna 3	PM_{10}	Addition of seasonal and weekly variation	13	2011-2012
Vienna 4	PM_{10}	Alternative statistical technique (NPR) using *Vienna 3* input data	13	2011-2012
Vienna 5	PM_{10}	Alternative statistical technique (ANN) using *Vienna 3* input data	13	2011-2012

Dublin 4 was developed using the same timeframe as *Dublin 3,* however this model included 2 more FSMs. A total of 7 FSMs were available in Dublin and provided data up to as recently as 2010 during this study however due to the amounts of missing data the most recent and reasonably complete dataset that could be used was 2007-2009. Also in 2009 2 of the 7 FSMs were not in operation. Therefore the objective of *Dublin 3* was to demonstrate the impact of increasing the amount of spatial coverage provided by the FSM network on model predictions (*i.e.* increasing from 5 to 7 monitors here).

Table 5.2: List of the predictor variables applied to each model developed.

Variable Name	Variable Code		Dublin					Vienna	
			1	1.1-1.4$	2-3	4	5-7	1-2	3-5
Air Mass History Rating	D_1	---	√	√					
Vehicle km travelled* (200m)	D_2		√						
Vehicle km travelled* (300m)	D_3	---			√	√	√		
Peak Traffic count at nearest intersection*	D_4	---	√	√					
Major Road" (350m)	---	V_1						√	√
Open Space area (1000m)	D_5	V_2		√	√	√	√	√	√
Population Density^^ (500m buffer)	---	V_3						√	√
Temperature* (C)	D_6	V_4		√				√	√
Rainfall/ Precipitation** (mm)	D_7	V_5				√	√	√	√
Wind speed*^ (m/s)	D_8		√	√	√	√	√		
Maximum sustained wind speed^ (km/h)	---	V_6						√	√
Dew Point* (C)	D_9	---	√		√	√	√		
Stability Class	D_{10}	---			√	√	√		
Major Road" (750m)	D_{11}			√					
Altitude (m)	D_{12}			√					
Wind Index	D_{13}			√					
Traffic volume in major road within 100m buffer ('000)	D_{14}			√					
Major road (100m)	D_{15}			√					
Season	D_{16}	V_7					√		√
Day of Week	D_{17}	V_8					√		√

Note: D_i represents independent variables utilised for Dublin and V_i represents the equivalent for Vienna; Numerical values in brackets indicate the corresponding buffer size; all length/distance is in km and an area is in km^2 unit; $ not all the tick marked predictors were included in all the models ;* indicates daily average, or average;^ indicates natural log transformed variables **indicates daily total," indicates length, and ^^ persons/km^2.

Dublin 5 was subsequently developed using the input data from *Dublin 4* with the addition of dummy variables representing seasonal and weekly variation. Thus, *Dublin 5* allowed the prediction of average daily PM_{10} concentration in Dublin City across the seasons and days of the week. The objective of *Dublin 5* was therefore to add temporal variations to the models prediction. Figure 5.1 represents variation of traffic in Dublin as a variation of anthropological activities that may affect the PM_{10} concentrations.

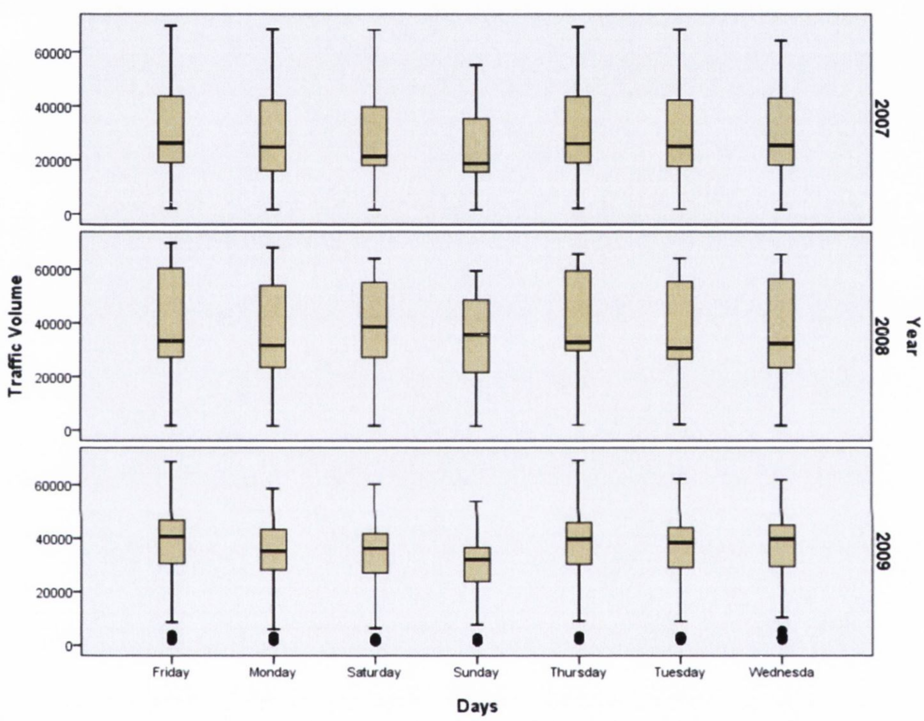


Figure 5.1: Traffic Volume at the intersections nearest to the FSMs

The models *Dublin 6* and *Dublin 7* were developed to demonstrate the effect on predictive performance of the use of alternative statistical modelling techniques to multiple linear regression within the land use framework. Both models used the predictor variables and input data applied to *Dublin 5*, where *Dublin 6* used NPR to relate average daily PM_{10} concentrations to the predictor variables, and *Dublin 7* used ANNs. These models also required a good number of observations, and thus data from consecutive years have been included in the model as the linear regression models reported stability of the model over the years.

Following the completion of the modelling exercise in Dublin a similar approach was taken in Vienna. The purpose of the repetition of this exercise in a differing European city was to examine the transferability of the methodology between locations. Dublin and Vienna presented differing types of city: Dublin was considerably smaller and located on a coastline in Western Europe; Vienna is a large inland city in Central Europe.

Vienna 1 was applied to the most recently available PM_{10} dataset from the FSMs network in Vienna city during the study. PM_{10} data from FSMs were available from 2011- 2012, and with an aim to capture the most recent data without missing temporal coverage, data from 2011-2012 were selected. Thus *Vienna 1* comprised 1 years input data from 13 FSMs and predicted the average daily PM_{10} concentration within Vienna City. The *Vienna 2* model was developed following the methodology of the *Dublin 4* model. Thus the objective of *Vienna 2* was similarly to assess the impacts of a longer period of historical input data on model performance (1 vs. 2 years).

Vienna 3 was developed using the input data for *Vienna 2* with the addition of dummy variables representing seasonal and weekly variation, again to add temporal variation to the model predictions. Finally, *Vienna 4* used NPR to relate average daily PM_{10} concentrations to the predictor variables, while *Vienna 5* used ANNs. Again the objective of these to final models was to assess the impacts of using a non-linear statistical technique within the land use modelling framework, to relate the dependent and predictor variables.

5.2.2 Data collection and processing: PM_{10} and other pollutants

PM_{10} pollutant concentration data were collected from local government FSMs as shown in Figure 5.2 (a) & 5.2 (b). The 7 FSMs in Dublin (EPA, 2013a) were diverse in nature; 3 of which were located in high density areas of the city centre, 1 in an open park and 2 near to the coast. One of the coastal sites was characterised by docking activity and low population density. Of the 13 FSMs in Vienna, 5 were located in the high density central area, 2 were in medium density areas, 3 were in mixed use areas, 1 in a forest area and 2 on the south border of the city. These monitors provided a wide coverage of the central area, outside core area and green areas for both cities.

PM_{10} data were collected using a gravimetric instrument, or analysed gravimetrically from sampled volumes of air in the Dublin area, whereas fine dust samplers were applied in Vienna (Vienna City Administration 2006; Irish EPA 2014). The average daily PM_{10} concentrations across the Vienna FSMs were 29.8 $\mu g/m^3$ and 24.7 $\mu g/m^3$ for the years 2011 and 2012 respectively, whereas the average daily PM_{10} concentrations for Dublin were 15.6 $\mu g/m^3$, 14.7 $\mu g/m^3$ and 13.8 $\mu g/m^3$ for the years 2007, 2008 and 2009.

For the other pollutants in Dublin, the number of available sites was five for year 2009, leaving out Marino and Phoenix Park (due to missing data). Hourly observations from the available stations were converted to daily totals. Oxides of Nitrogen in Dublin were measured using an API M200 NO_x analyser, later separated by the chemiluminescence method, whereas SO_2 was measured using an API M100 Sulphur Dioxide analyser by U.V. Fluorescence (Irish EPA, 2014). The average concentration of pollutants across all the monitoring stations were 3.08 $\mu g/m^3$, 46.36 $\mu g/m^3$, 17.75 $\mu g/m^3$ and 29.54 $\mu g/m^3$ for SO_2, NO_x, NO_2, and NO respectively. Average pollutant concentrations for all the pollutants across the monitoring stations can be found in the Tables C1-3, Appendix C.

(a)

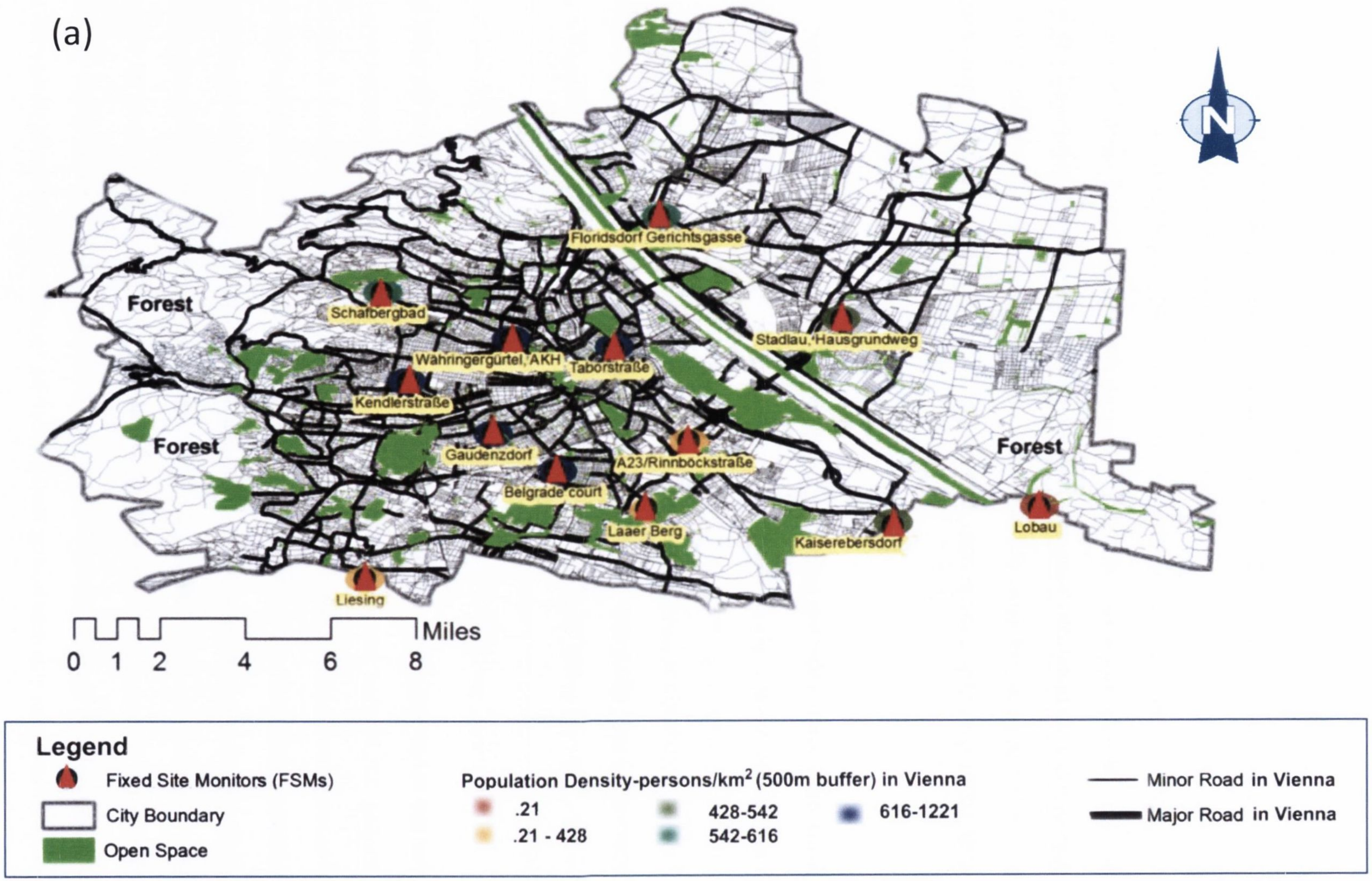


Figure 5.2(a): FSMs in Vienna

(b)

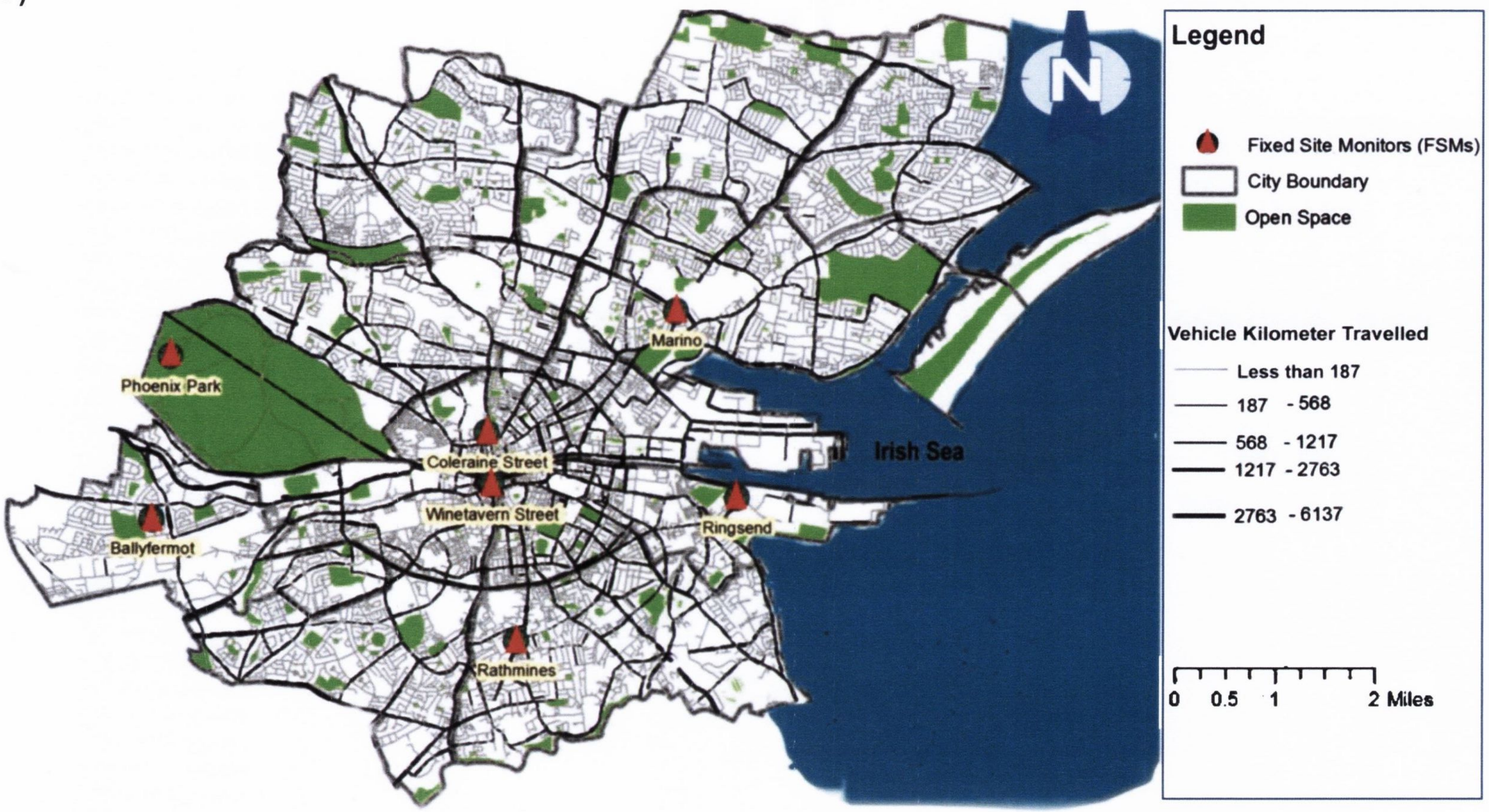


Figure 5.2(b): FSMs in Dublin.

Both the Municipal Government of Vienna and Irish EPA follow internal QA/QC procedures in order to maintain the highest quality of data and to meet EU standards. In addition to assure quality of the data, a further quality control has been maintained in this study. Figure 5.3 presents time series of the data applied for model development in both of the cities after removal of unnecessary and missing data. In Vienna, 1% of FSM data for PM_{10} were missing for 2012 and 2% data were missing for the 2011-2012 period, whereas 6% PM_{10} data were missing from the 7 FSMs, and 2% of the PM_{10} data were missing from 5 FSMs in the period of 2007-2009 in Dublin. For 2009, missing data was less than 1% for all the pollutants, including PM_{10}. In addition, some further data was excluded where data on associated independent variables (*e.g.* weather) were also missing, or contained unexpected values. For *Dublin 1*, an additional 3.5% of data were missing, due to missing daily peak hour traffic data. Due to missing data among predictor variables in the Vienna datasets, the 2012 and 2011-2012 periods were reduced by 1% and 2%. Less than 0.05% of data were removed due to unexpected values.

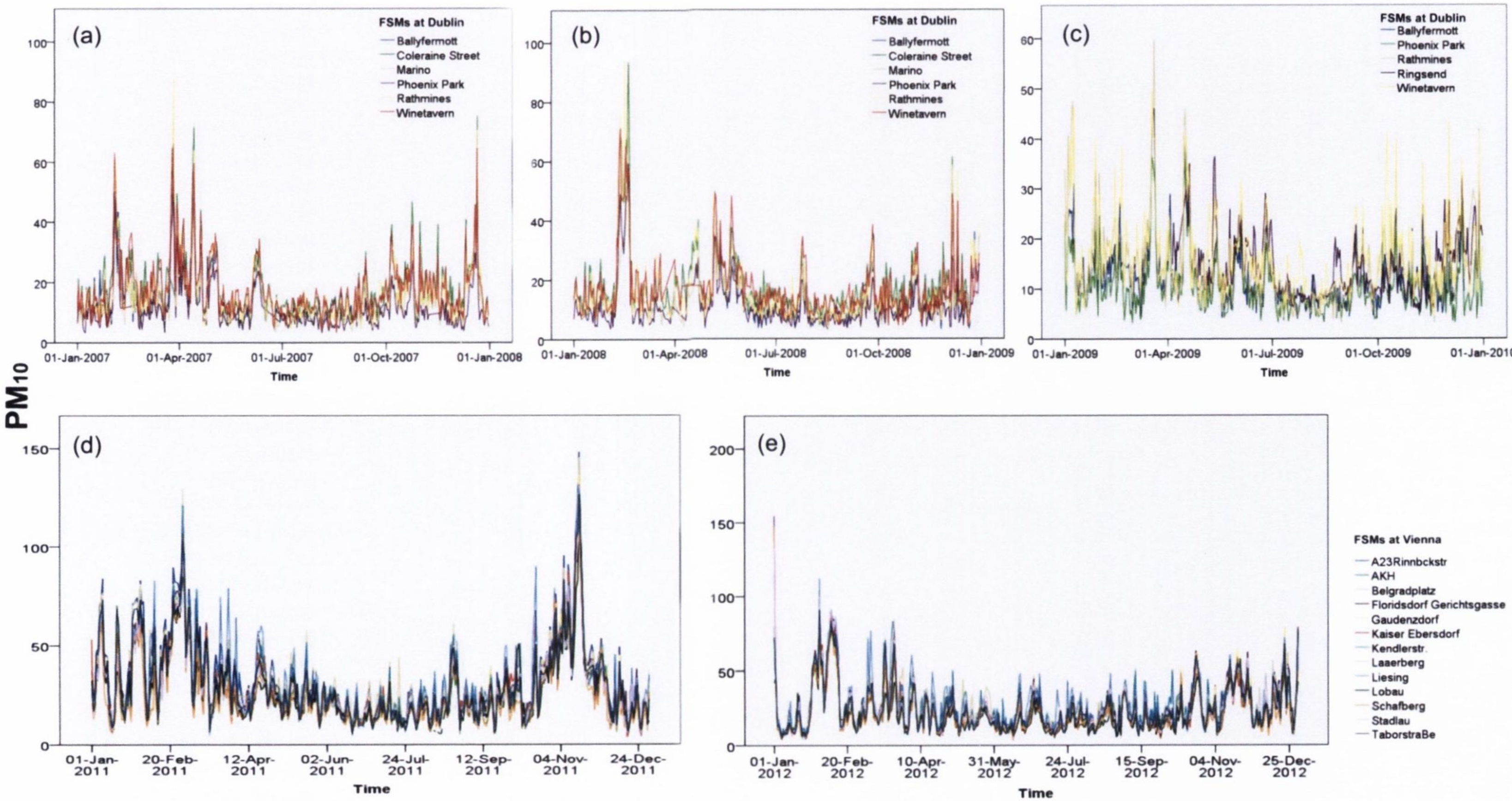


Figure 5.3: (a-c) PM_{10} concentrations in FSMs at Dublin; (d-e) PM_{10} concentrations in FSMs at Vienna

5.2.3 Data collection and processing: predictor variables

PM and weather data have been sorted in Excel software, whereas spatial data has been extracted in a GIS environment. Different overlay data management tools and spatial analysis tools have been deployed to obtain this data. To get information around the FSMs, buffer operations were applied in a GIS environment. A buffer in GIS is a zone around a point measured in units of distance (Figure 5.4). The distance of the buffers for each attribute (*e.g.* population, road length) was determined based on relevant literature review and site characteristics. The concept captures the physical properties of the areas that might have an influence on the PM_{10} and other pollutant concentrations in the FSMs.

Predictor variables included primary variables (*e.g.* population density), simply derived variables (*e.g.* vehicle kilometre travelled), and more complex derived variables (*e.g.* air mass history). In order to estimate vehicle kilometres travelled (VKT), annual average daily traffic (AADT) volume was multiplied by the length of road. Roads that were above the tertiary category were classified as major roads. VKT surrounding each of the FSMs was determined for different sizes of buffer (100m – 350m radius).

In addition, daily traffic count at the nearest junction to the FSMs was also obtained from real-time loop detectors (SCATS) in Dublin. While VKT in a buffer provided an indication of the spatial variation of the average traffic, SCATS data may provide additional information about temporal variation at the sites. Daily peak traffic for each intersection was estimated as an average count during morning peak (7-9am) and evening peak (4-6pm).

Land use GIS datasets were obtained from the European central database system (EEA, 2013b) and open street Map (OSM, 2013). Some land use layers of the GIS land use datasets for Dublin and Vienna were combined and re-classified based on their general spatial relationships with air pollution. These were: a) pollutant producing land use: Industrial and commercial land use (Dublin), and b) non-contributing land use: Open space (and similar use) in Vienna and Dublin.

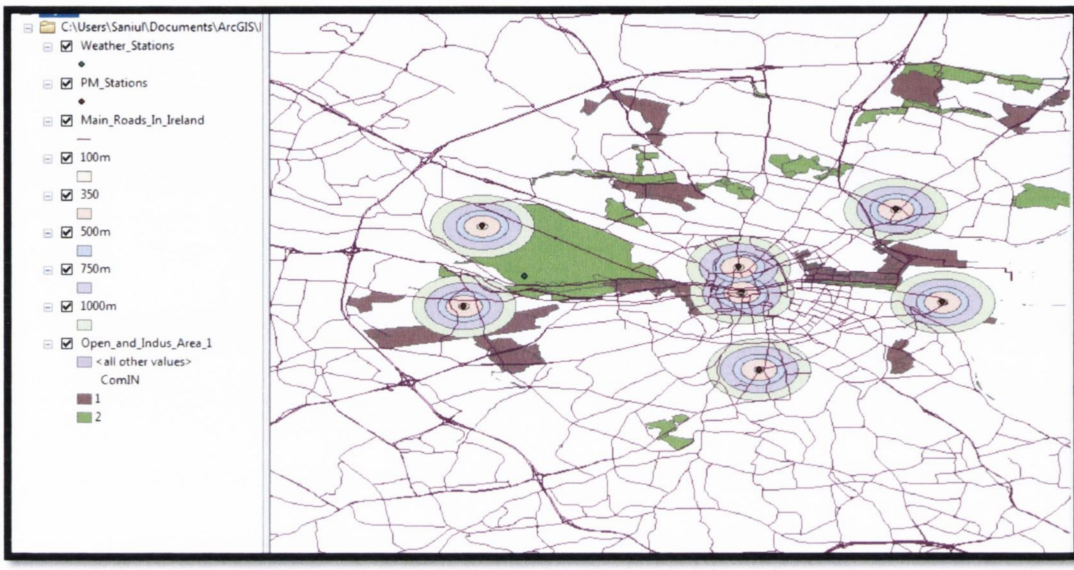


Figure 5.4: Different buffer sizes around the Air Quality monitors in Dublin

Population densities for Dublin were collected from the Central Statistics Office (CSO, 2013) and from the European central database system for Vienna (EEA, 2013c). Dublin meteorological data were combined from both Phoenix Park and Airport stations operated by Met Éireann. Vienna data were obtained from the Schwechat-Flughafen station and were validated against the 2012 dataset of Hohe Warte station (ZAMG, 2013). Natural log transformed wind variables were applied in all of the relevant models as their distribution was positively skewed, and the Anderson-Darling test confirmed that this data did not have a normal distribution.

5.2.4 Air mass history

In an attempt to improve model accuracy a means of describing the origins of the air mass was included in a PM_{10} model in Dublin (*Dublin 1*). Previous investigations applied wind back trajectory analysis in identifying the sources of pollutants (Lee *et al.*, 2013). To extend this concept to the current LUR based modelling framework representing a known source of PM_{10}, the air mass history was determined using the Hybrid-Single Particle Lagrangian Integrated Trajectory (HYSPLIT) model (ARL, 2013). The air mass history of 365 days in Dublin in 2009 were determined at a fixed hour of the day (12 pm). Each individual air mass history produced by the HYSPLIT model in the form of a trajectory was then overlaid onto a grid developed to produce a rating score indicating the likely degree of pollutant sources it encountered in the previous 48-hours. (*e.g.* Atlantic Ocean vs. UK or Northern Europe). Each trajectory was estimated for 48-hours backward in time as PM_{10} has been reported to survive for approximately two days in the atmosphere (WHO, 2006a). The receptor height was chosen as 500m, representative of the typical mixing height in Ireland and above ground level to avoid topographic friction (Donnelly, 2011a). The resulting air mass history ratings were subsequently included in the regression for *Dublin 1* using the 2009 dataset.

Figure 5.5 illustrates the grid developed to carry out the rating of air mass history in the North Western Europe region. The grid resolution was approximately 54 km^2, and due to the computational resources available this was the lowest grid size that could be accommodated during this study. Each grid cell was rated based on the average population density range using Europe wide population density data (CIESIN, 2013). The rating represented the level of urbanisation in respect to a lower threshold of urbanisation, as areas with population densities higher than 150 persons/km^2 are classified as urban (OECD, 1994). For population densities below 150 grid cells have been divided into five groups having a rating of 1 to 5. Grid cells with population densities greater than 150 persons/km^2 were equally sized and an increase in the rating of 1 corresponded to an increase of mean population density of 375 persons/km^2. Grids predominately occupied by water bodies, or the ocean were rated as zero.

The values of each cell that an individual trajectory passed through were summed to give an accumulative score to each trajectory. Relative to one another these scores gave an indication of the extent of trans-boundary air pollution in Dublin for each day in 2009.

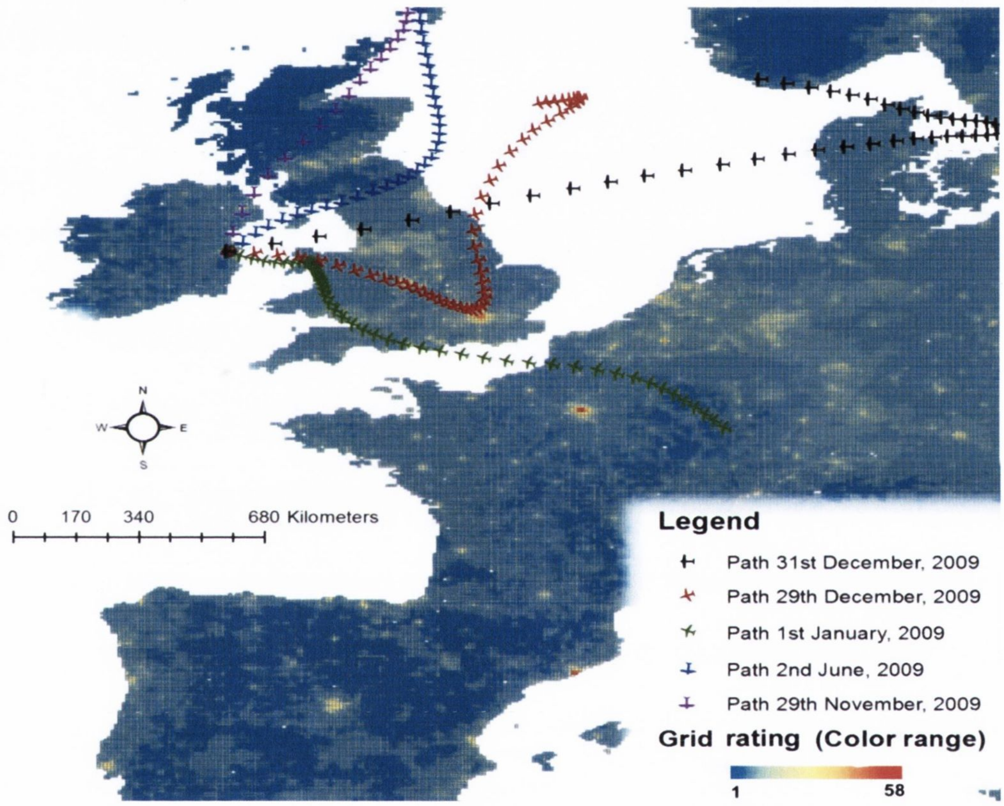


Figure 5.5: Air mass history rating grid based on population density and urbanisation

5.2.5 Wind index

Wind index for each monitoring station for daily wind direction in relation to the nearest major road were derived. FSMs directly upwind of the nearest major road, had a wind index were equal to zero, and FSMs directly downwind of the nearest major road had a wind index equal to one. This technique analysis the proximity impact of source on pollutant concentrations, however, has limitation about the volumetric impact from the source. The wind index has been calculated (Chen *et al.*, 2010a) based on Eq. (5.1):

$$\varphi = \frac{1-cos(\emptyset-\theta)}{2} \qquad \text{Eq.(5.1)}$$

Where, Wind Index=φ; $\emptyset$ = Euclidian direction from the nearest major road to monitoring site; θ = Wind direction in respect of true north.

5.2.6 Stability class

Stability class refers to the state of the atmosphere that is resisting or enhancing vertical motion. Different stability states can be categorised based on wind speed and solar radiation. Stability class for Dublin was adopted here as an additional explanatory variable (Pilla, 2012).

5.2.7 Assessment of variables for model

The relationship between predictors and pollutant concentrations were revealed in the process of developing LUR models. This provided a screen test for the predictors relationship with pollutant concentrations, such as traffic should be an anthropological source of PM_{10} if chosen. Secondly, such a list would be helpful for model selection as many variables were removed from the final models due to multicollinearity and singularities *i.e.* an extreme form of multicollinearity/perfect linear relationship existed between the variables. Selected predictor variables included available data on land use, traffic and meteorology in Dublin and Vienna. The selected independent variables and the selected predictors for the 16 different models are presented in Table 5.3, whereas excluded variables are presented in the Table C4, Appendix C.

Table 5.3: Information about selected variables for different model development

Dublin PM_{10} models/ 2007 2009datasets						
Variables for Dublin PM_{10} models	r_{2009}	Max_{2009}	Min_{2009}	$r_{2007-2009}$	$Max_{2007-2009}$	$Min_{2007-2009}$
Dew point* (C)	-0.33	16.44	-4.42	-0.31	16.44	-4.42
Wind speed^ (m/s)	-0.33	2.64	0.2	-0.37	2.66	0.2
Open space area (1000m)	-0.3	2.4	0.05	-0.28	2.4	0.05
Rainfall** (mm)	-0.12	38.8	0	-0.2	58.7	0
Stability Class[£]	0.23	5	3	0.23	5	4
Air Mass History Rating	0.26	1904	63	--	--	--
VKT (300m)	0.34	75998	848	0.31	75998	848
VKT (200m)	0.35	37150	353	0.3	37150	353
Peak Traffic count at nearest intersection ('000 for values)	0.36	8.690	1.85	--	--	--
Dublin models for PM_{10} and other pollutants: 2009 dataset						
	r_{2009}					
Variables for PM_{10} and other models	SO_2	NO_x	NO_2	NO	Min	Max
Temperature* (C)	0.03	-0.36	-0.37	-0.30	-0.90	18.29
Wind speed^ (m/s)	-0.15	-0.39	-0.38	-0.39	1.22	14.04
Altitude (m)	-0.04	-0.44	-0.39	-0.30	4.53	41.85
Open space area (1000m)	-0.61	--	--	--	0.00	0.29
Major road (750m)	0.43	0.47	0.49	0.34	4.36	14.70
Traffic volume within 100m buffer ('000)	0.35	0.20	0.16	0.06	1.95	270.45
Air Mass History Rating ('000 for values)	0.03	0.11	0.15	0.05	0.06	1.90
Peak Traffic count at nearest intersection ('000 for values)	0.28	0.09	0.12	0.24	1.85	8.69
Major road (100m)	0.15	0.41	0.41	0.29	0.00	0.44
Wind Index	0.13	0.07	0.02	0.04	0.00	1.00
Vienna PM_{10} models:2011,and 2011-2012 datasets						
Variables for Vienna PM_{10} models	r_{2012}	Max_{2012}	Min_{2012}	$r_{2011-12}$	$Max_{2011-12}$	$Min_{2011-12}$
Max. sustained wind speed^ (km/h)	-0.41	3.4	1.79	-0.42	3.4	1.1
Precipitation** (mm)	-0.22	38	-8	-0.25	87	0
Open space area (1000m)	-0.1	1.47	0	-0.1	1.47	0
Population Density (500m)	0.06	1221.5	0.21	0.05	1221.5	0.21
Temperature* (C)	-0.27	25	-14	-0.32	31	-11
Major road (0-350m)	0.08	13.1	3.6	0.08	4.46	0

Note: r= Pearson correlation coefficient with $Ln(PM_{10})$; numbers in subscript with the r, Min and Max shows the dataset years; * indicates daily average, or average; Numerical values in brackets indicate the corresponding buffer size; height in m, all length/distance is in km and an area is in km^2 unit;[£] Stability Class A to E represent the degree of stability (unstable to stable), were converted to number from 1 to 5 for regression; ^ indicates natural log transformed variables; **indicates daily total; road represents length; VKT= Vehicle km travelled; Coordinate in decimal degree, and density ($person/km^2$).

5.2.8 Adoptions of the LUR framework

Aside from static land use parameters for the development of LUR models, previous investigations have also included predictor variables on temporal factors to account for annual, seasonal, monthly, daily and hourly variations (Chen *et al.*, 2010a; Mölter *et al.*, 2010; MacIntyre *et al.*, 2011; Smith *et al.*, 2011; Dons *et al.*, 2013, 2014). Models have been developed which are capable of predicting pollutant concentrations in both annual and shorter time frames (*e.g.* hourly). Data on specific known sources of air pollution emissions, in addition to general land use factors, have also been included in various published LUR models. Examples of such sources include traffic and industrial point source data (Chen *et al.*, 2012a; Dons *et al.*, 2013, 2014). As such, in the current study additional new predictors, derived from complex process were assessed, such as air mass history rating.

The objective of many recent investigations utilising the LUR methodology has been to build on its ability to produce spatially and temporally accurate predictions of air pollution. These efforts, as outlined above, have included the addition of new variables and data types. While modelling of spatial variation in concentrations is the focus of most investigations, short term temporal variation is averaged out in most studies. In order to deal with daily temporal variation Chen *et al.* (2012b) applied a two-step modelling approach using data from 18 monitoring stations for a 2325 km^2 area in Taipei metropolitan area, Taiwan. Data were initially modelled with meteorological variables and temporal trends removed, while residuals were modelled with land use variables. On the other hand, models developed in one step with meteorological and land use variables together, can provide a complementary approach in the refinement of the statistical models used to relate predictor variables to air pollution data using non-linear approaches such as NPR and ANNs.

Air pollution data and some predictor variables are often not normally distributed and thus may not be suitable for use in MLR based techniques where a normal distribution is assumed (Donnelly *et al.*, 2011b). Donnelly *et al.* (2011b) used the NPR approach to predict the concentration of NO_2 at background monitoring stations where the amount of monitoring data was limited (due to gaps in datasets, *etc.*). The resulting models enabled the realistic prediction of long term concentration variations with wind speed and direction.

In addition, ANNs have also been used to predict air pollution concentrations based on the analysis of historic data records (Cobourn *et al.*, 2000; Chaloulakou *et al.*, 2003). Ibarra-Berastegi *et al.* (2008) applied ANNs to predict hourly concentrations of five urban pollutants in Bilbao up to 8 hours ahead of background measurements. The performance of these models varied depending on pollutant type and the background monitor in question (R^2= 0.15 to 0.88). While not strictly a form of regression, such statistical techniques may enable further improvement of models based on the land use conceptual framework.

Thus in the current study for air quality modelling, the temporal and spatial variation in PM_{10} concentration has been carried using a MLR methodology within the land use conceptual framework. The investigation included the development of a standard MLR based model for Dublin city, the predictive performance of which was subsequently refined using larger amounts of data and alternative statistical approaches. The alternative statistical approaches to MLR in land use regression included NPR and ANNs. The methodology was subsequently applied in Vienna city to examine its transferability between locations.

Mölter *et al.* (2010) discussed three approaches to modelling temporal aspects in LUR, namely: use of temporal trend derived from local background monitor, use of temporal variation of the predictors, and recalibration of the developed models in backward or forward in time. Here in this study, temporal variation of the predictors were applied along with available PM_{10} data from the FSMs to develop initial models, which were subsequently improved by the alternative statistical approaches.

5.2.8.1 Multiple linear regression

The models developed using the MLR statistical technique were of the form shown in Eq. (5.2).

$$E = C_0 + A_1X_1 + A_2X_2 + A_3X_3 ... + A_nX_n + \in \qquad \text{Eq. (5.2)}$$

Where, E = Average Daily PM_{10} Concentration; X_i= predictor variable i; $\in$ = Error; A_i= regression coefficient for predictor variable i.

As MLR assumes that the input data are normally distributed, natural logarithm transformation of PM_{10} and other pollutant data was carried out in all models. Both the Kolmogorov-Smirnov and Shapiro-Wilk tests for normality in the data confirmed the need for this transformation. To develop the MLR models (*Dublin 1-5, Vienna* 1-3) the forward selection procedure was applied where predictor variables with the highest simple correlation with the dependent variable were included step by step (Pardoe, 2012). At the end of each step the Variable Influential Factor (VIF) was checked to ensure no multicollinearity existed, and only statistically significant variables were retained in the models. The VIF was below 2 for the models which indicated no significant multicollinearity. Normality tests for all the models were conducted that confirmed an unbiased and homoscedastic relationship between residual and fitted values. Figure 5.6 (a) shows an unbiased and homoscedastic relationship between residual and fitted values, while Figure 5.6 (b) shows the residuals were normally distributed and scattered around the line. In addition, Cook's distance was checked for outliers and influential variables. The data were checked before model development using scatter plots to ensure that there were no missing values or unexpected values in the analysis. Selected variables (√) in the final models were presented in Table 5.3.

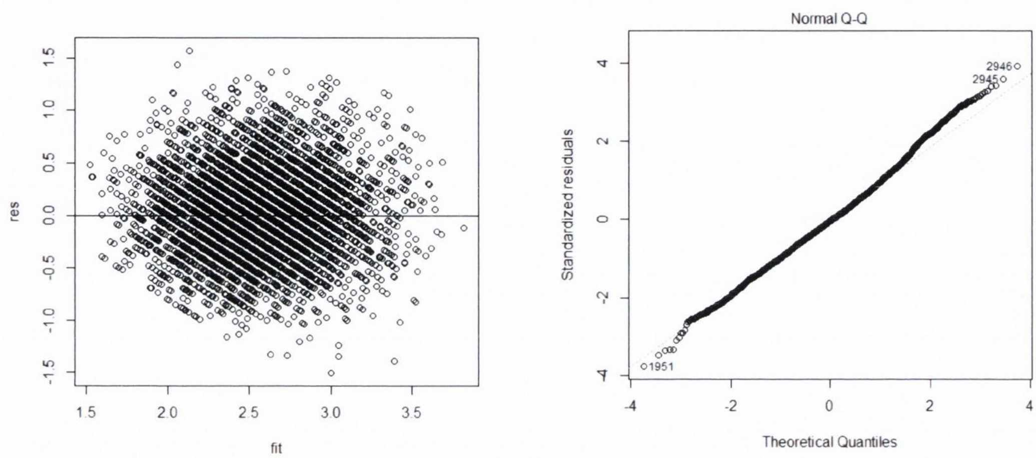


Figure 5.6: Normality Test (a). Residual vs. fitted value; (b). Normal Q-Q plot

The higher values in Figure 5.7 are logical values which are either caused by comparatively low/high values of PM_{10} without much change in independent variables; or high values in independent variables corresponding to moderate values in PM_{10}. But, all these values are within the acceptable range of each independent and dependent variables. Dons *et al.* (2013b) encountered high Cook's D values in some of their models, pointing to influential observations, and thus the values were kept as those turned out to be explainable. This may indicate that a similar situation may often be noticeable when high resolution datasets are in use for similar modelling strategies. Cook's distance was also tested for the Vienna model.

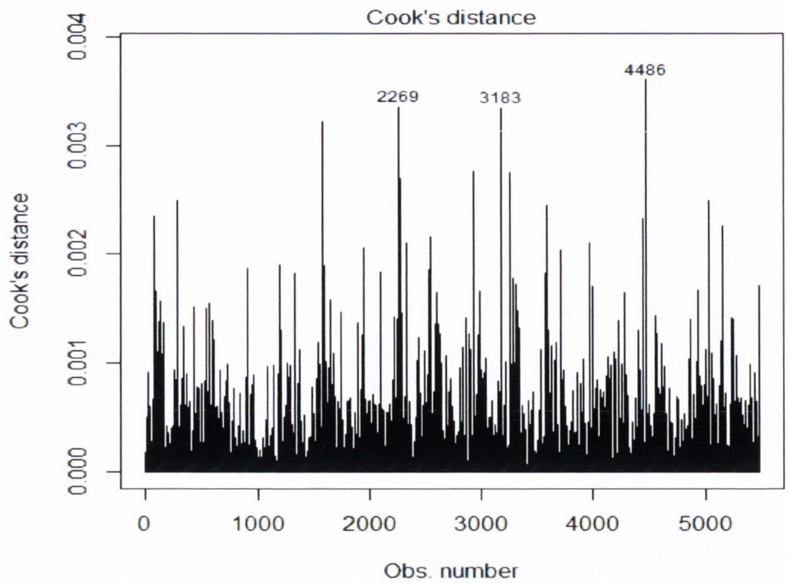


Figure 5.7: Cook's distance for Dublin Model

5.2.8.2 Non-parametric regression

NPR in the form of locally weighted scatter plot smoothing (LOWESS) was also conducted in this study. LOWESS operates by fitting simple models to localised subsets of the data to develop a function that describes the determining part of the variation in the data, point by point. A smooth curve through a set of data points is obtained where each smoothed value is given by a weighted least squares regression. At each point in the data set a low-degree polynomial is fitted to a subset of the data, with explanatory variable values near the point whose response is being estimated. The polynomial is fitted using weighted least squares, giving more weight to points near the point whose response is being estimated (*i.e.* neighbouring points) and less weight to points further away. The value of the regression function for the point is then obtained by evaluating the local polynomial using the explanatory variable values for that data point (Pitard *et al.*, 2004).

The size of the localised subsets or bandwidth was carried out in LOWESS using the K-nearest neighbour approach and this was optimised during model development by trial and error. The k-nearest neighbourhood size for Dublin and Vienna in the final models produced were 35% and 50% respectively.

Predictor variables for each neighbouring point were given a weight through the tri-cube weighting function. A weighted least-square model was also developed for each point, using only the nearest neighbour observations to minimise the weighted residual sum of the squares. The procedure was carried out for each point and finally the fitted values were connected to produce the LOWESS curve. A smoothing factor was also required in order to make a balance between bias and prediction noise. Cross-validation was applied to select smoothing factors for each model.

This LOWESS modelling technique of NPR was deployed for *Dublin 6* and *Vienna 4*. A higher smoothing factor was used for Dublin (0.6) compared to Vienna (0.3) which was derived by cross-validation in order to produce better prediction for the Phoenix Park observations. The Phoenix Park is the largest green space in a major city in Europe where the average pollutant concentration during this study was notably lower (11.01 $\mu g/m^3$) over the three years than the rest of the FSMs in Dublin (15.60 $\mu g/m^3$).

5.2.8.3 Artificial neural networks

ANN models (Figure 5.8) were also developed for *Dublin 7* and *Vienna 5.* ANN modelling is an information processing paradigm that is based on the way in which biological nervous systems, such as the brain, process information. In their general form, ANNs refer to parallel model architecture capable of performing numerical calculations based on distributed processing. A feed forward neural network (Levenberg-Marquardt backpropagation technique) was used in this study which comprises an input layer, a hidden layer, and an output layer. This ANN operates through each layer receiving a weighted input from a preceding layer and then transmitting its outputs to neurons in the next layer. The summation of weighted input signals is calculated, and this summation is then transferred by a nonlinear activation function. In this optimisation, the Levenberg-Marquardt backpropagation technique was applied which is widely used for non-linear least square regressions.

After several iterations with different numbers of hidden neurons (10, 15, 20, 25, 30, and 35), a best performing network architecture for each city was selected. The combination of "input-hidden layers - output" for Dublin (15-20-1-1) and (15-15-1-1) for Vienna yielded consistent satisfactory results (*i.e.* similar training and validation performance) for several iterations.

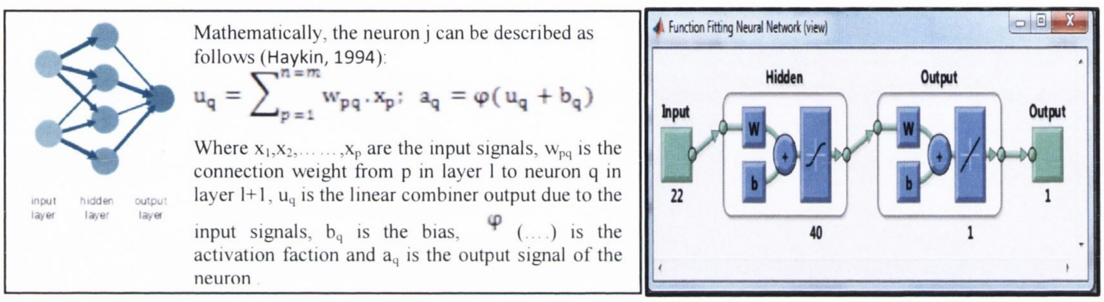


Figure 5.8: (a) Neural network basic structure; (b) MATLAB network outlook

5.2.9 Validation and result of Landuse Regression model

Model validation was carried out using the 'leave-one-out-cross validation' (LOOCV) technique, whereby one FSM was left out of model development and the model developed was then used to predict the average daily PM_{10} concentration at the remaining FSM (Wang *et al.*, 2012). For *n* FSMs, this process was repeated *n* times such that each FSMs was excluded in turn from model development and was subsequently used to compare model predictions with measured values.

The comparison of model predictions and measured values was carried out using model performance statistics such as the coefficient of determination (R^2) and the root mean square error (RMSE). Comparison of model predictions and measured values was also carried out in 2 phases, first comparing the model predictions of the measured values included in model development with the same measured values, and second comparing model predictions with measured values excluded from model development using the LOOCV technique. In the case of ANNs, models were developed using 70% of the available input data, while 15% was used for validation and 15% was used for testing.

The development of the standard LUR models was performed using R – statistical software. Alternative modelling techniques were developed using XLSTAT 2013 for Non-parametric Regression, and MATLAB for Neural Networks.

5.2.10 Results

5.2.10.1 MLR based models

The models produced using the MLR statistical technique are shown in Table 5.4 and Table 5.5. A few of the models for Dublin were developed using only one year's data and included 5 FSMs, as listed in Table 5.1. *Dublin 1* produced an R^2 of 43% predicting PM_{10} concentrations from 5 FSMs in 2009. The model predicting alternative pollutant types in this group performed better than *Dublin 1*. *Dublin 1.3* and *Dublin 1.4* yielded the highest R^2 values at among these models, both at 62%. *Dublin 1.2* for SO_2 performed the lowest with an R^2 of 42%. In *Dublin 2* using the same 5 FSMs and excluding a representation of air mass history and peak traffic count lowered model performance compared to *Dublin 1* with an R^2 of 38%. Individually, air mass history was found to explain 6.5% of the variation in PM_{10}, while peak traffic count accounted for 12.7%.

Table 5.4: LUR Models for air pollutants in Dublin

Model	Pollutant	Equation (having variables <=.001 Significance)	R^2	P	SE	N	Max. VIF
Dublin 1	PM_{10}	Ln(PM)= $3.071+4.936x10^{-04}D_1 +7.297x10^{-06}D_2 +4.904x10^{-05}D_4 - 4.554x10^{-01}D_8 -4.288x10^{-02}D_9$	0.43	<2.2 e^{-16}	0.41	1272	1.61
Dublin 1.1	NO	Ln(NO)= $3.37-9.46\ x10^{-02}D_6$ -2. $x10^{-01}D_8+5.57\ x10^{-02}D_{11}-1.63\ x10^{-02}D_{12}+1.47\ x10^{-04}D_4$	0.53	< 2.2 e^{-16}	0.70	1143	1.37
Dublin 1.2	SO_2	$Ln(SO_2)=1.28+4.77\ x10^{-06}\ (D_{14} *D_{15})-7.38\ x10^{-02}D_8-6.11D_5+1.61\ x10^{-1}D_{13}$	0.42	< 2.2 e^{-16}	0.83	1427	1.49
Dublin 1.3	NO_2	$Ln(NO_2)= 4.25-6.16\ x10^{-02}D_6- 1.31\ x10^{-01}\ D_8+4.68\ x10^{-02}\ D_{11}- 1.29\ x10^{-02}\ D_{12}+3.08\ x10^{-04}\ D_1$	0.62	< 2.2 e^{-16}	0.43	1745	1.22
Dublin 1.4	NO_x	$Ln(NO_x)= 5.04-7.73\ x10^{-02}D_6- 1.71x10^{-01}\ D_8+5.36\ x10^{-02}D_{11}- 2.08\ x10^{-02}D_{12}+2.15\ x10^{-04}\ D_1$	0.62	< 2.2 e^{-16}	0.55	1745	1.67

Table 5.5: MLR PM_{10} models for Dublin and Vienna

Model	Variables have less than or equal to 0.001 Significance	Adjusted R^{2*}	P	SE	N	Max VIF
Dublin 1	$Ln(PM)= 3.071+4.936\times10^{-04}D_1 +7.297\times10^{-06}D_2 +4.904\times10^{-05}D_4 -4.554\times10^{-01}D_8 - 4.288\times10^{-02}D_9$	0.43	$<2.2\ e^{-16}$	0.43	1273	1.61
Dublin 2	$Ln(PM)=2.968+4.042\times10^{-06}D_3-3.212\times10^{-01}D_5-4.243\times10^{-01} D_8-4.549\times10^{-02}D_9+1.207\times10^{-01}D_{10}$	0.38	$<2.2\ e^{-16}$	0.40	1624	1.75
Dublin 3	$Ln(PM)=2.736+4.090\times10^{-06}D_3-8.648\times10^{-02}D_5-4.964\times10^{-01} D_8-4.433\times10^{-02}D_9+2.108\times10^{-01}D_{10}$	0.39	$<2.2\ e^{-16}$	0.41	4116	1.93
Dublin 4	$Ln(PM)=2.630+4.107\times10^{-06}D_3-1.002\times10^{-01}D_5-9.688\times10^{-03}D_7-4.763\times10^{-01}D_8-4.169\times10^{-02} D_9+2.363\times10^{-01}D_{10}$	0.39	$<2.2\ e^{-16}$	0.41	5503	1.78
Dublin 5	$Ln(PM)= 2.485+4.016\times10^{-06}D_3-1.032\times10^{-01}D_5-8.901\times10^{-03}D_7-4.953\times10^{-01}D_8-3.002\times10^{-02}D_9 +2.118\times10^{-01}D_{10}+1.915\times10^{-01}Winter+8.677\times10^{-02} Tuesday+9.783\times10^{-02}Wednesday+1.310\times10^{-01}Thursday+1.115\times10^{-01}Friday+4.332\times10^{-02} Saturday-8.700\times10^{-02}Sunday$	0.42	$<2.2\ e^{-16}$	0.42	5503	1.33
Vienna 1	$Ln(PM)= 5.041+2.543\times10^{-02}V_1-8.970\times10^{-02}V_2+8.233\times10^{-06} V_3-1.935\times10^{-02}V_4-3.475\times10^{-02}V_5-6.869\times10^{-01} V_6$	0.35	$<2.2\ e^{-16}$	0.47	4624	1.08
Vienna 2	$Ln(PM)= 4.906+3.242\times10^{-02}V_1-9.933\times10^{-02}V_2+6.304\times10^{-06} V_3-2.098\times10^{-02}V_4-3.925\times10^{-02}V_5-5.936\times10^{-01}V_6$	0.37	$<<2.2\ e^{-16}$	0.47	9264	1.10
Vienna 3	$Ln(PM)= 4.707 +3.242\times10^{-02}V_1-9.934\times10^{-02}V_2+6.321\times10^{-06}V_3-1.599\times10^{-02}V_4-3.667\times10^{-02}V_5-6.061\times10^{-01}V_6+1.682\times10^{-01}Winter+7.794\times10^{-02}Tuesday +1.275\times10^{-01} Wednesday+1.569\times10^{-01}Thursday+3.743\times10^{-02}Friday-3.339\times10^{-02}Saturday-9.908\times10^{-02}Sunday$	0.39	$<2.2\ e^{-16}$	0.46	9264	1.28

For *Dublin 3* the increase in the length of the historical input data recorded marginally increased the R^2 result to 39% (up from 38% in *Dublin 2*). This demonstrated the stability of the model predictions across differing time periods. The subsequent increase in the number of FSMs available from 5 to 7 during this three year period in *Dublin 4* produced an R^2 of 39%. Finally the addition of seasonal and weekly variation using dummy variables for Dublin resulted in an improvement in R^2 to 42% (*Dublin 5*).

Considering Vienna, a similar performance to Dublin for *Vienna 1* was found with R^2 = 35%, and increasing the length of the historical input data in *Vienna 2* was found to produce an R^2=37%. Applying the seasonal and daily variation increased the R^2 marginally to 39%. Models stability over time could also be noticed when a comparison was made between *Vienna 1* and *Vienna 2*. *Vienna 3* with the addition of temporal variations showed an increase of model performance similar in magnitude to the increase for Dublin, 4% in both cases.

5.2.10.2 NPR & ANN models

The results of the land use models developed using the proposed alternative statistical modelling techniques are shown in Table 5.6. The NPR approach in *Dublin 6* provided a small improvement of 3% over *Dublin 4*, however a significant improvement of 12% was found for Vienna. Models using the ANN approach in Dublin and Vienna produced the highest performance statistics of all models examined at 51% and 66% respectively. A graphical representation of the results has also been included in Figure 5.9, showing the predictability of the different modelling techniques. In the Figure 5.9 log-transformed PM_{10} predicted data were plotted against observed data for a single predictor in the MLR, NPR & ANN models for Vienna and Dublin respectively. Figure 5.9 shows that ANN has predicted data coverage better than that of the other two for both Vienna and Dublin.

Table 5.6: Non-parametric and Neural Network models for Dublin and Vienna

Model	Model Structure	R^2	No of Data points
Vienna 4	LOWESS Method, Polynomial degree: 1; k nearest neighbours: % = 50; Kernel: Tricube; Bandwidth: Standard deviation; smoothing factor 0.1	0.51	9264
Vienna 5	Two layer Levenberg-Marquardt backpropagation (Network structure 15-15-1-1)	0.66	7875 (85%* of 9264)
Dublin 6	LOWESS Method, Polynomial degree: 1; k nearest neighbours: % = 35; Kernel: Tricube; Bandwidth: Standard deviation; smoothing factor 0.6	0.45	5503
Dublin 7	Two layer Levenberg-Marquardt backpropagation (Network structure 15-20-1-1)	0.51	4678 (85%* of 5503)

*70% for model training and 15% data of model generalisation which also ensure stop training before over fitting.

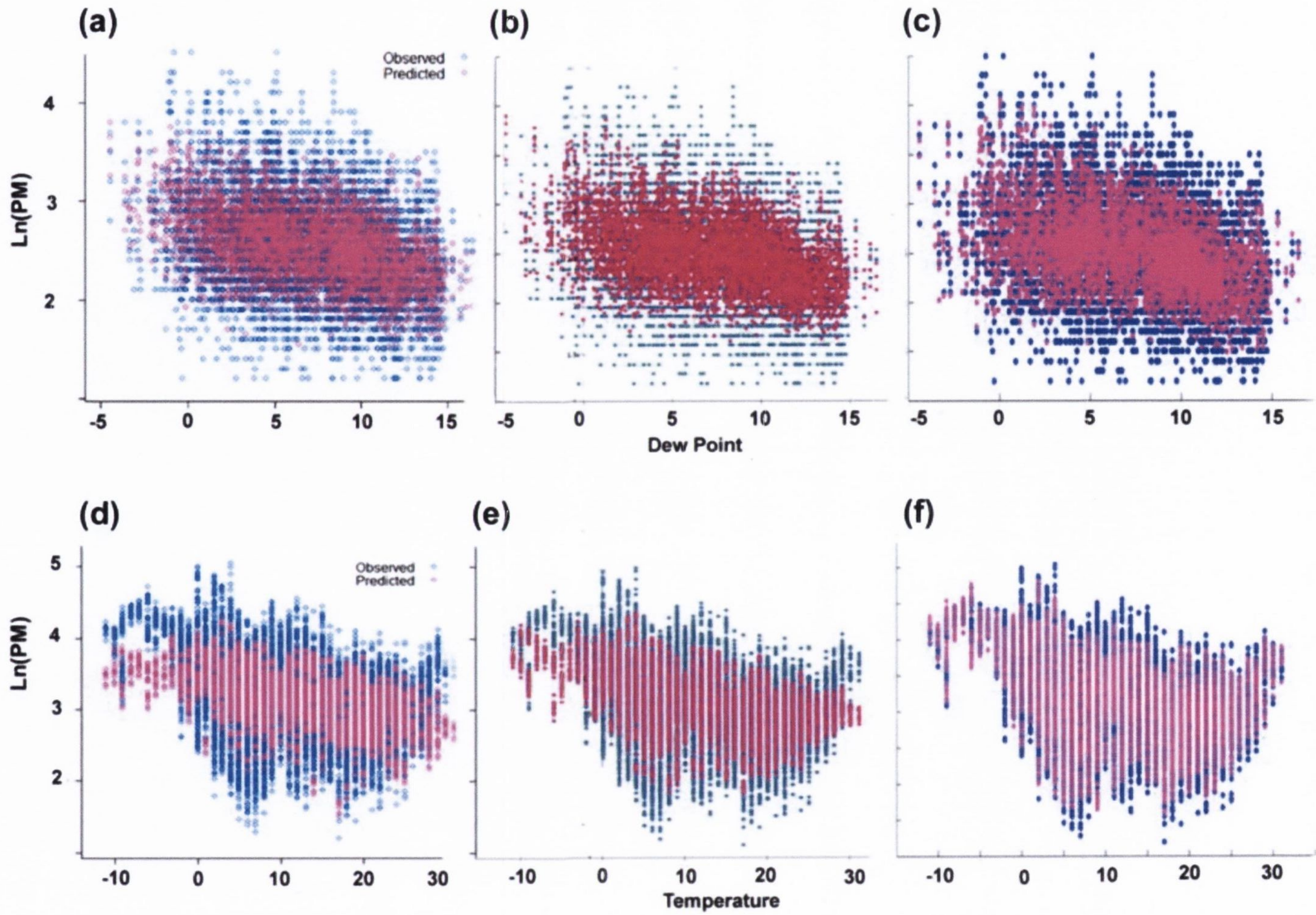


Figure 5.9:(a), (b) and (c) represent the MLR (Vienna-3), NPR (Vienna-4) & ANN (Vienna-5) model, and (d), (e) and (f) represent the MLR (Dublin-2), NPR (Dublin-3) & ANN (Dublin-4) models

5.2.10.3 Model validation results

The results of model cross validation using the LOOCV technique are shown together with the performance of the models in predicting the measured data involved in their original development in Table 5.7. As could be expected the models ability to predict the measured data using the LOOCV technique is less than that were predictions are made on the data used for model development. However, in most cases this reduction in performance is marginal with the exception of *Dublin 4* and *Dublin 5*. Both of these models produced poor predictions for the Phoenix Park FSM, which as noted earlier, was significantly different in nature to the other 6 FSMs in the study. Diem and Comrie (2002) noted that while FSMs are located in unique positions LOOCV may provide unreliable predictions at most of the monitors as each monitor may have critically important values for many of the independent variables. Again model predictions using the NPR and ANN techniques produced the best model performance statistics, where *Vienna 5* produced the most reliable PM_{10} predictions.

Table 5.7: Results from model validation

Models	No. of Sites	St. Dev. PM_{10} ($\mu g/m^3$)	Model R^2	Validation R^2	RMSE PM_{10} ($\mu g/m^3$)
Dublin 1	5	7.52	0.43	0.34	6.28
Dublin 2	5	7.80	0.38	0.37	6.28
Dublin 3	5	8.92	0.39	0.35	7.32
Dublin 4	7	9.18	0.39	0.28	8.17
Dublin 5	7	9.18	0.42	0.30	8.07
Dublin 6	7	9.18	0.45	0.39	7.33
Dublin 7	7	9.18	0.51	0.54	6.27
Vienna 1	13	15.77	0.35	0.36	12.96
Vienna 2	13	17.83	0.37	0.38	14.46
Vienna 3	13	17.83	0.39	0.39	14.36
Vienna 4	13	17.83	0.51	0.48	13.05
Vienna 5	13	17.83	0.66	0.65	10.69

As noted earlier the average daily PM_{10} concentrations in Vienna across the two year period in question was 27.3 µg/m^3. In relation to the RMSE error produced by the best performing model for Vienna 10.69 µg/m^3, this places the predictive performance of *Vienna 5* into the context of typical concentrations encountered there. Similarly in Dublin the mean concentration across the 3 years in question was 14.7 µg/m^3 while the RMSE of *Dublin 7* was 6.27 µg/m^3. Thus the RMSE was 39% and 42% of the mean value in Vienna and Dublin respectively.

5.2.11 Stability and sensitivity analysis of the models

To check the stability of the coefficients of the final MLR models before applying NPR and ANNs, the stability and sensitivity of the models were assessed. Both of the databases were segregated into five random subsets with different sample sizes. In the Figure 5.10 the regression coefficients for both models for different numbers of samples were plotted. The regression coefficients were found to be stable across a number of different data sub-sets.

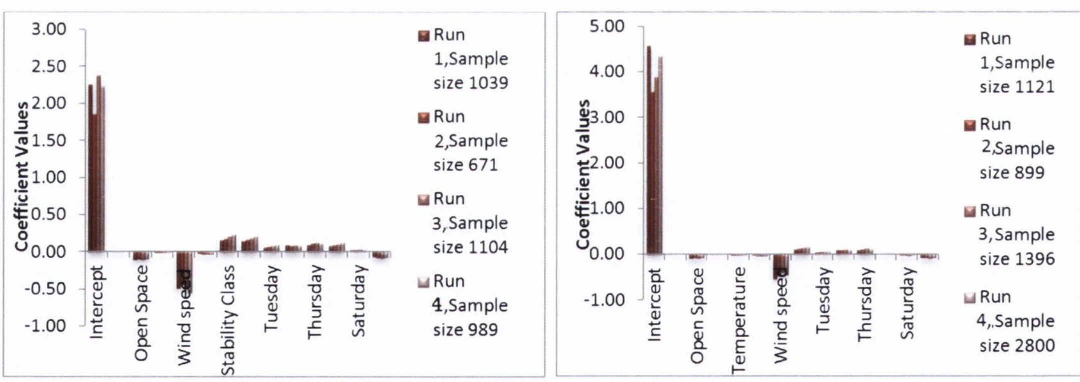


Figure 5.10: Sensitivity analysis for (a). Dublin model; (b). Vienna model

In order to assess the sensitivity of the parameters, a sensitivity index was derived. A sensitivity index is the ratio of the change in output to the change in input when varying one input parameter from its minimum to its maximum value, while all other parameters remain constant (Hoffmand and Gardner, 1993; Hamby, 1994). The equation for sensitivity Index is below Eq. (5.3):

$$SI = \frac{D_{Max} - D_{Min}}{D_{Max}} \quad \text{Eq. (5.3)}$$

Here, *SI*= Sensitivity index; D_{Max}= Maximum output; D_{Min}= Minimum output from the model.

The results of sensitivity analysis were given in the Table 5.8. The dummy variables for the models were set for winter Monday, and other parameters were set for their average values.

Table 5.8: Sensitivity analysis on the Dublin 5, and Vienna 3 models

Vienna									
Indicator/Variable	Coefficient	Data			$Ln(PM_{10})$			Sensitivity Index *	Rank
Intercept	4.71	Min	Max	Avg	Avg.	Min	Max		
Rainfall/ Precipitation (mm)	-0.04	0.00	87.00	43.50	1.79	3.39	0.20	-16.04	1
Maximum sustained wind speed km/h	-0.61	1.10	3.40	2.25	1.79	2.49	1.10	-1.27	2
Temperature (C)	-0.02	-11.00	31.00	10.00	1.79	2.13	1.46	-0.46	3
Open Space area sq. km-1000m	-0.10	0.00	1.47	0.74	1.79	1.87	1.72	-0.09	4
Major Road in m-350m	0.03	0.00	4.46	2.23	1.79	1.72	1.87	0.08	5
Population Density (persons/sq. km) -500m	$6.32\ e^{-06}$	2.13	12215	6108.56	1.79	1.76	1.83	0.04	6
Dublin									
Indicator/Variable	Coefficient	Data			$Ln(PM_{10})$			Sensitivity Index *	Rank
Intercept	2.49	Min	Max	Avg.	Avg.	Min	Max		
Wind speed (m/s)	-0.50	0.20	2.66	0.79	2.54	2.83	1.61	-0.76	1
Dew Point (C)	-0.03	-4.42	16.44	4.00	2.54	2.79	2.17	-0.29	2
Rainfall/ Precipitation** (mm)	-0.01	0.00	58.70	19.56	2.54	2.72	2.19	-0.24	3
Stability Class	0.21	3.00	5.00	2.74	2.54	2.60	3.02	0.14	4
Vehicle km travelled (300m)	$4.016\ e^{-06}$	848.00	75998	25615.3	2.54	2.44	2.74	0.11	5
Open Space area in sq. km(1000m)	-0.10	0.05	2.40	0.78	2.54	2.62	2.37	-0.10	6

5.2.12 Discussion

5.2.12.1 MLR based models

With the limited number of FSMs available in Dublin and Vienna using the MLR approach predictive performance was typically in the range of R^2 = 28 to 43%. Such a performance can be considered low and perhaps highlights the limitation of this approach with limited input data. However, it should be noted that in practice FSM data are limited in number as local government authorities have limited resources with which to measure urban air quality. Thus statistical air pollution models must be developed to make reliable predictions on air quality using the amount of readily available data, if these models are to be of practical use to practitioners and policy makers in this field.

Using the MLR statistical approach and predictor variables of *Dublin 1* produced the R^2 = 43% and these can be attributed to the addition of 2 new variables representing air mass history and peak traffic count. The result yields by the model for other models (*Dublin 1.1-1.4*) provided confidence in the reliability of the process and datasets to proceed for further development of the PM_{10} models. The models for oxides of nitrogen (Model 1.1, 1.2 and 1.4) are better fitted than that of SO_2 and PM_{10}, because the major source of NO_x is road transport (EPA, 2010). Although, the fitting and the performance for *Dublin 2* is lower in comparison to *Dublin 1*, the process initiated by *Dublin 2* lead to the development of the best performing model in *Dublin 7.*

It can also be noted that the performance of the models across two distinctly different European cities is quite consistent. Omitting *Dublin 1* from the result (as this was the only model to include air mass history) of MLR models gives a range of performance statistics of R^2 = 30 to 38%. Furthermore the stability of prediction from these models over time has been shown to be consistent in both Dublin and Vienna *i.e.* little change in performance statistics were noted when the amount of historical input data was increased by 1 to 2 years.

The inclusion of 2 additional FSMs in *Dublin 4* produced a decrease in performance (R^2 =0.28 against R^2 = 0.35 in *Dublin 3*) which was due to the ability of models developed excluding the Phoenix Park FSM to subsequently make predictions of concentrations at this station. As noted earlier, the Phoenix Park FSM was significantly different in nature to the other 6 and the models developed produced very poor predictions of concentration at this location during validation.

In addition, increasing the length of historic input data in the *Vienna 2* model, showed the stability of the modelling techniques that has been found by previous investigators (Gulliver *et al.*, 2011b, 2013; Gonzales *et al.*, 2012). However, the increasing variation (*i.e.* higher standard deviation) of the data yields a higher RMSE in Table 5 in comparison to the *Vienna 1*. Previous models were developed based on one year's data and were applied to consecutive years, however, models under this study were developed with two or three years of data together, which lead to a larger RMSE. This limitation of RMSE was subsequently tackled by using NPR and ANNs methods.

The *Dublin 5* model was developed following the *Dublin 2* model methodology which showed improvement in both model performance and RMSE, however, data variability in the *Dublin 5* model was lower than that of *Dublin 2* model both in the spatial and temporal sense.

5.2.12.2 NPR & ANNs

Using the alternative statistical modelling approaches to relate PM_{10} concentration to the predictor variables produced more favourable results. Using the NPR approach in both Dublin and Vienna, the validation coefficient of determination was at or close to 50%. Using ANNs produced the best predictive performance statistics with R^2 of 65% for Vienna and close to 50% for Dublin, and the lowest RMSE for both cities. This highlights the impact of the non-linear nature of the relationships between many of the variables and PM_{10} and the assumption of normality in the data using the MLR approach.

Previous investigations using advanced statistical models have also found that these have out-performed linear regression based techniques (Chaloulakou *et al.*, 2003). Here the improvements found were greater for Vienna than for Dublin. For example a 12% improvement was found using the NPR technique for Vienna while only 3% improvement was found for Dublin. Similarly a 27% improved was found for Vienna using the ANN technique while this was only 9% for Dublin. This may be explained by the differing characteristics of the two cities and the impact of the respective predictor variables. The sensitivity index for each variable in each city is shown in Table 5.8, and shows that the most important variable in Vienna was precipitation followed by max sustained wind speed. In Dublin it can be seen that the sensitivity index was more evenly distributed across the predictor variables. Comrie (1997) noted that the relationships between air pollution and weather are typically complex and non-linear. Therefore as weather variables were of more importance in Vienna than in Dublin the addition of non-linear statistical techniques in Vienna has achieved a greater level of improvement than those in Dublin.

5.2.12.3 Air mass history

The representation of air mass history as variable D_1 (in *Dublin 1*) demonstrated an increase in model performance over the *Dublin 2* from 38% to 43%. This finding highlights that LUR based model predictive performance may be increased significantly with the inclusion of a variable representing the contribution of trans-boundary air pollution.

This variable D_1 also produced a logical result for SO_2. In cross-national econometric studies, urbanisation and average household size are not found to be significant determinants of sulphur dioxide emissions (Cole & Neumayer, 2004).

The methodology applied here to the derivation of D_1 is a first attempt at the inclusion of such a variable and offers considerable scope for refinement and possible improvement in its explanatory power. Alternative rating systems, including negative scores for water bodies or green areas, could be investigated. Similarly, the density of the grid applied to the derivation may also offer scope for improvement. Other factors which may alter the eventual score attained by a trajectory include the selected height and hour of the day, *etc*.

Future research is required to examine the optimum approach to the derivation of D_1 and the extent to which improvements in its explanatory power are possible. Inclusion of different rating scores for areas with the large combustion plants and sources of natural dust *e.g.* ploughing, grazing activities could be incorporated within the grid for improvement of the model. Such improvements may provide an interesting comparison while applied in inland cities, where the urban background PM_{10} concentration is influenced by long range transport or secondary aerosols (Lenschow *et al.*, 2001).

It should also be noted that the production of 365 air mass histories for 2009 and the subsequent production of a rating score for each one was a labour intensive process in the current study. Future work may also be required to address the automation of this process for wider use in air pollution modelling.

5.2.12.4 Hourly traffic count

Different forms of traffic volume/intensity data have been used in many previous investigations of the LUR modelling technique. These included annual average daily traffic count (Briggs *et al.*, 2000; Mölter *et al.*, 2010) and simulated traffic data (Jason *et al.*, 2008; Smith *et al.*, 2011; Dons *et al.*, 2013b). In the present study, annual average daily traffic data have also been used to derive the VKT variable for models

Dublin 2-7. While data representing annual average daily traffic, or derived variables such as VKT count often becomes a useful parameter for incorporating spatial variability in models, hourly traffic count, such as applied in *Dublin 1,* obtained from the intelligent traffic management systems, *i.e.* loop detectors may provide additional temporal information for high resolution LUR based models. Such inclusion may be required for modelling of air quality variation in the shorter term for road users. Annual average traffic count may not always be useful for this purpose, because traffic variability is unpredictable, and traffic causing higher emissions often originates from outside the study area, or the city (Sider *et al.*, 2013).

5.3 Mapping of air quality

The final models produced for both cities can be applied at any location for the prediction of PM_{10} concentration, and this was applied here on a moderate size grid for discussion. Maps of Dublin and Vienna both were divided into a 400x400m grid and PM_{10} concentrations were predicted using the final models developed at the centroid of the each grid cell for a typical day in the winter. Ordinary kriging was subsequently applied to these data to interpolate between data points and produce maps of PM_{10} concentrations for both cities. This was carried out using ArcMap 10.1 software.

Figure 5.11 shows the results of this process as a typical graphical output for the best performing models in the study *Vienna 5*, and *Dublin 7* for a typical winter day. Figure 5.11(c) shows similarity in graphical output of the model developed in a recent study by Kurz *et al.* (2014). Kurz *et al.* (2014) applied a combined emission–dispersion model system to project PM_{10} concentrations in Vienna between 2005 and 2020, and a graphical representation of the model in 2010 showed that higher PM_{10} concentration areas were also modelled as high PM_{10} concentration areas under this study in a typical winter day.

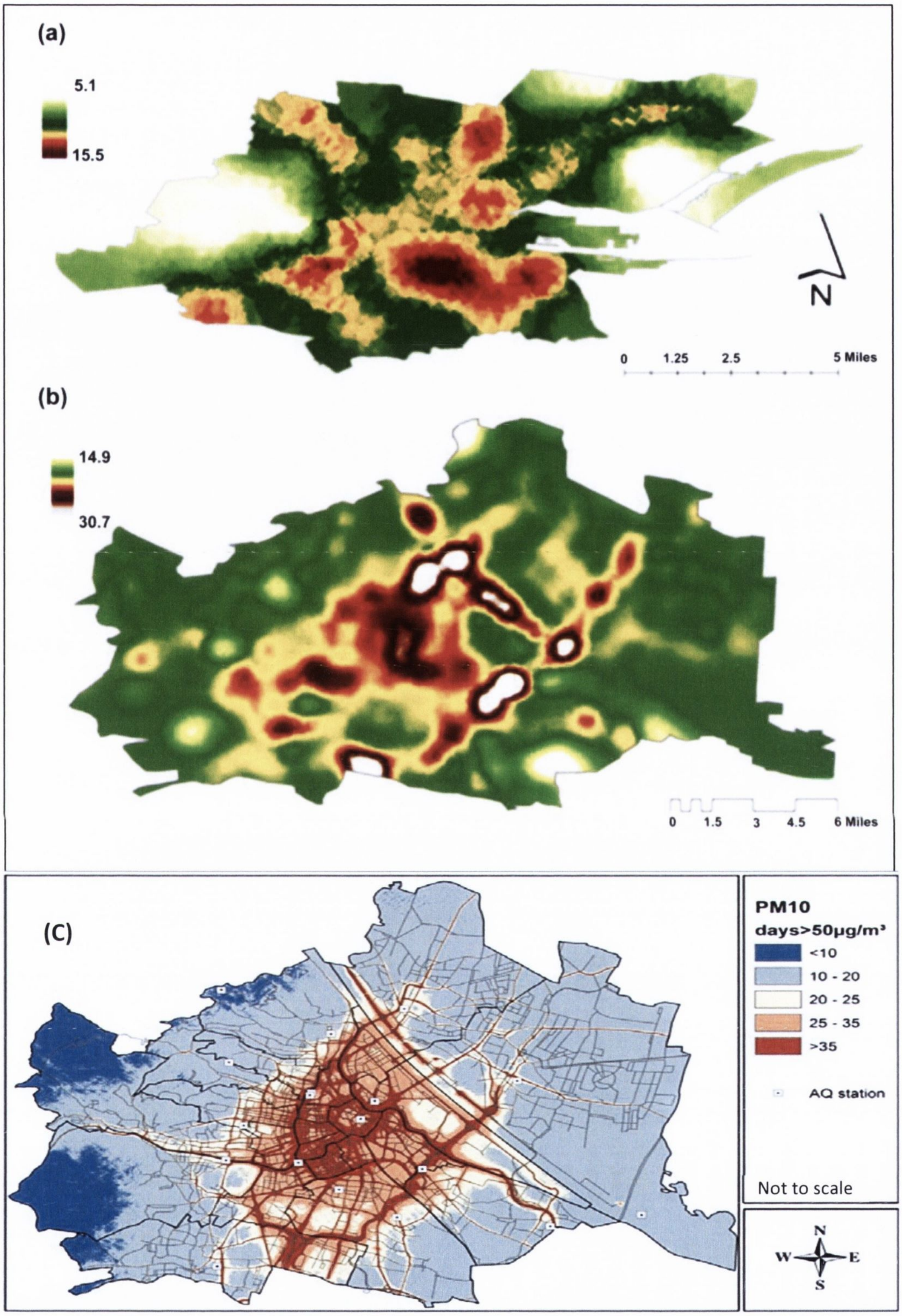


Figure 5.11: Graphical output of average daily PM_{10} concentration from (a) Dublin 6; (b) Vienna 5 for Winter Mondays; (c) Simulated exceedances of the daily mean value for PM_{10} for 2010 (Kurz *et al.*, 2014).

5.4 Personal exposure model/route level estimation

Using the ANN models followed by Krigging, the PM_{10} maps for Dublin city have been developed for seven weekdays across two seasons (winter and summer). Average values of the predictors for summer and winter days were applied for PM_{10} concentrations. These 14 maps were then overlaid with the road network using ArcMap (Figure 5.12).

Figure 5.12: Exposure map with road network (line)

The development of these maps facilitated a comparison of route choice prioritisation. Here a comparison was initially made for two routes (using real-time data) with the same origin and destination in Dublin where we consider one of the following as our priority in route choice:

i) the lowest running cost route
ii) the shortest distance route
iii) the shortest time route
iv) the lowest generalised cost route
v) the lowest air pollution dose route
vi) the lowest CO_2 emissions route

Subsequent to this further analysis was carried out using modelled data for 2 different origin destination pairs each producing multiple routes for each of the route choice priorities chosen. The lowest/shortest path for the above criteria was implemented using the Network Analyst toolkit in ArcMap, in which Dijkstra's algorithm was applied for the least cost route finding algorithm (ESRI, 2013). Dijkstra's algorithm solves any network having a single-source shortest path problem and non-negative edge path costs by producing a shortest path tree.

5.4.1 Determination of route choice factors

The commonly applied cost components for route choice, such as generalised cost, travel time, distance, and CO_2 emission were estimated based on the information given in Table 5.9. Initially, the speed limits for each road links in the ArcGIS road map was updated using the Speed Limit By Laws, 2011 of DCC (DCC, 2013), and a realistic speed for Dublin has been considered (Table 5.9). For CO_2 emission and other network attributes, a Euro III emission standard petrol powered vehicle (Y) has been chosen. This choice of a single vehicle was carried out for simplicity to facilitate the comparisons. Future work could include the assessment of route choice options for differing vehicle types which may have varying cost and emissions factors.

For value of time (VOT) estimation, an assumption of work trips with a vehicle occupancy of 1.31 was included. The required cost attributes were determined using the following equations (Eq. 5.4 to 5.7). As no comparison was made against public transport or considering parking fare policy, the generalised travel cost (GC_i) was estimated considering only in-vehicle time and vehicle running cost. The route choice cost factors were calculated using following equations, and unit cost factors were obtained from Table 5.9. The distance was calculated from GIS dataset. Running cost emissions for each route choice were calculated according to Eq. 5.4:

$$RC_i = RCP_i * L_i \qquad \text{Eq. (5.4)}$$

Where, RC_i = average running cost; RCP_i= average running cost per km; L_i= length of the link i.

Generalised travel costs (GC_i) for each route choice were calculated according to Eq. 5.5:

$$GC_i = VOT * TT_i + C_i * L_i \qquad \text{Eq.(5.5)}$$

Where, GC_i = generalised travel cost on the link i; VOT = Value of time of the travellers; TT_i= travel time on the link i; C_i= running cost of a vehicle on the link i, and L_i= length of the link i.

CO_2 emissions for each route choice were calculated according to Eq. 5.6:

$$E_i = EF_i * L_i \qquad \text{Eq.(5.6)}$$

Where, E_i = average CO_2 emission on the link i; EF_i = vehicle emission factor on the link i using the emission factor equation in Table 5.9 for free flow speed; L_i = length of the link i.

Air pollution dose was determined for each route according to Eq. 5.7:

$$D = \int_{t1}^{t2} C(t).IR(t,m).dt \qquad \text{Eq.(5.7)}$$

Here, D=dose (μg); $IR(t,m)$ = Inhalation rate (m^3/h) based on mode; time in hour; and $C(t)$ = Hourly concentration μg/m^3 ; the concentration in section 5.3 provided daily average concentrations over the area. Thus the resolution was further higher by multiplying the values by a global temporal adjustment (the morning peak hour factor generated by for NO_x from all FSMs in Figure C1; Table C5, Appendix C, Alam *et al.*, 2013c).

Table 5.9. Network setup for routing assessment

Attribute	Details	Value	Source
Link Speed at 8.00-9.00 am	City centre inside canal	10.2km/h	(RSA, 2012)
	Outside Canal residential	17.9km/h	
	Urban arterial outside canal	39.1km/h	
Vehicle model, Y	Euro III; Petrol Engine (1400-2000cc); <2.5 GVW*	--	--
Emission factor for Y	(2532.4+118.34x-0.43167x2+0.0066776x3)/x **	g/km	Boulter *et al.*, (2009)
CO_2 band for Y	Average emission 179g/km	E	--
Running cost, RC for Y	Petrol, Oil, Tyres, Servicing, Repairs & Replacement	0.30 €/km***	AA(2012)
Trip type	Work trip	----	--
Average occupancy		1.31	NRA, (2011)
Value of time, VOT		0.46 €/Min^	
Inhalation factor"	Car driver & passenger	0.57 m^3/h	US EPA (2009).

*Gross Vehicle Weight; **x= speed (range:5-140km/h); *** Cost per Km was based on 16,000VKT;^= per person; "Inhalation factor is sensitive to person's metabolism, breathing amount and physical activity; car travellers/drivers have minimum physical activity while driving.

From the above conventional cost factors can be grouped into time based cost factors such as: VOT and TT, whereas distance is predominating for running cost, and distance based routing. GC is equally dominated by TT and distance. CO_2 is also a function of both as emissions factor equation considered speed as a predictor which is a function of TT.

5.4.2 An assessment with SCATS travel time data

ITS (2010) provided real-time traffic data for several routes in Dublin. Two parallel routes (Figure 5.13) were selected and corresponding datasets were integrated in GIS format. The distance for route A was 9.6 km and corresponding travel time was 2.5 hour. The travel time and distance for route B were 47% and 56% lower in comparison to route A. The results were presented in Figure 5.14. Detail of the result has also been presented in Table C6, Appendix C.

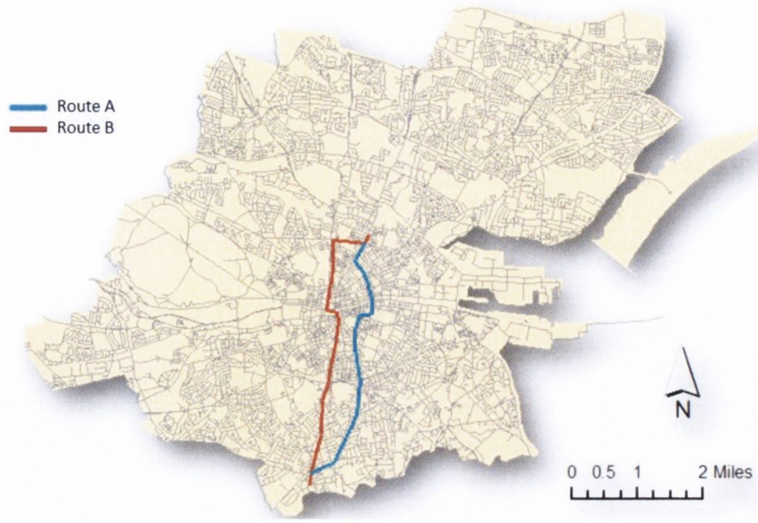


Figure 5.13: Exposure to PM_{10} for two alternative routes in morning peak hour in Dublin

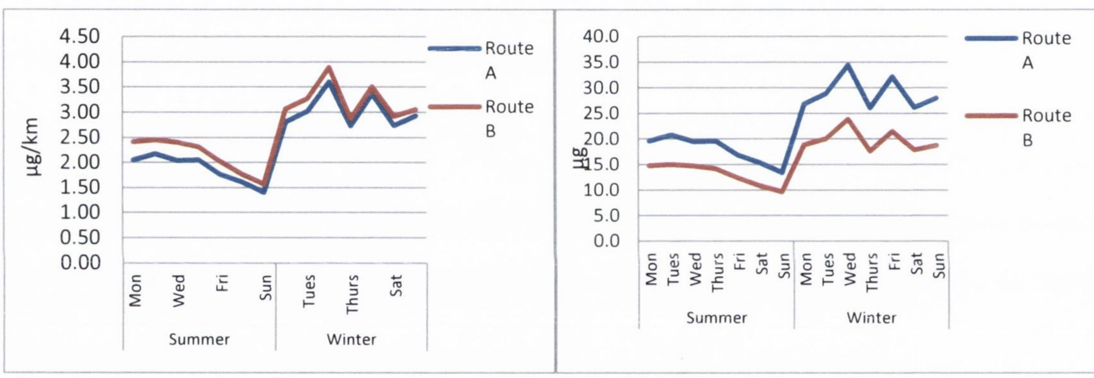


Figure 5.14: Dose of PM_{10} (per km vs. total) for two alternative routes in morning peak hour in Dublin.

The total dose for route A was higher than that of route B throughout the seasons. Although route A had higher travel time and distance, per kilometre dose was lower than that of Route B (by 9.5 to 18.3% in summer and 4.1 to 8.9% in winter). Thus, the healthy route choice is clearly route B here. This makes a significant difference against the traditional cost factors such as RC, VOT or GC which are mostly calculated on a per kilometre basis. On the other hand, the result of this comparison leads to the general assumption that lowest travel time might reduce the exposure to PM_{10}. However, these two paths were not least cost paths and thus, a further analysis has been conducted in section 5.2.3 below.

5.4.3 Vehicle routing assessment

The basic assumptions for the traffic assignment stage of transport modelling are that the individual will have complete information about the route and cost factors, and all travellers have identical perceptions of cost as well as the same route choice criteria, and will try to minimize costs. Thus, the driver of the work trip in the current test cases was considered to minimize either the travel cost, distance, travel time, CO_2, or PM_{10} dose. Two Origin-destination (OD) pairs have been considered and routes in terms of least PM_{10} dose and other attributes have been presented in Figure 5.15. Each origin and destination points were displayed as O_i & D_i. The shortest path tool of ArcGIS network analyst has been deployed for this analysis.

In addition, the actual dose while travelling may differ from the calculated average dose. The dose may increase as a result of travelling while pollution level is higher, or an increase in travel time due to congestion. This latter case is also true for an increase of CO_2, and cost. Thus, the following discussion has been drawn from average attribute values in a given traffic situation, however the findings should stand for all traffic conditions.

Figure 5.15 shows that the least PM_{10} dose routes are different from all other routes. However, as all the routes based on the least value of the conventional attributes overlapped with each other, Tables 5.10-5.13 may provide a clear picture. Details of the results are also available in Table C7 and Table C8 in Appendix C.

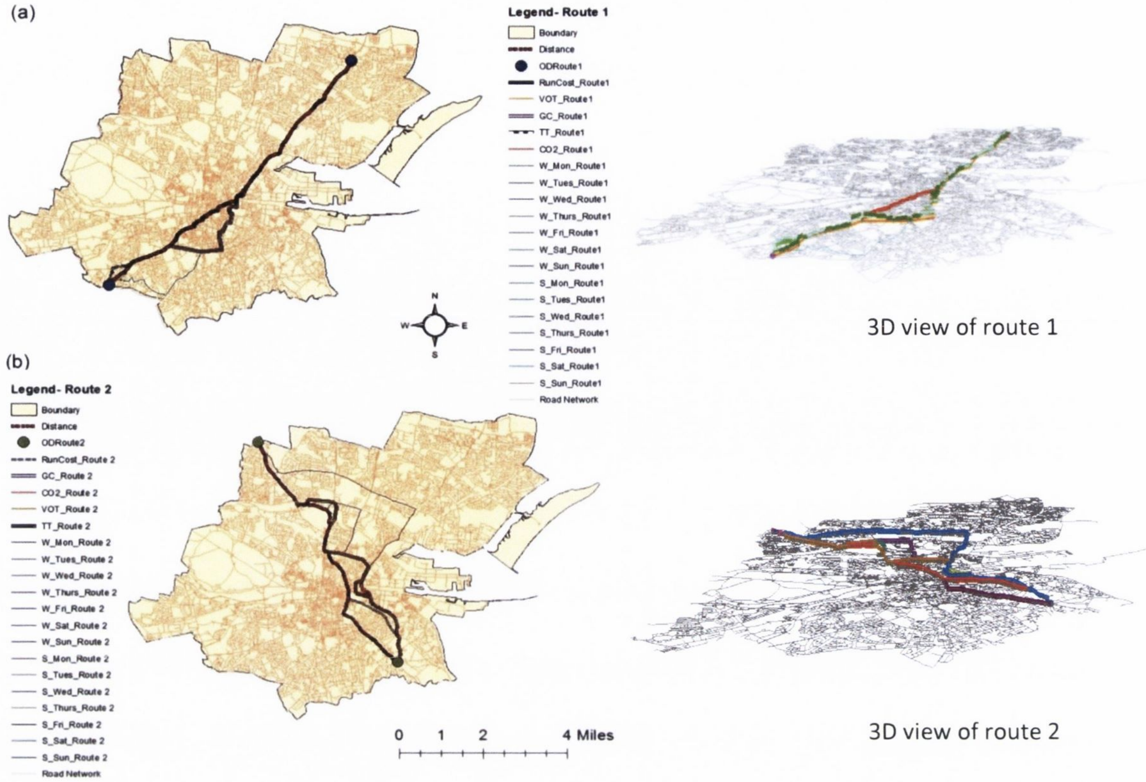


Figure 5.15: Vehicle routing assessment for two origin-destination pair

While taking lowest dose values for route 1 in Table 5.10, the conventional cost factors do not show much variation in summer. Lowest dose is found on Sunday; however, it is one of the lengthiest routes. In winter, the average dose is higher and showed lower standard deviation than that of summer. Average distance, and standard deviation of it are higher and these lead to similar statistics for VOT, RC and GC in comparison to summer values. However, TT is almost similar to the summer average values. In Table 5.11 average of the lowest dose values over the summer and winter in Table 5.10 were compared against the values yield by the shortest routes for conventional cost factors.

Table 5.10: Route 1 Lowest dose for different days of the seasons

	Route 1	Dose (μg)	Trip information Distance (km)	VOT (€)	Travel Time (Hour)	Running costs (€)	CO_2 (g)	Generalised costs (€)
Summer	Lowest Dose in Monday	3.65	15.34	13.91	0.50	4.60	2994.0	18.51
	Lowest Dose in Tuesday	3.54	15.57	13.71	0.50	4.67	3001.0	18.37
	Lowest Dose in Wednesday	3.46	15.24	13.72	0.50	4.57	2964.0	18.29
	Lowest Dose in Thursday	3.38	15.24	13.72	0.50	4.57	2964.0	18.29
	Lowest Dose in Friday	3.11	15.21	13.70	0.50	4.56	2959.0	18.26
	Lowest Dose in Saturday	2.66	15.26	13.76	0.49	4.57	2970.0	18.33
	Lowest Dose in Sunday	2.42	15.54	13.64	0.49	4.66	2991.0	18.31
	Average	3.17	15.34	13.74	0.50	4.60	2977.6	18.34
	Standard Deviation	**0.47**	**0.15**	**0.08**	**0.01**	**0.05**	**17.17**	**0.08**
Winter	Lowest Dose in Monday	4.37	15.22	13.72	0.50	4.56	2962.0	18.29
	Lowest Dose in Tuesday	5.02	15.26	13.75	0.50	4.58	2970.0	18.34
	Lowest Dose in Wednesday	5.31	16.23	15.67	0.47	4.87	3256.0	20.54
	Lowest Dose in Thursday	4.64	15.24	13.74	0.50	4.57	2967.0	18.31
	Lowest Dose in Friday	5.36	15.26	13.76	0.50	4.57	2970.0	18.34
	Lowest Dose in Saturday	4.52	15.22	13.73	0.50	4.57	2962.0	18.29
	Lowest Dose in Sunday	5.13	15.54	13.64	0.49	4.66	2990.0	18.30
	Average	4.91	15.42	14.00	0.49	4.63	3011.0	18.63
	Standard Deviation	**0.39**	**0.37**	**0.74**	**0.01**	**0.11**	**108.45**	**0.84**

Table 5.11 showed that while taking the lowest distance route, the travel distance was reduced by 8.4% on an average in comparison to the lowest dose, however, dose is increased by 15.5%. As the distance was reduced by 8.4%, the RC and CO_2 went down a little too. In addition, GC and VOT went up due to increase in TT.

While the lowest dose route was compared against shortest routes based on GC, VOT, and TT, lowest dose route only caused a small increase (<2%) in these values costing a small saving from dose (<3.8%). However, while route based on lowest CO_2 was considered, the small decrease in CO_2 values led to a large increase in dose (12.8%). If routing is based on lowest running cost, the dose may be as much as 16.8% higher in comparison to the lowest dose route. Although the lowest running cost route might save 8.5% running cost, minimised 7.8% in distance and 0.8% CO_2, overall TT and VOT were increased. In short, routes with lowest distance can heavily increase exposure to PM_{10} if employed in route 1.

Table 5.11: Route 1 routing assessment

Route 1		In comparison to average lowest dose						
		VOT (%)	Travel Time (%)	Running cost (%)	Generalised cost (%)	Distance (%)	CO_2 (%)	Dose (%)
Trip information	Lowest VOT (%)	-1.9	0.9	2.3	0	2.2	1	3.2
	Lowest Travel Time (%)	-0.7	-0.9	0.8	-0.1	0.8	-0.4	0.8
	Lowest Running cost (%)	8.4	11.2	-8.5	4.3	-7.8	-0.8	16.8
	Lowest Generalised cost (%)	-0.2	1.1	0.2	-1.2	0.1	0	3.8
	Lowest Distance (%)	7.4	9	-7.9	3.4	-8.4	-1.6	15.5
	Lowest CO_2 (%)	5.2	7.2	-7	2.2	-6.9	-1.7	12.8

For Route 2, similar to route 1, dose values were higher in winter in comparison to summer (Table 5.12). In addition, values for conventional cost factors are also higher in winter than that of summer. However, unlike route 1, the variations in values for conventional cost factors are similar in summer and winter. Table 5.13 showed that while taking the lowest distance route, the travel distance and running cost was reduced by 17.2%, and 17.5% on an average in comparison to the lowest dose route, however, dose value was increased by 22%. Decrease in values of cost factors for the lowest routes based on VOT, TT, GC and CO_2 were observed below 9.8% with a small increase of dose (<6.4%). In short, routes with lowest distance can heavily increase exposure to PM_{10} if employed in route 2. In addition, lowest TT in route 1 and route 2 offered excess 0.8% and 4.4% excess PM_{10} dose although dose is a function of travel time. In addition, lowest travel time increase distance of 0.1% over lowest distance in route 1 which is 14.6% for route 2 (Table C7-8, Appendix C). From table 5.12-5.13, lowest TT was found to increase distance by 0.8% for route 1 and decrease 1.8% for route 2 in comparison to the lowest dose route. Although, dose in a function of TT, the characteristics is not similar to TT, or any other similar cost factors derived from TT. It is also notable that saving CO_2 causes increase in dose, but in a different magnitude.

Table 5.12: Route 2 Lowest dose for different days of the seasons

Route 2		Dose (µg)	Trip information					
			Distance (km)	VOT (€)	Travel Time (Hour)	Running cost (€)	CO_2 (g)	Generalised cost (€)
Summer	Lowest Dose in Monday	3.33	14.16	11.60	0.42	4.25	2649.0	15.85
	Lowest Dose in Tuesday	3.23	14.15	11.59	0.42	4.24	2646.0	15.84
	Lowest Dose in Wednesday	3.17	15.79	13.53	0.49	4.73	3008.0	18.27
	Lowest Dose in Thursday	3.01	14.01	11.50	0.42	4.20	2621.0	15.70
	Lowest Dose in Friday	2.67	14.62	11.93	0.43	4.39	2730.0	16.32
	Lowest Dose in Saturday	2.20	15.78	13.52	0.49	4.73	3006.0	18.26
	Lowest Dose in Sunday	2.03	14.20	11.63	0.42	4.26	2654.0	15.89
	Average	2.81	14.67	12.19	0.44	4.40	2759.2	16.59
	Standard Deviation	**0.52**	**0.78**	**0.92**	**0.03**	**0.23**	**172.62**	**1.16**
Winter	Lowest Dose in Monday	4.58	15.64	13.43	0.49	4.69	2982.0	18.12
	Lowest Dose in Tuesday	3.33	15.79	13.53	0.49	4.74	3008.0	18.27
	Lowest Dose in Wednesday	4.13	15.62	13.41	0.49	4.69	2978.0	18.10
	Lowest Dose in Thursday	4.02	14.15	11.60	0.42	4.25	2646.0	15.84
	Lowest Dose in Friday	4.78	15.68	13.45	0.49	4.70	2987.0	18.16
	Lowest Dose in Saturday	3.90	14.27	11.68	0.42	4.28	2667.0	15.96
	Lowest Dose in Sunday	4.39	14.23	11.66	0.42	4.67	2661.0	15.93
	Average	4.16	15.05	12.68	0.46	4.57	2847.0	17.20
	Standard Deviation	**0.48**	**0.79**	**0.97**	**0.04**	**0.21**	**177.16**	**1.21**

Table 5.13: Route 2 routing assessment

Route 2		In comparison to average lowest dose						
		VOT (%)	Travel Time (%)	Running Cost (%)	Generalised cost (%)	Distance (%)	CO_2 (%)	Dose (%)
Trip information	Lowest VOT (%)	-6.9	-6.3	-5.3	-6.2	-4.7	-5.5	4.3
	Lowest Travel Time (%)	-6.8	-7.0	-5.5	-6.2	-4.8	-5.6	4.4
	Lowest Running cost (%)	5.1	5.0	-17.8	-0.7	-17.0	-7.9	18
	Lowest Generalised cost (%)	-5.4	-5.5	-13.1	-7.5	-12.5	-9.5	5.9
	Lowest Distance (%)	9.7	9.6	-17.5	2.6	-17.2	-6.1	22
	Lowest CO_2 (%)	-5.7	-5.7	-13.5	-7.2	-12.8	-9.8	6.4

5.5 Conclusion

In conclusion, the results of this investigation highlight that it is possible to predict air pollution concentrations using adaptations of the LUR methodology, to an acceptable level of accuracy using a limited number of FSMs. It has been shown that this is best achieved using non-linear statistical modelling techniques such as NPR or ANNs. The mapping shows that the daily variation of air quality is notably different across the city for summer and winter days, and thus the routing based on dose value will be constantly changing.

From these two route analyses, it was found that lowest travel time and distance does not offer lowest dose, and routing decisions based on time and distances and related parameters are most contradictory with the dose based routing exercise. The analysis introduces a citywide modelling exercise for routing analysis based on lowest exposure, and shows a smaller increase of dose with a small increase in travel time and large increase in dose for shorter distance. For different origin and destination pair the magnitude of the velues might be changed. However, the research questions regarding air quality mapping, routing exercise methodology development and comparative analysis with traditional cost factors were attained. Although only two routes from many thousands of possible OD pairs were analysed, the result provides a generic indication of the characteristics of air pollution dose as a route cost factor.

Eco-Routing

Chapter 6

6.1 Introduction

Chapter 2 sets out the need for developing an Eco-Routing model (based on lowest CO_2 emissions) that will overcome the limitation of existing static models, and work with minimum inputs so that it may be suitable for use in any standard mobile device, *e.g.* smartphones which is popular in modern days. In addition, the simplicity in the methodology and minimum complexity were other criteria considered for model development and were important for rapid information processing and lower calculation time.. Overly complex emissions models may present a barrier to their implementation in mobile devices at present due to the length of computation time involved. The estimations from the process is a key input for personalized recommendation for the improvement of user travel behaviour and achieving overall aim of Eco-routing.

The PEACOX project provides an excellent platform to incorporate an Eco-Routing model for passenger car with the other emissions modules of rest the road-based and rail based modes (Figure 6.1). A dynamic Eco-Routing model for passenger car will serve the requirement for the PEACOX project in addition of acquiring a position for research according to Chapter 2. The model architecture shown in Figure 6.1 does not include the entirety of the Eco-Routing model as emissions estimation for other modes or multimodal trips were also included. As the focus of this thesis lies with smarter driving, these elements of the model have not been reported here.

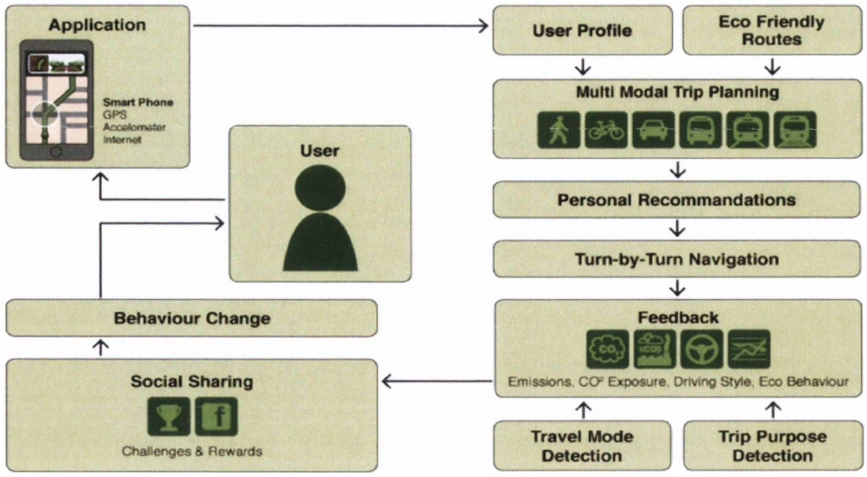


Figure 6.1: PEACOX Project overview (PEACOX, 2014)

Note: An overview of the different components of the PEACOX project can be found in Box-1, Appendix D

This chapter presents the development of the dynamic Eco-Routing model for passenger car which predicts the carbon footprint of an individual trip. This chapter also varies with the other two modeling exercises in Chapter 4 and 5, as the developed model for CO_2 Eco-Routing is a system design, and presents its functionality in comparison with a simplified model that is static in nature, whereas other models in the previous chapters presented various scenarios. For the purpose of the model development, the objectives are mentioned below:

- Objective 1: Ascertain applicability of emissions factors that assist in the development of an efficient, accurate and effective method of estimating CO_2 emissions.
- Objective 2: Develop and verify a dynamic an emissions model that will predict CO_2 emissions from transport before a trip is undertaken.

- Objective 3: Develop a simplified model and compare the result of two models using real world field trial data.
- Objective 4: Evaluate performance of the dynamic model for real time application.

The applicability of the emissions estimations that can be representative of congestion primarily depends on the selection of appropriate unit emission factors. Thus, the sensitivity of the emission factor generations in relation to congestion was analyzed to carry out the modelling task. After achieving a satisfactory result, a dynamic model was then developed. In addition, a static model (a simplified version) was also developed to make a comparison of the performance of the original model to existing approaches. After development of the original (dynamic) and static models, a verification of the functions of the models for Eco-Routing was analyzed to ensure that the models were connected well in a desired platform. Finally, data were obtained from the real-world experiments in order to analyse the performance of the models.

6.2 Modelling methodology

To calculate and predict emission as accurately as possible with existing knowledge on emission factors, the following general methodology (Figure 6.2) has been developed. The primary consideration was the input resolution of the model, especially, the vehicle trajectory of the model. Real time speed (from predictions based on real-time traffic information) of the vehicles may be a surrogate indicator for congestion, to some extent using the same logic argued by Smit *et al.* (2008a) for modal models (*i.e.*

considering instantaneous second by second vehicle trajectories speed and acceleration) which are capable of taking congestion into account. The modal model explicitly considers congestion, and this has been noted in chapter 2. Considering this, an emissions modeling methodology has been developed following a strategy where emission factors will be changed according to the real time speed of the vehicles. Thus, the model would consider congestion in a route with lower speed, in comparison to the other routes. In addition, some routes in reality may be comprised of roads with lower speed limits for safety reasons; the attractiveness of such a route in terms of emissions would also be covered by the same methodology.

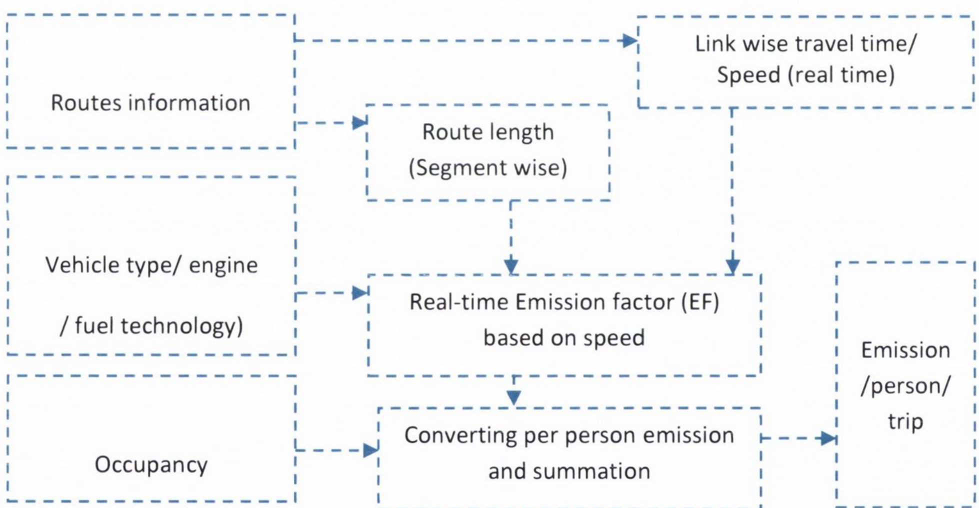


Figure 6.2: Basic emission modelling methodology

The model counts occupancy data according to peak and off peak hours, real-time speed, and both hot and cold start emissions. The model operates according to Eq. (6.1):

$$E = (E_1 + E_2)/O_f; \quad \text{Eq. (6.1)}$$

Where,

$E_1 = \sum_{k=1}^{n} EFH_k(S) * L_k$; or hot emissions from all the links in the route

$E_2 = EFC_n(TT, L_n, Temp, P)$; Cold emissions from the route;

O_f= Occupancy Factor; *L* = length, EFH_k = Hot emissions factor which is function of *S* = Speed in link 'k'; EFC_n = Cold emissions factor for all links 'which is function of *TT*= Travel time, Parking time (*P*) & Temperature (*T*), *etc.*; and number of links, k=1, 2, 3 ...., n

Thus, to get the best result, it was necessary to connect the input source with real time speed information systems like the Intelligent Transport System Infrastructure. It has been assumed that the real time link speed will be representative of the vehicle speed. Boriboonsomsin *et al.* (2012) noted that if the traffic speed is misrepresented in their developed Eco-Routing model, the fuel consumption and emissions estimates will not be accurate. Thus, with the appropriate input from any specific city, the model could be applied to any city for Eco-Routing. There are possible approaches that can be discussed for the use of speed input for predicting emissions, either by: i) obtain floating car speed data as input; ii) to connect the model with real time intelligent traffic management systems (SCOOT, SCATS or UTOPIA), or to any real time information source; iii) by adopting V2V or V2I technologies; and iv) building a driving cycle generation tool capable of working online based on real time variables (Brady, 2012).

Briante *et al.* (2014) noted various technologies to obtain Floating Car Data (FCD) such as GPS-based, phone-based passive cellular measurements, participatory (cellular only, hybrid cellular, off-loading-smartcar). Beckx *et al.* (2010) described a GPS based enhanced data collection tool for the assessment of vehicle exhaust emissions by converting the second-by-second global positioning system based travel data into emissions for individual vehicle trips. Herrera *et al.* (2010) noted that data from 2-3% of cell phone penetration in a traffic flow is equivalent to the traffic flow velocity.

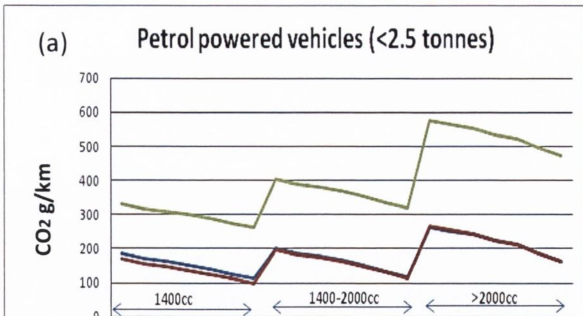
6.2.1 Hot emission factors

A study by Boulter *et al.* (2009) under TRL was carried out reviewing emission factors for hot exhaust emission from the vehicles. The CO_2 emissions factor equations were developed following 'real-world' driving conditions under that study. These emission factor equations were adapted in this Eco-Routing model. These emissions factors are slightly higher than that of conventional emissions factors, and are called 'ultimate' CO_2 (Figure D1, Appendix D). These ultimate emissions are the tail-pipe CO_2 emissions plus the other pollutants from the exhaust that eventually oxidise to CO_2 in the atmosphere. The emissions equations are valid for 5-140 km/h, however, it is expected that link speed would be closer to the minimum 5km/h. Speeds lower than 5km/h have been considered as 5km/h in the current study. The emission factors were estimated in the following form, Eq. (6.2):

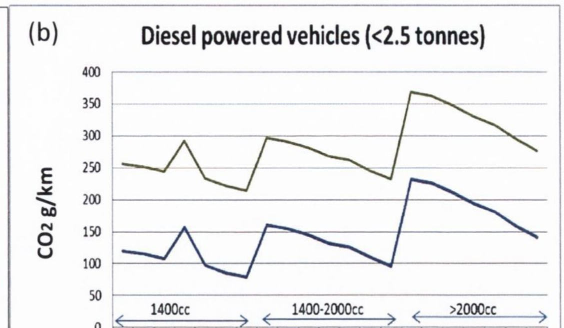
$$Y = (a + bx + cx^2 + dx^3 + ex^4 + fx^5 + gx^6)/x \qquad \text{Eq. (6.2)}$$

Where, *Y*= Emission factor in g/km; *x*= Speed in km/h; Coefficients = a, b, c, d, e, f and g

The model was designed to capture real-time speed from routes. As real time speed varies according to the level of traffic, the model explicitly considers congestion impact. Figures 6.3 and 6.4 present the impact of speed change on unit emission factor. It is noticeable that CO_2 emission rate is higher for lower speed, such as 10km/h than the other two speed categories. This is also consistent with the conventional emissions speed relationship depicted in Figure 2.1, Chapter 2.

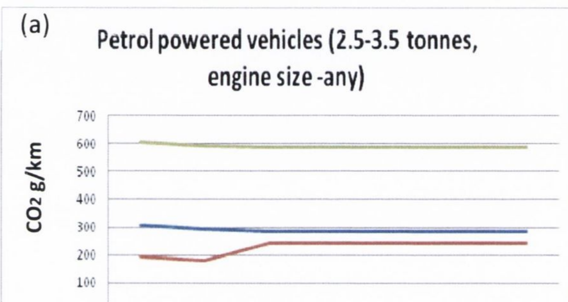


	Pre	I	II	III	IV	V	VI	Pre	I	II	III	IV	V	VI	Pre	I	II	III	IV	V	VI
100km/hr	185	170	162	152	142	126	114	202	187	179	167	153	134	118	264	251	242	223	212	184	161
50km/hr	171	155	148	138	127	112	99	199	184	176	164	149	131	115	267	254	244	226	214	187	164
10km/hr	332	317	309	299	289	274	261	403	387	379	368	353	335	318	576	563	553	535	523	496	473

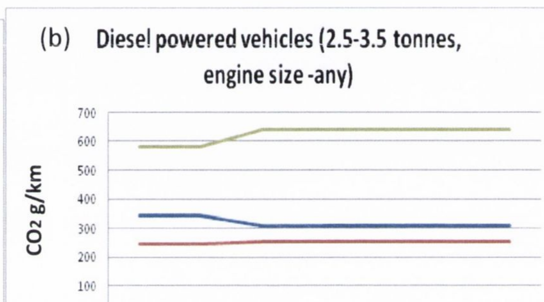


	Pre	I	II	III	IV	V	VI	Pre	I	II	III	IV	V	VI	Pre	I	II	III	IV	V	VI
10km/hr	256	252	244	293	234	221	215	296	291	281	268	262	246	233	369	362	348	330	318	296	277
50km/hr	119	115	107	156	97	85	78	160	154	144	131	125	109	96	232	225	211	194	181	159	140
100km/hr	120	116	108	157	98	86	79	161	155	145	132	126	110	97	233	226	212	195	182	160	141

Figure 6.3: CO_2 emission factors (g/km) for cars (a) Petrol; (b) Diesel: <2.5 tonnes



	Pre	I	II	III	IV	V	VI
100km/hr	309	296	283	283	283	283	283
50km/hr	195	182	244	244	244	244	244
10km/hr	604	590	586	586	586	586	586



	Pre	I	II	III	IV	V	VI
100km/hr	345	345	311	311	311	311	311
50km/hr	247	247	255	255	255	255	255
10km/hr	579	579	642	642	641	641	641

Figure 6.4: CO_2 emission factors (g/km) for cars (a) Petrol; (b) Diesel: 2.5-3.5 tonnes

6.2.2 Sensitivity of the hot emissions factors to speed change

The primary aim of this analysis was to detect whether the car emission factors (hot) used in the model was sensitive to congestion, and whether speeds close to zero can make any significant impact on emissions estimation for Eco-Routing. Thus, micro-simulation has been applied to private car trips. CO_2 information from car trips was generated from the VISSIM environment, and corresponding road speed and travel time data have been modelled and recorded for several routes during peak hours. The road speed and travel time data was then input to the developed Eco-Routing model (MATLAB), and the CMEM model for comparison purposes.

6.2.2.1 VISSIM environment setup and data modelling

A portion of the Dublin city centre road network near Trinity College (Figure 6.5) has been selected to be the test network. The same sources of data as that used in Chapter 4 were applied here: speed limit of the roads, turn movements for each junction and traffic flow direction, average evening peak hour traffic in 2011 (Figure D6, Appendix D), traffic composition- 3% bus and 97% car traffic in peak hour, have been applied to this simulation.

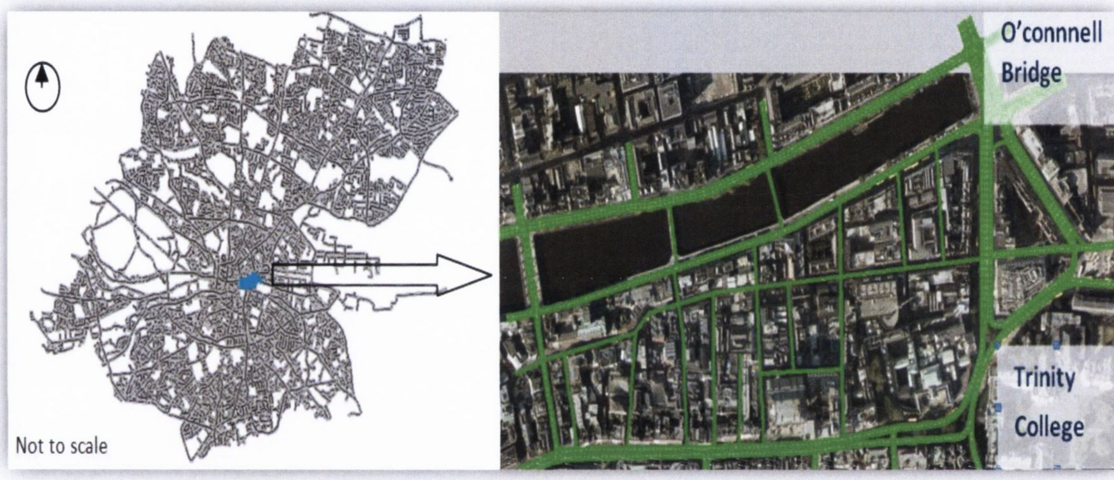


Figure 6.5: Selected network and digitized roads (in green) for simulation

The simulation time has been chosen as 500 seconds based on the purpose of the simulation. The target of the simulation was to analyse the impact of various levels of traffic on CO_2 emission factors of an individual vehicle, where the calibration and validation of the network is redundant. For verification, the network was designed with priority rules and conflict areas, instead of with traffic signals. The network was simulated (Figure 6.6) using the static routing function of the traffic counts.

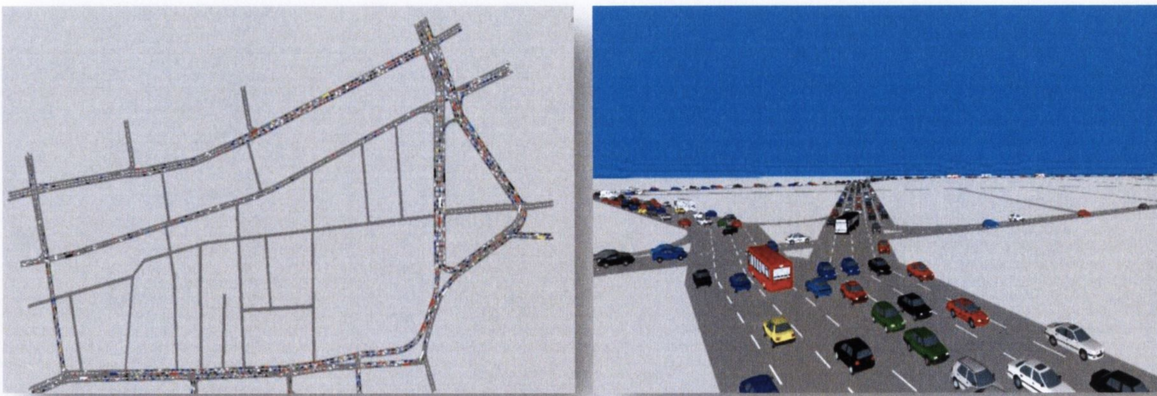


Figure 6.6: (a) Simulated traffic in the network; (b) Simulated traffic at O'Connell bridge

The embedded emission factors within VISSIM were based on Volkswagen emission data, which was not available to the current study (See Section 3.3.2.1, chapter 3). Thus, following the concept of emission factors relationship in vehicle trajectory and the VISSIM user manual, engine map data were derived using real world driving data in Dublin, and CO_2 emissions equations from a vehicle. The CO_2 emissions factors have been derived in a desired format from a real world driving profile data (captured using Garmin GPS for validation purposes on an 11.3 km route over 56 minutes in December, 2012) and the emissions factors equation of a petrol powered Euro III emission class vehicle (Gross Vehicle Weight <2.5 tonnes Engine size: 2000cc) that has been adopted in this study. In the trajectory data all speed lower than 5km/h has been considered as 5km/h speed. The desired format of the CO_2 emission factor was a 3D matrix of speed (km/h), acceleration*speed (m^2/s^3) and emission factors (mg/s) which has been derived for the emission module of VISSIM (Figure 6.7). On the other hand, the detailed vehicle trajectory data has also been inputted into CMEM.

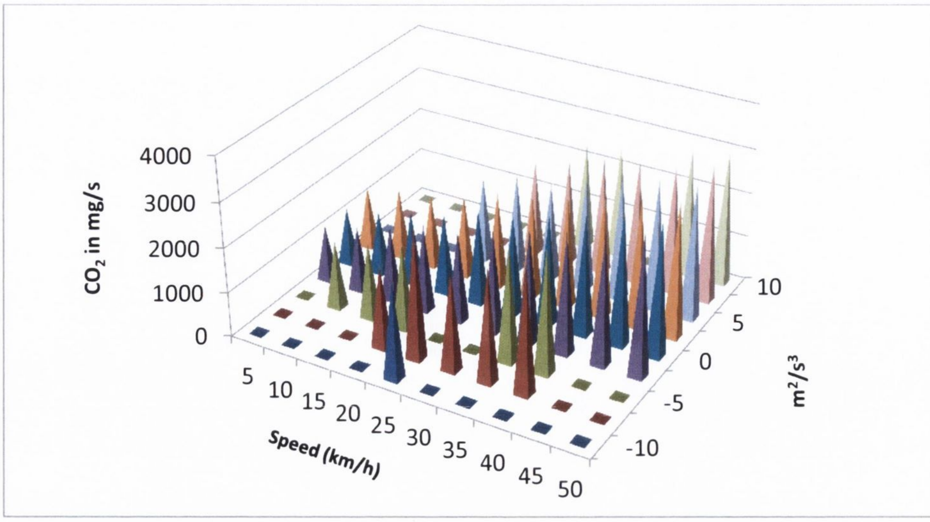


Figure 6.7: Emission factor matrix of CO_2 for VISSIM

6.2.2.2 CO_2 estimations from the trips in VISSIM

The simulation has been carried out for peak hour traffic, and thus, a direct comparison was possible of VISSIM CO_2 emission output with the results of Eco-Routing emission model (because the occupancy factor used in the emission model is 1 in peak hour). However, VISSIM is not designed for trip by trip emission estimation (rather it produces link or fleet based emissions estimations). Thus, the following procedure has been applied for CO_2 emission estimation from a vehicle and data modeling.

The car fleet for the simulation has been restricted to one category of vehicle. During each simulation, a unique number of vehicles have been specified for recording of the vehicle trajectory and corresponding CO_2 emission figures, road number and corresponding time as well as travel distance on each road. There was no control over the trip origin and destination point for any specific vehicle using this approach. However, that did not have any impact on the objective of this section of the chapter. During simulation runs, four vehicles: number - 30 (started at 3 second), 50(started at 6 seconds), 200 (started at 27 seconds) and 450 (started at 58 seconds) have been specified randomly and the route and trajectory of these vehicles has been presented in Figure 6.8.

Figure 6.9 shows the CO_2 emission profile in deci-seconds for vehicle number 30. Table D1, Appendix D presents the database format of each vehicle. CO_2 emission has been summarized from this database. A similar database has been stored for each link of the network during the simulation that contained a time stamp, volume, density and link speed. From the time stamp and link number, link speed has been identified where selected vehicles (*e.g.* 30) traversed in the network. This selected information has been fed into the Eco-Routing model and CMEM model for comparison and CO_2 information has been calculated. Estimation has been presented for vehicle 30 in the Table D2, Appendix D. The traffic volume on the link, density, *etc.* has also been observed from Table D3, Appendix D.

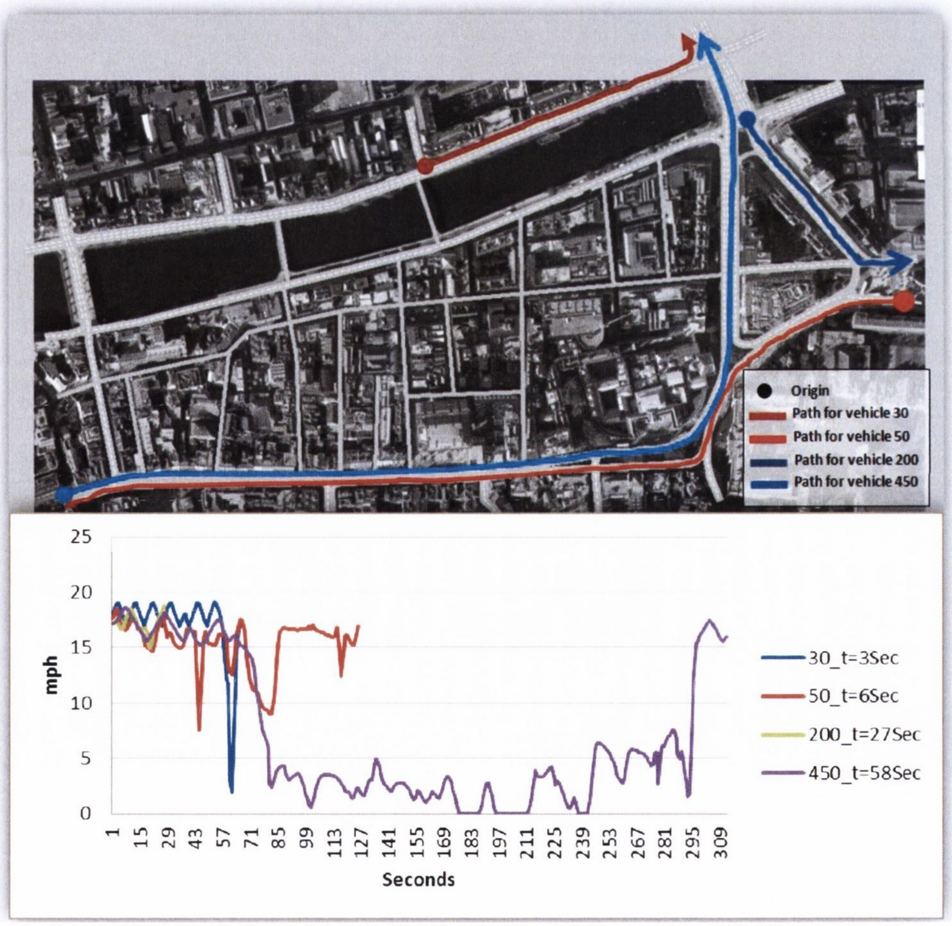


Figure 6.8: Vehicle movement paths and trajectory in VISSIM

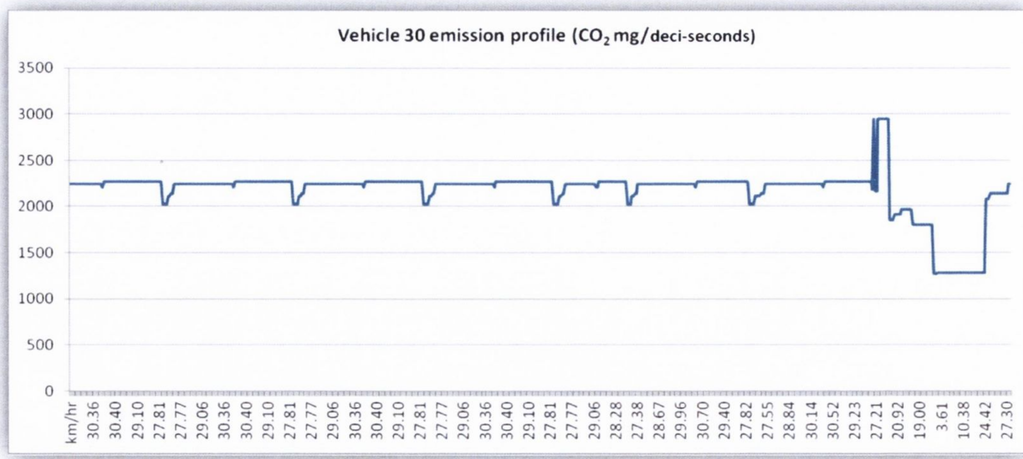


Figure 6.9: CO_2 emission profile for vehicle-30

The CO_2 estimations of the VISSIM and Eco-Routing models were surprisingly close in Table 6.1 below, although the methodology of emission estimation is different. VISSIM applies the methodology of a power based emissions model whereas; the Eco-Routing model developed here follows speed based logic. However, similar results occurred because the emission factors used for VISSIM were originally generated from the same source as those used in Eco-Routing. The results were not exact because VISSIM estimations were based on a second by second analysis whereas the PEACOX Eco-Routing estimations were based on link speed.

On the other hand, the CMEM model was developed for Light Duty Vehicles (LDV) and not for any specific vehicle (unlike Eco-Routing), and thus, model results cannot be entirely matched. However, the sensitivity of the models to speed change, showed similarity.

The important feature of the analysis is that vehicles faced different levels of traffic volume and congestion while traversing the network. The simulated network has been taken from a 30km/h zone and the speed limit on the roads was designated as 30km/h. However, the table confirmed that the vehicle was forced to follow different speeds due to different levels of traffic congestion, and produced emissions according to that speed. The average link speed was as low as 13 km/h for vehicle no. 450. When this link information was included in the Eco-Routing model, the generated emission was found to be similar to the estimations of the CMEM and VISSIM modules in the Table 6.1.

The cold start emission factor that has been used in Eco-Routing was not included in this analysis. However, cold start emission factors were previously validated by the ARTEMIS project, and inclusion of this will enrich the emissions outcome of the Eco-Routing model.

Table 6.1: Estimated emission from VISSIM software and Eco-Routing model

Vehicle No.	Distance (m)	VISSIM : Link Speed (km/h)	VISSIM : Vehicle Travel Time (s)	CO_2(g)		
				VISSIM Estimated	Eco-Routing Estimated	CMEM Estimated
30	494.08	28.95	64.8	141.1	139.1	120.8
50	242.47	26.02	131	242.5	254.9	194.0
200	192.77	27.52	52.7	53.02	55.6	38.6
450	935.88	13.25	369.1	474.6	465.1	363.8
Pearson correlation coefficient, r				0.9989		--
				--	0.9982	

6.2.3 Cold emissions factors and cold distance

To ensure accuracy, the model will take account of the effect of cold start emissions which is dependent upon ambient temperature. Cold Start Emissions are the excess emissions when the emissions-control equipment has not yet reached its optimal operating temperature. As cold start emissions are highest when engine is started, gradually decrease as the operating temperature approaches, cold start is associated with time, or travel distance in running condition (Colls & Tiwary, 2010) which is often called 'cold distance'. To account for the "Excess cold start emission per start" equations developed by the ARTEMIS Project have been included in the model (Boulter and Lathlam, 2009). The general cold start equation is Eq. (6.3):

$$EE(T,V,\delta,t) = \omega * f(T,V).\frac{1-e^{a\delta}}{1-e^{a}}.g(t) \qquad \text{Eq. (6.3)}$$

Where, *EE* = excess emission for a trip in g; *V* = Mean Speed in km/h during cold period; *T* = ambient temperature in ^oC; *t* = Parking time in hours; *δ = d/dc (T, V)*, dimensionless travelled distance = travelled distance, *ω* = reference excess emission at 20°C and 20km/h.

6.2.4 Occupancy factors

Occupancy of the vehicles has been considered to estimate individual carbon footprint CO_2 in kg/person-km (Figure D2, Appendix D). 95% of cars were found to have single occupancy during peak hour in Dublin (NRA, 2004). In off-peak periods these emissions were further divided by an average occupancy factor of 1.4 persons. However, access to occupancy data for each mode is not convenient in real time applications and thus the models consider low resolution occupancy factors according to weekdays and weekends in the form of peak and off-peak periods (Figure 6.10).

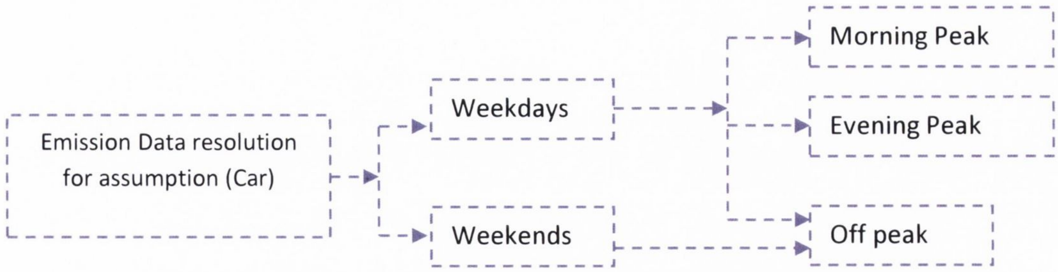


Figure 6.10: Occupancy factor for peak and off peak periods.

Taking Dublin as a case study, it has been found from NRA (2004, 2009) that the peak period in weekdays remains stable, at 7am-9am for morning peak and 4pm-6pm for evening peak (as evidenced from the years 2003 and 2008, Figures D3 and D4 in appendix D). As, there is no distinct peak in weekends (Figure D5 in Appendix D), the whole day has been considered an off-peak period. It has been assumed in the models that minimum occupancy occurs for peak periods and normal occupancy in an off-peak period and this will be stable throughout the day.

6.3 Dynamic Eco-routing model

The dynamic Eco-routing model developed here will give a prediction of CO_2 on the emission for the routes on a trip and per person basis (*i.e.* the carbon footprint of individual travel). Emissions can be predicted for different routes, and an optimal route can be selected based on the least emissions route. The emissions will be based on the specific car that user owns, or in other words the model is sensitive to the vehicle mass, engine size, catalyst converter and emission standard of the vehicle. In addition to that model is also sensitive to peak and off-peak conditions, city temperature, and speed variation.

6.3.1 Assumptions of the model

As the modeling methodology involves the selection of different factors from literature, a few assumptions were required for achieving the overall aim of the model. Accepted assumptions were included below:

- Weekends will be considered off peak throughout the day.
- Morning Peak Period: 7-9 am and Evening Peak Period: 4-7 pm for the week days.
- Peak and off peak hour emission factor or occupancy are assumed to be constant for the peak and off-peak period respectively.
- Peak and off-peak road situations are assumed to be constant throughout the day and will be applicable for overall transportation network.
- ARTEMIS Cold Start Euro 4 emission equations for petrol have been taken for Euro 5 and 6. Similarly, Euro 3 cold start emission equation has been taken for Euro 4, 5 and 6 vehicles.
- Cold Start emission equations are not subject to engine capacity. Where such equations are not available, equations for vehicles with similar characteristics have been taken into account.
- Parking time is calculated from the last time the engine was started.

6.3.2 Input requirement

The prediction model will take input for requested route IDs, length and use those data against emission factors/equations and other variables in the model for predicting emission. The emissions prediction model requires the following data input:

- Modes and segment length according to route segment IDs for an entire trip.
- Real time speed (based on real time traffic) according to route segment IDs.
- Vehicle profile information (Private vehicle type-Euro category, vehicle weight and engine size, fuel technology and catalyst converter, *etc.*).
- Real time ambient temperature.
- Private vehicle occupancy.
- Database of Emission Equations for private cars.
- Time and Date.

6.3.3 Model architecture

The architecture of the Eco-Routing emission model has been included in Figure 6.11. The model was designed to work with route recommendation engines (as part of the PEACOX project a route recommendation engine was developed by other partners, and was available for use here). Alternative routes were identified and inputted into the emissions model and these could be obtained from any recommendation engine. The model takes link information on the routes, such as link ID, and link distance for all the routes. Link ID finds its match with the links ID from the real-time data provided and captures real-time speed information. If the link ID system is different, link can be matched based on geo-points (*e.g.* latitude and longitude). From the Eco-Routing model user profile, the vehicle characteristics are called at the same time when the emission model is called for estimation. The vehicle characteristic information obtained generates appropriate codes for hot emissions and cold equations for a vehicle class that the user owns. In the first step, the real time information enters into the emissions equation to generate link by link CO_2 emissions factors which were later multiplied by the distances of the corresponding links. The values for different links were stored in a database according to the differing route options.

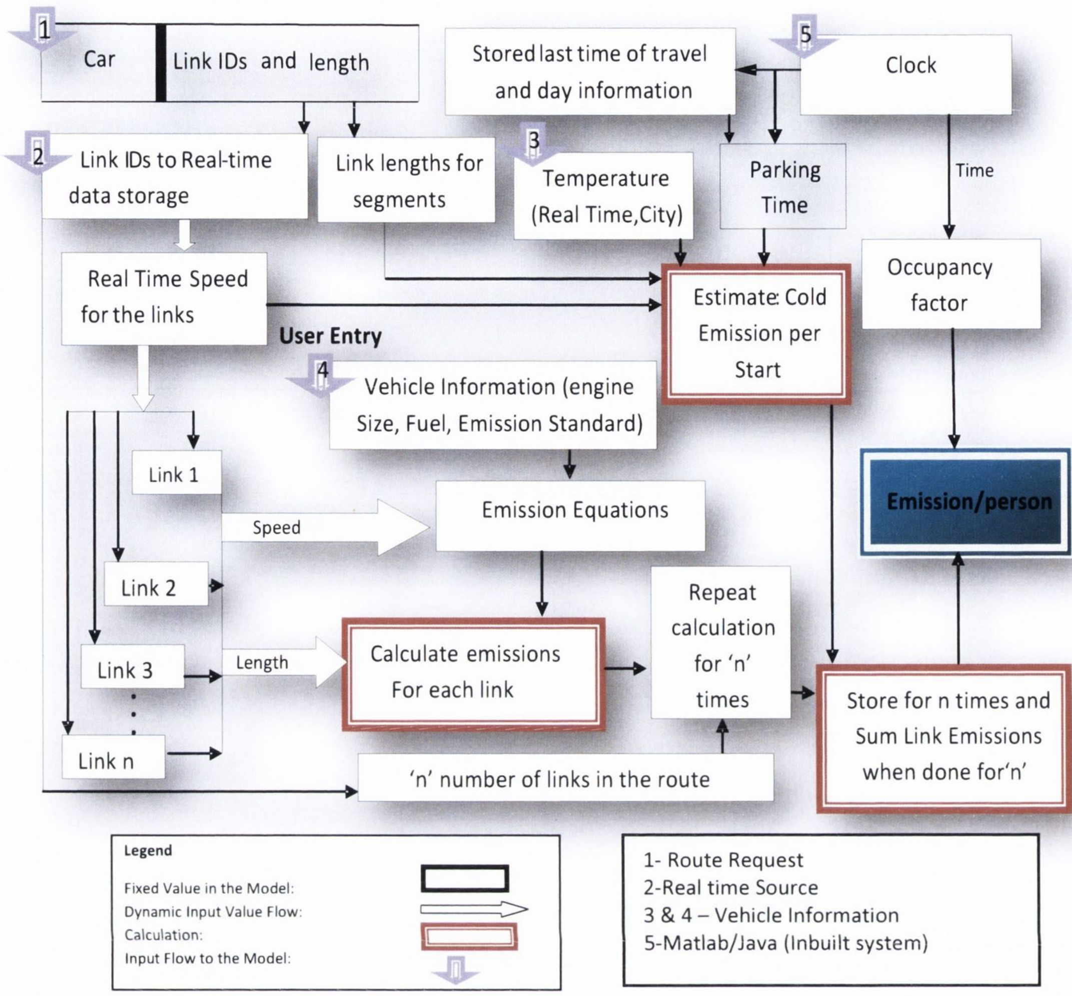


Figure 6.11: Eco-routing model architecture

While these calculations are performed, another part of the model calculates cold start emissions. To calculate cold start, the model requires the total distance for the route, time since the car was parked (parking time), ambient temperature and travel time information. The model can be connected with a static database for average ambient temperature for a city, or obtain real-time city temperature from online sources. The later was designed for the current dynamic model.

The model generates cold start emissions per start according to the vehicle speed and the aforementioned information. These emissions were then added with the hot emissions figure.

At the time emission model is enacted to carry out a calculation, a search function awakens to find out the difference between last trip time and current trip time (as part as a smartphone application of this model). If the difference is more than 12 hours, the model assumes that the catalyst is completely cool. This search function also finds out the day of the week and time of the day to identify whether the trip is being conducted at peak or off-peak hour. In a database inside the model, information regarding city specific peak and off-peak occupancy information were stored which can be updated according any city, or can be connected to ITS infrastructure (in the current project this was carried out for Dublin and Vienna). The final emissions figures were then modified according to the occupancy before presenting this information to the users of a smartphone.

6.4 Simplified model

A simplified model representing the conventional Eco-Routing approach was also developed (Figure 6.12). This model is a static distance based model which was applied as a platform to compare the performance of the original (dynamic) model described in section 6.4.

There were 96 equations in the original model (section 6.4) for petrol and diesel vehicles that differed according to engine size, euro emission standard, *etc*. However, only static emissions factors for one specification (*e.g.* Euro-6 for four engine sizes) for all petrol and diesel has been applied in the simplified model. This simplification, as mentioned earlier was conducted in part to increase the running speed of the application as well as for comparison purposes. Cold-emissions factors were not included as a part in the simplified model, because it included many complex equations, and required additional inputs (*e.g.* real time city temperature, catalyst converter and last trip information). The differences in design in the simplified model in comparison to the original model are summarised below:

- No temporal variation in congestion (Peak/off-peak).
- Number of car category's reduced to 8.
- No cold start emissions included.
- Car emissions are no longer sensitive to speed changes.

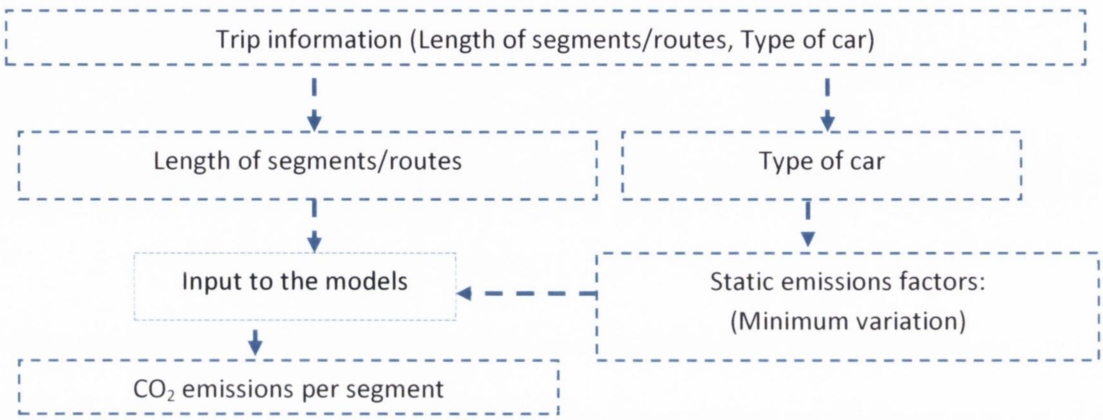


Figure 6.12: Simplified emission modelling methodology

In the simplified model, total emissions are the product of static emissions factors in relation to the distance, and broad category of the vehicle the user owns. In comparison to the original model, the simplified model does not have any emissions equation; rather the model has static emission factors for a limited vehicle technology in terms of engine size, and fuel type. The model (Eq. 6.4) is given below and is typical of the approach of many static Eco-Routing models highlighted in Chapter 2:

$$T = \sum_{1}^{n} EF_{n,m} * L_n \qquad \text{Eq. (6.4)}$$

Where, T = Total emissions from the link; EF = Emissions factors according to the vehicle m; L = Link length; and n = number of links.

6.5 Model algorithm

To calculate the vehicle emission according to the given input for each model, vehicle characteristics have been coded in the Tables D4-D10 in appendix D for the original model and D11, Appendix D for simplified model. Cold start emission equations and associated values, as well as hot emission coefficients were also included in the Tables D5-8 in the appendix. These factors and equations have been used to develop the models. Initially, the original model was developed in MATLAB (Box D2, Appendix D), and later model was recoded in Java as a module in the PEACOX Project mobile app (Figure 6.13). Appropriate vehicle characteristics input for the above category was designed in the user profile of the app for the emission module.

The app is available online at:

https://play.google.com/store/apps/details?id=com.fluidtime.android.peacox (Last accessed on 17.12.2014).

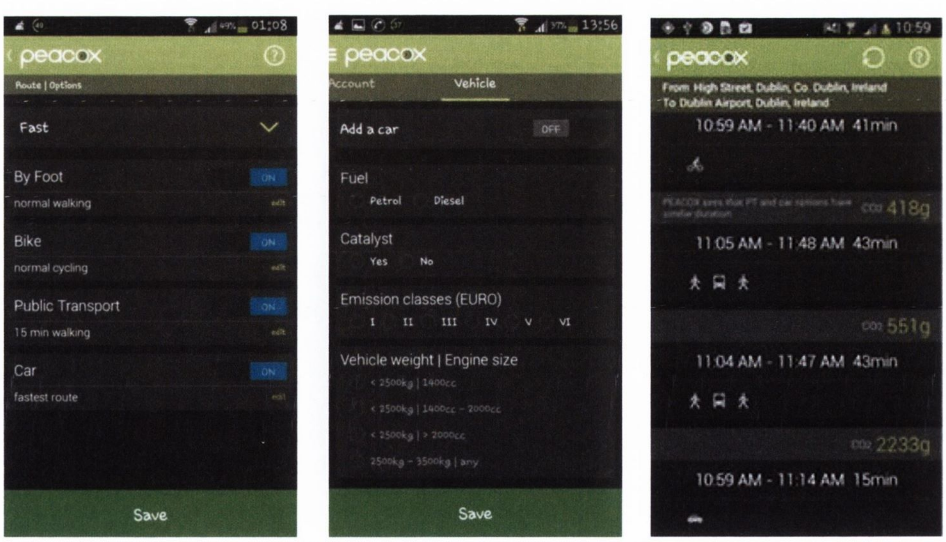


Figure 6.13: Different interfaces of the PEACOX App: (a) Mode selection priority; (b) Vehicle technology selection interface; (c) result from emissions modelling

The users of this app have options to choose their priority over different travel modes (Figure 6.12a), and also are able to choose the vehicle technology they are going to use (Figure 6.12b). The user can find the alternative routes for passenger car if car options are selected in the preferred mode option.

6.6 Model verification

To ensure the functionality of the model in the mobile platform a few samples were taken from field trial data and analyzed. These samples have been collected from the Eco-Routing emission model recorded online from user activities, and the assessment of these provided an indication of the functionality of the model during a field trial which took place in summer 2013 in Vienna. This analysis also confirmed that the model was correctly implemented on the mobile devices with respect to the conceptual model that was described in section 6.4. This analysis was also required as the model has been transferred to Java format from its original MATLAB code and the various input sources were segregated amongst various other PEACOX project components. Five sample requests were made during the second week of September 2013 (Table 6.2). The result was satisfactory.

There was a cold start emission component along with the displayed CO_2 figure. For this reason, unit emission from the car trip has been estimated for the trip length and compared with the unit emission factor in Table 6.2. The unit CO_2 factors (g/km) were within acceptable limits. Besides, the small car produced lower CO_2 emission (request 1 vs. request 2) and diesel vehicle (request 3) produced higher emission in comparison to a similar petrol-powered counterpart (request 4).

Table 6.2: Requested routes and corresponding CO_2 values

Date	Irish Time and request	Origin	Destination	Displayed car route in Mobile App	Vehicle Info	Distance (km)	Duration (h)	Speed (km/h)	Trip CO_2 (g/km)
11/09/2013	11:31; Reques t 1	Yachthafen	berufsschule fur holzbearbeit ung	4	Catalyst-no,Euro-1,Engine size: 1400,Vehicle weight: 1400,Fuel:petrol	52.88	1.45	36.42	131.4 0
11/09/2013	11:47; Reques t 2	Bira	Aukettel	6	Catalyst-Yes,Euro-3,Engine size: 1500,Vehicle weight: 2400,Fuel:petrol	6.25	0.15	41.64	163.2 3
12/09/2013	00:16 Reques t 3	Kgv thayagasse	egon-friedell-gasse	6	Catalyst-Yes,Euro-4,Engine size: 2000,Vehicle weight: 2600,Fuel:diesel	1.61	0.08	19.32	220.3 2
12/09/2013	16:.58; Reques t 4	Austrabe	Ahornweg	5	Catalyst-Yes,Euro-4,Engine size: 2000,Vehicle weight: 2600,Fuel:petrol	26.804	0.63	42.3	180.1 2
12/09/2013	19:01; Reques t 5	am abhang	Fahnenweg	7	Catalyst-Yes,Euro-3,Engine size: 4000,Vehicle weight: 2600,Fuel:diesel,	7.768	0.32	24.48	201.9 3

6.7 Model evaluation

The performance of the model was evaluated using field trial data. In order to assess the applicability of the dynamic model in real time application both improved performance of the dynamic model in relation to simplified model and time performance were considered.

6.7.1 Model comparison: Dynamic vs. Static

In August 2014 the PEACOX mobile app was tested by field trials from 25 users of the app in Vienna and 25 users in Dublin were selected after analyzing a screening questionnaire that were forwarded to them. Users used a route planner developed by the PEACOX project for eight weeks where both the original and simplified Eco-Routing models were included as a part of a multi-modal Eco-Routing navigation tool. Both of the input and output of the models were stored in an online server. Stored data were obtained through pgAdminIII open source software (Figure 6.14).

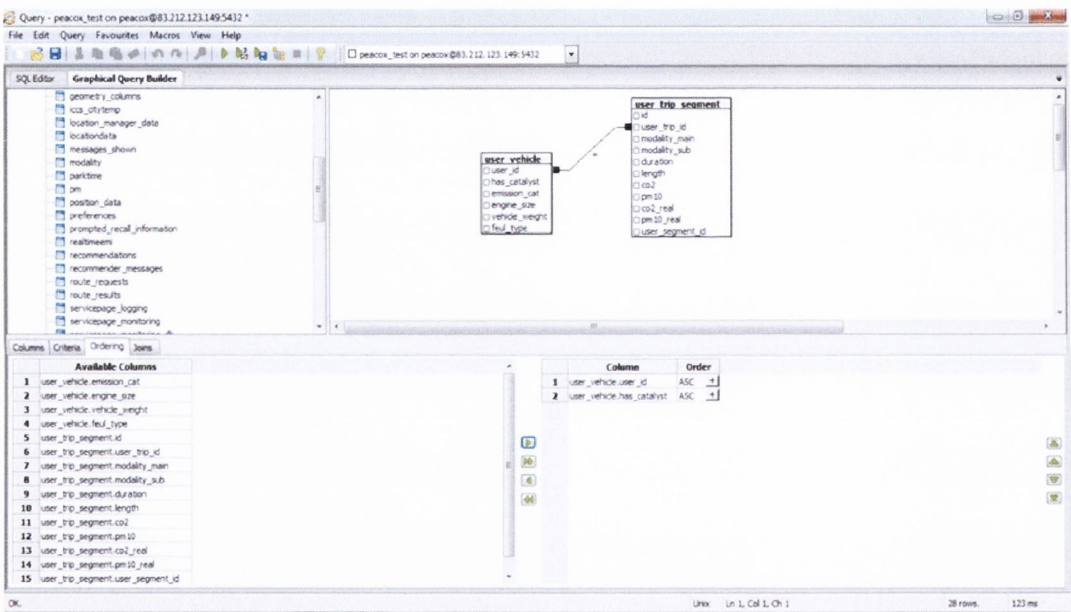


Figure 6.14: Car emissions factors generated by models

6.7.1.1 Estimated emissions during field trial

The results that were presented in the PEACOX application in the field trial were stored in the server according to road segments/links. Figure 6.15 shows the estimation of CO_2 figures for passenger cars during the field trial. The analysis was conducted on the results that were based on routing options provided by the recommendation algorithm. The users had options to guide the recommendation engine to develop recommendations of Eco-Routes for car only or for routes using different modes (Figure 6.12a). However, the users mostly used the default options of multi-modal routes, and thus, a comparative analysis of two alternative routes for cars-only could not be performed using the data obtained.

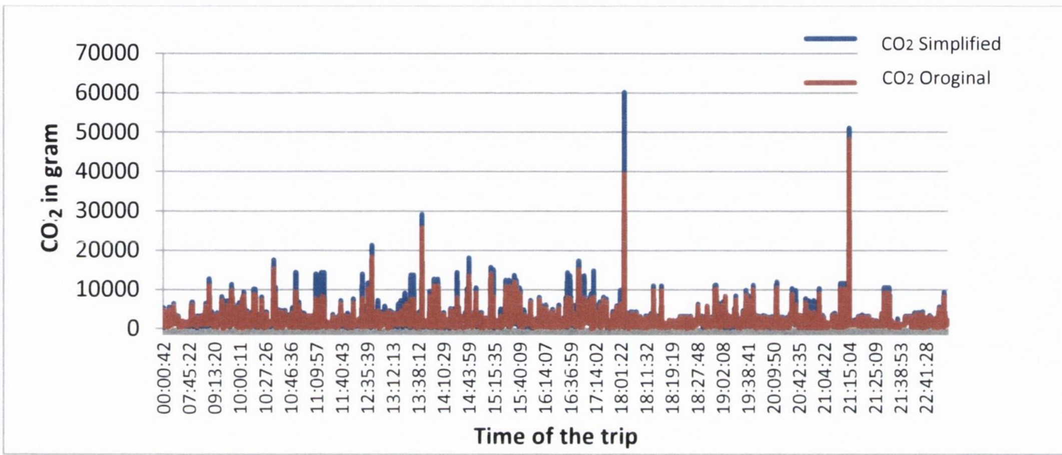


Figure 6.15: Car emissions factors generated by models

It can be noted in the Figure 6.15 that the estimations are similar between the original and simplified models. The models CO_2 estimations (g) were averaged over the trips estimated by the models and results were presented in the Table 6.3. For a fair comparison between the original and simplified models, the cold start emissions were not included in this analysis.

Table 6.3: Model generated unit CO_2 emissions

Mode	Pearson r	Average CO_2 (g) from all the trips		Standard deviation for unit emissions g/km	
		Simplified Model	Original Model	Simplified Model	Original Model
Car	0.975	2204.759	2080.959	0.000	67.848

Although, it can be noted that the Pearson r for the original and simplified models is acceptable, the average values and standard deviation shows a significant variation in the initial model whereas no deviations were present in the simplified model. This indicates that simplified model underestimates or over estimates the emissions figures. From the emissions and speed relationship in Chapter 2, it is understandable that in lower speed and higher speed, the simplified model underestimates the emissions and speed in between overestimates the emissions. Figure 6.16 presented the variation of unit factors for CO_2 emissions.

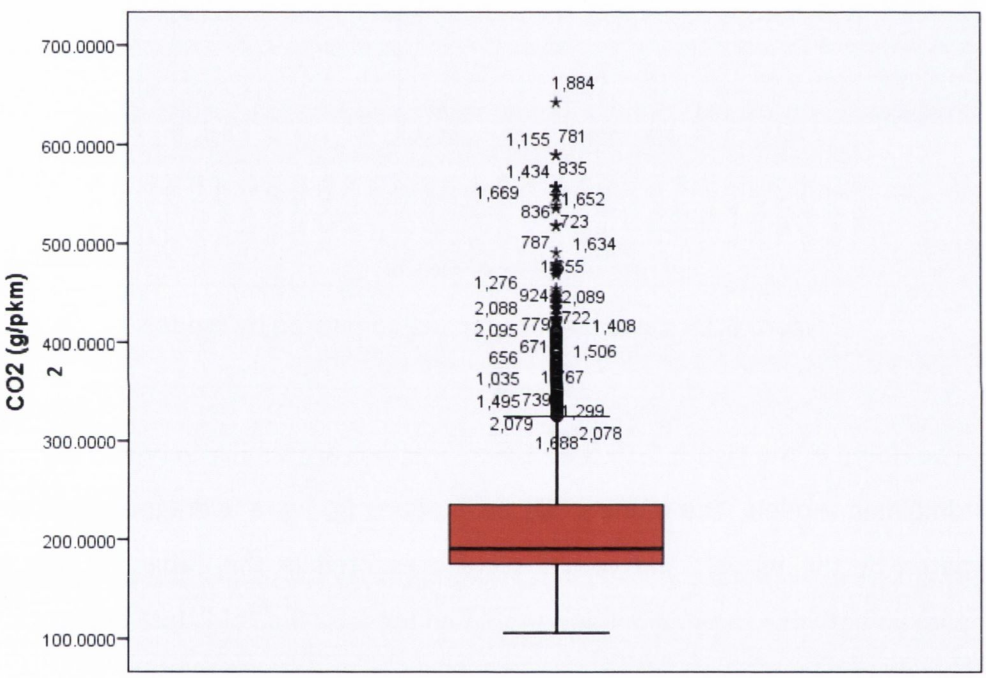


Figure 6.16: Box plot of the emissions factors generated by the original model

The spacings between the different parts of the red box in the Figure 6.16 indicate the degree of dispersion of the data. The top and bottom lines of the box show the 75th and 25h percentile of the data. Thus, half of the data are within 180-230 g/km range are found. The horizontal line in the middle of the box shows the median value and thus it can be understood that the distribution of the data is skewed towards the higher values. This skewness is also observed from the black dotted points or outliers.

However, there are not any unexpected values in the figure. Higher emissions factors in the outliers can generate as a result of a higher weight/engine of a passenger car in lower speed route in the presence of low catalyst temperature.

6.7.1.2 Causes of variation in emissions estimations in Eco-Routing

The generated results of the original emissions model in the PEACOX app that was presented to the users during field trial were modelled again in order to identify that the factors that might affect emissions variation. Table 6.4 shows that the variation due to peak and off-peak factors, and other factors that were considered in the model. Table 6.5 and Figure 6.17 show the Analysis of Variance (ANOVA) table and diagnosis plot respectively of the developed model in Table 6.4. The results were mostly well explained by the regression model (R^2=96%) in Table 6.4, however, a few systematic deviations may be observed in the residual plots. This shows the quadratic nature of the equations applied in the Eco-Routing model.

Table 6.4: Model generated unit CO_2 emissions

Regression model based on the emissions factor generated by the Eco-Routing model
CO_2 (g)=122.019+Peak*30.664+Duration*1295.797+Length*134.282
Max VIF= 2.89; R^2=0.96

Table 6.5: Analysis of CO_2 estimation of the modelled data

ANOVA Table	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Peak	1	2.760e+06	2.760e+06	12.36	0.000448 ***
Duration	1	8.351e+09	8.351e+09	37382.04	< 2e-16 ***
Length	1	3.070e+09	3.070e+09	13741.46	< 2e-16 ***
Residuals	2249	5.024e+08	2.234e+05		

Level of Significance: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

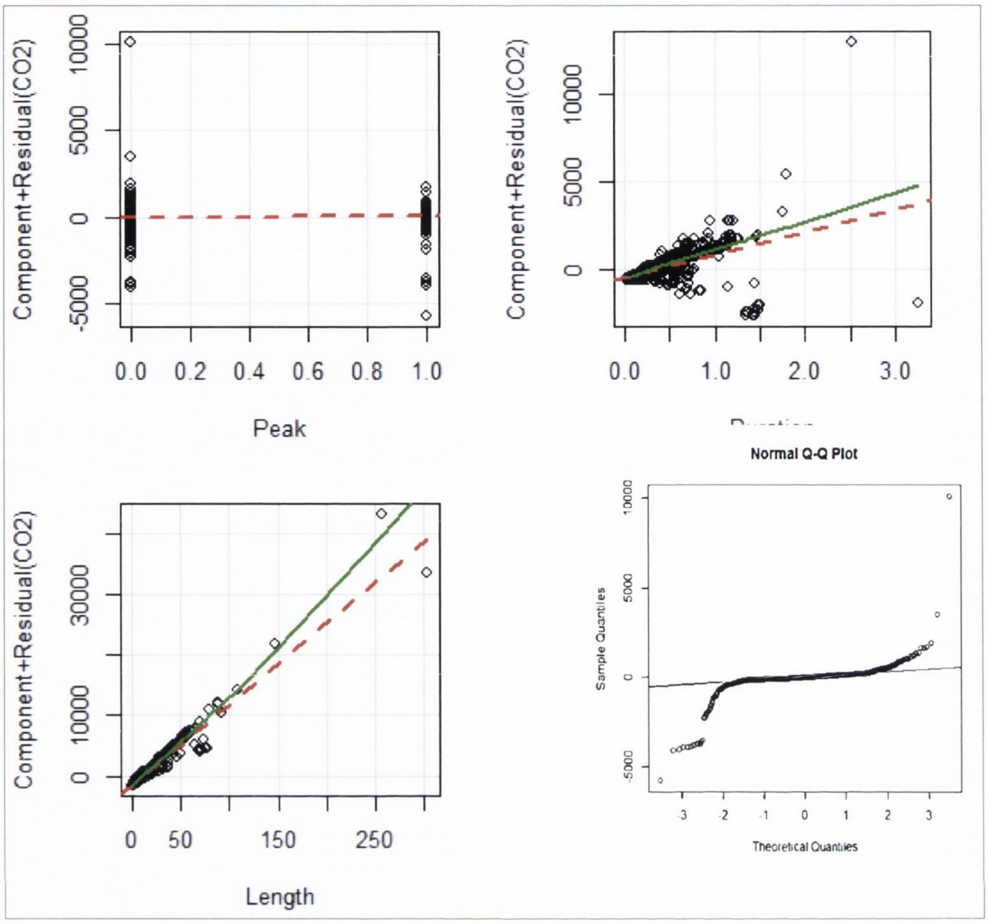


Figure 6.17 : Analysis of CO_2 estimation of the modelled data

6.7.1.3 Cold start emissions and cold distance

The additional emissions that were estimated in the dynamic emissions model were cold start emissions which were in the range of 189-350 g/start, and were added with the hot emissions for each alternative trip.

Figure 6.18 presents cold start distance for different trips requested by the users in the field trials. As cold emissions distance is a function of travel time, distance, parking time and ambient temperature, the variation of travel time and distance offered by differing alternative routes will provide more precise CO_2 information of the routes and thus a different attractiveness of the routes.

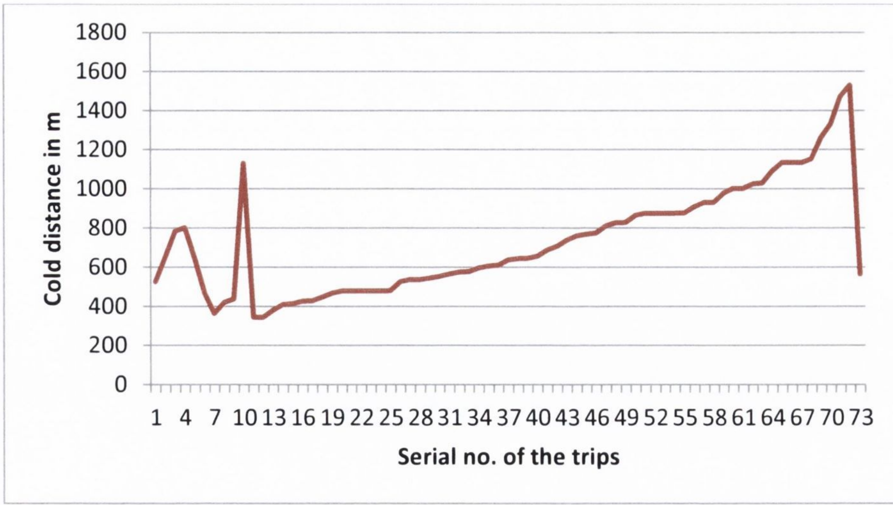


Figure 6.18: Car emissions factors generated by models

6.7.2 Model performance against actual GPS tracks

The actual representativeness of the model has been assessed using GPS track data from the field trial users. Table 6.6 shows a sample of user IDs which participated in the field trial. This time CMEM was used to compare emissions estimates.

In order to carry out this analysis, the car trips that were selected by the users were separated from a large dataset. One part of the PEACOX mobile app provided automatic mode identification using accelerometer data. Thus, in order to be certain that recommended car trips was actually performed by the users, accelerometer readings were matched against the Eco-Routing IDs, and GPS tracks were identified for the trips. The tracks were later inputted into the CMEM with actual on-site speed and secondly, with the speed that was inputted into the PEACOX emissions model (link-based average speeds).

Table 6.6: Model generated unit CO_2 emissions

User	Emissions models called at (DD:MM: YYYY; HH:MM:SS)	Mode detection module: Trip Begin (DD/MM/ YYYY; HH:MM:SS)	Mode detection module: Trip End (DD/MM/YYYY; HH:MM:SS)	Actual Speed (km/h)	CMEM output with actual speed (CO_2 g/km)	Given speed to the model (CO_2 g/km)	CO_2 g/km: P CMEM	CO_2 g/km: Q Original (dynamic) Model	CO_2 g/km: Simplified (static) Model
403	13.08.201;4 18:03:19	13/08/2014; 18:12:20	13/08/2014; 18:28:38	13.80	369.00	29.97	118	129	198
403	25.08.2014; 12:38:25	25/08/2014; 12:40:43	25/08/2014; 12:51:58	35.20	225.00	11.69	259	147	198
417	23.08.2014; 17:43:44	23/08/2014; 18:39:48	23/08/2014; 19:16:35	21.51	249.00	11.50	263	180	198
433	18.08.2014; 12:40:39	18/08/2014; 13:16:46	18/08/2014; 13:25:10	13.99	379.00	16.14	258	170	198
437	28.08.2014; 20:42:35	08/09/2014; 20:42:59	08/09/2014; 20:57:38	42.27	189.00	14.44	261	172	198

The result shows a Pearson r of 0.82 between CO_2 estimations while comparison was made with similar input for Eco-Routing and CMEM (Column P and Q). However, while actual speed is used the results were not similar, as the actual speed and inputted speed has a co-relation of -0.55. This shows the importance of real-time speed requirements for Eco-Routing models.

As highlighted above, the simplified static model did not include real time speed information for comparison with existing approaches and to enable the PEACOX app to run faster. The limitations of the existing approach to Eco-Routing and the limitation of simplifying the dynamic model are clear here. Where the primary target of the PEACOX project was encouraging people to make environmentally friendly passenger car routing decisions, models based on static emissions factors were not useful. Thus, the simplified model representative of conventional routing approaches is not useful. In the original dynamic model, two important factors have always been preserved for Eco-Routing. That is: the estimated emission always maintains the order of magnitude of the CO_2 from different routes, and secondly, for car trips, the emission must be congestion sensitive for cars. This is important as a shortest path may not be eco-friendly because of congestion. Validation from VISSIM confirmed this capability in the model. In addition, online and offline validation of samples confirmed realistic estimation of CO_2 for Eco-Routing. However, the result also implies that the model input is crucial for any success of such modeling approach or, overall successfulness of the Eco-Routing strategy.

6.7.3 Time performance

The simplified model produces results for alternative routes in less than 1 second using the PEACOX App. However, the original model required comparatively higher processing time. The time performance check showed that the MATLAB model is capable of yielding results within seven seconds if there are 140 links (Figure 6.19). Minimum time for running this model is 2 seconds. However, the Java version of the model shows a different scenario (Figure 6.20). In the first trial, the result appeared overly time consuming with around 5-40 seconds depending on the request. The differences in these comparisons arise due to differences in the MATLAB and Java versions involving different structures and codes. One works online with complexity of calling servers, getting data from various sources and storing values, while the other (MATLAB) works with data contained all within the developed programme.

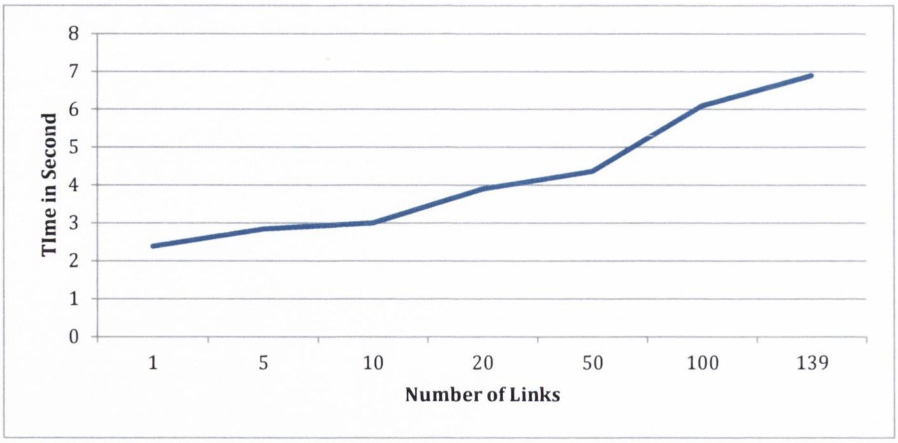
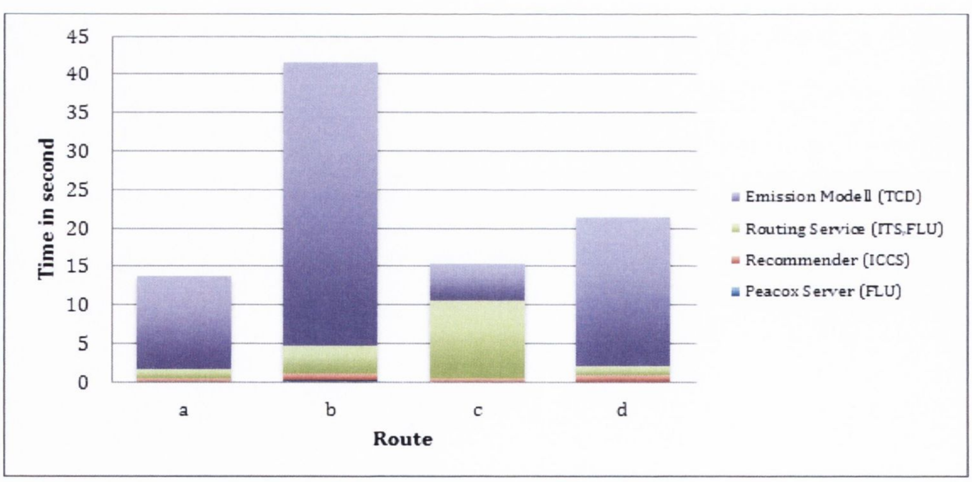


Figure 6.19: Time performance analysis of emissions model in MATLAB

This raises two issues, one related to the technological advancement and optimization of Eco-Routing models, and secondly the time sensitivity of the users in relation to making Eco-Routing decisions. Previous investigation of advanced Eco-Routing models did not highlight any issue regarding any of these points, perhaps, as mentioned in chapter 2, due to the fact that the majority of Eco-Routing models to date are static in nature. Therefore this research highlights a need to overcome the computational requirements of an advanced Eco-Routing model if this is to be widely deployed as a smart phone application. Many users are unlikely to tolerate a response time of up to 40 seconds for the current version which could discourage the use of the software.



Source: Fluidtime(2013)

Figure 6.20: Time performance analysis of four routes different PEACOX app components.

6.8 Conclusion

The Eco-Routing model highlights its limitation while inputs are not representative of the real world driving situation. It was also observed that original model is advantageous over static emissions based model, or distance priority based models. However, this modelling exercise raised an issue about the complexity of the model which might cause the model to be computationally time consuming. Thus, model developers should be aware of the time sensitiveness of route choice decision making. A balance may be required between the complexity of the model developed here and acceptable computational time for real-time estimation. It was also noted that cold start emissions might add a significant amount of emission especially when alternative routes are significantly different in distance, and parking time is higher.

Discussion

Chapter 7

7.1 Eco-Driving experiments

In experiment 1, speed profiles with lower overall speed showed higher travel time and it would be understandable that lower overall speed under 30km/h will cause higher emissions (Figure 2.1, chapter 2). Keeping this in mind, it is also understandable that in low traffic volume scenarios, emissions will be slightly higher in the cases where speed is comparatively lower in the links. However, in high traffic volume, intersections play a vital role to develop congestion while Eco-Driving cars penetrate the network. Even for general traffic, traffic intersections caused poor urban air to variations in vehicle speeds as they approach and leave (Pandian *et al.*, 2009). Qian & Chung (2011) reported that automobiles contribute to excessive fuel consumption and emissions near traffic intersections. In the micro-simulation in Chapter 4, it was noticeable that delay has increased as the level of Eco-car penetration increased. In the network performance, delay is simply the measure of the inconvenience for drivers caused by traffic signals (Qiao *et al.*, 2002), and measured as a weighted average of 'idling', 'acceleration' and 'deceleration' modes at the intersection. Qian *et al.* (2013) reported that during the delay the emission rates of vehicles are higher in comparison to a vehicle in motion and thus, recommended highly to take delay into consideration while evaluating Eco-Driving strategy.

The impact of the intersections is evident further from the results of Experiment 2 where intersections were replaced by roundabouts. A negligible transport impact was found during the lowest traffic scenarios. But, large negative impact was observed for high traffic volume scenarios with the increase level of Eco-car penetration. Previous investigations found traffic signals at intersections generate more emissions than roundabouts (Mustafa *et al.*, 1993; Mandavilli *et al.*, 2008) and during heavy traffic, signals cause larger emissions of HC, almost double of that at roundabouts (Mustafa *et al.*, 1993). Reductions of fuel consumption of 30% and 28% were found at a roundabout with/without replacing traffic signals by roundabout (Niittymaki and Hoglund, 1999; Varhelyi, 2002). Mandavilli *et al.* (2008) found that a modern roundabout performs better than the existing intersection control with stop signs in cutting down vehicular emissions. But, Eco-Driving regardless of intersection, and roundabout showed poor performance with the increase of Eco-car penetration rate during a high traffic volume scenario. This is because Eco-Driving deteriorated queue discharge performance (Qian *et al.*, 2013).

Queue discharge flow rate/ headway has an impact on saturation flow rate, and thus general models were derived from the earlier one to estimate the other (Akcelik *et al.*, 1999). The saturation flow rate in VISSIM is sensitive to two parameters preferred time headway, and maximum deviation of the preferred following distance (PTV, 2011). Li *et al.* (2013) also noted a threshold for entering the state 'following, oscillation acceleration deceleration' from a standstill also effects the saturation flow rate. Viti *et al.* (2008) found that all of these parameters are sensitive to the speed and acceleration profiles of vehicles in the network. However, the departure headways at different positions are almost deterministically dependent on each other, although it may not be the case in reality (Tan *et al.*, 2013), because the first few departure headways include driver reaction time and vehicle acceleration time.

TRB (2000) reported in Highway Capacity Manual that the saturation departure headway is assumed to be reached when the fifth vehicle crosses the stop line. But, in a recent study, Qian *et al.* (2013) reported that an Eco-Driver regardless of it's position in a queue at an intersection affects the progression of 3 to 7 following vehicles. When a number of Eco-Driver present at a queue, the saturation departure headway would be different and the discharge of the vehicles in the intersection would be lower. Lam (1994) previously reported driver behaviour has an impact on the variation of saturation flow rates at different intersections. The result causes a lengthy queue at an intersection that leads to an increase in congestion. This will cause poor performance of the network in terms of traffic impact that has been evident in Experiments 1 to 4.

When congestion was built up by Eco-Driving cars, the vehicles in the queue at intersections cause further emissions due to stop and go behaviour. Rouphail *et al.* (2001) studied the effects of traffic flow on real-time vehicle emissions, and revealed that the vehicular emissions were higher when the vehicles transited from idle to acceleration mode, and the switching from free-flow to congested flow accounts for all four driving modes leading to higher emissions. It was also reported that the stop-and-go waves with many accelerating and decelerating behaviours produce substantial fuel consumption and emissions (Barth and Boriboonsomsin, 2009).

When an overall better speed profile has been applied, Eco-Driving lead to a better situation than what was evident from Experiment 1 and 2. Eco-Driving with the modern technology for dynamic speed adjustment has been highlighted in the literature (Xia *et al.*, 2011; Wang *et al.*, 2012). Wang *et al.* (2012) applied an EcoACC system representing V2V or V2I that reduces congestion and increases average fleet speed even in congested conditions. In experiment 3, it is found that if the fleet speed variation can be reduced and mean speed can be increased towards the speed limit using similar a methodology along with Eco-Driving, Eco-Driving could be beneficial.

7.2 Healthier routing analysis

In order to conduct healthier routing analysis, an air quality model for PM_{10} was developed. In this modelling process dynamic predictors along with many static predictors were analysed. Dons *et al.* (2013b) found that using dynamic (modelled) predictors instead of static predictors, *i.e.* hourly traffic intensities and hourly population densities, did not significantly improve the models' performance. In *Dublin 1* model while dynamic variables were replaced in the *Dublin 2* model with static variables, the model lost's some of its explanatory power (by 5%). Individually, the variables representing trans-boundary air pollution and peak traffic count were found to account for 6.5% and 12.7% of the variation in average daily PM_{10} concentration. The variable representing trans-boundary air pollution that was derived from air mass history (from back trajectory analysis) and population density has demonstrated a positive impact on model performance. Future research is required to examine the optimum approach to the derivation of D_1 and the extent to which improvements in its explanatory power are possible.

Aggregating more years' data over one year did not prove to be very useful unless non-parametric and artificial neural network were deployed. Model fitting and validation R^2 both went up and RMSE went down for these models. But, the artificial neural networks outperformed the non-parametric regression. In addition, the final models accounted for two more FSMs in the model development in Dublin. In the overall process, different meteorological variables impacted on the two city models (*i.e.* Vienna and Dublin) differently which were found by carrying out model sensitivity analysis.

The final estimation of daily average exposure to PM_{10} using the available fixed site monitoring stations in Dublin has been carried out using artificial neural network within the land use modelling framework. In the model, open space is a static variable where meteorological variables are dynamic. However, the vehicle km travelled may change, and a drastic change in this will be limited in a well-developed city when no dramatic change in the land use pattern is certain. The important predictors are metrological values with land use and traffic variables. In addition to these variables, dummy variables representing seasons and days of the weeks were included. The characteristics of the variables included in the model and presence of dummy variables allowed the prediction of temporal variation within a spatial contrast. The temporal variability in the monitoring stations (Figure 5.2, Chapter 5 or, Figure C1 appendix C) was consistent which also means that the spatial variability is consistent as found in previous studies (Wheeler *et al.*, 2008; Crouse *et al.*, 2009). However, this is in contrast to hourly models developed by Dons *et al.* (2013b). Thus, the dataset offers a limitation for hourly temporal variation. The model may provide hourly temporal variation more accurately near to the monitors than further away.

The second limitation leads to the predictability of land use regression modelling for personal exposure. Montagne *et al.* (2013) evaluated LUR models, which predict long-term concentrations, against short-term personal measurements. Predicted NO_2 LUR exposures were not found to be associated with personal NO_2. This could have been influenced by temporal differences in the concentrations. Montagne *et al.* (2014) recently reported that LUR models developed for a city could not predict measured variation of elemental composition of $PM_{2.5}$. The study compared annual LUR model output against personal exposure data converted to annual average concentrations. In addition, McNabola *et al.* (2009) reported from a principal component analysis in Dublin that personal exposure concentrations in motorised forms of transport were influenced to a higher degree by traffic congestion. Dons *et al.* (2012) reported in-car concentrations are higher during peak hours compared to off-peak, and are elevated on weekdays compared to Saturdays and even more so on Sundays. Dons *et al.* (2013a) further reported that driving on roads with low traffic intensities resulted in lower exposures than driving on roads with higher traffic intensities (from 5.6 $\mu g/m^3$ for roads with less than 500 veh/h, up to 12 $\mu g/m^3$ for roads with over 2500 veh/h).

Thus it is noted that the modelled output from the current approach such as applied in Chapter 5 has limited capability of explaining high resolution variation. Nonetheless, the spatial variability of the output provides an understanding of healthier routing choice. From the above discussion it is understandable that model lacks high resolution temporal variation, however, spatial variation of the pollutant concentration is well predicted. In this light result could be drawn from average attribute values in a given traffic situation, however the similar result may be obtained from any network.

Applying the model developed to route choice analysis, it was found that lowest dose in the routes analysed was in weekends in summer and winter (except Saturday, which is slightly higher than Monday). Dons *et al.* (2011b) showed that exposure is higher in a weekday in summer (April) than that of weekend. In case of the lowest PM_{10} value in this study, recommended route choices were found to be significantly different from the conventional cost factors.

From these two route analyses, it was found that lowest travel time and distance does not offer lowest dose, and routing decisions based on time and distances and related parameters are most contradictory with the dose based routing exercise. The analysis introduces a citywide modelling exercise for routing analysis based on lowest exposure, and shows a smaller increase of dose with a small increase in travel time and large increase in dose for shorter distance. For different origin and destination pairs the magnitude might be changed drastically, but the pattern will be similar. As dose is a function of travel time and speed, the difference between lowest dose based route and lowest travel time (or, similar factors) will be lower in comparison to the lowest distance based route. Even, CO_2 saving and PM_{10} dose based routing were not found similar to each other. This is because, the exposure factor was heavily dependent on local factors such as anthropologic activities and land use patterns around the road along with the traffic itself. The result provides a generic indication of the characteristics of air pollution dose as a route cost factor.

7.3 Eco-Routing

When a static emissions factor is used in the model reported in Chapter 6, the model was either over or under estimating the total emissions for the trips. The original dynamic model was much more representative than that of simplified model.

If static emissions model were used, the lowest distance routes would be predicted as most preferable, even though congestion might have an impact on emissions and on an overall trip on that route in reality. On the other hand, routing based on the lowest travel time may increase the distance and may increase the fuel consumption and thus increase emissions. Kang *et al.* (2011) noted that Eco-Routes provided lower environmental impacts in terms of lowest emissions and fuel consumptions over distance priority routes, and time priority routes. As noted in Chapter 2, Eco-Routing has been reported to save fuel consumption and emissions ranging from 0.35 –42% and the extent of the variation depends heavily of the level of congestion present, with low congestion levels limiting the impact of Eco-Routing. In order to capture this benefit, Eco-Routing models should be dynamic and account real-time data.

In addition, the existing Eco-Routing emissions models that are commercially available were based on historical data or average speeds, and also have other simplifications of the modelling process. These limitations reduce the accuracy of CO_2 emission predictions. However, these models work very fast due to these simplifications of the emission estimation procedure. On the other hand, the original model shows a little delay to processing of the requests. For the advanced model this might be an issue for a real-time application. These issues about time performance were not discussed rigorously in the literature, and may be focused in further research.

Furthermore, the original dynamic model developed in this research is most applicable to flat landscape where road grade does not significantly affect emissions. Road grade was not included in the original model due to difficulties in obtaining sufficient input data. However this addition would have introduced another layer of complexity to the model further increasing its computational expense.

An actual representativeness of the model in field trial has not been evaluated as no comparison was made between two different routes. However, models prediction capability shows that a various range of CO_2 emissions (g/km) were predicted by the model because of both variation in the speed, vehicles weight, engine size, catalyst convertor, and emissions standard. Cold start emissions impact would be very little, unless the alternative routes have significant difference in distance as a cold emission per start distance based methodology, has been included. It was observed that trips during the field trial had considerable cold distances, and accounting for that in the model is believed to improve the accuracy of the prediction.

With the lack of appropriate dataset for model validation, the actual vehicle trajectories were inputted in the CMEM model and found that the models prediction is sensitive to the speed which was previously tested with VISSIM micro-simulation. Where the primary target of the project was encouraging people to make environmentally friendly passenger car routing decisions, models based on static emissions factors were not useful. Thus, the simplified model representing conventional routing approaches is not useful. In the original model, two important factors have always been preserved for Eco-Routing. That is: the estimated emission always maintains the order of magnitude of the CO_2 from different routes, and secondly, for car trips, the emission must be congestion sensitive for cars. In order to do that the models are required to connect with real-time input sources. Previous investigations (Boriboonsomsin *et al.* 2012) as well as the current methodology and field trial data emphasised on it's importance.

Conclusions

Chapter 8

8.1 Major findings

A number of findings were revealed from the literature review, micro-simulation and modelling works regarding the smarter driving.

1. Eco-Driving at high traffic volume in complex urban settings

Impacts of Eco-Driving policy from both individual and network viewpoint were evaluated, and the evidence of Eco-Driving benefits was identified as sometimes opposing, or unclear for network level impacts. In addition, Eco-Driving technologies, their methodologies and limitations were highlighted. Micro-simulation work concluded that Eco-Driving car penetration has effects on the environmental and network performance of a road network as it results in added delays at intersection level. This effect is mostly visible during high traffic volumes. At low traffic flow, the negative impact is also visible; however, the impact primarily depends on the road network configuration. However, Eco-Driving can provide benefits if it can trigger both improvements in acceleration/deceleration and speed profile of the flow. It can be easily observed that the Eco-Driving policy has the worst performance in high traffic volume while there are a number of intersections present.

2. Eco-Driving with advanced vehicle control technology

It is highly unlikely that a driver can be a master of gentle acceleration/deceleration and optimal speed in relation to overall traffic flow, unless V2V or V2I technology becomes widespread. This benefit however is subject to the variation of the traffic composition.

3. Eco-Driving and network configuration

The impact of traffic intersections could be seen where signalised intersections were replaced by roundabouts in the micro-simulation work. Negligible transport impact was found during the lowest traffic scenarios. However, large negative impacts were observed for high traffic volume scenarios with the increase in the level of Eco-car penetration. Thus, without modern technologies, benefits and limitations of Eco-Driving are concluded as contextual.

4. Air Quality model in Healthier route analysis:

In healthier routing analysis, PM_{10} models developed in the first step provided many interesting findings for modellers and epidemiologists. The three bullet points highlight the major findings from the air quality model in the Land use regression framework:

- Use of long range data has been tested for spatial-temporal model development and found to provide improvements in model performance statistics.
- Alternative statistical models in addition to standard additive regression were applied and found to improve model performance.
- Using the limited amount of readily available data in a European city it was possible to develop a reasonably accurate low cost air quality prediction model, providing spatial and temporal variation on pollutant concentrations.

5. Healthier route in comparison to other routes:

The analysis introduces a city-wide modelling exercise for routing analysis based on lowest exposure, and shows a smaller increase of dose with a small increase in travel time and large increase in dose for shorter distance route recommendations. The result has been concluded from a limited number of sample routes, but the pattern was detectable.

6. Eco-Routing:

A model that would be applicable to any city, capable of accounting for congestion was developed. The modelling exercise verified its functionality and the additional findings from this exercise have been highlighted below:

- CO_2 emissions model were proven to be useless for the purpose of Eco-Routing if they were not connected with real-time data.
- Complexity in the computational process in the original model causes delay which may discourage usage of the model in mobile phone Eco-Routing applications.

8.2 Policy Implication

The findings highlighted in section 8.1 have impacts on policy formulation, current scientific application and further research.

Having more information about Eco-Driving and its network wide impacts, policy makers could now contribute more on effective policy formulation integrating concept and technology. In an information and communications technology (ICT) based energy efficiency solutions review, Klunder et al. (2009) reported that Eco-Driver coaching is applicable both in free flowing and congested traffic. However, new findings have highlighted a potential limitation on the effectiveness of the policy in congested urban traffic situations. As a remedy of such limitation, vehicle equipped with V2V or V2I could be introduced or at-least introduction of policies related to placement of cautionary signs of in-effective areas of Eco-driving is required.

The implications of air quality research, on the other hand, would suggest that it is possible to produce a model of ambient air quality on a city wide scale using the readily available data in most European cities. This part of the research highlights that using land use, meteorological and traffic predictor variables in combination with advanced statistical techniques such as NPR or ANNs will produce reasonably accurate predictions of ambient air quality across a city, including temporal variations. Therefore this approach reduces the need for additional measurement data to supplement existing historical records, and enables a lower cost method of air pollution model development for practitioners and policy makers. Using these modelling techniques, it would be possible to identify the areas in a city that are not complying with the daily limits of air pollution concentrations.

On the other hand, as it is was found that the healthier routes offer higher travel time and distance in comparison to the lowest path routes, general people may not likely to use such routes. Healthier routing strategy could however be implemented for particular at-risk age groups, e.g. school children, elderly and commuters with health issues.

Finally, this research concluded that a benefit from Eco-routing is achievable. The methodology for generating Eco-Routing information for the commuter is already established. However, the technologies such as system acquiring and disseminating real-time information, road grade that will make these methodologies effective are yet far from being wide spread and easily accessible. A good amount of investment is necessary to develop such infrastructure to promote Eco-Routing; thus begs a point of attention of the policy makers.

8.3 Future research

1. Eco-Driving:

From the results of this thesis, it can be easily understand that the Eco-Driving policy has the worst performance in high traffic volume while there are a number of intersections present. Further investigation is necessary to accurately determine this effect. Accurate headway in relation to size and type of junction could be tested obtaining real world data, either from survey or from loop detector data.

2. Air quality modelling

- The methodology applied here to the derivation of trans-boundary air pollution is a first attempt at the inclusion of such a variable and offers considerable scope for refinement and possible improvement in its explanatory power. Alternative rating systems, including negative scores for water bodies or green areas, could be investigated. Similarly, the density of the grid applied to the derivation may also offer scope for improvement. Other factors which may alter the eventual score attained by a trajectory include the selected height and hour of the day, *etc*. The analysis would be more effective in inland city, such as in Vienna than a coastal city Dublin.

- An application of daily level PM_{10} model could be carried out to assess the air quality impact on the local residents. The final modelling methodology presents a combination of ANN and Kriging that could be applied for assessing policy compliance or reduction of health risk of daily PM_{10} exposure of the citizens using available monitoring data by the local authorities. WHO (2014) reported a reduction of PM_{10} pollution from 70 $\mu g/m^3$ to 20 $\mu g/m^3$, could reduce air pollution-related deaths by around 15%. Thus, due to protection of human health, 50 $\mu g/m^3$ PM_{10} for a 24 hour time frame has been set that cannot be exceeded not more than 35 times in a calendar year (WHO, 2006b; EU, 2008). The objective of the future modelling exercise could focus on estimating PM_{10} concentration level at daily level for any area or city-wide scale for pollutant hot spots, health risk assessment, or policy formulation to protect human health.

3. Models for healthier routing:

A more refined modelling strategy is required for routing analysis as the research findings outlined here for routing analysis were developed from a top down approach which may fail to distinguish high resolution congestion events in the roadway network. In order to account for such impact, a modelling exercise is required in a more complex platform such as integrating a high resolution dataset.

4. Impact of Eco-Routing:

Eco-Routing does not always reduce all emissions from vehicles. Bandeira *et al.* (2013) identified a trade-off between reducing CO_2/fuel consumption and local pollutants (*e.g.* CO, NO_x and HC) while faster inter-city routes were chosen. Bandeira *et al.* (2014) further applied average speed based model and instantaneous model to a database of more than 13,330 km of GPS data in six different Origin-Destination (OD) pairs and 9 different routes and noted that estimation of CO_2 emissions (and fuel consumption) have shown similar for two models, however, different for local pollutants. Thus, the impact of Eco-Routing on other pollutants in different types of traffic and roadway condition may be assessed in the citywide scale using existing knowledge gathered from this research. One choice of an individual vehicle can be carried out at ArcGIS network analyst taking the information from a VISSIM simulation run. The shorted path identified in the network analyst, may be rerun in VISSIM and resultant trajectory of a selected vehicle on that minimum path can be inputted in CMEM to analyse the overall impact of route choice on different emissions.

5. Improvement of Eco-Routing:

The developed Eco-Routing model can be improved using a different strategy that will allow the model to be more applicable in a non-flat terrain. Replacing the road grade concept, an uphill ratio from a Digital Terrain model, in a smaller grid cell could be included in the route choice (Corréïa *et al.* 2010). However, this requires further research about the slope and it's effect on emissions and fuel consumption of the vehicle in relation to the vehicle direction, speed and acceleration. This would benefit this developed model to be useful for non-flat terrain more effectively without the need of actual road grade.

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List of Appendices

Appendix

Review of different modelling strategies A

Appendix A

A1: Review of common micro-simulation software

- PARAMICS

PARAMICS (PARAllel MICroscopic Simulation) was developed in late 1980s and is marketed by two companies- Quadstone and SIAS, and thus same product of these companies are known as Q-PARAMICS and S-PARAMICS. Both of the software were developed with similar principals. However variations between the two exist with visualisation and some functionality (Boulter and McCrae, 2007).

PARAMICS was created based on several models. The car following model is similar to Wiedemann's car-following model, and is also based on a psycho-physical model developed by Fritzche (1994). In Fritzche (1994) car following theory the main parameter is the target headway (in seconds) which determines the spacing of the follower vehicle as a function of its speed. The values of the parameter can be both global and specific according to the link.

For the lane changing model, two zones are defined in PARAMICS. For the 1st lane changing zone, the vehicle is at a distance from a junction and the only reason for its lane changes is to overtake a slower vehicle. For the lane changing zone two, the vehicle is approaching the junction and it may choose not to overtake anymore. The lane changes in this zone are only for reaching the appropriate lane to make a turn (Jiménez *et al.*, 2004).

- *S-PARAMICS*

S-PARAMICS can be applied for trunk, urban, suburban, inter-urban and rural roads for a very wide range of situations. S-PARAMICS represents the actions and interactions of individual vehicles as they travel through a road network. It models the detailed physical road layout, including features such as bus operations, traffic signal settings, driver behavioural characteristics and vehicle kinematics. As a consequence, S-

PARAMICS can accurately portray the variable circumstances that lead to congestion in all types and sizes of road network, and present its output as a real-time visual display for traffic management and road network design.

S-PARAMICS represents the complex and apparently random nature of traffic flow by requiring the user to provide limited and simple components in the form of a description of the road network and the traffic demand. S-PARAMICS uses a descriptive methodology of controlling driver behaviour rather than one of prescribing the desired effect which gives the model a more robust predictive ability.

- *Q-PARAMICS*

Q-PARAMICS can model from as small as a single intersection to a very large network. Q-PARAMICS uses unit vectors to describe behaviour at junctions. The vector provides guidance of both future and movement direction from current location. The software follows a random release of vehicles onto the network.

In Q-PARAMICS, lane changing is defined by many parameters such as aggressiveness, signposting and sign-range parameters. The aggressiveness parameter affects the gap acceptance behaviour during lane changing, whereas signposting and sign-range parameters define the distance range at which drivers become aware of the need that they have to change lane.

- AIMSUN

AIMSUN (Advanced Interactive Microscopic Simulator for Urban and Non-Urban Networks) is an integrated transport modelling software, developed and marketed by Transport Simulation Systems (TSS) based in Barcelona, Spain (Xiao *et al.*, 2005).

The car following model, and the lane-changing model used in AIMSUN is based on the model developed by Gipps (1981) and Gipps (1986). The lane-changing model considers the speed of the following vehicle to be either free or constrained by the leading vehicle. The lane-changing model is also a decision based model which addresses three questions: The necessity, desirability and feasibility of the lane change. The gap-acceptance model, on the other hand provides the behaviour of each single vehicle of the entire simulation period (TSS, 2006).

AIMSUN is capable of producing various real traffic networks and conditions. In addition, AIMSUN includes the capability of modelling a traffic network in detail and producing a number of measures of effects. New visualization modes were included in the latest versions that facilitate select link analysis, generation-attraction plots, and public transport assignment loads. AIMSUN has also a programming interface, which enables it to communicate with some user-defined applications, and third party tools, such as signal optimisation with TRANSYT–AIMSUN or emissions modelling with VERSIT^{+micro}.

It is noted that each of the software packages followed some built-in principle, and no obvious benefit was noted in one over the others. Thus, among these candidate simulation platforms, VISSIM software has been chosen for modelling.

A2: Review of Modal/ Instantaneous emissions models

- Power based Models

Generic/Physical Model

A generic power demand model was reported by Barth *et al.* (1996). An instantaneous power demand function is the fundamental basis of this physical model. Based on the power demand the fuel use and tail-pipe emissions are calculated using following equations (A3.1-A3.5). The figure 3.2 shows the overall concept of the Physical model.

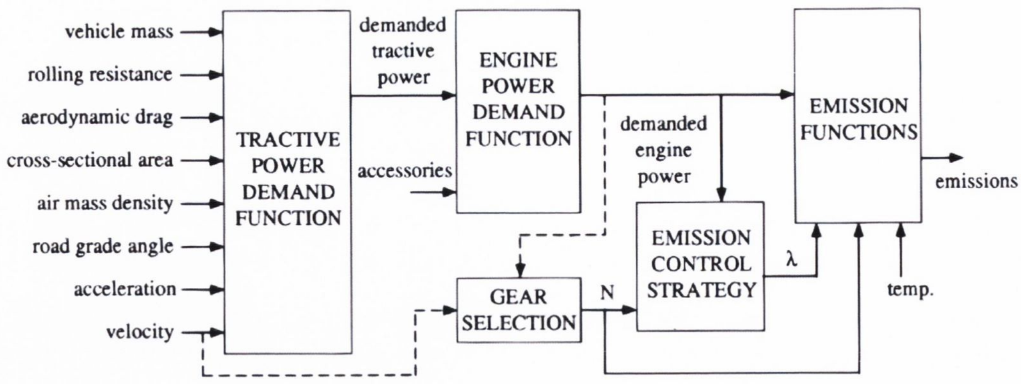


Figure 3.2: Power-demand emissions modelling methodology (Barth *et al.*, 1996)

Power Demand Function (the total tractive power requirements (in kilowatts) placed on a vehicle (at the wheels)):

$$P_{tractive} = \frac{M}{1000} * V * (a + g * sin\,\theta) + (M * g * C_r + \frac{\rho}{2} * V^2 * A * C_a)\frac{V}{1000} \quad \text{Eq.(A3.1)}$$

Where, M = vehicle mass (kg); V = vehicle velocity (m/sec); a = vehicle acceleration (m/s^2); g = gravitational constant (9.81 m/s^2); θ = road grade angle; C_r = rolling resistance coefficient; ρ = mass density of air (1.225 kg/m^3, depending on temperature and altitude); A = cross-sectional area (m^2), and C_a = aerodynamic drag coefficient.

$$P_{engine} = \frac{P_{tractive}}{\eta_{tf}} + P_{accessories} \quad \text{Eq.(A3.2)}$$

Where, η_{tf} = combined efficiency of the transmission and final drive; $P_{accessories}$ = engine power demand for accessories, *e.g.* air conditioning Emission Control Strategy and Equivalence Ratio ($\boldsymbol{\lambda}$),

$$\lambda = \frac{(A/F)_0}{(A/F)}$$ Eq. (A3.3)

Where, $(A/F)_0$ = air/fuel ratio at stoichiometry (≈14.7), and (A/F) is the commanded air/fuel ratio.

Fuel Use Model (after An and Ross, 1993, Ross and An 1993):

Fuel use rate (in kilowatts): $\frac{dF}{dt} = \lambda(k * N * D + \frac{P_{engine}}{\eta_{engine}}$ Eq. (A3.4)

Where, k = engine friction factor (representing the fuel energy used at zero power output to overcome engine friction per engine revolution and unit of engine displacement); N = engine speed; D = engine displacement, and η_{engine} = measure of indicated engine efficiency.

Tailpipe Emission Functions:

$$EMissions_{trailpipe} = \frac{dF}{dt} * \frac{(\frac{dCO}{dt})}{(\frac{dF}{dt})} * CPF$$ Eq. (A3.5)

Where, dF/dt = the fuel-use rate in g/s; dCO/dt = the engine-out emissions (for CO) in grams/s, and CPF = the catalyst pass fraction, a function primarily of temperature and equivalence ratio.

PHEM

Passenger car and Heavy-duty Emission Model (PHEM) was developed obtaining data from The ARTEMIS project and the COST Action 346. Initially the model was developed for Heavy-duty vehicles and was extended later to be applicable for passenger cars and for light commercial vehicles by obtaining engine maps for steady state engine tests and transient driving cycles. The model estimates fuel consumption and emissions based on the instantaneous engine power demand and engine speed during a driving pattern specified by the user (Rexeis *et al.*, 2005). The main inputs are a user-defined vehicle speed (driving pattern), road gradient and vehicle characteristics. For every second of the driving pattern and road gradient, PHEM calculates the actual engine power demand based upon vehicle driving resistances and transmission losses, and calculates the actual emission. To take transient influences on the emission levels into consideration, the results from the emission maps are adjusted by means of transient correction functions. The model results then are the high resolution courses of engine power, engine speed, fuel consumption and emissions of CO, CO_2, HC, NO_x, NO, PM ,*etc*. The model also includes a cold start tool which is based on simplified heat balances and emission maps for cold start extra emissions.

Vehicle Specific Power (VSP) based model

Vehicle Specific Power is the sum of external forces opposing vehicle motion multiplied by vehicle speed and divided by vehicle mass. Values for different VSP are created and emission rates, according to the VSP were modelled as matrix form. Emissions from the vehicles were usually estimated from that matrix. Jimenez-Palacios, (1999) showed that CO, VOC, and NO_x emissions were better correlated with Specific Power than with other common single parameters such as speed, acceleration, or power.

Few emission models have been based on VSP. Successful applications of VSP have been conducted for prediction of emission using simplified equations (Zhang and Frey, 2006; Boriboonsomsin *et al.*, 2010; Wang and Fu, 2010) while avoiding the consideration of wind effects. The original research based of the VSP (Jimenez-Palacios, 1999) provides an equation (Eq. A3.6) which takes account of wind impact. However, it only accounts for the effect of the headwind (windward) into the vehicle (m/s).

$$VSP = \frac{\frac{d(KE+PE)}{dt} + Frolling.v + Faerodynamic.v}{m}, \text{ or}$$

$$VSP = \frac{\frac{d}{dt}\left(\frac{1}{2}.m.(1+\varepsilon i).v^2 + mgh\right) + C_R.mg.v + \frac{1}{2}\rho.C_D.A(v+v_W)v}{m}, \text{ or}$$

$$VSP = v.(a.(1+\varepsilon i) + g.grade + g.C_R.) + \frac{1}{2}.\frac{\rho.C_D.A.(v+v_W)^2.v}{m}, \text{ or}$$

$$VSP(kW/MetricTon) = v.(1.1.a + 9.8.grade(\%) + .132) + \frac{1}{2}.\frac{1.207.C_D.A.(v+v_W)^2.v}{m}; \text{Eq.(A3.6)}$$

Here, *m*= vehicle mass; *v*= vehicle speed (m/s); *a* = vehicle acceleration(m/s^2); $\boldsymbol{\varepsilon_i}$ = "Mass factor", which is the equivalent translational mass of the rotating components (wheels, gears, shafts, *etc.*) of the power train. The suffix i indicates that E_i is gear-dependent(Typical values of $\boldsymbol{\varepsilon_i}$ for a manual transmission are 0.25 in 1st gear, 0.15 in 2nd gear, 0.10 in 3rd gear, 0.075 in 4th gear; *h*=altitude of the vehicle; grade= vertical rise/slope length; *g*= acceleration of gravity (9.8 m/s2);$\boldsymbol{C_R}$= coefficient of rolling resistance (dimensionless; this value depends on the road surface and tire type and pressure, with a small dependence on vehicle speed. Typical values range from 0.0085 to 0.016. A value of 0.0135 has been used here for all vehicles); $\boldsymbol{C_D}$= drag coefficient (dimensionless); *A*= frontal area of the vehicle; p= ambient air density (1.207 kg/m3 at 20°C = 68 °F); V_w = headwind into the vehicle (m/s).

- **Velocity-acceleration based models**

In the simplest type of instantaneous emission model, emissions and fuel consumption rates are defined for different combinations of instantaneous speed and acceleration (Pischinger and Hagliofer, 1984; Joumard *et al.*, 1995). Joumard (1995) presented a model to calculate emissions as a function of the vehicle type and its instantaneous speed and acceleration in the form of a two-dimensional matrix for all vehicle types. However, this two dimensional relationship does not always fully represent road gradient, engine speed or engine load factors. In addition, several forms of regression models were also developed to calculate instantaneous emissions.

MODEM

MODEM was originally produced during the European Commission's DRIVE program, and modifications were conducted to improve its accuracy in the latest version. MODEM was based on the principle that the engine power determines the rate of emission, and the power required depends upon the speed and the rate of acceleration (Joumard *et al.*, 1995). The emission rates for a particular vehicle category and pollutant were therefore defined in the form a two-dimensional matrix. The column of the matrix represented speed intervals (km/h), and the rows represented the multiplication product of the speed and acceleration intervals (m^2 s^3). Each cell defined by row and column contained the emission factors. The accuracy of the model was defined by the resolution of the matrix, such as the finer the resolution of the emission factor matrix, the higher the model accuracy. However, improving resolution also increased the complexity of the calculations.

Nonlinear regression

Int Panis *et al.* (2006) developed a model for evaluating emissions for each vehicle by deriving instantaneous speed and acceleration as parameters using non-linear multiple regression (Eq. A3.7) techniques.

$$E_n(t) = max[E_0 f_1 + f_2 v_n(t) + f_3 v_n(t)^2 + f_4 a_n(t) + f_5 a_n(t)^2 + f_6 v_n(t) a_n(t)]; \quad \text{Eq. (A3.7)}$$

Where, V_n *(t)* and a_n *(t)* are the instantaneous speed and acceleration of vehicle '*n*' at time '*t*'. E_0 is a lower limit of vehicle and pollutant specific emission (g/s) and f_1 to f_6 are emission constants specific for each vehicle and pollutant type determined by the regression analysis.

<u>VT-Micro</u>

Virginia Tech Microscopic energy and emissions model (VT-Micro) is a regression based model that was developed using instantaneous speed and acceleration levels as independent variables. Numerous polynomial combinations of speed and acceleration such as Linear, quadratic, cubic, and quartic terms of speed and acceleration were tested and selected using chassis dynamometer data collected at the Oak Ridge National Laboratory (ORNL).

The first regression model produced reasonable fits to the original data except when negative dependent values were produced (Eq. A3.8). To solve this problem, a new log-transformed model was introduced in Eq. A3.9. Consequently, separate regression models were developed for positive and negative accelerations (Eq. A3.10).

$$MOE_e = \sum_{i=0}^{3} \sum_{j=0}^{3} (K_{i,j}^{e} u^i a^j) \qquad \text{Eq. (A3.8)}$$

$$MOE_e = e^{\sum_{i=0}^{3} \sum_{j=0}^{3} (K_{i,j}^{e} u^i a^j)} \qquad \text{Eq. (A3.9)}$$

$$MOE_e = \begin{cases} e^{\sum_{i=0}^{3} \sum_{j=0}^{3} (L_{i,j}^{e} u^i a^j);} & ; for \quad a \geq 0 \\ e^{\sum_{i=0}^{3} \sum_{j=0}^{3} (K_{i,j}^{e} u^i a^j)} & ; for \quad a < 0 \end{cases} \qquad \text{Eq. (A3.10)}$$

Where, MOE_e is the instantaneous fuel consumption(l/s) or emission rate (mg/s), $\boldsymbol{K_{i,j}^{e}}$is the regression model coefficient at speed power "i" and acceleration power "j", $\boldsymbol{u}$ is the instantaneous vehicle speed (km/h), and a is the instantaneous vehicle acceleration (km/h/s).

VERSIT^{+micro}

VERSIT^{+micro} was developed after modification original VERSIT^{+} in order to link to traffic micro simulation programmes by reducing the number of category and splitting the category for to run for the urban and rural/highway environment. The VERSIT model was developed by TNO, Netherlands (Smit *et al.*, 2005; 2007) to simulate the traffic emissions of CO_2, NO_x and PM_{10} . The VERSIT^{+micro} model produces instantaneous vehicle emissions in g/s, on the basis of instantaneous speed 'v' and acceleration 'a'. The model is capable of modelling the effects of congestion on emission as it is based on driving pattern data. VERSIT^{+micro} can easily be combined with GIS tools to visualize emission hotspots; the interface with the microscopic traffic simulation program VISSIM is commercially available with the product name EnViver and is marketed by Vialis.

In order to work with VERSIT^{+micro} a dynamic variable 'w, values in the Eq. A3.11 is needed to be defined (Ligterink and DeLange, 2009):

*W=a+.014*v* Eq. (A3.11)

For constant w, emissions were found to vary only slowly with speed, and the speed v was further modified according to urban, rural and freeway driving, and dynamic domains (stationary, dynamic and aggressive). Finally, the emission 'e' in g/s is given by the following set of piecewise linear equations-Eq. A3.12 (Ligterink and De Lange, 2009):

$$f(x) = \begin{cases} \mu_0 \, ; & (v < 5, a < .5) \\ \mu_1 + \mu_2|w| + \mu_3|w-1|_+ \, ; & (v < 50) \\ \mu_4 + \mu_5|w| + \mu_6|w-1|_+ \, ; & (50 < v < 80) \\ \mu_7 + +\mu_8\left|w - \frac{1}{2}\right|_+ + \mu_9|w - \frac{3}{2}|_+ \, ; & (v > 80) \end{cases} \qquad \text{Eq. (A3.12)}$$

Where, the function $|x|_+$ yields 0 for x <0, and x otherwise. The first line in Eq. (3.12) models the air pollutant emissions during idling. The 10 coefficients $\boldsymbol{\mu}_\mathbf{i}$ in each of the regions of the speed-acceleration space were, for each air pollutant type, determined through a maximum likelihood method (Coensel *et al.*, 2012).

A3: Air quality models

- **Dispersion modelling**

<u>Box Model:</u>

The box model is the simplest of the model types which assumes a given volume of atmospheric air in a geographical region is in the shape of a box. It also assumes that the air pollutants inside the box are homogeneously distributed and uses that assumption to estimate the average pollutant concentrations anywhere within the volume of atmospheric air. The flow of air is assumed to be in from one end and out to the other. The sources within the box are modelled as a completely mixed and dispersed area source (Allen *et al.*, 1975). The equation (Eq. A3.13) for this model is:

$$C = q_o + \frac{Q}{DHU};$$ Eq. (A3.13)

Where, *C*= concentration anywhere in the box; q_o=Background pollution; *Q*=Source strength within the box; *D*=width of the area; *H*= mixing Height; *U*=Wind speed.

Lyons et al. (2003) applied a box model to assess direct air pollution benefits from minimising the outward growth of cities. The model may useful for policy analysis, or impact assessment, however, the accuracy of the prediction of dispersion of air pollutants is limited as because the assumption of homogeneous pollutant distribution is much too simple. Besides, urban emissions from point and line sources do not get uniformly back-mixed within a clearly defined rectangular volume. At certain places within the box, the pollution level would be much higher or much lower than that calculated (Allen *et al.*, 1975).

Gaussian plume models

Plume model treat sources individually rather than combining them as in the box model while a plume moves downwind it spreads vertically and horizontally, which makes the model more acceptable (Allen *et al.*, 1975). This concept developed in 1930s or earlier and most popular form of the equation is (Beychok, 2005) noted by (Pilla, 2012) and given in Eq. A3.14:

$$C(x,y,z) = \frac{Q}{\mu} * \frac{exp[-y^2 \;\; 2\sigma_y{}^2]}{\sigma_y \; 2\pi} * \frac{g}{\sigma_z 2\pi}; \qquad \text{Eq. (A3.14)}$$

Where, $C(x,y,z)$ = Concentration of emissions, in g/m^3 (at any receptor located x meters downwind from the emission source point, y meters crosswind from the emission plume centre line, z meters above ground level); Q = source pollutant emission rate, in g/s; μ = horizontal wind velocity along the plume centre line, m/s; σ_z=vertical standard deviation of the emission distribution, in meter; σ_y = horizontal standard deviation of the emission distribution, in meter; vertical dispersion parameter, $g = g_1 + g_2 + g_3$,and for each of the $g_{x=1,2\,\&\,3}$ in the equation has separate sub equations and those are highly related with pollutant plume's centre line height above ground level (H_e), and height from ground level to bottom of the inversion aloft (L).

There has been uncertainty about the pollutant plume's centreline height above ground level (H_e), which can be solved by Briggs fume rise equation. Briggs first published his plume rise observations and comparisons in 1965 (Briggs, 1965) and final modification was carried out by him in 1972 (Briggs, 1972). In his equation, four general categories characterising the environmental condition are separated where the fume will rise differently, and for using the value in the original equation (Eq. A3.14), the plume's height can be calculated with a combination of a logic diagram (Beychok, 2005).

A general form of Gaussian Model (Eq. A3.15) applied in estimating concentration of pollutants from road traffic (Karim, 1999) has been included below for understanding the breakdown of calculation applied by Luo *et al.*, (2013) in section 2.10, Chapter 2. For a ground level relays (usually for vehicle emission), release height is, *H*= 0, the concentration of pollutants at a point (x, y, z) generated by a continuous line source can be estimated using the expression as:

$$\delta(x, y, z) = \frac{Q}{\pi\sigma_y\sigma_z\mu} exp[-\left(\frac{y^2}{2\sigma_y} + \frac{z^2}{2\sigma_z}\right)] ; \qquad \text{Eq. (A3.15)}$$

Where, σ_z is the vertical dispersion length (m), σ_y the horizontal dispersion length (*m*), *u* the wind speed (m/s), *z* the height of the receptor above ground (m), and *Q* is the rate of emission in g/s in Eq. (A3.16).

$$Q = \sum_{m=1}^{8} 2.777 * 10^{-7} * q_m * r_m ; \qquad \text{Eq. (A3.16)}$$

Where *q*= traffic flow in Vehicle/h; r_m= is the emission rate calculated from Eq. (3.17).

$$r_m = \sum_{n=0}^{N} a_n V^n ; \qquad \text{Eq. (A3.17)}$$

Where *m* (vehicle type= 1; 2; . . . ; *n*=0; 1; 2; . . . ; *N* is the degree of polynomial, r the rate of emission in g/km/veh, '*a*' is the constant (coefficient of polynomial), *V* is the vehicle speed in km/h.

However, there are circumstances where Gaussian plume models have limitations. This model assumes that the concentration within the plume is proportional to the emission rate and inversely proportional to the wind speed at the point of release. Therefore, at wind speed close to zero, the predicted concentration approaches infinity and the Gaussian representation of the plume is no longer valid (Pilla, 2012). In non-uniform meteorological conditions that may also be affected by topography, the model is not valid and Dispersion over large distances the steady-state assumption is unlikely to be consistent with reality (Marnane *et al.*, 2010).

Lagrangian models

Pull models are one of the complex models (Allen *et al.*, 1975), however, at meso-scale applications; the Lagrangian PUFF model has a higher computational efficiency (Egmond and Kesseboom 1983). Pollution plume parcels/particles in Lagrangian model are considered moving following a random walk process in the atmosphere. As particles moving from one position to another, the model calculates their dispersion by computing the statistics of the trajectories in relation to their position, orientation and time. The total concentration at the receptor is then calculated based on the contribution of all nearby puffs. Puff models lie between Gaussian and Lagrangian dispersion models. Pollutant the concentration in Puff model can be well described with a Gaussian distribution; however, the centre line of a fume follows Lagrangian trajectory rather than that of not being straight downwind direction. Thus, puff models still estimate a Gaussian dispersion, but are able to take into account temporal and spatial wind changes, in other words, Puff models may also use the Gaussian distribution to describe the dispersion of pollutants within each puff. Lagrangian models are exceptionally efficient close to the source. Popular models based on these concepts are: A Lagrangian Trajectory Volcanic Ash Tracking Model (Searcy, 2001), HYSPLIT - Hybrid Single Particle Lagrangian Integrated Trajectory Model (ARL, 2013).

- Geographical information systems (GIS) based Models

Extrapolation based on nearest monitoring site

Gulliver *et al*. (2011a) applied this method in order to compare this extrapolation method with other models for prediction concentration of pollutants. In this most simple kind of a model, pollutant concentration was extrapolated from the nearest monitoring site. The underlying model is thus that air pollution surfaces are flat around each monitoring site and represent a series of 'plates' (smaller area) focused on each monitoring site.

Appendix

Results of micro-simulation model B

Experiment 1 (Table B1-Table B24)

- **Speed profile1 in high traffic volume (Table B1- Table B4)**

Performance	Table B1: 0% Eco-Driving									
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6	Trial 7	Trial 8	Trial 9	Trial 10
Latent demand	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Total vehicle mile travelled	1988.6	1963.3	1975.8	1978.0	1973.9	1958.9	1970.7	1982.4	1973.8	1983.6
Total Stopped Delay, h	90.1	92.3	99.0	87.1	89.5	94.5	92.8	93.0	97.1	104.1
Average delay per vehicle, s	136.9	140.4	151.7	130.6	137.0	143.9	140.2	139.6	146.1	157.5
Vehicle in the network	308.0	339.0	331.0	325.0	331.0	374.0	332.0	308.0	331.0	328.0
Vehicle left	3042.0	3011.0	3019.0	3025.0	3019.0	2976.0	3018.0	3042.0	3019.0	3022.0
Total Travel time, h	260.3	262.1	273.0	253.6	259.0	264.8	262.2	262.6	268.0	278.8
Total vehicle Km travelled	3200.3	3159.6	3179.7	3183.2	3176.6	3152.6	3171.5	3190.4	3176.6	3192.4
Total vehicle in the network	3350.0	3350.0	3350.0	3350.0	3350.0	3350.0	3350.0	3350.0	3350.0	3350.0
Latent to total vehicle ratio	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Travel time (Min)per vehicle km	4.9	5.0	5.2	4.8	4.9	5.0	5.0	4.9	5.1	5.2
Average delay per vehicle, min	2.3	2.3	2.5	2.2	2.3	2.4	2.3	2.3	2.4	2.6

Performance	Table B2: 20% Eco-Driving									
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6	Trial 7	Trial 8	Trial 9	Trial 10
Latent demand	0.0	3.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Total vehicle mile travelled	1981.1	1952.7	1956.5	1967.5	1967.6	1963.6	1965.7	1977.5	1963.7	1977.8
Total Stopped Delay, h	96.4	97.1	104.7	96.1	91.2	93.3	94.7	99.4	102.5	108.2
Average delay per vehicle, s	146.3	148.9	162.9	146.5	138.3	142.1	142.7	149.4	156.1	163.4
Vehicle in the network	316.0	351.0	359.0	342.0	341.0	366.0	336.0	318.0	349.0	340.0
Vehicle left	3034.0	2996.0	2991.0	3008.0	3009.0	2984.0	3014.0	3032.0	3001.0	3010.0
Total Travel time, h	268.5	269.1	282.1	267.6	259.8	263.5	264.2	271.4	276.6	283.9
Total vehicle Km travelled	3188.3	3142.5	3148.6	3166.4	3166.5	3160.1	3163.5	3182.5	3160.3	3182.9
Total vehicle in the network	3350.0	3347.0	3350.0	3350.0	3350.0	3350.0	3350.0	3350.0	3350.0	3350.0
Latent to total vehicle ratio	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Travel time (Min)per vehicle km	5.1	5.1	5.4	5.1	4.9	5.0	5.0	5.1	5.3	5.4
Average delay per vehicle, min	2.4	2.5	2.7	2.4	2.3	2.4	2.4	2.5	2.6	2.7

Performance	Table B3: 50% Eco-Driving									
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6	Trial 7	Trial 8	Trial 9	Trial 10
Latent demand	0.0	5.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Total vehicle mile travelled	1972.9	1950.9	1957.7	1959.4	1959.9	1952.1	1958.9	1976.5	1959.0	1963.8
Total Stopped Delay, h	103.4	102.1	104.5	101.8	96.2	100.5	100.6	105.0	108.7	117.7
Average delay per vehicle, s	157.0	156.8	162.1	153.7	146.1	151.8	152.0	156.0	164.2	179.3
Vehicle in the network	330.0	350.0	365.0	358.0	357.0	393.0	349.0	324.0	354.0	365.0
Vehicle left	3020.0	2995.0	2985.0	2992.0	2993.0	2957.0	3001.0	3026.0	2996.0	2985.0
Total Travel time, h	277.9	276.2	281.4	273.8	266.5	271.7	272.4	277.4	283.9	297.7
Total vehicle Km travelled	3175.1	3139.7	3150.7	3153.3	3154.2	3141.7	3152.5	3180.9	3152.7	3160.4
Total vehicle in the network	3350.0	3345.0	3350.0	3350.0	3350.0	3350.0	3350.0	3350.0	3350.0	3350.0
Latent to total vehicle ratio	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Travel time (Min)per vehicle km	5.3	5.3	5.4	5.2	5.1	5.2	5.2	5.2	5.4	5.7
Average delay per vehicle, min	2.6	2.6	2.7	2.6	2.4	2.5	2.5	2.6	2.7	3.0

Performance	Table B4: 100% Eco-Driving									
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6	Trial 7	Trial 8	Trial 9	Trial 10
Latent demand	0.0	0.0	2.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Total vehicle mile travelled	1956.7	1950.9	1946.0	1966.3	1954.9	1944.8	1968.7	1971.7	1956.1	1965.2
Total Stopped Delay, h	113.5	101.3	111.9	102.8	104.1	105.2	100.9	110.3	115.6	118.9
Average delay per vehicle, s	169.0	156.2	173.9	154.4	156.8	159.6	150.0	162.0	173.7	180.2
Vehicle in the network	365.0	367.0	378.0	354.0	376.0	405.0	333.0	342.0	365.0	376.0
Vehicle left	2985.0	2983.0	2968.0	2996.0	2974.0	2944.0	3017.0	3008.0	2985.0	2974.0
Total Travel time, h	287.9	275.8	291.4	274.9	276.2	278.4	271.1	282.8	292.5	298.6
Total vehicle Km travelled	3149.0	3139.7	3131.9	3164.4	3146.1	3129.8	3168.4	3173.1	3148.1	3162.7
Total vehicle in the network	3350.0	3350.0	3346.0	3350.0	3350.0	3349.0	3350.0	3350.0	3350.0	3350.0
Latent to total vehicle ratio	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Travel time (Min)per vehicle km	5.5	5.3	5.6	5.2	5.3	5.3	5.1	5.3	5.6	5.7
Average delay per vehicle, min	2.8	2.6	2.9	2.6	2.6	2.7	2.5	2.7	2.9	3.0

- **Speed profile 1 in low traffic volume (Table B5- Table B8)**

Performance	Table B5: 0% Eco-Driving									
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6	Trial 7	Trial 8	Trial 9	Trial 10
Latent demand	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Total vehicle mile travelled	1023.0	1025.3	1029.1	1024.8	1030.4	1023.6	1025.9	1030.2	1026.2	1032.9
Total Stopped Delay, h	20.8	20.5	21.2	20.8	20.6	20.9	20.9	20.8	20.5	21.6
Average delay per vehicle, s	54.9	54.0	55.9	54.9	54.4	55.3	54.8	54.8	54.4	57.1
Vehicle in the network	100.0	77.0	89.0	88.0	91.0	105.0	92.0	85.0	90.0	96.0
Vehicle left	1575.0	1598.0	1586.0	1587.0	1584.0	1570.0	1583.0	1590.0	1585.0	1579.0
Total Travel time, h	93.5	93.2	94.1	93.6	93.4	93.7	93.5	94.1	93.5	95.0
Total vehicle Km travelled	1646.4	1650.1	1656.2	1649.2	1658.2	1647.3	1651.0	1658.0	1651.6	1662.3
Total vehicle in the network	1675.0	1675.0	1675.0	1675.0	1675.0	1675.0	1675.0	1675.0	1675.0	1675.0
Latent to total vehicle ratio	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Travel time (Min)per vehicle km	3.4	3.4	3.4	3.4	3.4	3.4	3.4	3.4	3.4	3.4
Average delay per vehicle, min	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	1.0

Performance	Table B6: 20% Eco-Driving									
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6	Trial 7	Trial 8	Trial 9	Trial 10
Latent demand	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Total vehicle mile travelled	1023.0	1025.2	1028.8	1024.8	1030.2	1023.3	1026.3	1030.1	1025.7	1032.5
Total Stopped Delay, h	20.8	20.6	21.4	20.8	20.7	20.9	20.8	20.9	20.6	21.6
Average delay per vehicle, s	55.2	54.6	56.6	55.1	54.9	55.5	54.8	55.3	54.9	57.3
Vehicle in the network	100.0	78.0	88.0	88.0	92.0	106.0	93.0	86.0	90.0	95.0
Vehicle left	1575.0	1597.0	1587.0	1587.0	1583.0	1569.0	1582.0	1589.0	1585.0	1580.0
Total Travel time, h	93.6	93.5	94.4	93.7	93.6	93.7	93.5	94.4	93.7	95.0
Total vehicle Km travelled	1646.4	1650.0	1655.7	1649.2	1657.9	1646.8	1651.7	1657.8	1650.8	1661.6
Total vehicle in the network	1675.0	1675.0	1675.0	1675.0	1675.0	1675.0	1675.0	1675.0	1675.0	1675.0
Latent to total vehicle ratio	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Travel time (Min)per vehicle km	3.4	3.4	3.4	3.4	3.4	3.4	3.4	3.4	3.4	3.4
Average delay per vehicle, min	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	1.0

Performance	Table B7: 50% Eco-Driving									
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6	Trial 7	Trial 8	Trial 9	Trial 10
Latent demand	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Total vehicle mile travelled	1022.7	1025.2	1029.0	1025.1	1030.5	1022.7	1025.9	1029.6	1025.8	1032.9
Total Stopped Delay, h	20.9	20.7	21.5	20.9	20.6	21.1	20.8	20.9	20.5	21.6
Average delay per vehicle, s	55.9	55.0	57.2	55.7	55.1	56.5	55.3	55.5	55.1	57.6
Vehicle in the network	100.0	77.0	88.0	88.0	91.0	103.0	91.0	86.0	91.0	96.0
Vehicle left	1575.0	1598.0	1587.0	1587.0	1584.0	1572.0	1584.0	1589.0	1584.0	1579.0
Total Travel time, h	93.9	93.7	94.7	94.0	93.7	94.2	93.7	94.4	93.8	95.2
Total vehicle Km travelled	1645.8	1650.0	1656.0	1649.7	1658.4	1645.9	1651.0	1657.0	1650.8	1662.2
Total vehicle in the network	1675.0	1675.0	1675.0	1675.0	1675.0	1675.0	1675.0	1675.0	1675.0	1675.0
Latent to total vehicle ratio	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Travel time (Min)per vehicle km	3.4	3.4	3.4	3.4	3.4	3.4	3.4	3.4	3.4	3.4
Average delay per vehicle, min	0.9	0.9	1.0	0.9	0.9	0.9	0.9	0.9	0.9	1.0

Performance	Table B8: 100% Eco-Driving									
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6	Trial 7	Trial 8	Trial 9	Trial 10
Latent demand	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Total vehicle mile travelled	1022.8	1025.0	1028.9	1025.2	1030.3	1022.6	1025.6	1029.4	1026.4	1032.1
Total Stopped Delay, h	20.8	20.6	21.3	20.8	20.6	21.2	20.8	20.8	20.7	21.8
Average delay per vehicle, s	56.0	55.4	57.2	56.0	55.5	57.0	55.5	56.0	56.2	58.5
Vehicle in the network	101.0	78.0	89.0	88.0	92.0	104.0	93.0	84.0	91.0	96.0
Vehicle left	1574.0	1597.0	1586.0	1587.0	1583.0	1571.0	1582.0	1591.0	1584.0	1579.0
Total Travel time, h	93.9	93.9	94.7	94.2	93.9	94.4	93.8	94.6	94.3	95.6
Total vehicle Km travelled	1646.0	1649.7	1655.9	1649.9	1658.1	1645.8	1650.6	1656.7	1651.8	1661.1
Total vehicle in the network	1675.0	1675.0	1675.0	1675.0	1675.0	1675.0	1675.0	1675.0	1675.0	1675.0
Latent to total vehicle ratio	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Travel time (Min)per vehicle km	3.4	3.4	3.4	3.4	3.4	3.4	3.4	3.4	3.4	3.5
Average delay per vehicle, min	0.9	0.9	1.0	0.9	0.9	1.0	0.9	0.9	0.9	1.0

- **Speed profile 2 in high traffic volume (Table B9- Table B12)**

Performance	Table B9: 0% Eco-Driving									
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6	Trial 7	Trial 8	Trial 9	Trial 10
Latent demand	0.0	9.0	0.0	0.0	0.0	0.0	0.0	0.0	2.0	0.0
Total vehicle mile travelled	1957.9	1940.8	1943.0	1958.6	1956.7	1943.5	1949.4	1951.8	1939.2	1951.6
Total Stopped Delay, h	105.6	110.1	121.9	100.7	108.8	107.1	111.2	123.6	124.6	123.0
Average delay per vehicle, s	164.1	173.1	191.5	158.2	166.2	167.6	172.1	190.6	192.7	191.3
Vehicle in the network	371.0	392.0	389.0	368.0	388.0	404.0	380.0	392.0	406.0	405.0
Vehicle left	2979.0	2950.0	2959.0	2982.0	2962.0	2944.0	2970.0	2958.0	2941.0	2945.0
Total Travel time, h	288.2	295.5	312.2	282.5	289.3	290.5	295.0	312.8	313.7	312.4
Total vehicle Km travelled	3150.9	3123.4	3127.0	3152.0	3149.0	3127.8	3137.2	3141.1	3120.8	3140.8
Total vehicle in the network	3350.0	3342.0	3348.0	3350.0	3350.0	3348.0	3350.0	3350.0	3347.0	3350.0
Latent to total vehicle ratio	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Travel time (Min)per vehicle km	5.5	5.7	6.0	5.4	5.5	5.6	5.6	6.0	6.0	6.0
Average delay per vehicle, min	2.7	2.9	3.2	2.6	2.8	2.8	2.9	3.2	3.2	3.2

Performance	Table B10: 20% Eco-Driving									
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6	Trial 7	Trial 8	Trial 9	Trial 10
Latent demand	0.0	3.0	0.0	0.0	0.0	0.0	0.0	0.0	2.0	0.0
Total vehicle mile travelled	1960.8	1933.3	1950.2	1953.7	1935.9	1931.7	1939.1	1947.8	1930.8	1950.9
Total Stopped Delay, h	109.1	111.8	115.8	106.8	124.4	112.5	118.3	123.4	133.2	124.4
Average delay per vehicle, s	169.9	175.0	182.0	165.2	188.8	174.8	182.7	190.1	205.4	194.8
Vehicle in the network	375.0	408.0	380.0	376.0	431.0	439.0	399.0	393.0	422.0	408.0
Vehicle left	2975.0	2939.0	2970.0	2974.0	2919.0	2909.0	2951.0	2957.0	2925.0	2942.0
Total Travel time, h	293.6	296.9	303.9	288.7	308.9	296.3	304.1	312.2	324.8	315.5
Total vehicle Km travelled	3155.6	3111.4	3138.6	3144.2	3115.5	3108.8	3120.7	3134.7	3107.3	3139.6
Total vehicle in the network	3350.0	3347.0	3350.0	3350.0	3350.0	3348.0	3350.0	3350.0	3347.0	3350.0
Latent to total vehicle ratio	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Travel time (Min)per vehicle km	5.6	5.7	5.8	5.5	5.9	5.7	5.8	6.0	6.3	6.0
Average delay per vehicle, min	2.8	2.9	3.0	2.8	3.1	2.9	3.0	3.2	3.4	3.2

Performance	Table B11: 50% Eco-Driving									
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6	Trial 7	Trial 8	Trial 9	Trial 10
Latent demand	0.0	15.0	17.0	0.0	0.0	4.0	0.0	0.0	0.0	2.0
Total vehicle mile travelled	1948.3	1926.0	1924.8	1938.6	1933.3	1933.1	1931.8	1945.8	1930.0	1942.5
Total Stopped Delay, h	119.3	116.7	130.3	118.7	124.0	112.1	128.2	126.9	138.6	128.1
Average delay per vehicle, s	183.0	182.9	203.8	179.5	189.2	171.7	196.1	193.5	212.7	199.3
Vehicle in the network	402.0	416.0	416.0	418.0	438.0	434.0	429.0	402.0	443.0	426.0
Vehicle left	2948.0	2920.0	2917.0	2932.0	2912.0	2912.0	2921.0	2948.0	2907.0	2922.0
Total Travel time, h	305.0	303.3	321.5	301.0	309.0	293.4	316.0	315.3	331.7	319.0
Total vehicle Km travelled	3135.5	3099.6	3097.7	3119.8	3111.3	3111.1	3109.0	3131.4	3106.0	3126.1
Total vehicle in the network	3350.0	3336.0	3333.0	3350.0	3350.0	3346.0	3350.0	3350.0	3350.0	3348.0
Latent to total vehicle ratio	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Travel time (Min)per vehicle km	5.8	5.9	6.2	5.8	6.0	5.7	6.1	6.0	6.4	6.1
Average delay per vehicle, min	3.1	3.0	3.4	3.0	3.2	2.9	3.3	3.2	3.5	3.3

Performance	Table B12: 100% Eco-Driving									
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6	Trial 7	Trial 8	Trial 9	Trial 10
Latent demand	0.0	7.0	0.0	0.0	0.0	0.0	4.0	0.0	7.0	1.0
Total vehicle mile travelled	1939.5	1922.1	1927.2	1934.3	1921.4	1933.7	1920.1	1934.7	1914.6	1931.7
Total Stopped Delay, h	133.0	127.1	130.4	128.2	134.6	114.0	133.5	134.5	142.3	139.2
Average delay per vehicle, s	202.9	197.9	205.6	196.8	207.6	174.6	208.2	205.7	220.9	215.6
Vehicle in the network	423.0	436.0	439.0	436.0	458.0	445.0	439.0	435.0	456.0	452.0
Vehicle left	2927.0	2907.0	2909.0	2914.0	2892.0	2905.0	2903.0	2915.0	2885.0	2897.0
Total Travel time, h	322.9	317.1	324.1	316.7	325.4	296.4	326.0	325.8	337.7	333.7
Total vehicle Km travelled	3121.3	3093.3	3101.6	3112.9	3092.3	3112.0	3090.1	3113.6	3081.2	3108.8
Total vehicle in the network	3350.0	3343.0	3348.0	3350.0	3350.0	3350.0	3342.0	3350.0	3341.0	3349.0
Latent to total vehicle ratio	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Travel time (Min)per vehicle km	6.2	6.2	6.3	6.1	6.3	5.7	6.3	6.3	6.6	6.4
Average delay per vehicle, min	3.4	3.3	3.4	3.3	3.5	2.9	3.5	3.4	3.7	3.6

- **Speed profile 2 in low traffic volume (Table B13- Table B16)**

Performance	Table B13: 0% Eco-Driving									
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6	Trial 7	Trial 8	Trial 9	Trial 10
Latent demand	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Total vehicle mile travelled	1022.0	1023.0	1028.5	1023.3	1026.6	1021.4	1025.6	1029.6	1024.4	1031.9
Total Stopped Delay, h	20.9	20.1	21.3	21.2	21.2	21.5	20.8	21.3	21.1	22.0
Average delay per vehicle, s	58.0	56.3	58.7	59.0	58.5	59.6	57.3	58.7	58.7	61.0
Vehicle in the network	105.0	94.0	90.0	99.0	94.0	115.0	87.0	90.0	89.0	93.0
Vehicle left	1570.0	1581.0	1585.0	1576.0	1581.0	1560.0	1588.0	1585.0	1586.0	1582.0
Total Travel time, h	97.4	97.0	97.9	98.1	97.4	98.2	97.2	98.6	98.1	99.1
Total vehicle Km travelled	1644.8	1646.4	1655.2	1646.8	1652.2	1643.7	1650.6	1657.1	1648.6	1660.6
Total vehicle in the network	1675.0	1675.0	1675.0	1675.0	1675.0	1675.0	1675.0	1675.0	1675.0	1675.0
Latent to total vehicle ratio	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Travel time (Min)per vehicle km	3.6	3.5	3.6	3.6	3.5	3.6	3.5	3.6	3.6	3.6
Average delay per vehicle, min	1.0	0.9	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0

Performance	Table B14: 20% Eco-Driving									
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6	Trial 7	Trial 8	Trial 9	Trial 10
Latent demand	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Total vehicle mile travelled	1022.8	1023.7	1028.3	1022.6	1027.2	1020.9	1025.7	1029.2	1024.4	1032.0
Total Stopped Delay, h	21.0	20.0	21.3	21.2	21.1	21.5	20.8	21.6	21.1	21.8
Average delay per vehicle, s	58.4	56.2	59.0	59.2	58.7	60.0	57.8	59.7	58.9	60.7
Vehicle in the network	105.0	94.0	90.0	102.0	95.0	116.0	86.0	89.0	89.0	94.0
Vehicle left	1570.0	1581.0	1585.0	1573.0	1580.0	1559.0	1589.0	1586.0	1586.0	1581.0
Total Travel time, h	97.7	97.0	98.1	98.2	97.6	98.3	97.4	99.0	98.3	99.0
Total vehicle Km travelled	1646.1	1647.5	1654.8	1645.7	1653.2	1642.9	1650.8	1656.3	1648.6	1660.9
Total vehicle in the network	1675.0	1675.0	1675.0	1675.0	1675.0	1675.0	1675.0	1675.0	1675.0	1675.0
Latent to total vehicle ratio	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Travel time (Min)per vehicle km	3.6	3.5	3.6	3.6	3.5	3.6	3.5	3.6	3.6	3.6
Average delay per vehicle, min	1.0	0.9	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0

Performance	Table B15: 50% Eco-Driving									
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6	Trial 7	Trial 8	Trial 9	Trial 10
Latent demand	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Total vehicle mile travelled	1022.8	1023.3	1028.1	1022.8	1026.9	1021.7	1025.3	1029.4	1024.9	1031.8
Total Stopped Delay, h	21.2	20.2	21.4	21.4	21.2	21.6	20.7	21.5	21.1	22.3
Average delay per vehicle, s	59.1	56.9	59.5	60.0	59.0	60.7	57.7	59.8	59.2	62.1
Vehicle in the network	105.0	94.0	91.0	98.0	96.0	115.0	86.0	89.0	89.0	95.0
Vehicle left	1570.0	1581.0	1584.0	1577.0	1579.0	1560.0	1589.0	1586.0	1586.0	1580.0
Total Travel time, h	98.0	97.3	98.3	98.5	97.7	98.7	97.4	99.1	98.4	99.6
Total vehicle Km travelled	1646.0	1646.9	1654.6	1646.1	1652.7	1644.3	1650.0	1656.6	1649.3	1660.5
Total vehicle in the network	1675.0	1675.0	1675.0	1675.0	1675.0	1675.0	1675.0	1675.0	1675.0	1675.0
Latent to total vehicle ratio	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Travel time (Min)per vehicle km	3.6	3.5	3.6	3.6	3.5	3.6	3.5	3.6	3.6	3.6
Average delay per vehicle, min	1.0	0.9	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0

Performance	Table B16: 100% Eco-Driving									
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6	Trial 7	Trial 8	Trial 9	Trial 10
Latent demand	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Total vehicle mile travelled	1022.0	1022.9	1028.1	1023.1	1026.5	1021.9	1025.2	1029.2	1024.2	1031.8
Total Stopped Delay, h	21.0	20.2	21.3	21.3	21.3	21.6	20.8	21.4	21.1	22.3
Average delay per vehicle, s	59.2	57.6	59.8	60.3	59.8	61.2	58.5	59.9	60.1	62.8
Vehicle in the network	105.0	93.0	92.0	101.0	96.0	113.0	87.0	91.0	90.0	94.0
Vehicle left	1570.0	1582.0	1583.0	1574.0	1579.0	1562.0	1588.0	1584.0	1585.0	1581.0
Total Travel time, h	97.9	97.6	98.5	98.7	98.0	98.9	97.7	99.1	98.8	99.9
Total vehicle Km travelled	1644.7	1646.3	1654.6	1646.4	1651.9	1644.6	1649.8	1656.4	1648.2	1660.5
Total vehicle in the network	1675.0	1675.0	1675.0	1675.0	1675.0	1675.0	1675.0	1675.0	1675.0	1675.0
Latent to total vehicle ratio	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Travel time (Min)per vehicle km	3.6	3.6	3.6	3.6	3.6	3.6	3.6	3.6	3.6	3.6
Average delay per vehicle, min	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0

- **Speed profile 3 in high traffic volume (Table B17- Table B20)**

Performance	Table B17: 0% Eco-Driving									
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6	Trial 7	Trial 8	Trial 9	Trial 10
Latent demand	3.0	26.0	3.0	0.0	12.0	15.0	30.0	12.0	0.0	0.0
Total vehicle mile travelled	1909.5	1897.9	1916.8	1907.1	1891.1	1891.7	1889.7	1891.9	1907.9	1914.4
Total Stopped Delay, h	151.9	137.8	144.1	141.6	152.2	142.4	151.9	159.7	142.5	160.7
Average delay per vehicle, s	235.8	216.9	223.8	218.9	238.2	220.0	238.0	247.1	218.6	246.7
Vehicle in the network	491.0	479.0	468.0	496.0	527.0	526.0	479.0	512.0	496.0	502.0
Vehicle left	2854.0	2850.0	2876.0	2854.0	2811.0	2812.0	2843.0	2822.0	2854.0	2848.0
Total Travel time, h	367.9	348.6	356.8	352.0	367.2	351.3	366.8	377.0	352.7	377.9
Total vehicle Km travelled	3073.1	3054.3	3084.8	3069.2	3043.4	3044.4	3041.3	3044.7	3070.5	3080.9
Total vehicle in the network	3345.0	3329.0	3344.0	3350.0	3338.0	3338.0	3322.0	3334.0	3350.0	3350.0
Latent to total vehicle ratio	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Travel time (Min)per vehicle km	7.2	6.8	6.9	6.9	7.2	6.9	7.2	7.4	6.9	7.4
Average delay per vehicle, min	3.9	3.6	3.7	3.6	4.0	3.7	4.0	4.1	3.6	4.1

Performance	Table B18: 20% Eco-Driving									
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6	Trial 7	Trial 8	Trial 9	Trial 10
Latent demand	0.0	40.0	8.0	4.0	8.0	29.0	17.0	8.0	19.0	2.0
Total vehicle mile travelled	1911.0	1880.9	1900.9	1887.5	1893.3	1875.2	1899.6	1882.0	1889.6	1905.8
Total Stopped Delay, h	148.1	144.0	156.1	153.1	150.0	144.4	147.7	166.8	149.1	166.5
Average delay per vehicle, s	228.9	228.0	243.9	241.1	235.8	226.3	231.5	259.0	232.6	257.4
Vehicle in the network	492.0	495.0	488.0	531.0	523.0	534.0	474.0	546.0	494.0	515.0
Vehicle left	2858.0	2820.0	2852.0	2813.0	2820.0	2780.0	2857.0	2791.0	2832.0	2833.0
Total Travel time, h	361.9	356.8	374.0	370.7	365.5	354.2	362.3	387.4	362.4	387.2
Total vehicle Km travelled	3075.5	3027.0	3059.2	3037.6	3047.0	3017.8	3057.1	3028.8	3041.0	3067.1
Total vehicle in the network	3350.0	3315.0	3340.0	3344.0	3343.0	3314.0	3331.0	3337.0	3326.0	3348.0
Latent to total vehicle ratio	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Travel time (Min)per vehicle km	7.1	7.1	7.3	7.3	7.2	7.0	7.1	7.7	7.2	7.6
Average delay per vehicle, min	3.8	3.8	4.1	4.0	3.9	3.8	3.9	4.3	3.9	4.3

Performance	Table B19: 50% Eco-Driving									
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6	Trial 7	Trial 8	Trial 9	Trial 10
Latent demand	30.0	35.0	26.0	8.0	16.0	26.0	5.0	8.0	13.0	0.0
Total vehicle mile travelled	1871.1	1879.1	1882.6	1883.2	1882.3	1865.0	1901.4	1879.7	1881.9	1901.1
Total Stopped Delay, h	167.4	147.0	161.8	157.0	156.6	153.3	155.5	171.6	160.4	168.1
Average delay per vehicle, s	261.7	232.3	256.3	245.9	246.3	241.2	241.3	267.6	251.8	260.3
Vehicle in the network	530.0	515.0	510.0	532.0	535.0	556.0	493.0	551.0	520.0	529.0
Vehicle left	2789.0	2808.0	2814.0	2806.0	2800.0	2765.0	2847.0	2794.0	2814.0	2821.0
Total Travel time, h	387.0	361.2	383.0	374.5	373.8	367.8	372.0	395.8	380.2	389.6
Total vehicle Km travelled	3011.2	3024.2	3029.7	3030.8	3029.2	3001.4	3060.0	3025.1	3028.6	3059.6
Total vehicle in the network	3319.0	3323.0	3324.0	3338.0	3335.0	3321.0	3340.0	3345.0	3334.0	3350.0
Latent to total vehicle ratio	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Travel time (Min)per vehicle km	7.7	7.2	7.6	7.4	7.4	7.4	7.3	7.9	7.5	7.6
Average delay per vehicle, min	4.4	3.9	4.3	4.1	4.1	4.0	4.0	4.5	4.2	4.3

Performance	Table B20: 100% Eco-Driving									
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6	Trial 7	Trial 8	Trial 9	Trial 10
Latent demand	3.0	45.0	21.0	15.0	17.0	28.0	10.0	21.0	31.0	36.0
Total vehicle mile travelled	1873.3	1855.6	1877.1	1868.1	1855.5	1855.9	1879.0	1863.4	1852.8	1869.8
Total Stopped Delay, h	171.7	161.0	171.2	163.2	169.1	160.7	168.5	182.9	171.4	183.8
Average delay per vehicle, s	270.7	253.8	268.9	256.7	269.8	253.0	261.9	286.9	271.9	285.6
Vehicle in the network	570.0	548.0	532.0	554.0	583.0	571.0	544.0	566.0	561.0	554.0
Vehicle left	2775.0	2764.0	2798.0	2778.0	2749.0	2747.0	2793.0	2760.0	2753.0	2764.0
Total Travel time, h	397.5	378.4	394.6	382.9	393.2	377.7	389.3	410.9	395.2	408.2
Total vehicle Km travelled	3014.8	2986.2	3020.9	3006.4	2986.1	2986.8	3024.0	2998.8	2981.7	3009.1
Total vehicle in the network	3345.0	3312.0	3330.0	3332.0	3332.0	3318.0	3337.0	3326.0	3314.0	3318.0
Latent to total vehicle ratio	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Travel time (Min)per vehicle km	7.9	7.6	7.8	7.6	7.9	7.6	7.7	8.2	8.0	8.1
Average delay per vehicle, min	4.5	4.2	4.5	4.3	4.5	4.2	4.4	4.8	4.5	4.8

- **Speed profile 3 in low traffic volume (Table B21- Table B24)**

Performance	Table B21: 0% Eco-Driving									
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6	Trial 7	Trial 8	Trial 9	Trial 10
Latent demand	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Total vehicle mile travelled	1019.7	1019.2	1024.2	1020.1	1025.9	1017.8	1021.6	1025.4	1021.0	1029.0
Total Stopped Delay, h	20.9	20.9	22.1	20.8	21.7	21.2	20.7	21.5	21.0	22.1
Average delay per vehicle, s	60.9	60.6	63.5	60.9	62.6	62.7	59.8	62.0	61.0	64.4
Vehicle in the network	115.0	100.0	105.0	101.0	108.0	124.0	103.0	96.0	106.0	100.0
Vehicle left	1560.0	1575.0	1570.0	1574.0	1567.0	1551.0	1572.0	1579.0	1569.0	1575.0
Total Travel time, h	107.3	107.2	108.5	107.4	107.8	108.0	106.9	108.8	107.8	109.3
Total vehicle Km travelled	1641.1	1640.2	1648.3	1641.7	1651.1	1638.0	1644.1	1650.3	1643.1	1656.0
Total vehicle in the network	1675.0	1675.0	1675.0	1675.0	1675.0	1675.0	1675.0	1675.0	1675.0	1675.0
Latent to total vehicle ratio	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Travel time (Min)per vehicle km	3.9	3.9	4.0	3.9	3.9	4.0	3.9	4.0	3.9	4.0
Average delay per vehicle, min	1.0	1.0	1.1	1.0	1.0	1.0	1.0	1.0	1.0	1.1

Performance	Table B22: 20% Eco-Driving									
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6	Trial 7	Trial 8	Trial 9	Trial 10
Latent demand	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Total vehicle mile travelled	1020.1	1019.0	1024.5	1019.7	1026.0	1017.4	1021.9	1025.6	1020.5	1028.8
Total Stopped Delay, h	20.9	20.9	22.0	21.1	21.7	21.2	20.6	21.6	21.0	22.2
Average delay per vehicle, s	60.8	61.0	63.7	61.7	62.6	62.7	59.9	62.6	61.2	64.7
Vehicle in the network	115.0	102.0	103.0	102.0	107.0	123.0	102.0	96.0	105.0	103.0
Vehicle left	1560.0	1573.0	1572.0	1573.0	1568.0	1552.0	1573.0	1579.0	1570.0	1572.0
Total Travel time, h	107.3	107.4	108.6	107.8	107.8	108.0	106.9	109.1	107.9	109.5
Total vehicle Km travelled	1641.7	1640.0	1648.7	1641.0	1651.2	1637.4	1644.5	1650.5	1642.4	1655.8
Total vehicle in the network	1675.0	1675.0	1675.0	1675.0	1675.0	1675.0	1675.0	1675.0	1675.0	1675.0
Latent to total vehicle ratio	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Travel time (Min)per vehicle km	3.9	3.9	4.0	3.9	3.9	4.0	3.9	4.0	3.9	4.0
Average delay per vehicle, min	1.0	1.0	1.1	1.0	1.0	1.0	1.0	1.0	1.0	1.1

Performance	Table B23: 50% Eco-Driving									
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6	Trial 7	Trial 8	Trial 9	Trial 10
Latent demand	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Total vehicle mile travelled	1019.9	1018.9	1024.3	1019.7	1025.5	1018.1	1021.2	1026.1	1020.6	1029.4
Total Stopped Delay, h	21.1	21.1	22.3	21.2	21.8	21.3	20.8	21.5	21.1	22.5
Average delay per vehicle, s	61.3	61.7	64.5	62.3	63.4	63.3	60.6	62.5	61.6	65.3
Vehicle in the network	114.0	101.0	105.0	102.0	108.0	125.0	103.0	96.0	106.0	102.0
Vehicle left	1561.0	1574.0	1570.0	1573.0	1567.0	1550.0	1572.0	1579.0	1569.0	1573.0
Total Travel time, h	107.5	107.7	109.0	108.0	108.1	108.3	107.2	109.1	108.1	109.8
Total vehicle Km travelled	1641.4	1639.8	1648.5	1641.1	1650.4	1638.4	1643.4	1651.3	1642.6	1656.7
Total vehicle in the network	1675.0	1675.0	1675.0	1675.0	1675.0	1675.0	1675.0	1675.0	1675.0	1675.0
Latent to total vehicle ratio	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Travel time (Min)per vehicle km	3.9	3.9	4.0	3.9	3.9	4.0	3.9	4.0	3.9	4.0
Average delay per vehicle, min	1.0	1.0	1.1	1.0	1.1	1.1	1.0	1.0	1.0	1.1

Performance	Table B24: 100% Eco-Driving									
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6	Trial 7	Trial 8	Trial 9	Trial 10
Latent demand	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Total vehicle mile travelled	1019.9	1019.1	1024.6	1019.9	1025.3	1018.3	1020.6	1025.4	1021.0	1028.7
Total Stopped Delay, h	21.2	20.9	21.8	21.2	21.7	21.5	20.7	21.3	20.8	22.5
Average delay per vehicle, s	62.1	61.7	63.6	62.6	63.4	64.1	60.9	62.3	61.2	65.7
Vehicle in the network	114.0	104.0	94.0	101.0	108.0	124.0	102.0	96.0	105.0	103.0
Vehicle left	1561.0	1571.0	1581.0	1574.0	1567.0	1551.0	1573.0	1579.0	1570.0	1572.0
Total Travel time, h	107.8	107.8	108.6	108.2	108.1	108.6	107.3	109.0	107.9	109.9
Total vehicle Km travelled	1641.3	1640.1	1648.9	1641.4	1650.1	1638.8	1642.5	1650.2	1643.2	1655.5
Total vehicle in the network	1675.0	1675.0	1675.0	1675.0	1675.0	1675.0	1675.0	1675.0	1675.0	1675.0
Latent to total vehicle ratio	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Travel time (Min)per vehicle km	3.9	3.9	4.0	4.0	3.9	4.0	3.9	4.0	3.9	4.0
Average delay per vehicle, min	1.0	1.0	1.1	1.0	1.1	1.1	1.0	1.0	1.0	1.1

Experiment 2 (Table B29- Table B32)

- **Roundabout High traffic volume (Table B25- Table B28)**

Performance	Table B25: 0% Eco-Driving									
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6	Trial 7	Trial 8	Trial 9	Trial 10
Latent demand	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Total vehicle mile travelled	2089.0	2085.2	2083.8	2080.2	2081.1	2084.3	2077.0	2085.6	2086.7	2097.0
Total Stopped Delay, h	4.2	3.6	3.2	3.3	2.8	3.8	3.2	3.5	3.2	4.2
Average delay per vehicle, s	19.4	18.0	16.7	16.8	15.2	18.1	16.4	17.8	16.9	19.2
Vehicle in the network	151.0	146.0	134.0	159.0	150.0	171.0	156.0	140.0	166.0	140.0
Vehicle left	3199.0	3204.0	3216.0	3191.0	3200.0	3179.0	3194.0	3210.0	3184.0	3210.0
Total Travel time, h	157.7	156.4	154.6	154.5	152.7	156.2	154.1	156.3	155.3	157.7
Total vehicle Km travelled	3361.9	3355.8	3353.6	3347.8	3349.3	3354.3	3342.6	3356.5	3358.2	3374.7
Total vehicle in the network	3350.0	3350.0	3350.0	3350.0	3350.0	3350.0	3350.0	3350.0	3350.0	3350.0
Latent to total vehicle ratio	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Travel time (Min)per vehicle km	2.8	2.8	2.8	2.8	2.7	2.8	2.8	2.8	2.8	2.8
Average delay per vehicle, min	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3

Performance	Table B26: 20% Eco-Driving									
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6	Trial 7	Trial 8	Trial 9	Trial 10
Latent demand	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Total vehicle mile travelled	2088.3	2084.4	2083.7	2080.1	2080.7	2084.3	2076.9	2085.3	2086.5	2095.8
Total Stopped Delay, h	5.6	4.0	3.9	3.9	3.6	4.6	3.3	3.9	4.4	4.0
Average delay per vehicle, s	22.7	18.9	18.6	18.8	17.0	20.1	16.7	19.3	20.4	18.9
Vehicle in the network	159.0	152.0	138.0	160.0	153.0	170.0	157.0	141.0	166.0	141.0
Vehicle left	3191.0	3198.0	3212.0	3190.0	3197.0	3180.0	3193.0	3209.0	3184.0	3209.0
Total Travel time, h	160.7	157.2	156.4	156.3	154.5	158.1	154.5	157.6	158.6	157.3
Total vehicle Km travelled	3360.8	3354.5	3353.4	3347.7	3348.5	3354.3	3342.4	3355.9	3357.9	3372.8
Total vehicle in the network	3350.0	3350.0	3350.0	3350.0	3350.0	3350.0	3350.0	3350.0	3350.0	3350.0
Latent to total vehicle ratio	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Travel time (Min)per vehicle km	2.9	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8	2.8
Average delay per vehicle, min	0.4	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3

Performance	Table B27: 50% Eco-Driving									
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6	Trial 7	Trial 8	Trial 9	Trial 10
Latent demand	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Total vehicle mile travelled	2084.1	2083.8	2083.8	2079.9	2080.2	2083.9	2076.7	2085.1	2086.8	2096.8
Total Stopped Delay, h	5.7	4.6	5.6	4.2	3.8	5.4	4.4	4.9	5.5	4.8
Average delay per vehicle, s	23.8	21.1	22.8	19.2	18.4	23.5	20.0	22.1	23.5	21.7
Vehicle in the network	175.0	150.0	137.0	161.0	158.0	172.0	155.0	143.0	166.0	139.0
Vehicle left	3175.0	3200.0	3213.0	3189.0	3192.0	3178.0	3195.0	3207.0	3184.0	3211.0
Total Travel time, h	161.4	159.2	160.2	156.7	155.7	161.2	157.5	160.2	161.4	160.0
Total vehicle Km travelled	3354.1	3353.6	3353.5	3347.3	3347.7	3353.7	3342.2	3355.7	3358.4	3374.5
Total vehicle in the network	3350.0	3350.0	3350.0	3350.0	3350.0	3350.0	3350.0	3350.0	3350.0	3350.0
Latent to total vehicle ratio	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Travel time (Min)per vehicle km	2.9	2.8	2.9	2.8	2.8	2.9	2.8	2.9	2.9	2.8
Average delay per vehicle, min	0.4	0.4	0.4	0.3	0.3	0.4	0.3	0.4	0.4	0.4

Performance	Table B28: 100% Eco-Driving									
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6	Trial 7	Trial 8	Trial 9	Trial 10
Latent demand	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Total vehicle mile travelled	2083.7	2084.1	2083.7	2079.0	2079.5	2083.1	2076.0	2084.7	2086.1	2095.4
Total Stopped Delay, h	7.0	6.5	8.7	5.2	4.4	8.3	7.8	6.0	7.0	9.5
Average delay per vehicle, s	29.0	25.8	32.9	22.5	20.5	30.8	29.2	25.2	28.4	36.4
Vehicle in the network	170.0	152.0	135.0	165.0	158.0	175.0	160.0	144.0	169.0	146.0
Vehicle left	3180.0	3198.0	3215.0	3185.0	3192.0	3175.0	3190.0	3206.0	3181.0	3204.0
Total Travel time, h	166.3	163.5	169.6	159.6	157.5	167.9	165.9	163.1	165.9	173.5
Total vehicle Km travelled	3353.3	3354.0	3353.3	3345.8	3346.6	3352.5	3341.0	3354.9	3357.2	3372.2
Total vehicle in the network	3350.0	3350.0	3350.0	3350.0	3350.0	3350.0	3350.0	3350.0	3350.0	3350.0
Latent to total vehicle ratio	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Travel time (Min)per vehicle km	3.0	2.9	3.0	2.9	2.8	3.0	3.0	2.9	3.0	3.1
Average delay per vehicle, min	0.5	0.4	0.5	0.4	0.3	0.5	0.5	0.4	0.5	0.6

- **Roundabout Low traffic volume (Table B29- Table B32)**

Performance	Table B29: 0% Eco-Driving									
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6	Trial 7	Trial 8	Trial 9	Trial 10
Latent demand	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Total vehicle mile travelled	1043.6	1044.7	1043.6	1046.3	1045.0	1046.3	1045.1	1049.3	1051.7	1047.6
Total Stopped Delay, h	0.2	0.2	0.2	0.2	0.2	0.2	0.1	0.2	0.2	0.2
Average delay per vehicle, s	4.0	3.8	3.8	4.3	4.2	4.4	3.9	4.3	4.5	4.2
Vehicle in the network	77.0	67.0	62.0	72.0	65.0	81.0	73.0	66.0	75.0	67.0
Vehicle left	1598.0	1608.0	1613.0	1603.0	1610.0	1594.0	1602.0	1609.0	1600.0	1608.0
Total Travel time, h	71.1	71.1	70.8	71.3	70.8	71.3	70.9	71.8	71.9	71.2
Total vehicle Km travelled	1679.4	1681.3	1679.5	1683.8	1681.8	1683.9	1681.9	1688.6	1692.6	1685.9
Total vehicle in the network	1675.0	1675.0	1675.0	1675.0	1675.0	1675.0	1675.0	1675.0	1675.0	1675.0
Latent to total vehicle ratio	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Travel time (Min)per vehicle km	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.6	2.5	2.5
Average delay per vehicle, min	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1

Performance	Table B30: 20% Eco-Driving									
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6	Trial 7	Trial 8	Trial 9	Trial 10
Latent demand	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Total vehicle mile travelled	1043.4	1044.6	1043.6	1046.2	1045.0	1046.3	1045.1	1049.3	1051.8	1047.5
Total Stopped Delay, h	0.2	0.2	0.2	0.2	0.2	0.2	0.1	0.2	0.2	0.2
Average delay per vehicle, s	4.0	4.0	4.0	4.3	4.4	4.4	3.9	4.5	4.5	4.5
Vehicle in the network	78.0	67.0	62.0	72.0	67.0	81.0	73.0	66.0	75.0	65.0
Vehicle left	1597.0	1608.0	1613.0	1603.0	1608.0	1594.0	1602.0	1609.0	1600.0	1610.0
Total Travel time, h	71.1	71.2	70.8	71.3	70.9	71.3	70.9	71.8	71.9	71.3
Total vehicle Km travelled	1679.1	1681.1	1679.5	1683.8	1681.7	1683.8	1681.8	1688.6	1692.7	1685.7
Total vehicle in the network	1675.0	1675.0	1675.0	1675.0	1675.0	1675.0	1675.0	1675.0	1675.0	1675.0
Latent to total vehicle ratio	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Travel time (Min)per vehicle km	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.6	2.5	2.5
Average delay per vehicle, min	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1

Performance	Table B31: 50% Eco-Driving									
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6	Trial 7	Trial 8	Trial 9	Trial 10
Latent demand	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Total vehicle mile travelled	1043.3	1044.7	1043.6	1046.3	1045.0	1046.5	1045.1	1049.0	1051.8	1047.5
Total Stopped Delay, h	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2
Average delay per vehicle, s	4.1	4.1	4.1	4.4	4.4	4.4	4.0	4.4	4.6	4.4
Vehicle in the network	77.0	66.0	62.0	72.0	65.0	78.0	73.0	69.0	75.0	65.0
Vehicle left	1598.0	1609.0	1613.0	1603.0	1610.0	1597.0	1602.0	1606.0	1600.0	1610.0
Total Travel time, h	71.1	71.2	70.9	71.3	70.9	71.3	71.0	71.8	72.0	71.3
Total vehicle Km travelled	1679.1	1681.3	1679.5	1683.8	1681.8	1684.1	1681.9	1688.2	1692.7	1685.7
Total vehicle in the network	1675.0	1675.0	1675.0	1675.0	1675.0	1675.0	1675.0	1675.0	1675.0	1675.0
Latent to total vehicle ratio	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Travel time (Min)per vehicle km	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.6	2.6	2.5
Average delay per vehicle, min	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1

Performance	Table B32: 100% Eco-Driving									
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6	Trial 7	Trial 8	Trial 9	Trial 10
Latent demand	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Total vehicle mile travelled	1043.3	1044.8	1043.6	1046.3	1045.0	1046.1	1045.1	1048.9	1051.8	1047.5
Total Stopped Delay, h	0.2	0.2	0.2	0.2	0.2	0.2	0.1	0.2	0.2	0.2
Average delay per vehicle, s	4.2	4.3	4.4	4.6	4.6	4.7	4.1	4.7	4.7	4.7
Vehicle in the network	78.0	67.0	62.0	72.0	65.0	80.0	73.0	66.0	75.0	65.0
Vehicle left	1597.0	1608.0	1613.0	1603.0	1610.0	1595.0	1602.0	1609.0	1600.0	1610.0
Total Travel time, h	71.1	71.4	71.0	71.4	71.0	71.4	71.0	71.9	72.0	71.4
Total vehicle Km travelled	1679.1	1681.5	1679.5	1683.8	1681.8	1683.5	1681.8	1688.0	1692.7	1685.7
Total vehicle in the network	1675.0	1675.0	1675.0	1675.0	1675.0	1675.0	1675.0	1675.0	1675.0	1675.0
Latent to total vehicle ratio	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Travel time (Min)per vehicle km	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.6	2.6	2.5
Average delay per vehicle, min	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1

Experiment 3 (Table B33- Table B40)

- **ECO-I (Table B33- Table B36)**

Performance	Table B33: 0% Eco-Driving									
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6	Trial 7	Trial 8	Trial 9	Trial 10
Latent demand	907	1201	849	1259	1533	1072	1103	1134	1248	1161
Total vehicle mile travelled	2590	2453	2675	2389	2184	2451	2443	2436	2400	2401
Total Stopped Delay, h	507	605	528	606	667	585	571	557	635	608
Average delay per vehicle, s	431	510	442	517	577	498	486	474	543	528
Vehicle in the network	1265	1340	1338	1356	1305	1351	1312	1273	1352	1361
Vehicle left	3865	3636	3966	3528	3325	3652	3662	3672	3574	3533
Total Travel time, h	788	869	832	863	889	857	836	816	904	879
Total vehicle Km travelled	4168	3948	4305	3845	3515	3944	3932	3920	3863	3863
Total vehicle in the network	5130	4976	5304	4884	4630	5003	4974	4945	4926	4894
Latent to total vehicle ratio	0	0	0	0	0	0	0	0	0	0
Travel time (Min)per vehicle km	11	13	12	13	15	13	13	12	14	14
Average delay per vehicle, min	7	8	7	9	10	8	8	8	9	9

Performance	Table B34: 20% Eco-Driving									
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6	Trial 7	Trial 8	Trial 9	Trial 10
Latent demand	809	985	813	1101	1453	1198	1069	940	1303	1509
Total vehicle mile travelled	2621	2626	2669	2464	2251	2366	2461	2555	2360	2161
Total Stopped Delay, h	497	558	520	598	643	594	565	536	640	680
Average delay per vehicle, s	418	471	432	504	558	516	481	445	546	604
Vehicle in the network	1307	1326	1326	1359	1263	1339	1334	1329	1323	1326
Vehicle left	3915	3877	4008	3655	3445	3535	3672	3809	3525	3212
Total Travel time, h	782	857	819	868	881	858	833	808	893	906
Total vehicle Km travelled	4219	4226	4295	3966	3622	3808	3960	4112	3798	3479
Total vehicle in the network	5222	5203	5334	5014	4708	4874	5006	5138	4848	4538
Latent to total vehicle ratio	0	0	0	0	0	0	0	0	0	0
Travel time (Min)per vehicle km	11	12	11	13	15	14	13	12	14	16
Average delay per vehicle, min	7	8	7	8	9	9	8	7	9	10

Performance	Table B35: 50% Eco-Driving									
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6	Trial 7	Trial 8	Trial 9	Trial 10
Latent demand	926	1254	813	952	1291	1012	954	895	1190	1297
Total vehicle mile travelled	2509	2418	2686	2560	2328	2494	2536	2577	2432	2319
Total Stopped Delay, h	537	612	541	570	657	588	558	527	643	649
Average delay per vehicle, s	455	525	452	482	563	497	469	440	547	574
Vehicle in the network	1345	1355	1375	1373	1368	1368	1356	1344	1357	1373
Vehicle left	3740	3567	3957	3795	3489	3706	3774	3841	3612	3389
Total Travel time, h	811	880	850	865	916	869	838	807	918	915
Total vehicle Km travelled	4037	3892	4323	4119	3747	4014	4081	4147	3913	3732
Total vehicle in the network	5085	4922	5332	5168	4857	5074	5130	5185	4969	4762
Latent to total vehicle ratio	0	0	0	0	0	0	0	0	0	0
Travel time (Min)per vehicle km	12	14	12	13	15	13	12	12	14	15
Average delay per vehicle, min	8	9	8	8	9	8	8	7	9	10

Performance	Table B36: 100% Eco-Driving									
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6	Trial 7	Trial 8	Trial 9	Trial 10
Latent demand	841	1459	1418	1012	1404	1148	1012	876	1369	1312
Total vehicle mile travelled	2581	2274	2273	2507	2253	2439	2539	2640	2331	2301
Total Stopped Delay, h	556	650	632	609	675	603	567	532	628	633
Average delay per vehicle, s	463	565	541	510	596	530	489	447	554	564
Vehicle in the network	1398	1350	1311	1424	1385	1362	1342	1322	1329	1392
Vehicle left	3789	3362	3425	3683	3353	3578	3726	3873	3467	3355
Total Travel time, h	841	893	864	893	936	891	858	824	894	898
Total vehicle Km travelled	4154	3660	3658	4035	3627	3925	4087	4249	3752	3703
Total vehicle in the network	5187	4712	4736	5107	4738	4940	5068	5195	4796	4747
Latent to total vehicle ratio	0	0	0	0	0	0	0	0	0	0
Travel time (Min)per vehicle km	12	15	14	13	15	14	13	12	14	15
Average delay per vehicle, min	8	9	9	9	10	9	8	7	9	9

- **ECO-II (Table B37- Table B40)**

Performance	Table B37: 0% Eco-Driving									
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6	Trial 7	Trial 8	Trial 9	Trial 10
Latent demand	907	1201	849	1259	1533	1490	1447	1134	1248	1161
Total vehicle mile travelled	2590	2453	2675	2389	2184	2210	2236	2436	2400	2401
Total Stopped Delay, h	507	605	528	606	667	669	671	557	635	608
Average delay per vehicle, s	431	510	442	517	577	582	587	474	543	528
Vehicle in the network	1265	1340	1338	1356	1305	1342	1378	1273	1352	1361
Vehicle left	3865	3636	3966	3528	3325	3326	3327	3672	3574	3533
Total Travel time, h	788	869	832	863	889	903	917	816	904	879
Total vehicle Km travelled	4168	3948	4305	3845	3515	3557	3598	3920	3863	3863
Total vehicle in the network	5130	4976	5304	4884	4630	4668	4705	4945	4926	4894
Latent to total vehicle ratio	0	0	0	0	0	0	0	0	0	0
Travel time (Min)per vehicle km	11	13	12	13	15	15	15	12	14	14
Average delay per vehicle, min	7	8	7	9	10	10	10	8	9	9

Performance	Table B38: 20% Eco-Driving									
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6	Trial 7	Trial 8	Trial 9	Trial 10
Latent demand	886	980	1073	1166	1365	1440	1515	911	1273	1351
Total vehicle mile travelled	2573	2622	2536	2434	2291	2247	2204	2610	2395	2295
Total Stopped Delay, h	501	556	574	584	682	684	686	501	641	653
Average delay per vehicle, s	422	470	491	496	583	594	604	415	541	580
Vehicle in the network	1263	1327	1296	1327	1380	1373	1366	1292	1330	1359
Vehicle left	3862	3870	3779	3624	3422	3348	3274	3899	3555	3350
Total Travel time, h	771	851	860	843	928	926	924	772	892	909
Total vehicle Km travelled	4141	4219	4081	3918	3687	3617	3546	4201	3854	3694
Total vehicle in the network	5125	5197	5075	4951	4802	4721	4640	5191	4885	4709
Latent to total vehicle ratio	0	0	0	0	0	0	0	0	0	0
Travel time (Min)per vehicle km	11	12	13	13	15	15	16	11	14	15
Average delay per vehicle, min	7	8	8	8	10	10	10	7	9	10

Performance	Table B39: 50% Eco-Driving									
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6	Trial 7	Trial 8	Trial 9	Trial 10
Latent demand	702	1200	689	1314	1426	1421	1415	755	1177	1366
Total vehicle mile travelled	2720	2414	2784	2319	2255	2263	2270	2713	2487	2245
Total Stopped Delay, h	482	610	496	620	650	669	689	467	603	650
Average delay per vehicle, s	400	514	402	529	556	583	610	386	515	574
Vehicle in the network	1338	1372	1321	1322	1310	1367	1423	1329	1330	1378
Vehicle left	4009	3590	4142	3487	3435	3371	3307	4020	3660	3311
Total Travel time, h	767	862	788	855	877	912	946	748	872	891
Total vehicle Km travelled	4377	3885	4481	3732	3629	3641	3654	4366	4003	3613
Total vehicle in the network	5347	4962	5463	4809	4745	4738	4730	5349	4990	4689
Latent to total vehicle ratio	0	0	0	0	0	0	0	0	0	0
Travel time (Min)per vehicle km	11	13	11	14	14	15	16	10	13	15
Average delay per vehicle, min	7	9	7	9	9	10	10	6	9	10

Performance	Table B40: 100% Eco-Driving									
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6	Trial 7	Trial 8	Trial 9	Trial 10
Latent demand	631	770	872	903	1151	1106	1061	704	1283	1153
Total vehicle mile travelled	2747	2740	2629	2678	2481	2501	2521	2729	2385	2399
Total Stopped Delay, h	455	487	534	531	621	606	591	472	618	603
Average delay per vehicle, s	371	393	431	445	505	503	500	387	524	521
Vehicle in the network	1293	1338	1335	1320	1371	1354	1336	1334	1302	1345
Vehicle left	4128	4088	3946	3908	3668	3717	3765	4036	3566	3534
Total Travel time, h	724	757	791	807	857	859	860	742	852	850
Total vehicle Km travelled	4420	4410	4230	4310	3993	4025	4058	4392	3839	3861
Total vehicle in the network	5421	5426	5281	5228	5039	5070	5101	5370	4868	4879
Latent to total vehicle ratio	0	0	0	0	0	0	0	0	0	0
Travel time (Min)per vehicle km	10	10	11	11	13	13	13	10	13	13
Average delay per vehicle, min	6	7	7	7	8	8	8	6	9	9

Experiment 4 (Table B41- Table B64)

- **Single profile – Average peak traffic (Table B41- Table B44)**

Performance	Table B41: 0% Eco-Driving									
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6	Trial 7	Trial 8	Trial 9	Trial 10
Latent demand	59	163	68	162	127	157	294	45	85	133
Total vehicle mile travelled	2753	2690	2772	2721	2670	2649	2630	2817	2750	2680
Total Stopped Delay, h	140	200	167	201	208	216	234	132	185	193
Average delay per vehicle, s	164	215	190	218	225	231	243	156	206	216
Vehicle in the network	604	739	628	731	700	718	713	588	665	679
Vehicle left	4213	4090	4262	4080	4094	4026	3965	4250	4191	4104
Total Travel time, h	416	480	456	487	489	495	504	413	475	479
Total vehicle Km travelled	4431	4328	4460	4379	4297	4263	4233	4533	4426	4313
Total vehicle in the network	4817	4829	4890	4811	4794	4744	4678	4838	4856	4783
Latent to total vehicle ratio	0	0	0	0	0	0	0	0	0	0
Travel time (Min)per vehicle km	6	7	6	7	7	7	7	5	6	7
Average delay per vehicle, min	3	4	3	4	4	4	4	3	3	4

Performance	Table B42: 20% Eco-Driving									
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6	Trial 7	Trial 8	Trial 9	Trial 10
Latent demand	61	81	111	81	121	330	161	50	85	155
Total vehicle mile travelled	2796	2762	2739	2749	2647	2560	2694	2814	2788	2676
Total Stopped Delay, h	134	174	167	179	214	240	227	134	168	198
Average delay per vehicle, s	161	189	191	196	234	255	241	160	189	224
Vehicle in the network	548	700	608	721	725	700	685	555	610	688
Vehicle left	4268	4226	4237	4166	4075	3884	4139	4277	4249	4079
Total Travel time, h	410	450	447	457	494	502	509	412	448	482
Total vehicle Km travelled	4499	4445	4408	4424	4260	4120	4336	4528	4487	4306
Total vehicle in the network	4816	4926	4845	4887	4800	4584	4824	4832	4859	4767
Latent to total vehicle ratio	0	0	0	0	0	0	0	0	0	0
Travel time (Min)per vehicle km	5	6	6	6	7	7	7	5	6	7
Average delay per vehicle, min	3	3	3	3	4	4	4	3	3	4

Performance	Table B43: 50% Eco-Driving									
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6	Trial 7	Trial 8	Trial 9	Trial 10
Latent demand	45	114	90	60	112	201	138	51	69	119
Total vehicle mile travelled	2812	2750	2752	2771	2724	2607	2666	2799	2800	2702
Total Stopped Delay, h	129	176	170	166	188	221	210	139	166	175
Average delay per vehicle, s	153	189	195	185	210	233	219	165	188	198
Vehicle in the network	521	662	594	665	663	715	667	554	614	649
Vehicle left	4311	4228	4280	4238	4155	3993	4170	4279	4259	4159
Total Travel time, h	390	437	444	434	459	476	469	405	437	440
Total vehicle Km travelled	4526	4425	4429	4460	4384	4196	4291	4504	4506	4348
Total vehicle in the network	4832	4890	4874	4903	4818	4708	4837	4833	4873	4808
Latent to total vehicle ratio	0	0	0	0	0	0	0	0	0	0
Travel time (Min)per vehicle km	5	6	6	6	6	7	7	5	6	6
Average delay per vehicle, min	3	3	3	3	3	4	4	3	3	3

Performance	Table B44: 100% Eco-Driving									
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6	Trial 7	Trial 8	Trial 9	Trial 10
Latent demand	21	31	14	41	41	152	126	22	20	65
Total vehicle mile travelled	2860	2897	2898	2884	2859	2712	2797	2912	2920	2817
Total Stopped Delay, h	118	146	141	162	168	200	195	121	138	157
Average delay per vehicle, s	138	155	163	175	188	208	206	139	154	178
Vehicle in the network	480	610	544	628	590	672	621	482	504	585
Vehicle left	4375	4363	4400	4297	4295	4079	4233	4384	4417	4272
Total Travel time, h	358	389	399	413	427	438	446	363	386	409
Total vehicle Km travelled	4602	4663	4663	4641	4601	4365	4501	4686	4699	4534
Total vehicle in the network	4855	4973	4944	4925	4885	4751	4854	4866	4921	4857
Latent to total vehicle ratio	0	0	0	0	0	0	0	0	0	0
Travel time (Min)per vehicle km	5	5	5	5	6	6	6	5	5	5
Average delay per vehicle, min	2	3	3	3	3	3	3	2	3	3

- **Single profile – 20% less of average peak traffic (Table B45- Table B48)**

Performance	Table B45: 0% Eco-Driving									
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6	Trial 7	Trial 8	Trial 9	Trial 10
Latent demand	0	0	0	0	0	0	0	0	0	2
Total vehicle mile travelled	2312	2405	2427	2366	2371	2359	2435	2379	2420	2375
Total Stopped Delay, h	73	68	63	80	80	75	77	63	74	76
Average delay per vehicle, s	106	99	92	115	117	109	110	92	108	110
Vehicle in the network	349	343	306	343	323	361	339	333	312	335
Vehicle left	3523	3591	3655	3585	3594	3550	3638	3557	3611	3558
Total Travel time, h	280	282	276	296	296	288	296	269	291	289
Total vehicle Km travelled	3720	3870	3906	3808	3816	3796	3919	3828	3895	3823
Total vehicle in the network	3872	3934	3961	3928	3917	3911	3977	3890	3923	3893
Latent to total vehicle ratio	0	0	0	0	0	0	0	0	0	0
Travel time (Min)per vehicle km	5	4	4	5	5	5	5	4	4	5
Average delay per vehicle, min	2	2	2	2	2	2	2	2	2	2

Performance	Table B46: 20% Eco-Driving									
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6	Trial 7	Trial 8	Trial 9	Trial 10
Latent demand		23		4						
Total vehicle mile travelled	2406	2429	2456	2463	2412	2431	2462	2425	2472	2415
Total Stopped Delay, h	75	76	78	80	86	81	97	78	86	82
Average delay per vehicle, s	105	105	108	110	121	114	130	111	119	118
Vehicle in the network	354	340	343	353	303	377	381	362	295	342
Vehicle left	3647	3724	3736	3718	3732	3674	3734	3669	3758	3689
Total Travel time, h	284	287	294	297	302	297	319	292	305	299
Total vehicle Km travelled	3872	3908	3952	3963	3881	3913	3962	3903	3979	3886
Total vehicle in the network	4001	4064	4079	4071	4035	4051	4115	4031	4053	4031
Latent to total vehicle ratio	0	0	0	0	0	0	0	0	0	0
Travel time (Min)per vehicle km	4	4	4	4	5	5	5	4	5	5
Average delay per vehicle, min	2	2	2	2	2	2	2	2	2	2

Performance	Table B47: 50% Eco-Driving									
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6	Trial 7	Trial 8	Trial 9	Trial 10
Latent demand										
Total vehicle mile travelled	2340	2396	2422	2377	2398	2384	2440	2339	2396	2370
Total Stopped Delay, h	67	64	66	73	72	73	75	65	69	73
Average delay per vehicle, s	98	92	95	104	105	105	105	95	98	107
Vehicle in the network	324	301	296	310	287	326	305	307	268	308
Vehicle left	3548	3633	3665	3618	3630	3585	3672	3583	3655	3591
Total Travel time, h	259	258	264	270	272	271	275	256	264	270
Total vehicle Km travelled	3767	3856	3898	3825	3859	3837	3927	3764	3856	3814
Total vehicle in the network	3872	3934	3961	3928	3917	3911	3977	3890	3923	3899
Latent to total vehicle ratio	0	0	0	0	0	0	0	0	0	0
Travel time (Min)per vehicle km	4	4	4	4	4	4	4	4	4	4
Average delay per vehicle, min	2	2	2	2	2	2	2	2	2	2

Performance	Table B48: 100% Eco-Driving									
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6	Trial 7	Trial 8	Trial 9	Trial 10
Latent demand	0	0	0	0	0	0	0	0	0	0
Total vehicle mile travelled	2441	2525	2495	2515	2504	2529	2526	2466	2515	2483
Total Stopped Delay, h	70	63	70	65	73	74	78	66	70	73
Average delay per vehicle, s	97	86	95	89	100	102	106	91	95	101
Vehicle in the network	304	284	286	269	274	307	309	307	247	273
Vehicle left	3568	3650	3675	3659	3643	3604	3668	3583	3676	3626
Total Travel time, h	251	246	255	249	259	263	269	247	255	259
Total vehicle Km travelled	3928	4063	4015	4048	4030	4070	4065	3969	4048	3995
Total vehicle in the network	3872	3934	3961	3928	3917	3911	3977	3890	3923	3899
Latent to total vehicle ratio	0	0	0	0	0	0	0	0	0	0
Travel time (Min)per vehicle km	4	4	4	4	4	4	4	4	4	4
Average delay per vehicle, min	2	1	2	1	2	2	2	2	2	2

- **Single profile – 20% more of average peak traffic (Table B49- Table B52)**

Performance	Table B49: 0% Eco-Driving									
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6	Trial 7	Trial 8	Trial 9	Trial 10
Latent demand	459	618	652	717	719	796	755	591	630	891
Total vehicle mile travelled	2988	2971	2896	2909	2829	2830	2839	2909	2928	2754
Total Stopped Delay, h	244	292	290	296	329	321	325	268	298	320
Average delay per vehicle, s	249	288	301	297	325	318	327	270	300	318
Vehicle in the network	815	804	811	809	869	807	794	814	813	798
Vehicle left	4569	4562	4462	4476	4346	4364	4407	4481	4485	4250
Total Travel time, h	586	642	647	644	673	660	674	606	650	642
Total vehicle Km travelled	4809	4782	4661	4682	4552	4554	4569	4682	4712	4432
Total vehicle in the network	5384	5366	5273	5285	5215	5171	5201	5295	5298	5048
Latent to total vehicle ratio	0	0	0	0	0	0	0	0	0	0
Travel time (Min)per vehicle km	7	8	8	8	9	9	9	8	8	9
Average delay per vehicle, min	4	5	5	5	5	5	5	5	5	5

Performance	Table B50: 20% Eco-Driving									
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6	Trial 7	Trial 8	Trial 9	Trial 10
Latent demand	655	629	672	663	854	955	803	555	699	893
Total vehicle mile travelled	2841	2960	2881	2931	2742	2665	2816	2942	2893	2761
Total Stopped Delay, h	262	292	294	289	340	358	335	267	301	314
Average delay per vehicle, s	271	288	305	286	338	352	337	272	301	318
Vehicle in the network	774	805	793	806	842	896	793	815	803	777
Vehicle left	4409	4551	4464	4537	4238	4109	4357	4517	4440	4266
Total Travel time, h	587	633	644	628	666	673	675	606	638	636
Total vehicle Km travelled	4572	4763	4637	4718	4412	4289	4532	4734	4655	4444
Total vehicle in the network	5183	5356	5257	5343	5080	5005	5150	5332	5243	5043
Latent to total vehicle ratio	0	0	0	0	0	0	0	0	0	0
Travel time (Min)per vehicle km	8	8	8	8	9	9	9	8	8	9
Average delay per vehicle, min	5	5	5	5	6	6	6	5	5	5

Performance	Table B51: 50% Eco-Driving									
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6	Trial 7	Trial 8	Trial 9	Trial 10
Latent demand	572	601	706	848	718	892	672	548	633	840
Total vehicle mile travelled	2899	2960	2849	2827	2835	2775	2917	2948	2962	2769
Total Stopped Delay, h	257	282	285	307	314	327	306	253	289	311
Average delay per vehicle, s	263	279	297	303	316	318	308	260	295	311
Vehicle in the network	805	798	783	806	822	787	803	777	801	777
Vehicle left	4469	4594	4441	4343	4392	4279	4487	4564	4493	4325
Total Travel time, h	575	611	618	618	644	630	642	580	628	623
Total vehicle Km travelled	4666	4763	4585	4549	4563	4466	4694	4745	4767	4456
Total vehicle in the network	5274	5392	5224	5149	5214	5066	5290	5341	5294	5102
Latent to total vehicle ratio	0	0	0	0	0	0	0	0	0	0
Travel time (Min)per vehicle km	7	8	8	8	8	8	8	7	8	8
Average delay per vehicle, min	4	5	5	5	5	5	5	4	5	5

Performance	Table B52: 100% Eco-Driving									
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6	Trial 7	Trial 8	Trial 9	Trial 10
Latent demand	449	529	541	580	594	630	684	415	573	813
Total vehicle mile travelled	3069	3074	3048	3063	2972	2947	2954	3101	3020	2830
Total Stopped Delay, h	230	257	261	264	283	283	303	231	272	302
Average delay per vehicle, s	236	250	275	262	284	278	299	233	274	297
Vehicle in the network	736	745	736	753	771	751	746	721	747	746
Vehicle left	4671	4711	4643	4666	4577	4566	4541	4751	4610	4374
Total Travel time, h	539	564	594	578	601	587	617	541	589	592
Total vehicle Km travelled	4938	4948	4905	4929	4782	4743	4755	4990	4861	4554
Total vehicle in the network	5407	5456	5379	5419	5348	5317	5287	5472	5357	5120
Latent to total vehicle ratio	0	0	0	0	0	0	0	0	0	0
Travel time (Min)per vehicle km	7	7	7	7	8	7	8	7	7	8
Average delay per vehicle, min	4	4	5	4	5	5	5	4	5	5

- **Three speed profile – Average peak traffic (Table B53- Table B56)**

Performance	Table B53: 0% Eco-Driving									
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6	Trial 7	Trial 8	Trial 9	Trial 10
Latent demand	41	74	71	57	60	162	101	14	42	63
Total vehicle mile travelled	2848	2823	2815	2820	2800	2730	2763	2904	2839	2822
Total Stopped Delay, h	127	163	159	164	171	184	194	118	157	149
Average delay per vehicle, s	144	170	173	175	182	192	200	136	166	167
Vehicle in the network	542	635	574	635	619	607	634	516	598	589
Vehicle left	4295	4300	4312	4272	4243	4138	4242	4358	4288	4276
Total Travel time, h	384	422	423	427	433	435	455	379	415	414
Total vehicle Km travelled	4583	4544	4530	4539	4506	4393	4447	4674	4569	4542
Total vehicle in the network	4837	4935	4886	4907	4862	4745	4876	4874	4886	4865
Latent to total vehicle ratio	0	0	0	0	0	0	0	0	0	0
Travel time (Min)per vehicle km	5	6	6	6	6	6	6	5	5	5
Average delay per vehicle, min	2	3	3	3	3	3	3	2	3	3

Performance	Table B54: 20% Eco-Driving									
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6	Trial 7	Trial 8	Trial 9	Trial 10
Latent demand	38	51	49	65	83	93	117	20	48	71
Total vehicle mile travelled	2820	2870	2839	2843	2805	2777	2792	2907	2844	2764
Total Stopped Delay, h	128	150	151	164	171	184	201	115	152	169
Average delay per vehicle, s	144	158	165	175	187	196	211	136	165	186
Vehicle in the network	549	622	600	613	602	638	641	488	567	654
Vehicle left	4287	4329	4310	4286	4243	4174	4220	4380	4319	4198
Total Travel time, h	378	404	411	425	435	444	468	374	410	431
Total vehicle Km travelled	4538	4619	4569	4575	4514	4469	4494	4679	4577	4448
Total vehicle in the network	4836	4951	4910	4899	4845	4812	4861	4868	4886	4852
Latent to total vehicle ratio	0	0	0	0	0	0	0	0	0	0
Travel time (Min)per vehicle km	5	5	5	6	6	6	6	5	5	6
Average delay per vehicle, min	2	3	3	3	3	3	4	2	3	3

Performance	Table B55: 50% Eco-Driving									
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6	Trial 7	Trial 8	Trial 9	Trial 10
Latent demand	19	56	113	64	54	122	149	35	50	83
Total vehicle mile travelled	2858	2820	2763	2815	2822	2725	2769	2879	2842	2786
Total Stopped Delay, h	121	162	168	166	160	190	202	125	158	161
Average delay per vehicle, s	140	174	180	180	174	201	211	143	174	181
Vehicle in the network	510	651	589	645	578	640	626	531	563	594
Vehicle left	4349	4295	4247	4256	4293	4139	4208	4320	4320	4246
Total Travel time, h	370	417	417	423	414	440	458	376	416	419
Total vehicle Km travelled	4600	4538	4447	4530	4542	4385	4456	4633	4573	4483
Total vehicle in the network	4859	4946	4836	4901	4871	4779	4834	4851	4883	4840
Latent to total vehicle ratio	0	0	0	0	0	0	0	0	0	0
Travel time (Min)per vehicle km	5	6	6	6	5	6	6	5	5	6
Average delay per vehicle, min	2	3	3	3	3	3	4	2	3	3

Performance	Table B56: 100% Eco-Driving									
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6	Trial 7	Trial 8	Trial 9	Trial 10
Latent demand	21	31	14	41	41	152	126	22	20	65
Total vehicle mile travelled	2860	2897	2898	2884	2859	2712	2797	2912	2920	2817
Total Stopped Delay, h	118	146	141	162	168	200	195	121	138	157
Average delay per vehicle, s	138	155	163	175	188	208	206	139	154	178
Vehicle in the network	480	610	544	628	590	672	621	482	504	585
Vehicle left	4375	4363	4400	4297	4295	4079	4233	4384	4417	4272
Total Travel time, h	358	389	399	413	427	438	446	363	386	409
Total vehicle Km travelled	4602	4663	4663	4641	4601	4365	4501	4686	4699	4534
Total vehicle in the network	4855	4973	4944	4925	4885	4751	4854	4866	4921	4857
Latent to total vehicle ratio	0	0	0	0	0	0	0	0	0	0
Travel time (Min)per vehicle km	5	5	5	5	6	6	6	5	5	5
Average delay per vehicle, min	2	3	3	3	3	3	3	2	3	3

- **Three speed profile – 20% less of average peak traffic (Table B57- Table B60)**

Performance	Table B57: 0% Eco-Driving									
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6	Trial 7	Trial 8	Trial 9	Trial 10
Latent demand	0	0	0	0	0	0	0	0	0	0
Total vehicle mile travelled	2372	2470	2450	2466	2420	2438	2466	2430	2469	2429
Total Stopped Delay, h	62	65	69	67	66	66	72	61	67	69
Average delay per vehicle, s	86	88	94	91	92	92	98	84	92	95
Vehicle in the network	315	291	294	291	263	310	322	311	263	309
Vehicle left	3557	3643	3667	3637	3654	3601	3655	3579	3660	3590
Total Travel time, h	251	261	267	265	261	263	273	254	265	265
Total vehicle Km travelled	3818	3975	3943	3969	3895	3924	3969	3910	3973	3909
Total vehicle in the network	3872	3934	3961	3928	3917	3911	3977	3890	3923	3899
Latent to total vehicle ratio	0	0	0	0	0	0	0	0	0	0
Travel time (Min)per vehicle km	4	4	4	4	4	4	4	4	4	4
Average delay per vehicle, min	1	1	2	2	2	2	2	1	2	2

Performance	Table B58: 20% Eco-Driving									
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6	Trial 7	Trial 8	Trial 9	Trial 10
Latent demand	0	1	0							
Total vehicle mile travelled	2479	2530	2527	2541	2511	2542	2562	2482	2549	2490
Total Stopped Delay, h	72	72	74	74	76	75	78	70	80	80
Average delay per vehicle, s	96	94	98	98	103	102	102	94	106	108
Vehicle in the network	332	331	314	315	298	323	332	328	283	333
Vehicle left	3669	3756	3765	3759	3737	3728	3783	3703	3770	3698
Total Travel time, h	270	273	277	278	280	281	284	268	286	284
Total vehicle Km travelled	3989	4071	4068	4090	4041	4092	4124	3994	4102	4007
Total vehicle in the network	4001	4087	4079	4074	4035	4051	4115	4031	4053	4031
Latent to total vehicle ratio	0	0	0	0	0	0	0	0	0	0
Travel time (Min)per vehicle km	4	4	4	4	4	4	4	4	4	4
Average delay per vehicle, min	2	2	2	2	2	2	2	2	2	2

Performance	Table B59: 50% Eco-Driving									
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6	Trial 7	Trial 8	Trial 9	Trial 10
Latent demand	0	0	0	0	0	0	0	0	0	0
Total vehicle mile travelled	2381	2470	2427	2487	2466	2442	2466	2450	2466	2425
Total Stopped Delay, h	64	64	75	65	79	72	75	64	72	69
Average delay per vehicle, s	90	87	102	90	109	100	102	90	99	97
Vehicle in the network	309	281	312	297	284	330	301	300	261	300
Vehicle left	3563	3653	3648	3631	3633	3581	3676	3590	3662	3599
Total Travel time, h	247	251	266	256	275	264	269	253	264	258
Total vehicle Km travelled	3831	3975	3907	4003	3968	3930	3969	3943	3968	3902
Total vehicle in the network	3872	3934	3960	3928	3917	3911	3977	3890	3923	3899
Latent to total vehicle ratio	0	0	0	0	0	0	0	0	0	0
Travel time (Min)per vehicle km	4	4	4	4	4	4	4	4	4	4
Average delay per vehicle, min	1	1	2	1	2	2	2	1	2	2

Performance	Table B60: 100% Eco-Driving									
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6	Trial 7	Trial 8	Trial 9	Trial 10
Latent demand	0	0	0	0	0	0	0	0	0	0
Total vehicle mile travelled	2441	2525	2495	2515	2504	2529	2526	2466	2515	2483
Total Stopped Delay, h	70	63	70	65	73	74	78	66	70	73
Average delay per vehicle, s	97	86	95	89	100	102	106	91	95	101
Vehicle in the network	304	284	286	269	274	307	309	307	247	273
Vehicle left	3568	3650	3675	3659	3643	3604	3668	3583	3676	3626
Total Travel time, h	251	246	255	249	259	263	269	247	255	259
Total vehicle Km travelled	3928	4063	4015	4048	4030	4070	4065	3969	4048	3995
Total vehicle in the network	3872	3934	3961	3928	3917	3911	3977	3890	3923	3899
Latent to total vehicle ratio	0	0	0	0	0	0	0	0	0	0
Travel time (Min)per vehicle km	4	4	4	4	4	4	4	4	4	4
Average delay per vehicle, min	2	1	2	1	2	2	2	2	2	2

- **Three speed profile – 20% more of average peak traffic (Table B61- Table B64)**

Performance	Table B61: 0% Eco-Driving									
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6	Trial 7	Trial 8	Trial 9	Trial 10
Latent demand	458	424	487	621	550	523	603	516	501	658
Total vehicle mile travelled	3018	3126	3015	3026	2973	3017	2991	3013	3018	2929
Total Stopped Delay, h	248	269	284	286	297	299	315	254	285	291
Average delay per vehicle, s	240	253	283	272	286	281	296	242	275	278
Vehicle in the network	781	777	802	810	812	823	789	781	778	763
Vehicle left	4616	4787	4615	4587	4578	4602	4577	4600	4651	4512
Total Travel time, h	561	600	627	609	627	625	641	564	615	603
Total vehicle Km travelled	4858	5030	4852	4869	4785	4855	4814	4849	4857	4714
Total vehicle in the network	5397	5564	5417	5397	5390	5425	5366	5381	5429	5275
Latent to total vehicle ratio	0	0	0	0	0	0	0	0	0	0
Travel time (Min)per vehicle km	7	7	8	8	8	8	8	7	8	8
Average delay per vehicle, min	4	4	5	5	5	5	5	4	5	5

Performance	Table B62: 20% Eco-Driving									
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6	Trial 7	Trial 8	Trial 9	Trial 10
Latent demand	395	518	682	785	514	791	573	506	541	556
Total vehicle mile travelled	3049	3082	2879	2901	2976	2857	2985	3035	3020	2975
Total Stopped Delay, h	239	275	306	303	287	321	302	248	281	284
Average delay per vehicle, s	239	261	295	285	279	299	298	239	274	279
Vehicle in the network	767	792	793	789	802	783	784	768	761	779
Vehicle left	4684	4686	4414	4439	4622	4379	4602	4624	4634	4589
Total Travel time, h	561	598	614	604	614	616	640	556	607	610
Total vehicle Km travelled	4906	4960	4634	4668	4790	4598	4803	4884	4860	4788
Total vehicle in the network	5451	5478	5207	5228	5424	5162	5386	5392	5395	5368
Latent to total vehicle ratio	0	0	0	0	0	0	0	0	0	0
Travel time (Min)per vehicle km	7	7	8	8	8	8	8	7	7	8
Average delay per vehicle, min	4	4	5	5	5	5	5	4	5	5

Performance	Table B63: 50% Eco-Driving									
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6	Trial 7	Trial 8	Trial 9	Trial 10
Latent demand	499	486	535	726	595	782	644	583	599	849
Total vehicle mile travelled	3009	3076	2996	2929	2959	2836	2939	2990	2971	2782
Total Stopped Delay, h	241	271	278	292	294	311	308	263	286	316
Average delay per vehicle, s	246	261	284	281	291	295	304	252	281	310
Vehicle in the network	772	786	761	775	794	777	787	783	779	763
Vehicle left	4579	4717	4611	4499	4550	4393	4522	4530	4564	4325
Total Travel time, h	556	594	613	598	620	604	634	561	605	614
Total vehicle Km travelled	4843	4950	4822	4714	4762	4565	4730	4813	4782	4477
Total vehicle in the network	5351	5503	5372	5274	5344	5170	5309	5313	5343	5088
Latent to total vehicle ratio	0	0	0	0	0	0	0	0	0	0
Travel time (Min)per vehicle km	7	7	8	8	8	8	8	7	8	8
Average delay per vehicle, min	4	4	5	5	5	5	5	4	5	5

Performance	Table B64: 100% Eco-Driving									
	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6	Trial 7	Trial 8	Trial 9	Trial 10
Latent demand	449	529	541	580	594	630	684	415	573	813
Total vehicle mile travelled	3069	3074	3048	3063	2972	2947	2954	3101	3020	2830
Total Stopped Delay, h	230	257	261	264	283	283	303	231	272	302
Average delay per vehicle, s	236	250	275	262	284	278	299	233	274	297
Vehicle in the network	736	745	736	753	771	751	746	721	747	746
Vehicle left	4671	4711	4643	4666	4577	4566	4541	4751	4610	4374
Total Travel time, h	539	564	594	578	601	587	617	541	589	592
Total vehicle Km travelled	4938	4948	4905	4929	4782	4743	4755	4990	4861	4554
Total vehicle in the network	5407	5456	5379	5419	5348	5317	5287	5472	5357	5120
Latent to total vehicle ratio	0	0	0	0	0	0	0	0	0	0
Travel time (Min)per vehicle km	7	7	7	7	8	7	8	7	7	8
Average delay per vehicle, min	4	4	5	4	5	5	5	4	5	5

Appendix

Data and analysis for healthier routing C

Table C1: PM_{10} in different monitoring stations (2007-2009)

Station	2007			2008			2009		
	Min µg/m^3	Max µg/m^3	Avg µg/m^3	Min µg/m^3	Max µg/m^3	Avg µg/m^3	Minimum µg/m^3	Maximum µg/m^3	Avg µg/m^3
Ballyfermott	2.64	78.47	14.82	2.50	43.19	11.64	1.53	46.10	12.44
Coleraine	4.31	75.28	18.43	4.58	93.47	18.54	-	-	-
Rathmines	1.20	87.92	16.69	1.00	101.30	16.91	2.36	59.58	14.74
Marino	1.67	74.31	13.41	2.50	75.00	12.62	-	-	-
PhoenixPark	1.53	66.19	11.72	1.39	59.44	10.74	2.08	38.89	10.19
Ringsend	-	-	-	-	-	-	5.20	36.52	14.40
Winetavern	3.19	93.47	18.30	1.69	82.36	17.49	1.39	55.83	17.29

Table C2: Average Daily concentration of SO_2, NO_x, NO_2, and NO in different monitoring sites

Station	Average Daily concentration µg/m^3			
	SO_2	NO_x	NO_2	NO
Ballyfermott	3.15	35.83	24.61	14.04
Coleraine	0.84	76.24	40.84	23.63
Rathmines	2.98	28.72	22.15	8.33
Ringsend	6.07	46.35	27.55	19.32
Winetavern	2.11	71.14	44.39	27.23

Table C3: PM_{10} in different monitoring stations (2011-2012) in Vienna

Station	2011			2012		
	Min µg/m^3	Max µg/m^3	Average µg/m^3	Min µg/m^3	Max µg/m^3	Average µg/m^3
A23/Rinnböckstraße	7.0	148.1	34.44	5.7	98.9	25.98
AKH, Südringweg	4.2	123.7	26.72	4.0	89.6	23.16
Belgradplatz	4.2	145.2	33.87	4.7	99.9	27.33
Floridsdorf Gerichtsgasse	7.9	135.4	31.25	8.0	154.5	27.45
Gaudenzdorf	7.1	136.2	30.51	6.3	106.7	25.57
Kaiser Ebersdorf	3.6	131.1	29.36	3.3	96.3	22.66
Kendlerstraße	6.7	128.3	30.35	4.6	115.4	26.47
Laaerberg	5.9	130.6	27.99	4.2	95.4	23.66
Liesing	4.7	131.7	31.62	4.3	112.1	27.30
Lobau	5.3	125.0	25.99	5.3	87.6	20.28
Schafbergbad	5.2	106.0	24.54	5.7	147.6	21.34
Stadlau	4.2	122.9	28.28	5.0	132.7	24.88
TaborstraBe	5.1	126.4	29.35	5.0	90.9	24.20

Table C4: Variables assessed (Non-selected) for different model development

Dublin PM_{10} models						
Variables for Dublin datasets	r_{2009}	Max_{2009}	Min_{2009}	$r_{2007\text{-}2009}$	$Max_{2007\text{-}2009.}$	$Min_{2007\text{-}2009.}$
Altitude (500m)	-0.33	53	5	-0.29	53	5
Open space area (500m)	-0.3	2.4	0.05	-0.28	2.4	0.05
Coast distance	-0.27	9.5	0.2	-0.22	9.5	0.2
Radiation (W/m2)	-0.21	123.41	1.09	-0.02	158.61	1.09
Industrial+ commercial area(1000m)	0.23	0.64	0	0.14	0.64	0
VKT (0-100m)	0.26	12510	139	0.25	12510	139
VKT (200-300m)	0.31	38848	495	0.3	38848	495
VKT (0-150m)	0.32	18571	250	0.27	18571	250
VKT (100-300m)	0.33	69397	709	0.3	69397	709
VKT (100-200m)	0.33	30549	214	0.29	30549	214
Temperature (C)	-0.33	18.29	-0.9	-0.28	18.29	-0.9
Dublin models for PM_{10} and other pollutants: Year 2009						
Variables for Dublin datasets	SO_2	NO_x	NO_2	NO	Min	Max
	r_{2009}					
Humidity (C)	0.02	0.24	0.20	0.28	62.96	99.29
Dew point (C)	0.03	-0.31	-0.34	-0.24	-4.42	16.44
Radiation* (W/m2)	0.10	-0.27	-0.27	-0.24	1.09	123.41
Rainfall (mm)	0.03	-0.07	-0.06	-0.05	0.00	38.80
Stability Class	0.03	0.24	0.19	0.24	3.00	5.00
Coast Distance (km)	-0.11	-0.37	-0.33	-0.20	0.20	9.50
Vienna PM_{10} models						
Variables for Vienna datasets	r_{2012}	Max_{2012}	Min_{2012}	$r_{2011\text{-}12.}$	$Max'_{11\text{-}12.}$	$Min'_{11\text{-}12}$
Min. Temperature (C)	-0.28	32	0	-0.35	25	-14
Nearest major road distance	-0.09	2.89	0.01	-0.07	2.89	0.01
Co-ordinate (X+Y)	-0.06	64.69	64.43	-0.04	64.69	64.43
Minor Road (0-350m)	0.05	12.7	2.91	0.04	12.7	2.91
Building centroid	0.06	2313	6	0.04	2313	6
Minor Road (0-750m)	0.07	4.46	0	0.06	51.05	13.15
Total road (0-350m)	0.08	9.66	0	0.07	13.1	3.6
Minor Road (350-750m)	0.08	14.11	0	0.07	43.13	9.55
Major road (350-750m)	0.08	51.05	13.15	0.07	9.66	0
Total road (350-750m)	0.08	43.13	9.55	0.08	47.83	9.55
Major road (0-750m)	0.09	47.83	9.55	0.08	14.11	0
Total road (0-750m)	0.09	56.86	13.15	0.08	56.86	13.15
Max. Temperature* (C)	-0.25	31	-11	-0.28	38	-8
Altitude (500m)	-0.02	297.75	152.43	-0.03	297.75	152.43

Note: r=parsons correlation coefficient

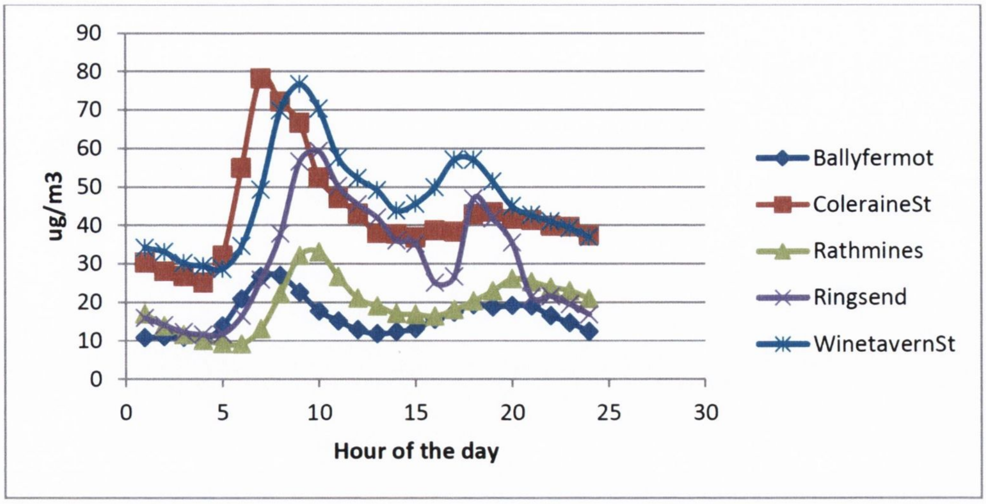


Figure C1: Average NO_x concentration in the monitoring stations (2007-2009)

Table C5: List of Time Factors

Serial No.	Factor Name	Time Period	Time Factor
1	Early morning factor	5am -6.59am	0.74
2	Morning Peak Factor	7am-10.59am	1.35
3	Settling Factor: Noon	11am-13.59pm	0.96
4	Average Traffic Factor	14pm-15.59pm	0.96
5	Evening Peak	16pm-18.59pm	1.16
6	Settling Factor: Night	19pm-21.59pm	0.95
7	Night factor	22pm-4.59am	0.66

Note: Time segregation (*e.g.* Peak and off-peak hour) have been conducted based on the traffic situation in Dublin (NRA, 2004, 2009).

Table C6: Exposure to PM_{10} for two alternative routes in morning peak hour in Dublin

Route		Route A	Route B	Route A	Route B	Saving from in Route A	
		Total	Total	Average	Average		
Trip info	Travel Time (Hour)	2.5	1.7	--	--		
	Distance (km)	9.56	6.13			Value	%
Summer (Dose)	Mon	19.58	14.85	2.05	2.42	0.37	18.31
	Tues	20.79	14.99	2.17	2.44	0.27	12.41
	Wed	19.44	14.72	2.03	2.40	0.37	18.05
	Thurs	19.58	14.18	2.05	2.31	0.26	12.93
	Fri	16.88	12.42	1.77	2.03	0.26	14.78
	Sat	15.39	10.80	1.61	1.76	0.15	9.44
	Sun	13.37	9.59	1.40	1.56	0.17	11.85
Winter (Dose)	Mon	26.87	18.77	2.81	3.06	0.25	8.93
	Tues	28.89	20.12	3.02	3.28	0.26	8.59
	Wed	34.43	23.90	3.60	3.90	0.30	8.25
	Thurs	26.06	17.69	2.73	2.88	0.16	5.86
	Fri	32.13	21.47	3.36	3.50	0.14	4.19
	Sat	26.19	17.96	2.74	2.93	0.19	6.92
	Sun	27.95	18.77	2.92	3.06	0.14	4.72

Table C7: Routing assessment for route 1

Route 1		Trip information						Summer							Winter						
		Lowest VOT (€)	Lowest Travel Time (Hour)	Lowest Running cost (€)	Lowest Generalised cost (€)	Lowest Distance (km)	Lowest CO2 (g)	Lowest Does in Monday	Lowest Does in Tuesday	Lowest Does in Wednesday	Lowest Does in Thursday	Lowest Does in Friday	Lowest Does in Saturday	Lowest Does in Sunday	Lowest Does in Monday	Lowest Does in Tuesday	Lowest Does in Wednesday	Lowest Does in Thursday	Lowest Does in Friday	Lowest Does in Saturday	Lowest Does in Sunday
Trip information	**Distance (km)**	**15.7**	**15.5**	**14.2**	**15.4**	**14.1**	**14.3**	**15.3**	**15.6**	**15.2**	**15.2**	**15.2**	**15.3**	**15.5**	**15.2**	**15.3**	**16.2**	**15.2**	**15.3**	**15.2**	**15.5**
	VOT (€)	**13.6**	**13.8**	**15.0**	**13.8**	**14.9**	**14.6**	**13.9**	**13.7**	**13.7**	**13.7**	**13.7**	**13.8**	**13.6**	**13.7**	**13.8**	**15.7**	**13.7**	**13.8**	**13.7**	**13.6**
	Travel Time (Hour)	**0.5**	**0.5**	**0.6**	**0.5**	**0.5**	**0.5**	**0.5**	**0.5**	**0.5**	**0.5**	**0.5**	**0.5**	**0.5**	**0.5**	**0.5**	**0.5**	**0.5**	**0.5**	**0.5**	**0.5**
	Running cost (€)	**4.7**	**4.7**	**4.2**	**4.6**	**4.3**	**4.3**	**4.6**	**4.7**	**4.6**	**4.6**	**4.6**	**4.6**	**4.7**	**4.6**	**4.6**	**4.9**	**4.6**	**4.6**	**4.6**	**4.7**
	CO2 (g)	**3023.0**	**2983.0**	**2969.0**	**2994.0**	**2947.0**	**2944.0**	**2994.0**	**3001.0**	**2964.0**	**2964.0**	**2959.0**	**2970.0**	**2991.0**	**2962.0**	**2970.0**	**3256.0**	**2967.0**	**2970.0**	**2962.0**	**2990.0**
	Generalised cost (€)	**18.5**	**18.5**	**19.3**	**18.3**	**19.1**	**18.9**	**18.5**	**18.4**	**18.3**	**18.3**	**18.3**	**18.3**	**18.3**	**18.3**	**18.3**	**20.5**	**18.3**	**18.3**	**18.3**	**18.3**
Summer (Dose)	**Monday**	**3.7**	**3.7**	**4.1**	**3.7**	**4.1**	**4.0**	**3.7**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**
	Tuesday	**3.6**	**3.5**	**4.1**	**3.6**	**4.1**	**3.9**	**0.0**	**3.5**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**
	Wednesday	**3.5**	**3.5**	**4.0**	**3.5**	**4.0**	**3.9**	**0.0**	**0.0**	**3.5**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**
	Thursday	**3.4**	**3.4**	**3.9**	**3.4**	**3.9**	**3.9**	**0.0**	**0.0**	**0.0**	**3.4**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**
	Friday	**3.2**	**3.1**	**3.4**	**3.2**	**3.4**	**3.7**	**0.0**	**0.0**	**0.0**	**0.0**	**3.1**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**
	Saturday	**2.7**	**2.7**	**3.1**	**2.7**	**3.0**	**2.9**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**2.7**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**
	Sunday	**2.5**	**2.4**	**2.7**	**2.5**	**2.7**	**2.6**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**2.4**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**
Winter (Dose)	**Monday**	**5.1**	**4.4**	**5.7**	**5.0**	**5.7**	**5.5**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**4.4**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**
	Tuesday	**5.1**	**5.1**	**5.8**	**5.1**	**5.8**	**5.6**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**5.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**
	Wednesday	**5.4**	**5.3**	**6.4**	**5.3**	**6.4**	**6.1**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**5.3**	**0.0**	**0.0**	**0.0**	**0.0**
	Thursday	**4.8**	**4.7**	**5.3**	**4.7**	**5.2**	**5.1**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**4.6**	**0.0**	**0.0**	**0.0**
	Friday	**5.5**	**5.5**	**6.5**	**5.5**	**6.4**	**6.1**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**5.4**	**0.0**	**0.0**
	Saturday	**4.6**	**4.6**	**5.1**	**5.3**	**5.1**	**5.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**4.5**	**0.0**
	Sunday	**5.2**	**5.2**	**5.8**	**5.2**	**5.7**	**5.6**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**	**5.1**

Table C8: Routing assessment for route 2

		Trip information						Summer							Winter						
Route 2		Lowest VOT (€)	Travel Time (Hour)	Running cost (€)	Generalised cost (€)	Distance (km)	Lowest CO2 (g)	Lowest Does in Monday	Lowest Does in Tuesday	in Wednesday	Lowest Does in Thursday	Lowest Does in Friday	Lowest Does in Saturday	Lowest Does in Sunday	Lowest Does in Monday	Lowest Does in Tuesday	Lowest Does in Wednesday	Lowest Does in Thursday	Lowest Does in Friday	Lowest Does in Saturday	Lowest Does in Sunday
Trip information	Distance (km)	14.1	14.1	12.3	13.0	12.3	12.9	14.1	14.1	15.7	14.01	14.6	15.7	14.19	15.6	15.7	15.62	14.1	15.67	14.2	14.2
	VOT (€)	11.5	11.5	13.0	11.7	13.6	11.7	11.6	11.5	13.5	11.5	11.9	13.5	11.63	13.4	13.5	13.41	11.6	13.45	11.6	11.6
	Travel Time (Hour)	0.42	0.41	0.47	0.42	0.49	0.42	0.42	0.42	0.49	0.416	0.43	0.49	0.421	0.49	0.49	0.486	0.42	0.487	0.42	0.42
	Running cost (€)	4.25	4.24	3.69	3.9	3.7	3.88	4.25	4.24	4.73	4.2	4.39	4.73	4.26	4.69	4.74	4.69	4.25	4.7	4.28	4.67
	CO2 (g)	2648	2646	2583	2536	2632	2527	2649	2646	3008	2621	2730	3006	2654	2982	3008	2978	2646	2987	2667	2661
	Generalised cost (€)	15.8	15.8	16.7	15.6	17.3	15.6	15.8	15.8	18.2	15.69	16.3	18.2	15.89	18.1	18.2	18.10	15.8	18.16	15.9	15.9
Summer (Dose)	Monday	3.36	3.36	3.75	3.38	3.85	3.42	3.33	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Tuesday	3.24	3.24	3.70	3.28	3.83	3.29	0.00	3.23	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Wednesday	3.20	3.20	3.59	3.23	3.66	3.25	0.00	0.00	3.17	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Thursday	3.04	3.04	3.39	3.06	3.47	3.06	0.00	0.00	0.00	3.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Friday	2.69	2.69	3.04	2.71	3.13	2.73	0.00	0.00	0.00	0.00	2.67	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Saturday	2.21	2.21	2.50	2.24	2.59	2.25	0.00	0.00	0.00	0.00	0.00	2.20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Sunday	2.05	2.05	2.36	2.08	2.48	2.08	0.00	0.00	0.00	0.00	0.00	0.00	2.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Winter (Dose)	Monday	4.62	4.62	5.08	4.71	5.17	4.73	0.00	0.00	0.00	0.00	0.00	0.00	0.00	4.58	0.00	0.00	0.00	0.00	0.00	0.00
	Tuesday	4.59	4.63	5.09	4.70	5.22	4.74	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	3.33	0.00	0.00	0.00	0.00	0.00
	Wednesday	4.46	4.46	5.12	4.48	5.39	4.52	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	4.13	0.00	0.00	0.00	0.00
	Thursday	4.02	4.02	4.55	4.10	4.71	4.12	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	4.02	0.00	0.00	0.00
	Friday	5.08	5.08	5.76	5.20	5.90	5.24	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	4.78	0.00	0.00
	Saturday	3.93	3.93	4.55	4.00	4.74	4.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	3.90	0.00
	Sunday	4.41	4.40	5.10	4.48	5.37	4.47	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	4.39

Appendix

Data and analysis for Eco-Routing model D

Appendix D

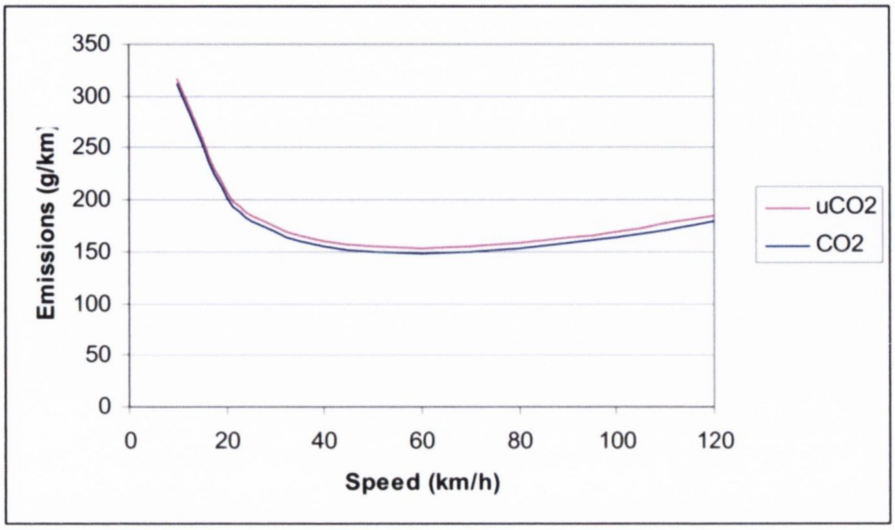


Figure D1: Tailpipe and ultimate CO_2 emissions for a Euro 1, <1400cc petrol car, Source (Boulter *et al.*, 2009)

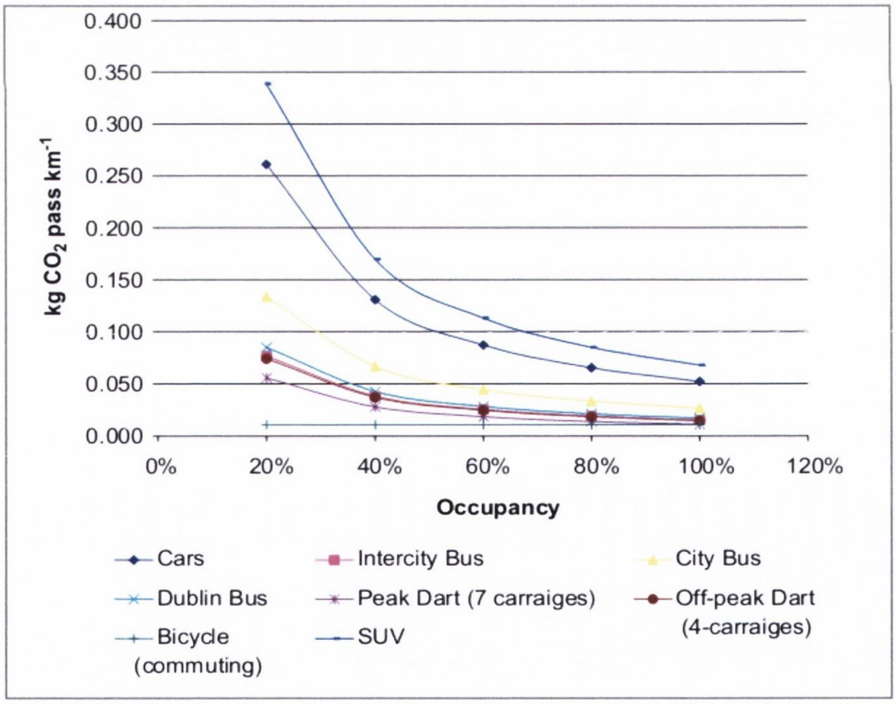


Figure D2: Effect of occupancy on overall transport emission, Source (Walsh *et al.*, 2008)

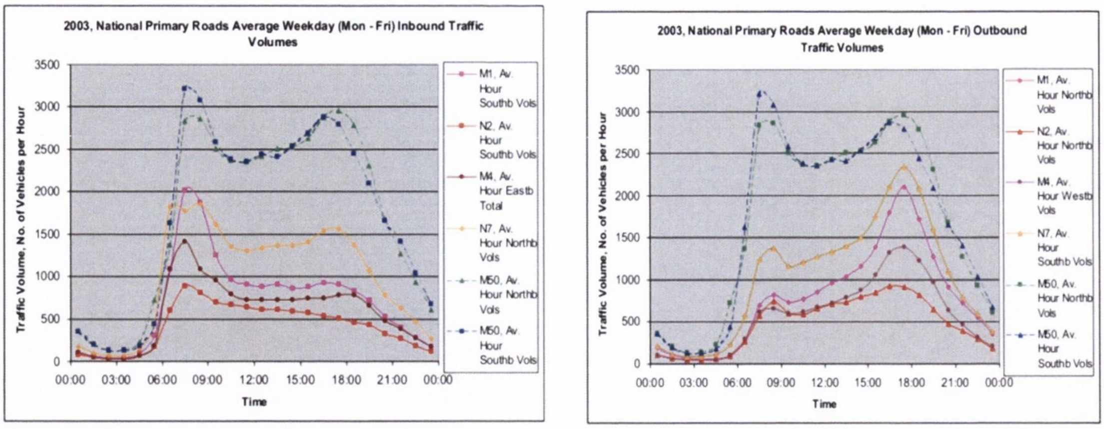


Figure D3: Dublin inbound traffic (left) and outbound for weekdays (Source: NRA 2004)

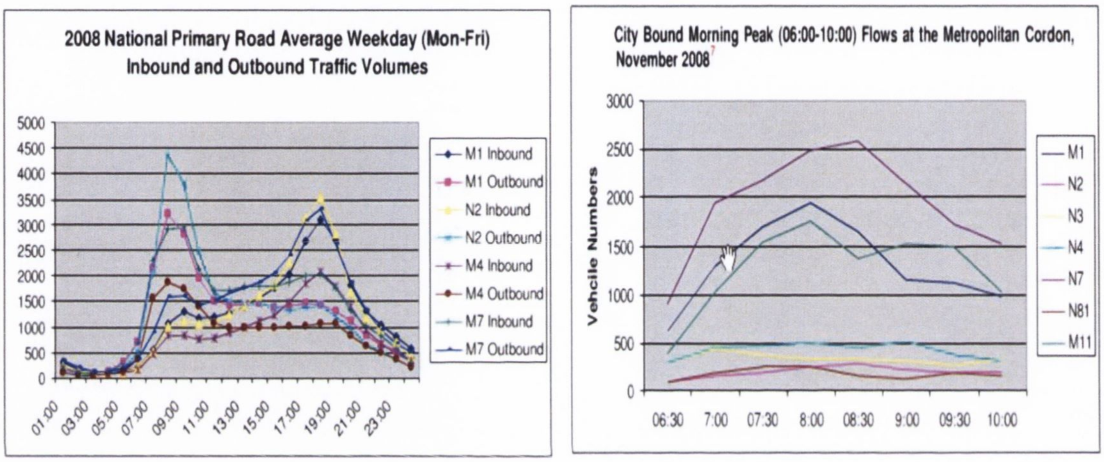


Figure D4: Dublin Traffic inbound and outbound (left), and city bound traffic flow for weekdays-2008 (Sources: NRA 2009)

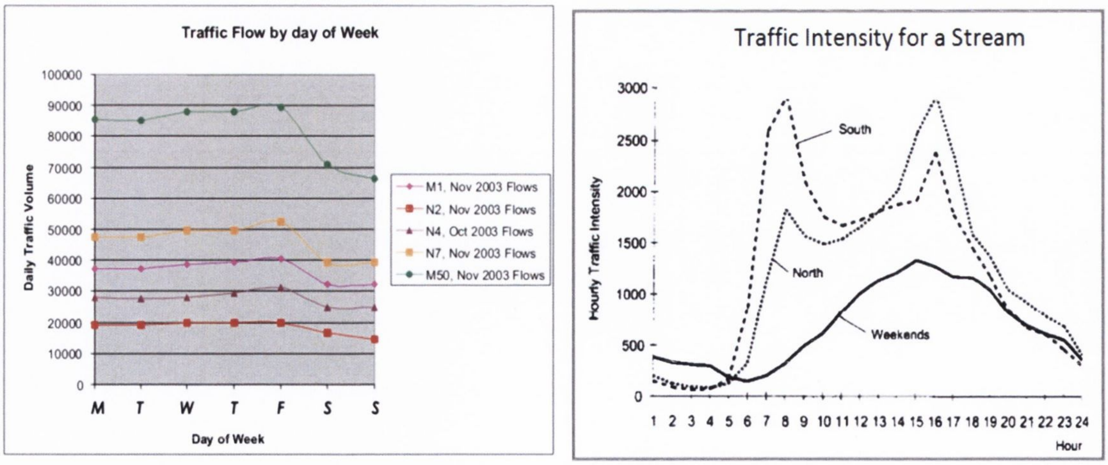
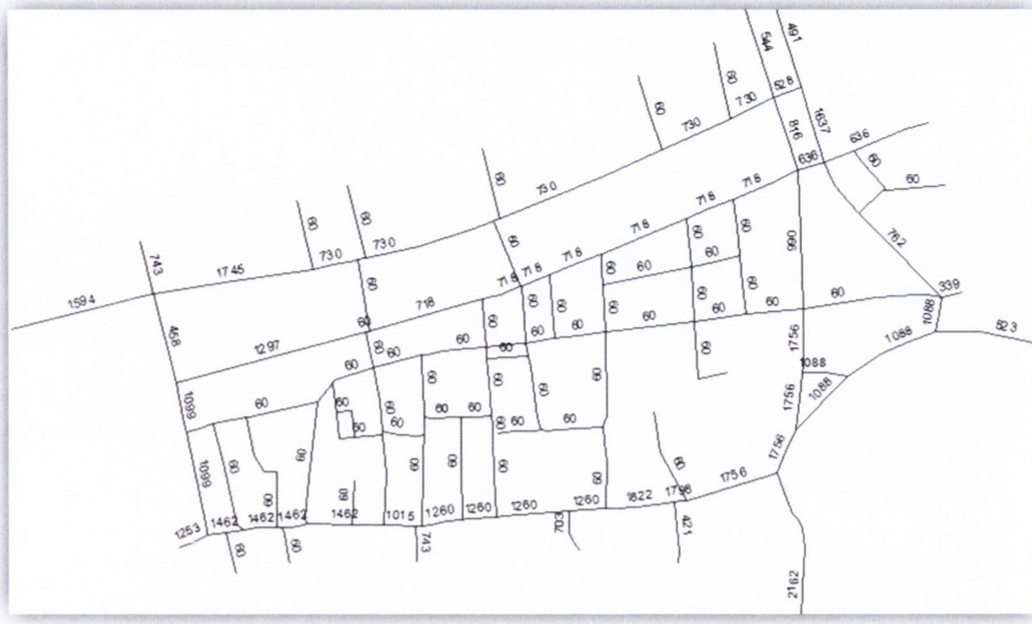


Figure D5: Traffic goes down in the weekends –left figure and there is no distinct peak usually as confirmed by the literature (source: NRA, 2004,2009)



Source: Traffic Noise & Air Quality Unit, Dublin City Council

Figure D6: Average Peak Traffic Volume (5.00-6.00PM), 2011

Table D1: VISSIM -Vehicle record database- sample vehicle no. 30

Link	km/hr	Cum Distance	m	CO2 mg/s	mg	STim	Tot time	Cum Time	Time
7	29.15	0.808658267	0.808658267	2239	223.9	3.4	0	3.4	0.1
7	30.53	14.06997559	0.846808019	2239	223.9	3.4	0	5	0.1
7	30.61	14.91918036	0.849204777	2239	223.9	3.4	0	5.1	0.1
7	30.70	15.7707819	0.851601535	2239	223.9	3.4	0	5.2	0.1
7	30.79	16.62478019	0.853998293	2239	223.9	3.4	0	5.3	0.1
7	30.87	17.48117524	0.856395052	2239	223.9	3.4	0	5.4	0.1
7	30.96	18.33996705	0.85879181	2239	223.9	3.4	0	5.5	0.1
7	30.97	19.20015562	0.860188568	2207	220.7	3.4	0	5.6	0.1
7	30.92	20.05974095	0.859585326	2271	227.1	3.4	0	5.7	0.1
7	30.83	20.91732627	0.857585326	2271	227.1	3.4	0	5.8	0.1
7	30.74	21.77251484	0.855188568	2271	227.1	3.4	0	5.9	0.1
7	30.66	22.62530665	0.85279181	2271	227.1	3.4	0	6	0.1
7	27.90	48.64915624	0.776095548	2271	227.1	3.4	0	9.2	0.1
7	27.81	49.42285503	0.77369879	2271	227.1	3.4	0	9.3	0.1
7	27.72	50.19415707	0.771302032	2271	227.1	3.4	0	9.4	0.1
7	27.64	50.96306234	0.768905273	2271	227.1	3.4	0	9.5	0.1
7	27.55	51.72957085	0.766508515	2271	227.1	3.4	0	9.6	0.1
7	27.46	52.49368261	0.764111757	2022	202.2	3.4	0	9.7	0.1
7	27.38	53.25539761	0.761714999	2022	202.2	3.4	0	9.8	0.1
7	27.29	54.01471585	0.759318241	2022	202.2	3.4	0	9.9	0.1
7	27.21	54.77163733	0.756921482	2022	202.2	3.4	0	10	0.1
7	27.19	55.52716206	0.755524724	2111	211.1	3.4	0	10.1	0.1
7	27.25	56.28329002	0.756127966	2111	211.1	3.4	0	10.2	0.1
7	27.34	57.04141799	0.758127966	2143	214.3	3.4	0	10.3	0.1

Table D2: VISSIM data applied as Eco-Routing model- vehicle 30

Link	Time on the link	Distance (m)	Distance (km)	Link Speed	Eco-Routing CO2 (g/km)	CO2 (g)
7	3.4sec-20sec	147.8	0.147846965	29.42	279.0361403	41.25465
10007	20sec-30sec	48.5	0.048530294	30.04	276.2606548	13.40701
8	30sec-50sec	254.5	0.254485958	28.5	283.380006	72.11623
10008	50sec-60sec	15.7	0.015736746	28.3	284.3620106	4.474933
56	60sec-70sec	27.5	0.027479743	28.5	283.380006	7.78721
Total						139.04

Table D3: VISSIM- Sorted Link Data- vehicle 30

Link	Time Interval	Volume	Link Speed	Density (vehicle/km)
7	10	197	29.42	6.7
7	20	409	30.04	13.6
10007	30	362	29.6	12.221
8	40	1521	28.63	53.116
8	50	1361	29.39	46.3
10008	60	118	23.55	5.022
56	70	578	28.54	25.023

Table D4: Code for vehicle category, catalyst convertor, fuel type and emission standard

Vehicle Emission Standard	
Class	Code
Pre-Euro	100
Euro I	1
Euro II	2
Euro III	3
Euro IV	4
Euro VI	5
Euro VI	6
Fuel Technology	
Type	Code
Petrol	11
Diesel	12
Vehicle weight and Engine Size	
Class	Code
<2500 (1400cc)	21
<2500 (1400-2000cc)	22
<2500 (>2000cc)	23
2500-3500 (any)	240
Catalyst Converter	
Class	Code
Yes	31
No	32

Table D5: Defining vehicle category in a numeric value according to engine, fuel type and emission standard

Primary Code	Vehicle characteristics (engine size <2.5 tonnes)			Primary Code	Vehicle characteristics(engine size >2.5 tonnes)		
	Fuel Technology	Vehicle weight and Engine Size	Vehicle Emission Standard		Fuel Technology	Vehicle weight and Engine Size	Vehicle Emission Standard
1100	Petrol	<2.5 tonnes (1400cc)	Pre-Euro	1200	Diesel	<2.5 tonnes (1400cc)	Pre-Euro
11	Petrol	<2.5 tonnes (1400cc)	Euro I	12	Diesel	<2.5 tonnes (1400cc)	Euro I
22	Petrol	<2.5 tonnes (1400cc)	Euro II	24	Diesel	<2.5 tonnes (1400cc)	Euro II
33	Petrol	<2.5 tonnes (1400cc)	Euro III	36	Diesel	<2.5 tonnes (1400cc)	Euro III
44	Petrol	<2.5 tonnes (1400cc)	Euro IV	48	Diesel	<2.5 tonnes (1400cc)	Euro IV
55	Petrol	<2.5 tonnes (1400cc)	Euro VI	60	Diesel	<2.5 tonnes (1400cc)	Euro VI
66	Petrol	<2.5 tonnes (1400cc)	Euro VI	72	Diesel	<2.5 tonnes (1400cc)	Euro VI
24200	Petrol	<2.5 tonnes (1400-2000cc)	Pre-Euro	26400	Diesel	<2.5 tonnes (1400-2000cc)	Pre-Euro
242	Petrol	<2.5 tonnes (1400-2000cc)	Euro I	264	Diesel	<2.5 tonnes (1400-2000cc)	Euro I
484	Petrol	<2.5 tonnes (1400-2000cc)	Euro II	528	Diesel	<2.5 tonnes (1400-2000cc)	Euro II
726	Petrol	<2.5 tonnes (1400-2000cc)	Euro III	792	Diesel	<2.5 tonnes (1400-2000cc)	Euro III
968	Petrol	<2.5 tonnes (1400-2000cc)	Euro IV	1056	Diesel	<2.5 tonnes (1400-2000cc)	Euro IV
1210	Petrol	<2.5 tonnes (1400-2000cc)	Euro VI	1320	Diesel	<2.5 tonnes (1400-2000cc)	Euro VI
1452	Petrol	<2.5 tonnes (1400-2000cc)	Euro VI	1584	Diesel	<2.5 tonnes (1400-2000cc)	Euro VI
25300	Petrol	<2.5 tonnes (>2000cc)	Pre-Euro	27600	Diesel	<2.5 tonnes (>2000cc)	Pre-Euro
253	Petrol	<2.5 tonnes (>2000cc)	Euro I	276	Diesel	<2.5 tonnes (>2000cc)	Euro I
506	Petrol	<2.5 tonnes (>2000cc)	Euro II	552	Diesel	<2.5 tonnes (>2000cc)	Euro II
759	Petrol	<2.5 tonnes (>2000cc)	Euro III	828	Diesel	<2.5 tonnes (>2000cc)	Euro III
1012	Petrol	<2.5 tonnes (>2000cc)	Euro IV	1104	Diesel	<2.5 tonnes (>2000cc)	Euro IV
1265	Petrol	<2.5 tonnes (>2000cc)	Euro VI	1380	Diesel	<2.5 tonnes (>2000cc)	Euro VI
1518	Petrol	<2.5 tonnes (>2000cc)	Euro VI	1656	Diesel	<2.5 tonnes (>2000cc)	Euro VI

Table D6: Defining vehicle category in a numeric value according to catalyst convertor, fuel type and emission standard (engine size >2.5 tonnes)

Primary Code	Fuel Technology	Catalyst Converter	Vehicle Emission Standard
35200	Petrol	N	Pre-Euro
352	Petrol	N	Euro I
704	Petrol	N	Euro II
1056	Petrol	N	Euro III
1408	Petrol	N	Euro IV
1760	Petrol	N	Euro VI
2112	Petrol	N	Euro VI
34100	Petrol	Y	Pre-Euro
341	Petrol	Y	Euro I
682	Petrol	Y	Euro II
1023	Petrol	Y	Euro III
1364	Petrol	Y	Euro IV
1705	Petrol	Y	Euro VI
2046	Petrol	Y	Euro VI
38400	Diesel	N	Pre-Euro
384	Diesel	N	Euro I
768	Diesel	N	Euro II
1152	Diesel	N	Euro III
1536	Diesel	N	Euro IV
1920	Diesel	N	Euro VI
2304	Diesel	N	Euro VI
37200	Diesel	Y	Pre-Euro
372	Diesel	Y	Euro I
744	Diesel	Y	Euro II
1116	Diesel	Y	Euro III
1488	Diesel	Y	Euro IV
1860	Diesel	Y	Euro VI
2232	Diesel	Y	Euro VI

Table D7: Empirical Equations for cold start emission

New Code	Primary Code	Excess Emission	Correction CO-efficient, f	Cold Distance dc(T,V)	Value a
A1	38400	854.4-17.56*V	1.698-.035*V	-2.27+0.0321*V	-3.432
A2	35200,352, 704,1056, 1408,1760,2112	214.922-6.528*TT-.088*V	2.602-.079*TT-.01*V	2.807-.024*TT+.141*V	-2.33
A3	37200,34100	133.024-.306*V	1.048-.002*V	2.172+.126*V	-2.68
A4	372,384	374.171-8.405*TT-2.606*V	2.43-.055*TT-.017*V	3.474+.163*V	-4.078
A5	341	162.937-5.435*TT+.358*V	2.654-.089*TT+.006*V	3.838+.081*V	-2.714
A6	744,768	362.34-10.921*TT-.14*V	2.567-.077*TT-.001*V	4.31-.04*TT+.125*V	-3.767
A7	682	194.662-3.546*TT+.504*V	1.454-.026*TT+.004*V	4.048-.124*TT+.145*V	-2.563
A8	1116,1152,1488, 1536,1860, 192,2232,2304	171.52-..381*V	1.047-.002*V	9.093-.064*V	-3.389
A9	1023,2046,1705	186.055-5.365*TT+2.283*V	1.496-.043*TT+.018*V	2.461-.057*TT+.173*V	-3.662
A10	1364	168.005-5.165*TT	2.597-.08*TT	5.398-.142*TT	-2.686

Table D8: Coefficient for emission equations, petrol powered vehicle and <2.5 tonnes

Primary Code	a	b	c	d	e	f	g
1100	2.2606*10^3	1.0314*10^0	2.9263*10^-1	3.0199*10^-3	0	0	0
11	2.2606*10^3	8.7563*10^1	2.9263*10^-1	3.0199*10^-3	0	0	0
22	2.2606*10^3	8.0148*10^1	2.9263*10^-1	3.0199*10^-3	0	0	0
33	2.2606*10^3	7.0183*10^1	2.9263*10^-1	3.0199*10^-3	0	0	0
44	2.2606*10^3	5.9444*10^1	2.9263*10^-1	3.0199*10^-3	0	0	0
55	2.2606*10^3	4.4379*10^1	2.9263*10^-1	3.0199*10^-3	0	0	0
66	2.2606*10^3	3.1583*10^1	2.9263*10^-1	3.0199*10^-3	0	0	0
24200	2.5324*10^3	1.532*10^2	-0.43167	6.6776*10^-3	0	0	0
242	2.5324*10^3	1.3779*10^2	-0.43167	6.6776*10^-3	0	0	0
484	2.5324*10^3	1.2988*10^2	-0.43167	6.6776*10^-3	0	0	0
726	2.5324*10^3	1.1834*10^2	-0.43167	6.6776*10^-3	0	0	0
968	2.5324*10^3	1.034*10^2	-0.43167	6.6776*10^-3	0	0	0
1210	2.5324*10^3	8.4965*10^1	-0.43167	6.6776*10^-3	0	0	0
1452	2.5324*10^3	6.8842*10^1	-0.43167	6.6776*10^-3	0	0	0
25300	3.7473*10^3	2.0881*10^2	-0.8527	1.0318*10^-2	0	0	0
253	3.7473*10^3	1.9576*10^2	-0.8527	1.0318*10^-2	0	0	0
506	3.7473*10^3	1.8600*10^2	-0.8527	1.0318*10^-2	0	0	0
759	3.7473*10^3	1.6774*10^2	-0.8527	1.0318*10^-2	0	0	0
1012	3.7473*10^3	1.5599*10^2	-0.8527	1.0318*10^-2	0	0	0
1265	3.7473*10^3	1.2877*10^2	-0.8527	1.0318*10^-2	0	0	0
1518	3.7473*10^3	1.0571*10^2	-0.8527	1.0318*10^-2	0	0	0

Table D9: Coefficient for emission equations, diesel powered vehicle and <2.5 tonnes

Primary Code	a	b	c	d	e	f	g
1200	1.2988*10^3	1.4063*10^2	-1.5597	1.2264*10^-2	0	0	0
12	1.2988*10^3	1.3636*10^2	-1.5597	1.2264*10^-3	0	0	0
24	1.2988*10^3	1.2848*10^2	-1.5597	1.2264*10^-4	0	0	0
36	1.2988*10^3	1.770*10^2	-1.5597	1.2264*10^-5	0	0	0
48	1.2988*10^3	1.1846*10^2	-1.5597	1.2264*10^-6	0	0	0
60	1.2988*10^3	1.0596*10^2	-1.5597	1.2264*10^-7	0	0	0
72	1.2988*10^3	9.94974*10^1	-1.5597	1.2264*10^-8	0	0	0
26400	1.2988*10^3	1.809*10^2	-1.5597	1.2264*10^-9	0	0	0
264	1.2988*10^3	1.7576*10^2	-1.5597	1.2264*10^-10	0	0	0
528	1.2988*10^3	1.6567*102	-1.5597	1.2264*10^-11	0	0	0
792	1.2988*10^3	1.5249*10^2	-1.5597	1.2264*10^-12	0	0	0
1056	1.2988*10^3	1.4665*10^2	-1.5597	1.2264*10^-13	0	0	0
1320	1.2988*10^3	1.3055*10^2	-1.5597	1.2264*10^-14	0	0	0
1584	1.2988*10^3	1.1701*10^2	-1.5597	1.2264*10^-15	0	0	0
27600	1.2988*10^3	2.5320*10^2	-1.5597	1.2264*10^-16	0	0	0
276	1.2988*10^3	2.4671*102	-1.5597	1.2264*10^-17	0	0	0
552	1.2988*10^3	2.3270*10^2	-1.5597	1.2264*10^-18	0	0	0
828	1.2988*10^3	2.1490*10^2	-1.5597	1.2264*10^-19	0	0	0
1104	1.2988*10^3	2.0203*10^2	-1.5597	1.2264*10^-20	0	0	0
1380	1.2988*10^3	1.8015*10^2	-1.5597	1.2264*10^-21	0	0	0
1656	1.2988*10^3	1.6147*10^2	-1.5597	1.2264*10^-22	0	0	0

Table D10: Coefficient for emission equations, diesel powered vehicle and >2.5 tonnes

Primary Code	a	b	c	d	e	f	g
4400	5.8599*10^3	1.3439*10^1	2.0179*10^-1	2.1654*10^-2	0	0	0
44	5.8599*10^4	2.0636*10^-1	2.0179*10^-2	2.1654*10^-3	0	0	0
88	4.8313*10^3	9.3414*10^1	9.524*10^-1	8.4173*10^-5	4.5393*10^-5	0	0
132	4.8313*10^3	9.3414*10^1	9.524*10^-1	8.4173*10^-5	4.5393*10^-5	0	0
176	4.8313*10^3	9.3414*10^1	9.524*10^-1	8.4173*10^-5	4.5393*10^-5	0	0
220	4.8313*10^3	9.3414*10^1	9.524*10^-1	8.4173*10^-5	4.5393*10^-5	0	0
264	4.8313*10^3	9.3414*10^1	9.524*10^-1	8.4173*10^-5	4.5393*10^-5	0	0
4800	4.8313*10^3	8.8452*10^1	6.3429*1^-1	1.3351*10^-2	-0.000055094	6.6419*10^-7	0
48	4.8313*10^3	8.8452*10^1	6.3429*1^-1	1.3351*10^-3	-0.000055094	6.6419*10^-7	0
96	5.4190*10^03	9.2699*10^1	6.3429*1^-1	9.7033*10^-3	-0.000030613	3.4575*10^-07	0
144	5.4190*10^03	9.2348*10^1	6.3429*1^-1	9.7033*10^-3	-0.000030613	3.4575*10^-08	0
192	5.4190*10^03	9.2208*10^1	6.3429*1^-1	9.7033*10^-3	-0.000030613	3.4575*10^-09	0
240	5.4190*10^03	9.1992*10^1	6.3429*1^-1	9.7033*10^-3	-0.000030613	3.4575*10^-10	0
288	5.4190*10^03	9.1992*10^2	6.3429*1^-1	9.7033*10^-3	-0.000030613	3.4575*10^-11	0

Table D11: Car Emissions factors

Vehicle weight and Engine Size	g/km	Fuel Technology, Emission Standard at 60km/h
<2.5 tonnes (1400cc)	98	
<2.5 tonnes (1400-2000cc)	109	
<2.5 tonnes (>2000cc)	154	
2.5 - 3.5 tonnes (any)	241	Petrol, Euro VI
<2.5 tonnes (1400cc)	72	
<2.5 tonnes (1400-2000cc)	89	
<2.5 tonnes (>2000cc)	134	
2.5 - 3.5 tonnes (any)	253	Diesel, Euro VI

Box D1: Overview of the PEACOX (Persuasive Advisor for CO_2-reducing cross-modal trip planning) Project

The PEACOX project has set grounds for encouraging eco-friendly trips. The project website (PEACOX 2014) provides an overview of the app that includes:

- PEACOX integrates automated travel mode detection based on real-time GPS data into the trip planning thereby minimizing the need for explicit user input.
- PEACOX has the capability to automatically detect users' trip purpose through the analysis of behavioural patterns allowing tailoring trip suggestions to these purposes.
- PEACOX builds dynamic user models allowing personalizing recommendations based on prior trip choices and individual preferences.
- PEACOX develops advanced door-to-door emissions models that provide accurate feedback on the ecological/carbon footprint and exposure levels in planning as well as during travelling and car driving activities.
- PEACOX develops and utilizes persuasive interface strategies to give feedback about the ecological impact of individuals' behaviour as well as make the ecological friendliest behavioural pattern visible and attractive.

The information regarding app use can be found in the project report (System Design and Interface Definition by Fluidtime) at: http://www.project-PEACOX.eu/project_results/public_deliverables/, last accessed on 17.12.2014

Box D2: Matlab code of the Eco-routing model

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%Stage
1:DataImport&Setting%%%%%%%%%%%%%%%%%%%%%%
clc
clear
tic
[Head Car]=textread('Recommender Service.txt',...
'%.15s %.15s %.15s %.15s %.15s %.15s ');

C=str2num(cell2mat(Car(3)));    %%Car  Distance.
%              Cr=str2num(cell2mat(Car(2)))   %%String value denoting
Car Travel Route.

p=fix(clock);

if (strcmp(datestr(now, 'ddd'),'Sat') || strcmp(datestr(now,
'ddd'),'Sun') )              % Matlab builtin values for  days in week
1-7
        CO=1.4;
elseif 9>=p(4)>=7 || 18>=p(4)>=16
        CO=1;
else
        CO=1.4;
end

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%Stage 2%%%%%%%%%%%%%%%%%%%%%%%%%%%

[Link Speed Length]=textread('Speed.txt','%.15s %.15s %.15s');   %
Real time speed information
lkl=str2num(cell2mat(Length(2:length(Length),1)));    % Matrix
Linkwise Distance
lks=str2num(cell2mat(Speed(2:length(Speed),1)));       %Matrix
Linkwise Speed
Lcount=length(Link)-1;                 % Number of links
Sumspeed=sum(lks);           %lks=Speed
V=Sumspeed/Lcount;                    %V = Average Speed
T=C/V;                     %T=average Travel Time

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

%2.2Parking Time Calculation

%(a file containing '0' value named 'Last Trip Time' in the specified
format
%is given for the first time application)

%2.2.1 Open Last trip information
% fileID = fopen('Last Trip Time.txt','r');
[LTP Serial]=textread('Last Trip Time.txt','%.15f %.15f'); % Last Trip
information
Az = [LTP; Serial];
fileI = fopen('Park Time.txt','wt');
fprintf(fileI,'%6.2f %6.2f',Az);
% fprintf(fileI,'%6.2f %6.2f %6.2f %6.2f %6.2f %6.2f %6.2f %6.2f %6.2f
%6.2f %6.2f %6.2f',Az);
fclose(fileI);
```

Box D2: Continued

```
%2.2.2 Parking Time

if LTP(2)==p(2)&& LTP(3)==p(3)
%K=LTP(3:5)'; % Last Day Hour Minutes
    K=LTP(4)*60+LTP(3)*1+LTP(5)/60;
%Now=p(3:5);    % reference 1.3.2
    Now=p(4)*60+p(3)*1+p(5)/60;
    Pkt= Now-K;

elseif LTP(2)==p(2)&& LTP(3)==p(3)-1

    Pkt=(24-(LTP(4))-(LTP(5)/60)+p(4)+p(5)/60)*60; %Pkt= Parking time
in Minutes

else
    Pkt=722;
end


%2.2.3 Update Last Travel Information

nn=p;              % Reference :1.3.2
yy=[1 2 3 4 5 6]; %yy is used for just rating the time
% values for yy represent Year Month Date Time minute Second
A = [nn; yy];
fileID = fopen('Last Trip Time.txt','wt');
fprintf(fileID,'%6.2f %6.2f\n',A);
fclose(fileID);

%2.3 Obtain Temperature information

[City Temp]=textread('Location and Temperature.txt','%.15s %.15s');
TT=str2num(cell2mat(Temp(2)));



%%%%%%%%%%%Stage 3: Car Emission Calculation%%%%%%%%%%%%%%%

%%%%%%%%%%%Sub-stage: 3.1 Cold Start Emission %%%%%%%%%%%%%%%%%%%%%%%%

%3.1.1 Obtain vehicle information
[Fuel Emi EW Cat]=textread('User Information.txt',...
'%.15s %.15s %.15s %.15s');
Fuel=str2num(cell2mat(Fuel(2)));
Emi=str2num(cell2mat(Emi(2)));
EW=str2num(cell2mat(EW(2)));
Cat=str2num(cell2mat(Cat(2)));

% 3.1.2 parking time equation selection
syms z
J=Fuel*Cat;    % J= parking equation selection code
if (J==341)
    pktQ=[ .1349*z-2.915*10^-4*z, .136+.0012*z, 1]; %value for z is
given in the end of the section
elseif (J==352)
    pktQ=[5.287*10^-9*z+8.864*10^-6*z^2+5.035*10^-3*z, 1];
elseif (J==372 || J==384)
    pktQ=[ 4.339*10^-3*z-4.747*10^-6*z^2, .978+3.077*10^-5*z, 1]; end
```

Box D2: Continued

```
% 3.1.2 parking time factor calculation
z=Pkt;
if (J==341 && Pkt<=20)          % Pkt reference 2.2.2
    PF=subs(pktQ(1),z);               % PF= Value of Parking factor
will be obtain by this variable
elseif(J==341 && 21>Pkt<=720)
    PF=subs(pktQ(2),z);
elseif (J==341 && Pkt>720)
    PF=subs(pktQ(3),z);
elseif(J==352 && Pkt<720)
    PF=subs(pktQ(1),z);
elseif(J==352 && Pkt>720)
    PF=subs(pktQ(2),z);
elseif((J==372 || J==384) && Pkt<=460)
    PF=subs(pktQ(1),z);
elseif((J==372 || J==384) && 461>Pkt<=715)
    PF=subs(pktQ(2),z);
elseif((J==372 || J==384) && Pkt>715)
    PF=subs(pktQ(3),z);
end

% 3.1.3 Selection of excess emission, correction co-efficient, cold
distance
%equations

EFC=Fuel*Emi*Cat; % Emission Factor code EFC


%3.1.3.1 Equations Declaration

% Equations are in  amatrix form below as a sequence of excess
% emission, correction co-efficient, cold distance and fixed value 'a'

%value for V reference:2.1
%value for TT reference:2.3

A1=[854.4-17.56*V,  1.698-.035*V,   -2.27+0.0321*V, -3.432];
A2=[214.922-6.528*TT-.088*V,    2.602-.079*TT-.01*V,    2.807-
.024*TT+.141*V,   -2.33];
A3=[133.024-.306*V, 1.048-.002*V,   2.172+.126*V,   -2.68];
A4=[374.171-8.405*TT-2.606*V,   2.43-.055*TT-.017*V,    3.474+.163*V,
-4.078];
A5=[162.937-5.435*TT+.358*V,    2.654-.089*TT+.006*V,   3.838+.081*V,
-2.714];
A6=[362.34-10.921*TT-.14*V, 2.567-.077*TT-.001*V,   4.31-
.04*TT+.125*V, -3.767];
A7=[194.662-3.546*TT+.504*V,    1.454-.026*TT+.004*V,   4.048-
.124*TT+.145*V,   -2.563];
A8=[171.52-.381*V   1.047-.002*V,   9.093-.064*V,   -3.389];
A9=[186.055-5.365*TT+2.283*V,   1.496-.043*TT+.018*V,   2.461-
.057*TT+.173*V,   -3.662];
A10=[168.005-5.165*TT,  2.597-.08*TT,   5.398-.142*TT,  -2.686];



%3.1.3.2 Equations Selection

switch EFC
```

Box D2: Continued

```
case{38400}
            r=A1;
case 35200
            r=A2;
case 352
        r=A2;
case 704
        r=A2;
case 1056
        r=A2;
case 1408
        r=A2;
case 1760
        r=A2;
case 2112
        r=A2;
case 37200
        r=A3 ;
case 34100
            r=A3 ;
case 372
            r=A4;
case{341}
            r=A5
case 744
            r=A6;
case 768
        r=A6;
case{682}
            r=A7;
case 1116
            r=A8;
case 1152
        r=A8;
case 1488
        r=A8;
case 1536
        r=A8;
case 1860
        r=A8;
case 1920
        r=A8;
case 2232
        r=A8;
case 2304
        r=A8;
case 1023
            r=A9  ;
case 2046
        r=A9;
case 1705
        r=A9;
case{1364}
            r=A10  ;
otherwise
            r = 0;
end

%3.1.3.1 value for each individual components

%Cold Distance Impact Calculation
```

Box D2: Continued

```
Delta=C/r(1,3);
DelFac= (1-exp(r(1,4)*Delta))/(1-exp(r(1,4))); %Cold Distance factor

%r(1,1)=excess emission
%r(1,2)=correction co-efficient

% 3.1.4 Ecold=cold start emission per start

Ecol= DelFac*r(1,1)*r(1,2)*PF;   %PF reference: 3.1.2

Eco=Ecol/r(1,3);

if C>=r(1,3)
    Ecold=Ecol;
else
    Ecold=C*Eco;
end

%Sub-stage 3.2: Hot Emission Calculation
% 3.2.1 Reference number declaration for the cross ponding Coefficient

spd=Fuel*Emi*EW;  % Code for Speed Equation Selection (spd)
% Eqc refers to the number co-efficient equation in the model

spd_list= [23100    231 462 693 924 1155    1386    24200   242
484....
    726 968 1210    1452    25300   253 506 759 1012....
    1265    1518    25200   252 504 756 1008    1260....
    1512    26400   264 528 792 1056    1320    1584....
    27600   276 552 828 1104    1380    1656    26400....
    264 528 792 1056    1320    1584    28800   288 576....
    864 1152    1440    1728];

% 3.2.2 Co-efficient value decleration

% Baisc Equation y={(a+bx+cx^2+dx^3+ex^4+fx^5+gx^6)/x},     % y= g CO2
Emission/km

syms x;
eqn=[1 x x^2 x^3 x^4 x^5 x^6]/x;
Coff=[2.2606*10^3   2.2606*10^3 2.2606*10^3 2.2606*10^3 2.2606*10^3
2.2606*10^3 2.2606*10^3 2.5324*10^3 2.5324*10^3 2.5324*10^3
2.5324*10^3 2.5324*10^3 2.5324*10^3 2.5324*10^3 3.7473*10^3
3.7473*10^3 3.7473*10^3 3.7473*10^3 3.7473*10^3 3.7473*10^3
3.7473*10^3 1.2988*10^3 1.2988*10^3 1.2988*10^3 1.2988*10^3
1.2988*10^3 1.2988*10^3 1.2988*10^3 1.2988*10^3 1.2988*10^3
1.2988*10^3 1.2988*10^3 1.2988*10^3 1.2988*10^3 1.2988*10^3
1.2988*10^3 1.2988*10^3 1.2988*10^3 1.2988*10^3 1.2988*10^3
1.2988*10^3 1.2988*10^3 5.8599*10^3 5.8599*10^4 4.8313*10^3
4.8313*10^3 4.8313*10^3 4.8313*10^3 4.8313*10^3 4.8313*10^3
4.8313*10^3 5.4190*10^03    5.4190*10^03    5.4190*10^03
5.4190*10^03    5.4190*10^03
1.0314*10^0 8.7563*10^1 8.0148*10^1 7.0183*10^1 5.9444*10^1
4.4379*10^1 3.1583*10^1 1.532*10^2  1.3779*10^2 1.2988*10^2
1.1834*10^2 1.034*10^2  8.4965*10^1 6.8842*10^1 2.0881*10^2
1.9576*10^2 1.8600*10^2 1.6774*10^2 1.5599*10^2 1.2877*10^2
1.0571*10^2 1.4063*10^2 1.3636*10^2 1.2848*10^2 1.770*10^2
```

Box D2: Continued

```
1.1846*10^2 1.0596*10^2 9.94974*10^1    1.809*10^2  1.7576*10^2
1.6567*102  1.5249*10^2 1.4665*10^2 1.3055*10^2 1.1701*10^2
2.5320*10^2 2.4671*102  2.3270*10^2 2.1490*10^2 2.0203*10^2
1.8015*10^2 1.6147*10^2 1.3439*10^1 2.0636*10^-1    9.3414*10^1
9.3414*10^1 9.3414*10^1 9.3414*10^1


9.3414*10^1 8.8452*10^1 8.8452*10^1 9.2699*10^1 9.2348*10^1
9.2208*10^1 9.1992*10^1 9.1992*10^2
2.9263*10^-1    2.9263*10^-1    2.9263*10^-1    2.9263*10^-1
2.9263*10^-1    2.9263*10^-1    2.9263*10^-1    -0.43167    -0.43167
-0.43167    -0.43167    -0.43167    -0.43167    -0.43167    -0.8527 -
0.8527 -0.8527 -0.8527 -0.8527 -0.8527 -0.8527 -1.5597 -1.5597 -1.5597
-1.5597 -1.5597 -1.5597 -1.5597 -1.5597 -1.5597 -1.5597 -1.5597 -
1.5597 -1.5597 -1.5597 -1.5597 -1.5597 -1.5597 -1.5597 -1.5597 -1.5597
-1.5597 2.0179*10^-1    2.0179*10^-2    9.524*10^-1 9.524*10^-1
9.524*10^-1 9.524*10^-1 9.524*10^-1 6.3429*1^-1 6.3429*1^-1 6.3429*1^-
1 6.3429*1^-1 6.3429*1^-1 6.3429*1^-1 6.3429*1^-1
3.0199*10^-3    3.0199*10^-3    3.0199*10^-3    3.0199*10^-3
3.0199*10^-3    3.0199*10^-3    3.0199*10^-3    6.6776*10^-3
6.6776*10^-3    6.6776*10^-3    6.6776*10^-3    6.6776*10^-3
6.6776*10^-3    6.6776*10^-3    1.0318*10^-2    1.0318*10^-2
1.0318*10^-2    1.0318*10^-2    1.0318*10^-2    1.0318*10^-2
1.0318*10^-2    1.2264*10^-2    1.2264*10^-2    1.2264*10^-2
1.2264*10^-2    1.2264*10^-2    1.2264*10^-2    1.2264*10^-2
1.2264*10^-2    1.2264*10^-2    1.2264*10^-2    1.2264*10^-2
1.2264*10^-2    1.2264*10^-2    1.2264*10^-2    1.2264*10^-2
1.2264*10^-2    1.2264*10^-2    1.2264*10^-2    1.2264*10^-2
1.2264*10^-2    1.2264*10^-2    2.1654*10^-2    2.1654*10^-3
8.4173*10^-5    8.4173*10^-5    8.4173*10^-5    8.4173*10^-5
8.4173*10^-5    1.3351*10^-2    1.3351*10^-3    9.7033*10^-3
9.7033*10^-3    9.7033*10^-3    9.7033*10^-3    9.7033*10^-3
0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
0   0   0   0   0   0   0   0   4.5393*10^-5    4.5393*10^-5
4.5393*10^-5    4.5393*10^-5    4.5393*10^-5    -0.000055094    -
0.000055094    -0.000030613    -0.000030613    -0.000030613    -
0.000030613    -0.000030613
0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
0   0   0   0   0   0   0   0   0   0   0   0   0   6.6419*10^-7
6.6419*10^-7    3.4575*10^-07   3.4575*10^-08   3.4575*10^-09
3.4575*10^-10   3.4575*10^-11
0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
0   0];

% 3.2.2 Hot Emission factor calculation for eack link

multiplication=eqn*Coff(:,find(spd_list==spd));
Meqn= subs(multiplication,lks);    %Meqn is the main equation for
speed analysis

% Make a loop for each elemant of lks

x=lks;                                % lns Reference 2.1
H=Meqn          % H will be the matrix containing emission factors for
all links
```

Box D2: Continued

```
% 3.2.3 Link wise hot Emission  calculation in matrix form
% Multiply each element of U with the elemsnts of lnk matrix (length
for each speed)

U=lkl.*H ;                              % lkl Reference 2.1

% 3.2.4 Total Hot Emission from Car


En=sum(U);           % Total hot emission for the car route=En

%%%%%%Stage 4: Emission Calculation for entire Trip and print out

% 4.1 ToTal Car Emission (TE) for hot and cold

TE=Ecold+En;         % ToTal Car Emission TE (Reference: 3.1.4 and
3.2.4 )

TCEP=TE/CO;          % Total Car emission per person TEP (CO
reference:1.3.2)

% 4.2 Emission Reporting


Final =[TCEP]; % Emission Report a sequence of Bus Dart Luas Car Total

% 4.3 Emission Printing (Write in a text file)

% values for yy represent Year Month Date Time minute Second
fID = fopen('Predicted Emission Report.txt','wt');
fprintf(fID,'%6.80s \n', 'Car Total (kg CO2 Emission/person/trip)');
fprintf(fID,'%6.4f %6.4f %6.4f %6.4f %6.4f   \n', Final);
fclose(fileID);
toc
```

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Abstract

Promoting smarter driving may be a useful initiative to reduce the negative environmental impacts of travel in the present car dominated era. Smarter driving may include efficient driving and route choice which reduces fuel consumption, CO_2 emissions (Eco-Routing) as well as personal exposure to harmful pollutants. However, efficient driving and Eco-Route choice techniques possess some practical as well as technological limitations, primarily because of the real-time nature of their application. Efficient driving that refers to controlling/limiting acceleration and speed of vehicles may have a network wide impact of increased overall network travel time. Although, many investigations of such Eco-Driving have reported potential reductions in fuel consumption and CO_2 emissions ranging from 5% to 40% across various jurisdictions and initiatives, a review of the literature revealed contradictory impacts of Eco-Driving that required further investigated.

In congested city centre traffic, many conflicting views exist in the literature, resulting in some doubt over the effectiveness of the policy in such circumstances. Micro-simulation of the environmental and traffic performance of Eco-Driving has been conducted for the Dublin city road network, to assess its network level impacts. The results of this investigation showed that increasing levels of Eco-Driving in a road network resulted in significant environmental and traffic congestion detriments at the road network level in the presence of heavy traffic. In addition, the impacts of the intersections replacement by roundabouts were also evaluated. Negligible transport impacts were found from Eco-Driving in the presence of low traffic congestion for all scenarios. But, large negative impacts were observed for high traffic volume scenarios with the increase level of Eco-car penetration. Increases in CO_2 emissions of up to 18% were found from these studies. However, with the addition of vehicle to vehicle or vehicle to infrastructure communication technology, which facilitates dynamic driving control on speed and acceleration/deceleration in vehicles, improvements in CO_2 emissions and traffic congestion could be possible using Eco-Driving.

On the other hand, the literature review also revealed that the actual range of saving from Eco-Routing was 0.35 –42% fuel and the extent of the variation depended heavily of the level of congestion present. However, no serious issues were identified for Eco-Routing impact. Nonetheless, technological advancement of real time information system was not found to be connected with emission based Eco-Routing systems in practical use, and this may become a

serious flaw of this strategy if the practice becomes widespread. A solution for this has been outlined from an extensive literature review, and a model was developed that is sensitive to vehicle characteristics such as speed, temperature and occupancy. The model is suitable for deployment in any city and effectiveness was evaluated after a field trial in Dublin and Vienna. Several lessons were learned from the developed model, including the importance of real-time data integration, vehicle registration data integration and further modification of the model.

Analogous information that can be useful for the drivers for route choice is exposure information. Such information was required to investigate a comparison to the conventional route choice cost factors before deployment. Thus, the level of exposure to a particular pollutant, or dose of pollutant that a person inhales during travel were compared against choice factors such as: time, distance, generalised cost, CO_2, value of time, and running cost. At first the particular challenge was to estimate the exposure concentration of a pollutant along each road in a network. A possible low cost, yet effective approach to estimation of average daily exposure concentration at city scale is the Land Use Regression (LUR) method. Some methodological modifications have been conducted within the LUR framework and the daily level of air pollution concentration has been estimated in the presence of limited available input data. Concentrations estimated from the model were transferred to the road network level to estimate the exposure concentration along the roads. Hourly fluctuations of NO_x concentrations were applied further for the hourly prediction of the concentrations.

A series of 16 models were developed for PM_{10} air quality in Dublin, which included models for validation of the modified LUR methodology developed in this study. It was found that using a non-parametric regression model could out-perform linear regression based models, however to a lesser extent than that of Artificial Neural Networks. Some dynamic predictors such as a predictor representing trans-boundary air pollution, and vehicle count from loop detectors were assessed which open scope for future research. The final route level analysis revealed that a reduction of dose caused a small increase in travel time and large increase in distance. For different origin and destination pairs the magnitude might be changed drastically, but the pattern will be similar. The local setting was the primary reason for variation in the lowest dose based routes compared to the conventional cost factors of route choice. Such findings may pose a limit of the widespread use of routing based on exposure. However, dose could still be placed as an option in route choice modules for people with priority health issues.