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PLATAFORMA DE INFORMAÇÃO DE TRÁFEGO PARA REDUÇÃO DE CONSUMOS E EMISSÕES

ROAD TRAFFIC INFORMATION PLATFORM FOR ENERGY AND EMISSIONS SAVINGS

Tese apresentada à Universidade de Aveiro para cumprimento dos requisitos necessários à obtenção do grau de Doutor em Engenharia Mecânica, realizada sob a orientação científica da Professora Doutora Margarida Coelho, Professora Auxiliar do Departamento de Engenharia Mecânica da Universidade de Aveiro e do Professor Doutor Asad Khattak, Beaman Professor of Civil & Environmental Engineering, at the University of Tennessee, Knoxville.

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palavras-chave Escolha de rota, eco-navegação, gestão de tráfego, microsimulação, optimização, energia e emissões.

resumo

Apesar das recentes inovações tecnológicas, o setor dos transportes continua a exercer impactes significativos sobre a economia e o ambiente. Com efeito, o sucesso na redução das emissões neste setor tem sido inferior ao desejável. Isto deve-se a diferentes fatores como a dispersão urbana e a existência de diversos obstáculos à penetração no mercado de tecnologias mais limpas. Consequentemente, a estratégia “Europa 2020” evidencia a necessidade de melhorar a eficiência no uso das atuais infraestruturas rodoviárias. Neste contexto, surge como principal objetivo deste trabalho, a melhoria da compreensão de como uma escolha de rota adequada pode contribuir para a redução de emissões sob diferentes circunstâncias espaciais e temporais. Simultaneamente, pretende-se avaliar diferentes estratégias de gestão de tráfego, nomeadamente o seu potencial ao nível do desempenho e da eficiência energética e ambiental. A integração de métodos empíricos e analíticos para avaliação do impacto de diferentes estratégias de otimização de tráfego nas emissões de CO_2 e de poluentes locais constitui uma das principais contribuições deste trabalho.

Esta tese divide-se em duas componentes principais. A primeira, predominantemente empírica, baseou-se na utilização de veículos equipados com um dispositivo GPS *data logger* para recolha de dados de dinâmica de circulação necessários ao cálculo de emissões. Foram percorridos aproximadamente 13200 km em várias rotas com escalas e características distintas: área urbana (Aveiro), área metropolitana (Hampton Roads, VA) e um corredor interurbano (Porto-Aveiro). A segunda parte, predominantemente analítica, baseou-se na aplicação de uma plataforma integrada de simulação de tráfego e emissões. Com base nesta plataforma, foram desenvolvidas funções de desempenho associadas a vários segmentos das redes estudadas, que por sua vez foram aplicadas em modelos de alocação de tráfego.
Os resultados de ambas as perspetivas demonstraram que o consumo de combustível e emissões podem ser significativamente minimizados através de escolhas apropriadas de rota e sistemas avançados de gestão de tráfego. Empiricamente demonstrou-se que a seleção de uma rota adequada pode contribuir para uma redução significativa de emissões. Foram identificadas reduções potenciais de emissões de CO_2 até 25% e de poluentes locais até 60%. Através da aplicação de modelos de tráfego demonstrou-se que é possível reduzir significativamente os custos ambientais relacionados com o tráfego (até 30%), através da alteração da distribuição dos fluxos ao longo de um corredor com quatro rotas alternativas.

Contudo, apesar dos resultados positivos relativamente ao potencial para a redução de emissões com base em seleções de rotas adequadas, foram identificadas algumas situações de compromisso e/ou condicionantes que devem ser consideradas em futuros sistemas de eco navegação. Entre essas condicionantes importa salientar que: i) a minimização de diferentes poluentes pode implicar diferentes estratégias de navegação, ii) a minimização da emissão de poluentes, frequentemente envolve a escolha de rotas urbanas (em áreas densamente povoadas), iii) para níveis mais elevados de penetração de dispositivos de eco-navegação, os impactos ambientais em todo o sistema podem ser maiores do que se os condutores fossem orientados por dispositivos tradicionais focados na minimização do tempo de viagem.

Com este trabalho demonstrou-se que as estratégias de gestão de tráfego com o intuito da minimização das emissões de CO_2 são compatíveis com a minimização do tempo de viagem. Por outro lado, a minimização de poluentes locais pode levar a um aumento considerável do tempo de viagem. No entanto, dada a tendência de redução nos fatores de emissão dos poluentes locais, é expectável que estes objetivos contraditórios tendam a ser minimizados a médio prazo. Afigura-se um elevado potencial de aplicação da metodologia desenvolvida, seja através da utilização de dispositivos móveis, sistemas de comunicação entre infraestruturas e veículos e outros sistemas avançados de gestão de tráfego.

keywords

Route choice, eco-routing, traffic management, microsimulation, optimization, energy, emissions.

abstract

Despite recent technological innovations, transportation sector is still producing significant impacts on the economy and environment. In fact, the success in reducing transportation emissions has been lower than desirable due to several factors such as the urban sprawl and several barriers to the market penetration of cleaner technologies. Therefore, the “Europe 2020” strategy has emphasised the relevance of improving the efficiency in the transportation networks through the better use of the existing infrastructures. In this context, the main objective of this thesis is increasing the understanding of how proper route choices can contribute to reduce emissions output over different spatial and temporal contexts. Simultaneously, it is intended to evaluate the potential of different traffic management strategies in terms of traffic performance and energy/environmental efficiency. The integration of empirical and analytical methods to assess the impact of different traffic optimization strategies on CO_2 emissions and local pollutants constitutes one the main contributions of this work.

This thesis has been divided in two main parts. The first is predominantly empirical, using field data as the main source of information. Using GPS equipped vehicles, empirical data for approximately 13200 km of road coverage have been collected to estimate energy and emissions impacts of route choice in three different scenarios: a medium-sized urban area (Aveiro), a metropolitan area (Hampton Roads, VA) and an intercity corridor (Oporto-suburban area). The second part, predominantly analytical, is essentially based on the output of traffic simulators and optimization models. The analytical component was based on the capability of microscopic traffic models to generate detailed emissions information and to generate link-based performance functions. Then, different traffic management strategies were tested to evaluate road networks in terms of traffic performance and emissions.

Both outcomes of the empirical and analytical approaches have demonstrated that fuel use and emissions impacts can also be significantly reduced through appropriate route choices and advanced traffic management systems. The empirical assessment of route choice impacts has shown that both during off peak and peak periods, the selection of an appropriate route can lead to significant emissions reduction. Depending on the location, potential emissions savings of CO_2 up to 25% and local pollutants up to 60% were found. The analytical approach has demonstrated that it is possible to significantly reduce system environmental costs (30%) by modifying traffic flow distribution along a corridor with 4 alternative routes. However, despite the positive results in terms of the potential for emissions reduction based on appropriate route choices, a number of important trade-offs that need to be considered in future implementations of eco-routing systems. Among these trade-offs it is worth noting that: i) different pollutants may lead to different eco-routing strategies, ii) the minimization of pollutants emissions often involves choosing urban routes (densely populated), iii) for higher penetration levels of eco-routing devices considering local pollutants, system environmental impacts can be higher than if drivers were guided under the traditional devices focused on travel time.

With this research, it has been demonstrated that road traffic management strategies focused on minimizing CO_2 emissions and fuel consumption can be compatible with the minimization of system travel time. On the other hand the minimization of local pollutants may lead to considerable increases in travel time. However, given the trend rate of reduction in the emissions factors of local pollutants, it is expected that such trade-offs would tend to be minimized in medium term. Thus, the developed methodology has great potential for further real life application, either through the use of nomadic devices, infrastructures to vehicle communication or different advanced traffic management systems.

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NOMENCLATURE

ADT	Average Daily Traffic
AQS	Air Quality Station
ADAS	Advanced Driver Assistance Systems
ATIS	Advanced Traffic Information Systems
ATMS	Advanced Traffic Management Systems
CPF	Catalyst pass fraction (ratio of tailpipe to engine-out emission)
DALY	Disability-Adjusted Life Year (years lost due to ill-health, disability or early death)
EC	European Commission
ED	Environmental damage
EEA	European Environment Agency
EPA	(US) Environmental Protection Agency
EVRP	Emission Vehicle Routing Problem
GA	Genetic Algorithm
GDP	Gross domestic Product
GHG	Greenhouse Gases
GIS	Geographic Information Systems
GPS	Global Positioning System
IPCC	Intergovernmental Panel on Climate Change
ITS	Intelligent Transportation Systems
LB	Load Based
LDDV	Light Diesel Duty Vehicle
LDGV	Light Gasoline Diesel Vehicle
LDV	Light Duty Vehicle
NPH	Non-peak hour
OD	Origin-Destination
PH	Peak hour
RB	regression Based
RC	Recurrent Congestion
RGS	Route Guidance System
SAA	Simulated Annealing Approach
SB	Speed Based
SBA	Sensitive Bases Analysis
SE	System Equitable
SED	System Environmental Damage
SO	System Optimum
TMC	Traffic management centre
TMS	Traffic monitoring station
UC	Unexpected Congestion
UE	User equilibrium
VDF	Volume Delay functions
VDmF	Volume Damage Functions
VDOT	Virginia Department of Transportation
VEF	Volume Emission Functions
Vph/vpd	Vehicles per hour / Vehicles per day

VSP Vehicle Specific Power

NOMENCLATURE IN EQUATIONS

A - frontal area of the vehicle

a -vehicle acceleration

C_D - drag coefficient (dimensionless)

C_l - Estimated maximum capacity for link i (vph).

c_p - Cost factor for the associated with the emission of the pollutant p

CP_j - Cost of the pollutant j released in the air (€/g)

C_R - coefficient of rolling resistance (0.0135 -dimensionless)

D_{vspi}- Damage cost of VSP mode i (USD/s);

EC - Economic cost (€)

e_p - Emissions factor for a vehicle type, pollutant p and VSP mode i (g/s);

EP - Total emissions pollutant P (g)

f - Share of vehicle types in the fleet (%);

g - acceleration of gravity (9.8 m/s^2)

grade - vertical rise/grade length

h - altitude of the vehicle

i=VSP mode (1 to 14)

m - vehicle mass

$n_{vsp,i}$ - time (seconds) spent on mode i for all vehicles using the link l

Pa - ambient air density (1.207 kg/m^3 at 20°C)

P_{ji} - Total emissions of the pollutant j produced on route i (g);

q - General traffic flow (vph) or link i;

q_{er} - Traffic volume of eco-routing vehicles (vph);

Q_i - Total traffic volume on route i (vph)

QT - Total Demand (vph)

v - vehicle speed

V_w - headwind into the vehicle

XP = Emissions rate (g/s) (of the pollutant P from a particular vehicle) for VSP mode i

ε_i - "Mass factor", which is the equivalent translational mass of the rotating components (wheels, gears, shafts, etc.) of the power train

1 INTRODUCTION

Initially, this chapter presents the main motivation for this research. In order to justify the relevance of the research topic, recent data on the impact of the transportation system in the economy and the environment is discussed. Then, this work is contextualized in the framework of national and international policies for transportation. After the presentation of the motivation behind this work, the main objectives of this research are defined in Section 1.2.

Finally, the structure of the thesis and the contextualization of its chapters are summarized in section 1.3.

1.1 MOTIVATION

It is well known that transportation systems have directly and indirectly significant effects on the economy. Directly, when they are related to system inefficiencies, congestion and fuel costs but also indirectly, such as the externalities associated with pollutant emissions. Thus, this is the main motivation behind the present thesis: To contribute for improving the efficiency of the road transportation system, through a better understanding of the impact of route choice and related traffic management strategies on emissions and fuel consumption. The following paragraphs describe some important facts justifying the importance of this research.

1.1.1 Impact of road transportation system on economy and environment

The transportation sector has been assuming an increasingly prominent role in the global economy. According to the latest available data (2010), this sector accounts for approximately 5% of gross domestic product (GDP) and for over 5% of total employment in the European Union [1,2]. In Portugal, the transportation sector corresponds to 4% of the Portuguese GDP, in 2002 [3]. Since in Europe, car journeys comprised 82% of all passenger kilometers, in 2010 [2], any inefficiency of the system generates significant environmental, economic and social costs. In Europe, an increase in congestion costs of approximately 50% by 205O is anticipated [1].

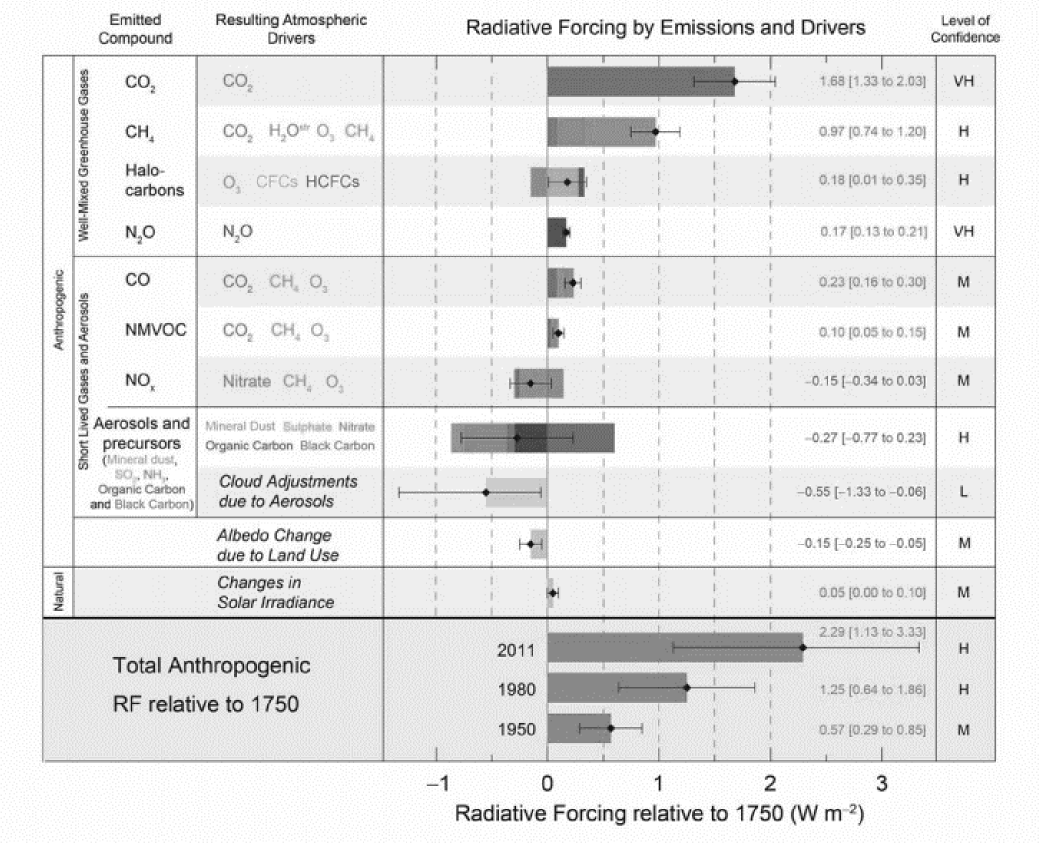
Despite policy efforts and technical progress, nowadays the transportation system still depends on oil products for 96% of its energy needs, in EU [1]. Specifically in Portugal, 70% of fossil fuel consumption (3% of GDP) occurs due to the transportation sector, in 2008 [4]. According to the preliminary results of the Survey on Energy Consumption in Domestic Sector [5], 51% of the energy consumption expenses is related to the private vehicles. As a result, 2010 was the first year in which this value exceeded the expenses related to energy consumed in domestic sector [6]. In addition to the economic issue, there is the challenging of reducing CO_2 emissions which are directly proportional to the amount of fuel consumption.

Numerous indicators have been showing that the environment is one of the central policy areas where additional investment is required. The EU impact assessment on the externalization reports that if no action is taken within the next few years, the environmental costs (air pollution, CO_2 emissions) could reach €210 billion by 2020 [7,8]. Therefore, a key goal of the Europe 2020 strategy for smart, sustainable, and inclusive growth is the gradual decarbonisation of transportation, towards the target of a 60% reduction of CO_2 emissions from transportation by 2050 [1].

The Intergovernmental Panel on Climate Change (IPCC) Fifth Assessment Report provides a comprehensive assessment of the physical science basis of climate change. This report demonstrates the total radiative forcing caused by anthropogenic sources is positive, and has contributed to an uptake of energy by the climate system. The largest contribution to total radiative forcing is caused by the increase in the atmospheric concentration of CO_2 since 1750 (Figure 1).

Taking into account the 1990 levels, no other area demonstrates the growth rate of greenhouse gas (GHG) emissions as high as in the transportation sector [9]. Between 1990 and 2005, road transportation-related emissions increased by 27 % while total EU-27 emissions felt by approximately 8% [10]. It should be noted that this increase has occurred although fleets have enhanced their energy efficiency. At the national level, and between 1990 and 2007, Portugal has shown an increase in transportation emissions of 97% which is one of the highest rates of the 32 European countries considered. Only from 2008 onwards, a very a slight reduction in CO_2 emissions is observed [2].

With demand-oriented incentives Member States can additionally speed up the reduction of average CO_2 emissions of new cars. Such incentives have already been implemented in some countries and include scrappage incentives, extra taxes on cars with high CO_2 emissions or purchase grants for low emission vehicles such as hybrids.



Values are global average radiative forcing partitioned according to the emitted compounds or processes that result in a combination of drivers. The best estimates of the net radiative forcing are shown as black diamonds with corresponding uncertainty intervals; the numerical values

Figure 1: Radiative forcing estimates in 2011 relative to 1750 and aggregated uncertainties for the main drivers of climate change Retrieved from [11]**.**

A lot of attention is being focused on greenhouse gas emissions. However, adopting such isolate approach would be unsuccessful, since some GHG mitigation strategies could have negative environmental impacts elsewhere and/or in other pollutants. Thus, proper planning actions to combat GHG should be designed to deliver positive environmental net benefits [6].

Hence, in addition to GHG, other transportation-related pollutants such as, nitrogen oxide (NO_X), particulate matter (PM) and carbon monoxide (CO) have noteworthy negative effects on human health such as problems on the cardiovascular system, lungs, liver, spleen and blood. In the last decade, there have been some substantial improvements, particularly through the implementation of strict emissions standards for new vehicles. The transportation sector reduced its NO_X and HC emissions by 31 % and 60% respectively, between 2002 and 2011 [12]. However road transportation sector stills contributing significantly to NO_X, PM and CO emissions (33, 13 and 27% respectively), in Europe [13]. Recent studies show that people living near congested European roads are still particularly exposed to air pollution. In 2010, urban traffic air quality stations recorded NO_2 and PM concentrations above legal limits in 44% and 33% of situations respectively [13].

1.1.2 Key policies for improvement transportation networks efficiency

One of the main challenge for road transportation system is the urban sprawl, as it brings about greater need for individual modes, which has congestion and environmental consequences [14]. All available evidences determine categorically that urban sprawl has accompanied the development of urban areas across Europe over the past 50 years. Portugal is identified as case of moderate increases of population but accompanied by a large expansion of urban areas [15]. To reverse this trend the implementation of "smart growth” policies is strongly recommended. However, the results of intelligent strategies on land use and smart planning can only be effective in the medium-long term.

Commonsensically, the market introduction of greener technologies and alternative fuels is a promising strategy in order to reduce emissions. Nevertheless, two main problems arise: I) more eco-friendly vehicles do not necessarily imply less congestion, ii) the market penetration rate of these vehicles is being lower than desirable. The full-scale deployment of clean energies has been delayed by three main obstacles: the high retail cost of vehicles, a low level of consumer acceptance and the lack of infrastructure for recharging and refueling [16]. The European Commission (EC) through the WHITE PAPER for transportation assumes that more efficient vehicles and cleaner fuels are unlikely to achieve on their own the necessary cuts in emissions [1].

Therefore, a more efficient management of existing infrastructures has been identified as a key policy with great potential to reduce emissions. These measures may include behavioral changes in the operation of vehicles (eco-driving) as well as the choice of routes with lower emissions impacts associated. In this context, the Eurovignette directive proposes a "user pays" and a "polluter pays" principle for heavy duty vehicles in Europe [17]. In order to encourage the move to transportation patterns with lower environmental impacts, the tolls price will vary according the vehicles' emissions, the distance travelled, and the location and the time of road use. In fact, drivers have not always enough information to identify among numerous routes, what is best for the economy and the environment. However, with smart pricing of externalities for all modes and means of transportation, they could make the correct choice just by selecting for the low-priced solution.

Upgrading the existing infrastructure through the utilization of improved traffic management and information systems is in many cases the cheapest way to enhance the overall performance of the transportation system [9]. Several measures such as the implementation of better electronic route planning and real time environment information delivery are strongly recommended. In this context, the European Commission plans to develop a strategy for investment in “new navigation, traffic monitoring and communication services to allow for the integration of information flows, management systems and mobility services”. In the urban context, a mixed strategy involving land-use planning and smart pricing schemes are also appointed as a solution to increase the efficiency of the European roads [1]. In fact, nowadays there is a strong need to make highway travel as efficient as possible. New traffic assignment methods play a decisive role in order to increase the efficiency of road networks. In these circumstances, it is fundamental to develop mechanisms that help route choice, either in the user's perspective or in the perspective of system optimization. It should be noted that the efficiency of a given network can be considered in several ways. In addition to the traditional concepts of time and travel distance, energy and pollution concerns should also be considered.

Thus, this investigation rests on some key considerations:

- Despite technological innovations the transportation system has a significant impact on the economy, the environment and the health of populations
- The urban sprawl and the barriers to penetration of new fuels contribute to a success rate in reducing emissions below the desirable
- It is urgent to improve the efficiency in the transportation network through the improved use of the existing infrastructures.

1.2 Research Objectives

On the basis of the evidence currently available, it seems fair to suggest that the implementation of eco-navigation systems has a considerable potential to reduce emissions of certain pollutants. However, there is a lack of understating on how the optimization route choices can allow an integrated minimization of different pollutants, under different contexts of traffic demand and network configuration. Furthermore the system wide-impacts of implementing eco-routing systems are still unknown. This work is meant to develop a combined empirical and analytical research capable of advancing knowledge on how can efficient route choices and traffic management strategies may contribute to a minimization of fuel consumption and atmospheric emissions.

GPS technology is increasingly being used for transportation-related studies. The use of GPS equipped-vehicles to collect traffic information becomes progressively cost-effective, so it is possible to collect traffic information in a large-scale and then incorporate this information in appropriate traffic and emissions models. Simultaneously, the increases in computing performance have yielded more practical use to be made of microsimulation traffic models, which allows a more refined analysis. The output of these models can be assimilated in instantaneous emissions models to evaluate the consequences of different traffic management policies applied to the road network. The present thesis aims to take advantage of these recent technological advances, in order to provide information based on experimental data, and to develop analytical models that might contribute to a more efficient use and management of the road infrastructure.

This thesis, predominantly, focuses on increasing the understanding on the following issues:

- How can route selection influence the emissions output in different spatial and temporal contexts?
- How can Intelligent Transportation Systems be used to provide eco-routing information?
- What strategies of traffic management can be applied to improve the efficiency of road infrastructure in terms of traffic performance, energy consumption and emissions?

Initially, this work provides an in-depth analysis of a broad set of case-studies, covering different scales, under different traffic conditions. The contents include vehicle dynamics data processing, statistical analysis on driver behavior, and the impact of route choice on emissions over different circumstances such as free-flow, recurrent congestion and non-recurrent congestion. Then, current state-of-the-art traffic and emissions models are used to estimate fuel consumption and emissions over different traffic management scenarios. The results of these models will be used in turn, to apply methodologies for optimizing traffic assignment under environmental objectives.

1.3 CHAPTER STRUCTURE

The structure of this thesis is shown in Figure 2.

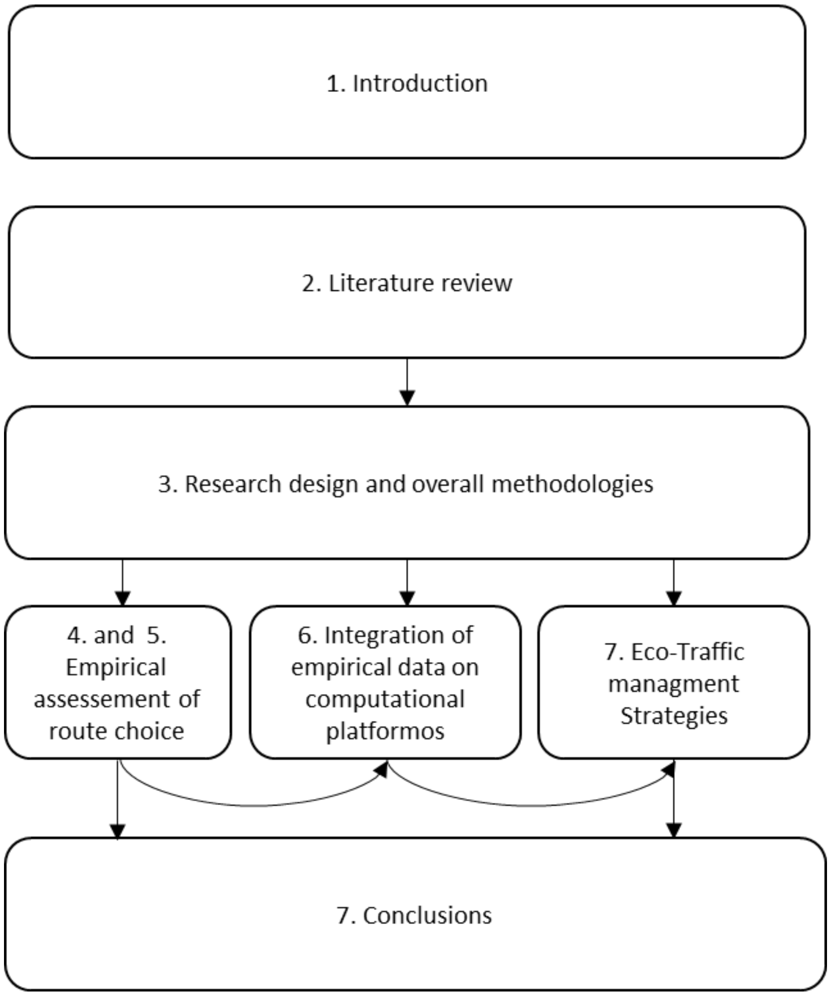


Figure 2 Chapter structure.

Chapter 2 offers a review of relevant literature on route choice and traffic assignment with environmental goals. A review of the most significant literature on traffic and emissions modelling platforms is also provided. Finally, noteworthy research on eco-ITS strategies and a synthetic review of patented work on eco-routing systems is also presented. Chapter 3 presents the research design, the conceptual framework of this work and an overview of methodologies. Chapter 4 and 5 are predominantly empirical. In chapter 4 the impact of route choice on emissions at three different spatial scales and under different circumstances of traffic congestion is analyzed. Moreover, further variables such as driving behavior, and vehicle type and are also considered. Chapter 5 uses also empirical data to provide an environmental perspective of the impacts of the introduction of tolls in a motorway. By using analytical tools and state-of-the art traffic simulators, chapter 6 explore tools for providing eco-routing information and presents an integrated microsimulation platform for assessing innovative traffic managements systems. While both chapters 4 and 6 focus on the impact of individual choices carried out over different case-studies, chapters 7 discusses and provides eco-routing strategies and traffic management strategies taking into account network wide impacts. In Chapter 8, the results are discussed from an overall perspective. Furthermore suggestions for further research are pointed out.

The vast majority of the contents presented in Chapters 4 to 7 are published or submitted to international peer-reviewed journals (Table 1). However, in order to eliminate repetition of contents, to follow the conceptual structure of the thesis, and for reasons of comfort of reading, some contents were note included and their order of presentation does not necessarily follow the same order of the articles. The nomenclature of some parameters was also modified to follow a coherent structure throughout the text.

Some of the research presented in this study has been carried out under the framework of the SMARTDECISION project. The candidate has participated specifically in the following tasks:

- Design of experimental research.
- Participation in field tests (covering approximately 10000 km).
- Empirical data management, development of a framework for estimation of emissions and traffic performance, data analysis and statistical analysis.
- Collaborative participation in traffic modelling, network design, calibration and validation.
- Development of traffic optimization tools, analysis and discussion.

Table 1 Relationship between the structure of chapters and published/submitted articles

SECTION	REFERENCE PAPER
4.1	Bandeira, J. M.; Almeida, Tiago G.; Khattak, Asad; Rouphail, Nagui M. C oelho, Margarida C. Generating Emissions Information for Route Selection: Experimental Monitoring and Routes Characterization. Journal of Intelligent Transportation Systems, v. 17, n. 1, p. 3-17, 2013. DOI:10.1080/15472450.2012.706197
4.2	Bandeira, J. M.; Carvalho, Dário; Fernandes, Paulo; Fontes, Tânia; Pereira, Sérgio R.; Rouphail, Nagui M.; Khattak, Asad J.; Coelho, Margarida C. Empirical assessment of route choice impact on emissions over different road types, traffic demands, and driving scenarios. Accepted for publication in International journal of sustainable Transportation, In press, 2013.
5.	Bandeira, J. M.; Coelho, Margarida C .; Pimentel, Miguel; Khattak, Asad J. Impact of Intercity Tolls in Portugal – An Environmental Perspective. Procedia - Social and Behavioral Sciences, v. 48, n. 1, p.1174-1183, 2012. DOI: 10.1016/j.sbspro.2012.06.1093
6.1	Gazis, Andreas; Fontes, Tânia; Pereira, Sérgio R.; C oelho, Margarida C.; Bandeira, J. M. Integrated Computational methods for traffic emissions route assessment. Proceedings of the 5th AC M SIGSPATIAL International Workshop on Computational Transportation Science - IWC TS '12., AC M Press, 2012, p. 8-13. DOI: 10.1145/2442942.2442945
6.2*	Fontes, Tânia; Fernandes, Paulo; Bandeira, J. M.; Pereira, Sérgio R.; Khattak, Asad J.; C oelho, Margarida C . Are eco-lanes a sustainable option to reducing emissions in a medium-sized European city?. Accepted (March 19, 2013) for publication in Transportation Research Part A: Policy and Practice, In press, 2013. (***only the methodological section has been considered)**
7.1	Bandeira, J. M.; Fernandes, Paulo; Fontes, Tânia; Pereira, Sérgio R.; Khattak, Asad J.; Coelho, Margarida C . Assessment of eco traffic assignment strategies in a urban corridor. Submitted (Oct 15, 2013) for Publication in Transportation Research part C.
7.2	Bandeira, J. M.; Coelho, Margarida C .; Khattak, Asad J.; Pereira, Sérgio R.; Fontes, Tânia; Fernandes, Paulo. An "Eco-Traffic" Assignment Tool. Selected (Jun-14, 2013) for publication as a book chapter of Springer series - Advances in Intelligent Systems and Computing.

2 LITERATURE REVIEW

The literature review is divided into three main sections. Taking into consideration that a significant part of the research effort is related to emissions modeling to assess route choice impacts, section 2.1 describes the most significant multi-scale applications for emissions and fuel consumption. In turn, section 2.2 reports the most recent advances linking microscopic traffic and emissions models. Section 2.3 focuses on existing research on route choice traffic assignment under energy consumption and environmental concerns. Finally, the most important conclusions of the literature review are summarized.

2.1 EMISSIONS AND TRAFFIC MODELS

State-of-the-art energy and emission models could be categorized as macroscopic, microscopic or mesoscopic. This section provides a brief summary of the most important modeling platforms that are employed nowadays.

2.1.1 Macroscopic Models

Macroscopic models are useful for estimating average emission rates at a regional level [18] and are typically based on simplified mathematical expressions integrating aggregated vehicle kinetic characteristics such as average speed over a driving cycle and average emission factors [19]. However, the use of standard driving cycles makes this type of model less suitable for the evaluation of the impacts of transient traffic interruptions [18]. COPERT [7], MOBILE [20], EMFAC [21], ATERMIS [22] and TREM [23] are all examples of macro-scale models.

COPERT model was developed by the Laboratory of Applied Thermodynamics - Aristotle University of Thessaloniki [24] and was designed to produce annual national emission inventories for on and off road mobile sources. This model is also part of the EMEP/CORINAIR Emission Inventory Guidebook [7]. This Guidebook is intended to support reporting under the EU directive on national emission ceilings. Inputs for a typical COPERT run include country fuel, country monthly temperatures, country, Reid vapor pressure, country cold-start parameters, activity data fleet, activity data traffic, and activity data evaporation share. Outputs from COPERT include the calculation of annual emissions of pollutants for all CORINAIR road traffic source categories for all defined territorial units and road classes. Pollutants analysis incorporates exhaust emissions of CO, NO_X, VOCs, CH_4, CO_2, NH3, sulfur oxides, diesel exhaust particulates (PM), polycyclic aromatic hydrocarbons (PAHs), and persistent organic pollutants, dioxins, furans, and heavy metals contained in the fuel (lead, cadmium, copper, chromium, nickel, selenium, and zinc). Finally, non-methane VOCs are split into alkanes, alkenes, alkynes, aldehydes, ketones, and aromatics.

MOBILE is an emission factor model developed by United States Environmental Agency (US EPA) to calculate emission rates for the highway motor vehicle fleet under a wide range of conditions. MOBILE employs current vehicle emission testing data collected by the EPA, the California Air Resources Board (CARB), automobile manufacturer, and from Inspection and Maintenance tests. This model also simulates the impact of different petroleum characteristics on vehicle emissions. A major characteristic of MOBILE is the addition of "off-cycle emissions," which involve aggressive driving with the air conditioning on [25]. The combination of the emissions factors estimated by vehicle types with activity data provides information that can be used in the development of emissions inventories or as inputs to air quality [20]. MOBILE6 is an emission factor model for predicting mass per unit of distance of Hydrocarbons (HC), CO, NO_X, CO_2, Particulate Matter (PM), and toxics from light duty vehicles, heavy duty vehicles and motorcycles under a range of conditions. However, it should be emphasized that MOBILE was replaced by the new modelling tool MOVES.

EMFAC, a model developed by CARB, is another travel-based model with similar structure and functions as the MOBILE model. EMFAC calculates emissions inventories for pollutants from LDGV and LDDV vehicles operating in California. This model is able to estimate both current year and back-cast and forecasted inventories for the calendar years 1970 to 2040 [26]. Emissions estimates are made for over 100 different technology groups and are reported for three distinct vehicle classes segregated by usage and weight [27]. EMFAC calculates the emission rates of total organic gas, reactive organic compounds, HC, CO, NO_X, PM, PM10, PM2.5, lead, SO_2, CH_4, and CO_2. EMFAC model outputs are generally used for project-level air quality assessments [27].

ARTEMIS tools were developed for three major purposes: (a) classical emission inventories (at the regional or national scale, per month or year), (b) scenario calculation for evaluating the consequences of different measures (time series over years), and (c) inputs for air quality models for assessing local and temporal impacts on the environment. The tools simulate the majority of the pollutants regulated (CO, HC, NO_X, PM, Pb, SO_2) as well as the fuel consumption and non-regulated pollutants (CO_2, methane, ammonia, benzene, toluene, xylene, polycyclic aromatic hydrocarbons, PM in size and number, 1.3-butadiene, acetaldehyde, acrolein, benzopyrene, ethylbenzene, formaldehyde, hexane). The model is able to simulate hot, cold start and evaporative emissions [22,28].

The Transport Emission Model for Line Sources (TREM) was developed at the University of Aveiro, to estimate emissions produced by road traffic with high temporal and spatial resolution [23]. Emission rates for several atmospheric pollutants and fuel consumption are estimated as a function of average speed. Different technologies (engine type, model year), engine capacities, and three road segment types are distinguished. The model is principally designed for line sources. Consequently, roads are considered as line sources and emissions induced by vehicles are estimated separately for each road segment taking into consideration detailed information on traffic flow. TREM results have also been used as inputs of air quality models [23,29].

2.1.2 Microscopic Models

Emissions during specific traffic events, (such as during phases of high acceleration) have been shown to have a great impact on emissions. Although the duration of such events is frequently only a few seconds, the emission level may be a multiple of the level during normal operation. This is particularly true for current gasoline vehicles with closed-loop catalytic converters, which have commonly a low basic emission level but show episodes of high emissions during open-loop operation [30]. Microscale models aim to provide accurate emissions estimates at the operation level. This category of models can be subdivided into load-based models and regression based models. Whereas the former types usually calculate emissions by simulating physical and chemical processes, the latter use linear or non-linear functions that employ primarily immediate speed and acceleration or alternatively modal variables as explanatory input factors [31].

2.1.2.1 Regression based models

One widely used approach based on regression based models is the estimate of emissions, through the concept vehicle specific power (VSP). VSP was a concept introduced by Jimenez-Palacios [32] in 1985, which is a upgrade of the "Positive Kinetic Energy" concept proposed by Watson et al. [33] (1983) and the "Specific Power", used by the EPA defined as speed * acceleration [34].

VSP has also been shown to be a useful explanatory variable for estimating variability in emissions, especially for CO_2, NO_X, and CO [35,36]. VSP approach has been used in several other studies, including for modeling of emissions over short road segments [37], the assessment of the influence of route selection and driver behavior on pollutant emissions and fuel consumption [38], or the evaluation of the effect of traffic signal control strategies on vehicle emissions by integrating a microscopic traffic simulation model [39]. VSP modeling approach is part of a set of externally observable variables based models that have practical value for traffic management or simulation applications [40]. Recently VSP approach was used to estimate real-time roadway emissions estimation using visual traffic measurements [41].

In 2010, EPA has presented MOVES 2010 in which emissions rates are a direct function of VSP. The objective of this tool is to provide a precise estimate of emissions from mobile sources under a wide range of user-defined conditions, and to help the user to answer "what if" questions such as "How would particulate matter emissions decrease on a typical weekday if truck travel was reduced during rush hour?" or “How does the total hydrocarbon emission rate change if a specific fleet switches to gasoline from diesel fuel?” [42]. MOVES 2010 can be used to estimate national, state, and county level inventories of local air pollutants, greenhouse gas emissions and some mobile source air toxins emitted by highway vehicles. Additionally, MOVES2010 can make projections for energy consumption (total, petroleum-based, and fossil-based) and it is also able to cover a range of pollutants on a multiple-scale analysis [42].

The model VT-Micro developed at Virginia Tech was designed to integrate traffic model simulator outputs, transportation planning models, and environmental impact models [43]. This tool estimates the instantaneous fuel consumption and HC, CO and NO_X emission rates for vehicles, based on their instantaneous speed and acceleration. These two elements have been shown to have significant impacts on fuel consumption and emission rates. A drawback of this approach is that it does not consider road grade. However, this model may consider grade effects on vehicle emissions by accounting for the additional acceleration factor in the direction of the vehicle movement as a consequence of the grade. Eq. 1 describes the general concept of the equations employed by the VT-Micro model to calculate the instantaneous emission rates and fuel consumption. Two sets of coefficients are used for this equation: coefficients for accelerating, idling, and cruising and coefficients for deceleration [25].

$$MOE_e = \begin{cases} \sum_{i=0}^{3}\sum_{i=0}^{3} \exp\left(L_{i,j}^{m} \cdot v^i \cdot a^j\right) for\ a \geq 0 \\ \sum_{i=0}^{3}\sum_{i=0}^{3} \exp\left(M_{i,j}^{m} \cdot v^i \cdot a^j\right)\ for\ a\ < 0 \end{cases} \qquad \text{Eq. 1}$$

MOEe - Instantaneous fuel consumption or emission rate (L/s or mg/s),

$L^{m}_{i,j}$ = Model regression coefficient for MOE “m” at speed power “i” and acceleration power “j”,

$M^{m}_{i,j}$ = Model regression coefficient for MOE “m” at speed power “i” and deceleration power “j”,

v - Instantaneous speed (km/h),

a - Instantaneous acceleration (km/h/s).

VeTEES (Vehicle Transient Emissions Simulation Software), is another example of a micro-scale that takes into account vehicle instantaneous speed. Its emissions rates are based on engine test benches for three cars. VeTESS computes emissions and fuel consumption on a second-by-second basis for a particular vehicle on a given speed profile and it is based on a detailed calculation of the engine power necessary to drive a given vehicle over any specific route [44]. However, although this method tries to consider the transient generation of emissions, the model predictions have demonstrated to be relatively inaccurate [45].

Other models have been conceived to accurately model specific criteria air contaminants. For instance, MicroFacNOx is a tool specifically designed for estimate NO_X emissions. The model converts driving cycle-based emission rates to real-world emissions by applying correction factors for such parameters as speed, ambient temperature, fuel composition, fleet composition and fraction of distance travelled with a cold engine [46].

2.1.2.2 Load-based models

One of the most representative and widely accepted modal and instantaneous emission models is the Comprehensive Modal Emissions Model (CMEM) developed at the University of California, Riverside. CMEM is a modal model designed to accurately estimate light-duty vehicle (LDV) emissions as a function of the vehicle's operating mode [43]. The model is capable of predicting emissions for numerous types of LDVs. Furthermore it is able to calculate second-by-second tailpipe (and engine-out) emissions and fuel consumption for a wide range of vehicle and technology categories in different condition states (e.g., functioning properly, deteriorated, malfunctioning) [47]. The main advantages of this model are its ability to predict vehicle emissions modally, its simplicity and transparency [27]. This model was built from an in-house dynamometer test on 300 real-world vehicles. Three dynamic variables, instantaneous speed, grade, and accessory use (such as air conditioning), were used as input operating variables. Instantaneous emissions were defined as the product of three components: fuel rate (FR), engine-out emissions indexes ($g_{emission}/g_{fuel}$), and catalyst pass fraction CPF Eq. 2 [48] .

$$tailpipe\ emissions = FR \cdot \left(\frac{g_{emission}}{g_{fuel}}\right) \cdot CPF \qquad \text{Eq. 2}$$

Where:

FR - fuel-use rate in grams/s;

$g_{emissions}/g_{fuel}$ - grams of engine-out emissions per grams of fuel consumed; and

CPF - the catalyst pass fraction, defined as the ratio of tailpipe to engine-out emission

A potential weakness of CMEM is the lack of updates for heavy-duty vehicles. Due to its demanding data requirements, CMEM must be regarded as a research-grade model [27].

EcoGest is a Visual Basic based software which allows the estimation of the energy use and emissions of vehicles under real world driving cycles. This is a road vehicle tank-to-wheel analysis tool that may be integrated with well-to-tank models [49]. The model uses 20 key input factors including, vehicle characteristics, transmission type, engine characteristics, exhaust after-treatment, ambient temperature, road topography and vehicle occupancy. The model database includes several steady-state fully-warm engine maps of fuel consumption and exhaust emissions of HC, CO and NO_X. EcoGest is capable to disaggregate fuel consumption and emission by mode (acceleration, cruise, deceleration and idle) and to simulate alternative fuels [49].

ADVISOR 2002 uses the Matlab environment with Simulink [50]. The modeling scheme is similar to that EcoGest. A catalytic converter model corrects the engine-out emissions and calculates the tailpipe emissions. The main difference when compared to EcoGest is that the database maps are transient maps (covering cold and fully warm regimes). Some engine maps in the database have information only on fuel consumption, therefore not allowing the simulation of emissions. ADVISOR’s main advantage is its ability to simulate hybrid and fuel cell vehicles [50].

2.1.3 Mesoscopic Models

As stated above, the majority of the macroscopic models are based on simplified mathematical expressions to simulate energy consumption and emissions rates which in turn depend on average link speeds. As a result of this fact, these models are not able to consider transient changes in a vehicles' speed and acceleration level as it moves on a road network. A particular problem takes place when comparing drive cycles with the same average speeds, as identical emission rates would then be estimated for all cycles despite differences in the second-by-second speed profiles. Although microscopic models are able to overcome some of these limitations, they can be often time consuming and require a considerable level of input data. Therefore, a number of mesoscopic tools were developed attempting to fill the gap between macro and micro simulation. In other words, these modeling tools are more precise than macroscopic models but less data demanding than microscopic models.

Coelho et al. [51] developed a mesoscopic modeling platform focused on the analysis of vehicle groups and traffic flows rather than individual vehicle movements (TEDS). This tool provides an overall evaluation of emissions caused by traffic interruptions such as pay tolls, roundabouts, and traffic signals, under any traffic demand patterns. Emissions estimates are based on the Vehicle Specific Power concept.

Based on VT-micro emission rates, the VT-meso model estimates average LDV fuel consumption and emission rates on a link-by-link basis with three independent variables, specifically: average travel speed, average number of stops per unit distance, and average stop duration [52]. The MEASURE Model is a GIS-based program which the main objective is to provide researchers and planners with means of evaluating reduction strategies of emissions [53]. This model includes two principal components: 1) start emissions module and 2) on-road emission module. Emission rates are based on a refined tree-based regression analysis of vehicle emission test data from EPA and California Air Resources Board. On-Road emission module estimate vehicle emissions based on different operating modes: idle, cruise, acceleration, and deceleration [53]. Table 2 summarizes some of the main advantages and drawbacks of the micro, meso and macro models found in literature.

Table 2 Summary of some drawbacks and advantages of road traffic emissions models and their scale and category

Scale	Name	Category	Main Disadvantages	Main Advantages
Macro	COPERT	SB	Less suitable for the evaluation of micro scale impacts.	Extensive range of pollutants. Friendly user interface
	MOBILE	SB	Limited Database, inaccurate PM estimations	Output able to be incorporated in air pollution models at various scales
	EMFAC	SB	Modelling system tailored specifically to California	Able to estimate both current year and forecast inventories
	ARTEMISE	SB	Less suitable for the evaluation of micro scale impacts	Scenario calculation tool. Easy incorporation of the outcome in air quality models
	TREM	SB	User interface	Extensive range of pollutants. Outcome can be easily incorporated in air quality models
Micro/Macro	MOVES	SB & VSP	Designed just for the US scenario / “close-box”	Multistage and able to include fuel life cycle calculations
Micro	VSP	RB	Little detail on fleet categories	Database consisting of data from on-board and laboratory dynamometer measurements.
	VT-MICRO	RB	Base model does not consider road grade	Possibility of being incorporated within microscopic traffic simulation models
	VETESS	RB	Inaccurate emissions prediction	Ability to compute emissions and fuel consumption second-by-second
	CMEM	LB	Demanding data requirements and Inaccurate emissions prediction at specific situations.	Ability to predict vehicle emissions by modes for numerous types of LDV
	ECOGEST	LB	Limited ability to predict short-term emissions of local pollutants	Ability to simulate alternative fuels and cold-start emissions
	ADVISOR	LB	Information only on fuel consumption for some engine maps	Capability to simulate hybrid and fuel cell vehicles
Meso	TEDS	VSP	Limited singularities (only tolls plazas, traffic signals and 1 lane roundabouts).	Capability to provide emissions impacts of traffic flows in a corridor, including different traffic singularities
	VT-Meso	VT -Meso	Focused only on LDV	Ability to estimate emission rates on a link-basis, function of average travel speed, average, stop duration
	Measure	EPA data base	Impacts of grade are not considered	To evaluate motor vehicle reduction strategies based on different operating modes

Note: SB – Speed base, AK – Aggregated kinetic, RB – Regression based; LD – Load Based

2.2 LINKING MICROSCOPIC TRAFFIC AND EMISSIONS MODELS

Recently, the increases in computing performance have yielded more practical use of micro-simulation traffic models, which allows a more refined analysis and improve the accurateness of the total emission estimations. The output of these models can be incorporated in microscale emissions models to evaluate the consequences of different traffic management policies applied to the road network, such as traffic signal coordination route diversion, variable speed limits, Advanced Traffic Information Systems and lanes management. In this section is not intended to perform a comparison of the performance of the most common traffic models, but rather, an overview of the type of work that is being done on microscopic simulation of traffic and emissions.

Table 3 summarizes the most relevant studies that linked microscale traffic models with external emissions models. In addition to the main variables analyzed and highlights of each study, the following data is provided: case study (real or theoretical), scale (intersection; road segment; or network), and traffic / emissions models used.

The majority of the studies linked PARAMICS [54] and VISSIM [55] traffic models with CMEM or MOVES emissions models, but other studies integrated different traffic models such as DRACULA [56], AIMSUN [57], INTEGRATION [58] with Mobile, EMFAC and VT-micro emission models [59–61]. Considering the cited studies in Table 3, VISSIM and PARAMICS are used in 50% and 30% of the studies respectively. Regarding the emissions models, CMEM has been widely used (one third of cases), but recently the MOVES and the VSP approach have been increasingly used.

Although almost all studies have been based on real case studies, the large majority of them did not evaluate the capability of the traffic models to capture the real-world vehicle power distributions. However, recent research [62] suggests that the VISSIM model tends to produce more aggressive acceleration and decelerations than in real-world.

Table 3 Relevant literature on integration of microscopic traffic and emissions models

Ref.	CS		Scale			Traffic model			Emissions Model				Variables/traffic management scenarios evaluated and highlights
	R	T	I	R	N	V	P	O	C	M	V	O	
[19]	■				■	■						■	**Traffic signal strategies**, **Bus lane –** Emissions can increase in some cases
[63]	■			■			■		■				**HOV lane configuration** - Freeway with continuous access of HOV lane produce lower emissions
[59]		■	■					■				■	**Roundabouts vs. Traffic signals** - CO_2 emissions depend upon turn demand and overall demand
[60]	■		■					■			■	■	**Dynamic traffic management measures –**
[64]	■				■			■				■	**Intelligent Speed Adaptation -** Net results with no significant impact on pollutant emissions
[61]	■		■					■				■	**Traffic Signal coordination, Types of bus stop –** How to minimize emissions at traffic intersections?
[62]	■			■		■				■			**Baseline scenario** - Model calibration
[65]	■				■	■			■				**Driver behavior -** Aggressive driving produced more emissions.
[66]		■			■	■			■				**Road capacity/Traffic flow** - Impacts are negligible for clean vehicles
[67]	■			■		■			■				**Traffic signal timing -** Impact on pedestrian exposure to emissions
[68]	■			■		■						■	**Traffic management at road maintenance** - Life Cycle Assessment should be considered
[39]	■				■	■						■	**Signal coordination -** Impact on emissions
[69]	■				■	■						■	**Road capacity/Traffic congestion -** Indicators with the best descriptive capabilities are identified
[70]		■	■			■				■			**Traffic signal coordination** - Reduction in emissions more correlated with stops than delay
[71]	■				■	■			■				**Traffic signal timing** - Most of the emission savings come from a reduction in the number of stops
[72]	■			■		■						■	**Traffic signal timing** - Emissions can be reduced by about 5% to 12%
[73]		■	■	■		■			■				**Lane configuration/traffic signal coordination** - Long-run emissions reductions are dubious
[74]	■		■			■					■	■	**Speed, fleet, traffic volume** - Reducing traffic demand by 20% led to 23% in CO_2 reduction
[75]	■				■		■						**Road capacity / Traffic flow** - Link speed data provide better estimates of emissions
[76]	■				■		■					■	**Traffic flow** - Pollutant concentrations in street canyons and backyards
[77]	■				■		■				■		**Speed limit; traffic signal coordination** - CO_2 and NO_X reduction from 10% to 25%
[78]	■			■			■		■				**Alternative fuels** - Considerable reductions in emissions
[79]		■		■			■				■		**Traffic signal** - Green wave allows reductions between 10% and 40%
[80]		■	■				■		■	■			**Roundabout vs. Traffic signal -** Emissions with roundabout are higher than simple pre-timed signal
[81]	■				■		■					■	**Electronic toll collection -** Reduces the overall network air pollution only in the short term
[82]	■			■			■						**Intelligent speed adaptation -** Allows CO emissions up to -48% and travel time +6%
[83]	■			■				■				■	**Based incident-management-** ITS strategies should be more weighted
[84]	■				■			■		■			**Green routing –** Emissions reduction but with higher travel times

Note: CS: Case study, R: Real; T: Theoretical; I: Intersection; R: Road segment; N: Network; P: PARAMICS; Vi VISSIM; O: Others; C: CMEM; M:MOVES/VSP; V: Versit+.

The traffic management policies analyzed are very different, however the coordination of traffic lights is the topic most frequently analyzed. Taking into consideration the main theme of this thesis, just one study has integrated microscopic traffic and emissions models to evaluate the impact of traffic assignment strategies and efficient route choices. Guo et al [84] have developed an integrated platform combining the Transportation Analysis and Simulation System (TRANSIMS) and MOVES to approximate "green user equilibrium," and to investigate the impact of market penetration on the likely environmental benefits of green routing.

2.3 ROUTE CHOICE AND TRAFFIC ASSIGNMENT WITH ENVIRONMENTAL OBJECTIVES

Firstly, in this section the scientific published works on route choice and traffic assignment with environmental goals are summarized. Then, some considerations about the patented work in this field are presented.

2.3.1 Scientific papers

Usually drivers take into account two main criteria when they select a specific a route: travel times and travel costs [85]. There is clear evidence that exposure to travel information is related to the higher likelihood of adjusting planned travel [86]. Nagurney and Dong [87], argued that it is realistic to assume that a number of drivers could consider an environmental criterion into their decision-making process with the increasing environmental concerns. Using a logit based stochastic user equilibrium (SUE) model under traveler information provision, a study has estimated the marginal cost pricing policy for a certain link from an economic, behavioral, and environmental viewpoints [88]. From an economic perspective Gaker et al. [89], concluded that trip-specific information related with greenhouse gas emissions has considerable potential of increasing sustainable behavior. The authors have quantified the "value of green" at around $0.50/pound of GHG avoided. Sharma & Mishra [90] highlighted that emission pricing on routes may be implemented ensuring that it does not adversely impact the composite network and the road user's travel costs.

Table 4 Relevant research on the impact of route choice in terms of emissions and energy use.

Ref.	Study location	Environmental Goals	Emissions Estimation	Highlights
[58]	Virtual	Fuel, CO_2	m (VT-micro)	Savings in fuel consumption of 15 % using the *Integration* model
[91]	Virtual	Generic	NA	Development of a multimodal network eq. model with emission pollution permits
[92]	Virtual	CO	M [f(av speed)]	Development of a trip-assignment model. Emissions savings over the European Union up to 25% %-
[93]	Virtual	CO_2	M [f(av speed)]	Emissions savings (up to 28%) if vehicles are routed taking emissions into account
[94]	Virtual	NO_X, VOC, CO	M [f(av speed)]	When a network is designed for minimal travel time, NO_x and CO emissions can increase
[95]	Virtual	Fuel, CO_2	M [f(av speed)]	Extension of the classical Vehicle Routing Problem (VRP). Significant CO_2 savings.
[96]	Virtual	CO	M [f(av speed)]	CO emission with minimized travel time when drivers take longer routes with low speed profiles
[97]	Virtual	CO_2	m (CMEM adapted)	Macroscopic models can provide inaccurate information to eco-drivers.
[38]	Two OD pairs North Carolina, USA	Fuel, CO_2, NO_X, HC, CO	PEMS & m (VSP)	NO_X savings up to 24% (comparing alternative routes over different periods)
[84]	Metropolitan network Greater Buffalo-Niagara, USA	Fuel, CO	m (Moves)	Assessed the impact of market penetration rates eco-routing vehicles on the system-wide
[98]	Urban network Taipei, Taiwan	CO	M (Local survey)	Development of a traffic-assignment method with multiple-objective decision making
[99]	Urban network Ottawa, Canada	CO	M [f(av speed)]	To minimize CO during peak hours, the system travel time may increase 2%
[100]	Urban network Lund, Sweden	Fuel, CO_2	m (VETESS)	8.2% fuel savings by using a fuel-optimized navigation system.
[101]	Highway system Los Angeles CA, USA	Fuel, CO_2, NO_X, HC, CO	m (CMEM)	A time minimization path can minimizes emissions (CO_2 savings up to 42%)
[102]	Arterial and Highway Northern Virginia, USA	Fuel, CO_2, NO_X, HC, CO	M&m (VT-micro, CMEM, Mobile6)	Savings over the European Union condition up to: CO_2 7%, NO_X 15%, HC 44%, CO 50%
[103]	Virtual + Urban network College Station, TX, USA	CO	M (Mobile 6.2)	Potential for reduce emissions concentrations with a marginal increase in travel time
[104]	Arterial and Highway Zoetermeer, Holland	Fuel	m (VT-CPFEM)	A provincial route can offer av. time savings of 25% and fuel savings of 45%
[105]	Metropolitan network Cleveland-Columbus,OH USA	Fuel	m (VT-micro)	When 20% of eco-routing vehicles are assigned on the network, vehicles consume higher fuel levels.

M – Macroscopic, m – microscopic, PEMS – Portable Emissions Measurement System

Several studies have examined roadway congestion in terms of lost productivity and wasted fuel. More specifically, in the last two decades, there has been a growing interest in the effect of route choice in reducing emissions. Table 4 lists the most relevant studies carried out in the field of route choice optimization, taking into account energy and emissions.

In 1993, Tzeng and Chen [98] carried out one of the first studies focusing the relationship between route-choice (or traffic assignment) and air quality. The authors tried to establish the most advantageous flow patterns using three objectives: time, travel distance, and emissions, particularly CO [98]. By means of multi-objective decision making and nonlinear programming techniques, a set of non-inferior solutions were generated. Then, an eigenvector weighting method was applied to solve continuous cases by performing simple pair wise comparisons. It should be noted that the developed model takes into assumption a system optimization in which a central controller is able to manage the traffic in a way that is most favorable from a system point of view.

In 1994, Rilett and Benedek [99] have studied the implications of using advanced traffic management system (ATMS) and advanced traffic information systems (ATIS) on traffic networks namely with regard to traffic congestion and other transportation by-products such as noise and air pollution. ATMS could be applied to achieve the environmental goals in either an active or passive way. While in the active method there is a centralized route guidance system (RGS) which informs drivers which routes they must follow, a passive system consist of an electronic toll collection system in which drivers are charged for their amount of emissions generated. Without denying the limitations of macroscopic traffic models, the authors pointed out that there would be a tradeoff between the reduction of the system travel time and pollution. In 1998, the same researchers explored this issue taking into account the advent of ITS [99]. Several methods of traffic assignment were tested on a calibrated network, using several approaches such as user equilibrium (UE) or system optimum (SO). CO emissions optimization was compared with UE and SO based on travel time. The researchers demonstrated that the traffic flows of the SO assignment based on CO emissions condition were roughly equivalent to the flows of the UE and SO conditions within a small error range.

Nagurney et al, [106] developed a multi-class and multi-criteria traffic network equilibrium model with an environmental criterion. The model was the first considering elastic travel demands in the presence of a permit or license market system, in order to reduce pollution emissions and taking into consideration both compliant and noncompliant behavior.

Using a macro scale emission model, Sugawara and Niemeier [92] designed an emission-optimized traffic assignment model using CO emission factors based on average speed. The experimental results showed moderate reduction in system-level vehicle emissions under emissions-optimized trip assignment compared with the conventional time-dependent UE and SO models. The researchers also concluded that the emission optimized assignment is more efficient when the network faces low or moderate levels of congestion. In these situations it is possible to save up to 30% CO emissions whereas in situations of high congestion, the reduction is only about 8%. This can be explained by the fact that under emissions-optimized conditions, less traffic volume is assigned to the freeway, since emissions levels are especially high at free flow speed.

Ericsson et al. [100] estimated the potential for reducing fuel consumption and CO_2 emissions, by means of a navigation system in which the optimization of route selection is based on the reduction of fuel consumption rather than the conventional shortest time or distance. The empirical analysis was based on a large database of real traffic driving patterns associated to the street network in the Swedish city of Lund. The classification of street types was based on several categories describing the function and origin of the road network in terms of: street function, type of environment, speed limit, density of traffic signals, traffic-calming measures and traffic flow conditions. The fuel consumption was estimated for each individual driving pattern using two vehicle simulation models (microscopic engine map models), VETESS and VETO. By means of the network analyst tool in ESRI’s Arc View program (based on Dijkstra’s algorithm [107]) the routes between the origin and destination were optimized considering: (1) the lowest fuel consumption, (2) the shortest time, and (3) the shortest distance. Then, the lowest fuel consumption routes were generated and compared with the original route which allowed concluding that trips based on a fuel optimized navigation system could save, on average, approximately 8 % of fuel. Moreover, it was reported that in approximately 50% of trips, the drivers do not choose the most fuel-efficient route.

In 2008, Ahn and Rakha [102], realized that the majority of previous research efforts have applied basic travel time functions and mathematical expressions to compute emissions rates based on average link velocities without considering momentary changes in a vehicle's speed and acceleration. To overcome some of these limitations in evaluating the impact of route choice, the researchers used and compared two microscopic models (CMEM and VT-Micro) and the macroscopic model MOBILE6. Two types of routes (highway or arterial) were tested using a probe car that kept the average speed of the traffic stream. Travel data were recorded at a 1-s resolution [102],. The study has demonstrated that macroscopic emission estimation models can generate inaccurate conclusions because the transient vehicle behavior along a route is not considered. This research also suggests that an emission/energy optimized traffic assignment can considerably improve emissions compared with typical UE and SO assignment methods. It was also shown that a slight section of the path involves a high engine-load condition which generates a considerable increase in emissions. This fact suggests that by reducing high-emitting driving behavior, emissions can be reduced considerably. Figure 3 shows the average total emissions for both routes according to the modeling tools used.

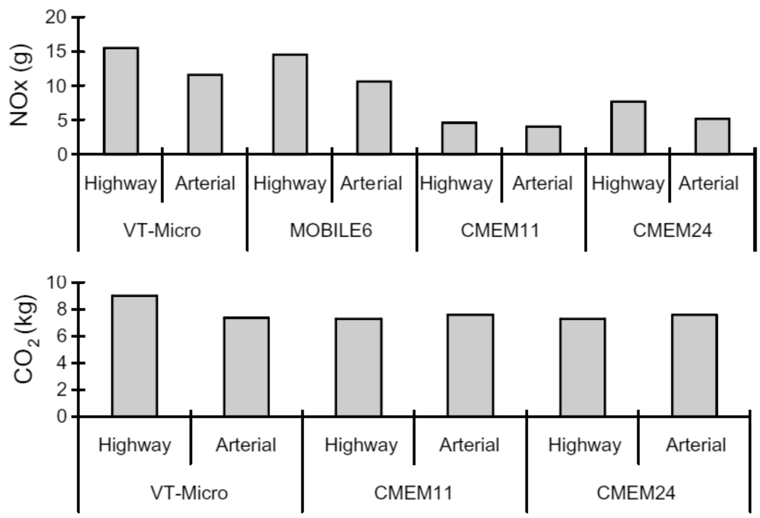


Figure 3 Estimated emissions and fuel consumptions on study corridors. Retrieved from [102]**.**

The results of the microscale models demonstrate that the less time consuming highway route choice is not the best option from an environmental and fuel consumption point of view [102]. In 2011, the same authors have also presented a framework for modeling eco-routing strategies [58].

Barth et al. [101] developed an environmentally-friendly navigation system. Firstly, the researchers collected an extensive vehicle activity data (second-by-second position and speed) using GPS-equipped probe vehicles. Then, through the CMEM microscopic model, functional relationships were established between the microscale speed patterns of individual vehicles and macro scale traffic measurements such as average traffic speed, density, and flow. Using these developed relationships between macro and microscale parameters, the system is able to estimate representative speed trajectories for different levels of measured congestion. Network-wide routing algorithms were developed in order to minimize energy consumption and emissions. Since energy and emissions are frequently higher at lower congested speeds, a congested (but shorter) path may not be the most environmentally friendly. In contrast, moderate congestion often provides a better choice from an environmental perspective.

Zhang et al. [103] modeled the emission levels in every location of a hypothetical network considering the influence of multiple links on global air quality. In order to consider mutually the travel cost and on-road emissions, the authors employed an additive objective function. Then, a genetic algorithm was implemented to solve the complex optimization problems with non-linear terms. The concept of a cell-based was also introduced to model emission concentrations in order to either the average emission, or the maximum emission could be considered in the optimization process. The researchers concluded that the developed optimization model is able to help the reduction of CO emissions concentration in the locations with worst environmental conditions which be accomplished with a minor increase in travel time and average emission concentration.

Other authors have focused on minimizing emissions in specific fleets. In 2010, Figliozzi [93] has created a new system (emission vehicle routing problem – EVRP) aiming the minimization of pollutant emissions from commercial vehicles. Here, a heuristic is proposed to decrease the level of emissions. CO_2 emissions are based on a polynomial expression that relates real-world CO_2 emissions and travel speed profiles. Previously, Tavares et al [108] developed a guidance system for minimum fuel consumption by using geographical information systems (GIS) and 3D route modeling software for the waste collection fleet of Cape Verde. The emission factors were based on COPERT macro-scale model.

The majority of research has been focused on limited study areas which require further evaluation under a wider range of driving circumstances. All study's conclusions pointed out that route choice has a significant impact on emissions and energy use. However, few studies have addressed the effect of rush periods on emissions [109]. The distribution of vehicle speeds and accelerations in traffic diverge by type of road facility and amount of traffic volume, generating large discrepancies in emission levels [110]. Possibly, this fact has contributed to some inconsistency on literature about this issue. On one hand research studies [38,77,101] point out that time minimization paths often also minimize energy use and emissions. On the other hand different work [99,104,111] verified that frequently the faster alternatives are not the best from an environmental viewpoint.

In addition to evaluate the impact of route choice in terms of emissions, it is also important to assess the effect of information on drivers' route-choice actions. This is particularly important since its effectiveness is dependent on a reliably system that is perceived as convenient by those affected by traffic problems [112].

Although ATIS have the intention of providing more precise real-time information, it is doubtful whether drivers would ever have total confidence in these systems. Considering the complexity of developments in the field of ITS, Höltl and Stefanraises [112] have raised the interesting question: "At what point do users start feeling overloaded and no longer able to handle all functionalities, ultimately rejecting using them?" Previous research point out that drivers adjust their behaviour according the accuracy level of information being provided [113]. Khattak et al. [114] established that driver's behaviour change with their personal characteristics and the purpose of the trip which could be an advantage to ATIS performance.

Informed drivers are more prone to risk-seeking and have greater understanding of the travel time variability. By contrast, drivers with no information show to be more risk-averse and less sensitive to variability [115]. Overall, It has been demonstrated that ATIS may overcome behavioural inertia and the employ of ATIS has demonstrated to yield lower system travel time and congestion levels [114]. However, persuade drivers to following eco-friendly route suggestions based on advanced driver assistance systems (ADAS) might be a difficult task since these systems do not provide visible direct effects. Hence, it is important to consider the attributes that ultimately make it useful and efficient from a user's point of view [112].

2.3.2 Patented work

Recently numerous patents related to eco-navigation systems have been registered worldwide. This confirms the importance of this issue in traffic management systems, aiming the reduction of energy consumption and pollutant emissions.

In recent times, several cities have taken measures to reduce air pollution by limiting the access of vehicles into certain critical areas. For example, such restrictions may be implemented by means of toll systems in which the driver of a vehicle is charged for entry into that area. For example, such restrictions may be implemented by means of toll systems in which the driver of a vehicle is charged for entry into that area. Consequently, an issue of major interest among navigation systems is to provide information and encourage drivers to avoid restricted emissions areas.

Instead of charging, Ayyildiz and Willrnbrock [116] from *Deutsche Telekom* proposed an alternative electronic solution to convince drives to use alternative routes and traffic modes with lower emissions impacts. The proposed device generates an urban traffic-related emission map in the form of yellow / green / red colored graphical layers, representing diverse CO_2 emission environments within the road network in order to the user decide which route he should select to get the highest bonus (savings in public transportation and parking fees). However, in this approach is not considered the fact that drivers can emit more emissions, for instance, by selecting longer routes in order to avoid the red emissions zones. No much detail is available about the process of emission calculation [116].

A inventor [28] has registered a European patent consisting of a navigation system that includes a storing unit for storing vehicles emission data. The device also includes a routing processing unit (CPU) for dealing with the emission data and for calculating the best route taking into account the vehicle type. Thus, this device can assist the driver in finding an appropriate route to a destination taking into account the existence of restricted road areas such as low emission zones (LEZ). A similar prototype was patented in US one year earlier [117].

The dynamic calculation of emissions under different road conditions is very important for providing accurate information on environmental impacts. In this context, a navigation device capable of calculating carbon emissions was patented. The estimation of CO_2 emissions is performed by using a set of pre-determined coefficients for road conditions, weather and vehicle parameters. Ginsberg [118] developed a system for automatic detection of road conditions yielding the minimization of emissions by determining whether proposed routes may be less efficient due to weather conditions. In South Korea, an eco-route planning and guidance method have been developed to indicate the optimum route (for energy saving) based on real driving conditions. This method takes into account real time traffic information and weighted values based on each road segment grade [119]. Gas mileage information, exhaust gas emission amount information, and real time traffic information is guided to the user using the searched eco driving route information. With similar objectives a Japanese patent presents a navigation method for indicating the best energy-saving route. In this case, fuel consumption on each link is calculated by using a function that depends on fuel type, travel time, average road grade, distance, vehicle weight, and the acceleration energy based on the number of stops [120]. Inventors from *Toyota Motor Corp*. patented a navigation system and an onboard navigation device which can accurately calculate and minimize the amount of gas emissions from a vehicle [121]. A system for identifying an environmentally-friendly and/or fuel saving travel route, was patented by Barth & Boriboonsomsin, [122] from the University of California. This system relates to vehicle navigation systems that utilize fuel use and emissions criteria as a parameter to determine directions between two locations.

2.4 SUMMARY OF LITERATURE REVIEW

Initially, a summary of available computational tools to analyze the impact of traffic management policies was conducted. This review led to the identification of the best tools that were applied during this research work. The second phase was based on the scientific literature focused on the impact of route choice under a perspective of energy efficiency and emissions. The main conclusions of the literature review are summarized in the following points:

- Regarding emissions modeling, the use of instantaneous emission models has been identified as the most appropriate method to evaluate different operational traffic scenarios, particularly, regression based models proved to be most efficient in the assessment of traffic management strategies under transient states of traffic conditions.
- Although travel time and costs are the aspects that have more influence on route choice decision, a sector of society would consider environmental issues in route selection decision process.
- From an individualistic perspective, there is potential for significant reduction of emissions and fuel consumption based on user route information. From the perspective of system optimization both scientific and technical literature have suggested the implementation of several methods to meet environmental goals, such as dynamic road pricing systems, variable message signals (VMS), and electronic incentives to eco-drivers.
- There is a lack of integration between experimental and analytical research. In general, empirical studies are focused on limited study areas under specific traffic conditions, without the capacity of assessing the network performance and a wide range of driving patterns conditions. On the other hand, the majority of analytical

research is based on traffic modeling tolls which are rarely validated in terms of field data, namely vehicle's dynamics.

- To the author´s best knowledge, very few publications can be found in the literature that addresses the issue of minimizing local pollutants and greenhouse gases simultaneously.
- There is an extensive range of patented systems to calculate and transmit information to users on routes with fewer emissions and/or with certain restrictions. However, no applications were found focused on the effective impacts of all emissions impacts an integrated way.

The previous literature highlighted the potential and applicability of a correct route choice as a tool for reducing emissions. This study aims to evaluate this potential under different contexts and then to develop a framework for future implementation of sustainable traffic management policies. Therefore, the research herein will contribute new knowledge to this this field, by including a more extensive analysis, different scales, driving contexts, traffic demands and different types of vehicles. Taking into account the identified gaps in the literature, namely the lack of integration between experimental and analytical research, a strong empirical component will be integrated with state of the art analytical models and optimization tools. The conceptual structure of this work will be discussed in the next chapter.

3 RESEARCH DESIGN AND METHODOLOGY

The purpose of this chapter is first to outline the conceptual framework of the thesis, and second to describe the study domain and the common methodological concepts to the following chapters of the study.

3.1 OVERVIEW OF CONCEPTUAL STRUCTURE

This thesis has two main parts. The first one is predominantly empirical, using field data (vehicle dynamics) as the main source of information. The second part, predominantly analytical, is mainly based on output data of traffic models.

The empirical component aims to assess the potential of appropriate route choices for energy and emissions savings. Simultaneously, the use of equipped GPS-probe-vehicles as a valid method to generate accurate information on emissions in different links of the network is assessed.

The analytical component attempts to evaluate the potential of traffic models to generate detailed emissions information and to extrapolate results from an individual perspective to the whole system under analysis. The output of these models is then used to explore different traffic assignment methods, in terms of emissions and network performance.

Both components are evaluated under different constraints and contexts as schematized in Figure 4. The impact of route choice is empirically assessed in three distinct scenarios (urban, intercity and metropolitan area). All routes have been evaluated under free flow conditions and under recurrent congestion. A specific event of extreme and unexpected congestion has been also analyzed from the environmental point of view.

The second-by-second data on vehicle' dynamics were used to estimate the emissions of gasoline and diesel light vehicles. The effect of driver behavior on emissions was also evaluated.

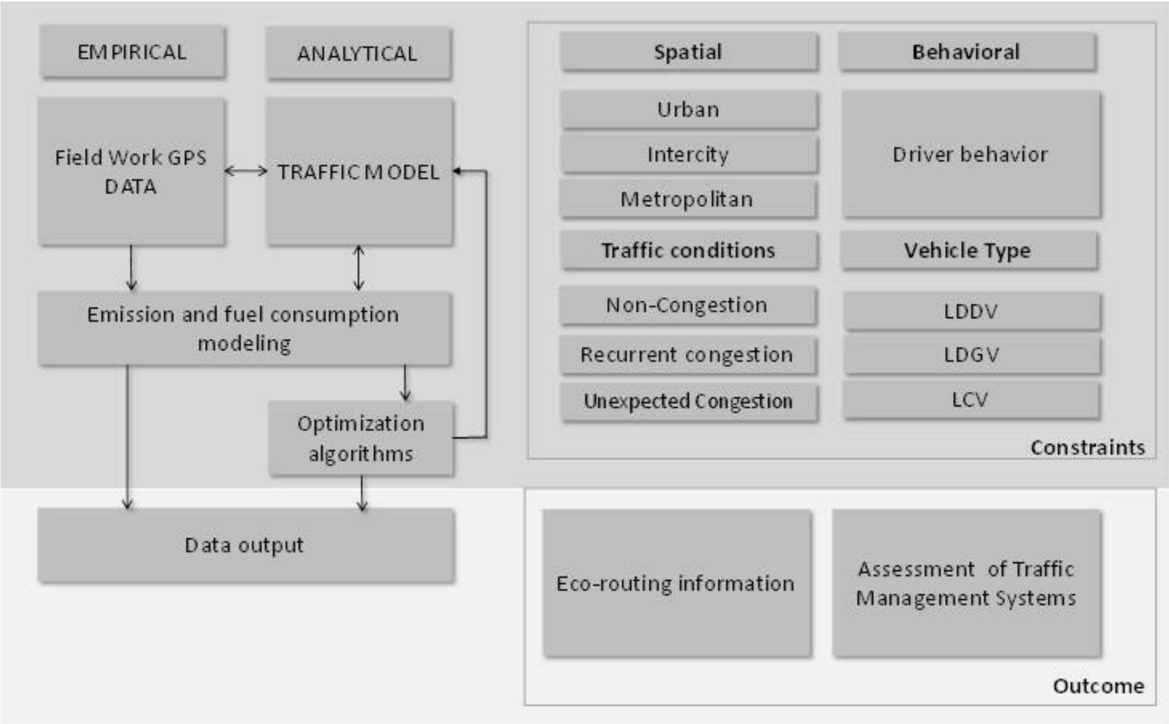


Figure 4 Summary of the methodology

In a second phase, analytical models were used to assess different routing and traffic assignment strategies. Similarly, this analysis has been conducted over different scenarios and under different traffic demands. The average fleet composition observed in each study area was used to estimate the overall impacts on emissions.

Summarizing, the empirical component of the thesis provides a practical assessment of the potential for fuel consumption and emissions minimization based on correct route choices. In a second step, these data are used to validate traffic models that enables to extend the analysis from historical data towards stochastic simulations, and therefore from an individual to a system perspective.

A wide variety of different research methods are applied for answering the research questions, including field work, traffic, emissions and fuel consumption modelling and traffic assignment optimization. The fundamental methods are explained in the next sections, however, additional methodological details can be found in chapters 4, 5, 6 and 7.

3.2 STUDY DOMAIN

The data used in thesis to estimate energy and emissions impacts of route choice behavior were collected in Aveiro, Oporto suburban region (Portugal) and Hampton Roads, Virginia, USA. Table 5 shows the study areas, total distance covered, and the period of analysis in each scenario: Urban (U), Intercity (I) and Metropolitan area (M). Data for approximately 13 200 km of road coverage over the course of 222 hours have been collected. In order to ensure realistic options, for all origin/destination pairs (OD pairs), the study routes were selected based on a web trip-planning software (Google-maps) suggestion.

Table 5 Study areas, distance and the period of analysis in each scenario

Scenario	Urban	Intercity	Metropolitan
Location	City of Aveiro, Portugal	Oporto suburban region	Hampton Roads, VA USA
OD-Pairs	Centre<->suburbs	Aveiro<->Porto	Norfolk<->Chesapeake
Nº of routes	3	4	2
Distance traveled (km)	550	11000	1650
Periods	Jan. - Mar. 2010 and 2011, Sept. 2011	Jan. - Mar. 2010/2011, Sept. 2011	Feb. 2012

For each case different routes were selected: motorways (m), highways (h), urban roads (u) and arterial roads (a). To identify each route the following notation was used: the first capital letter identifies the study area and the second lower case letter identifies the dominant type of road on each route. Figure 5 and Figure 6 show the map and photos of representative sections of the study routes, respectively.

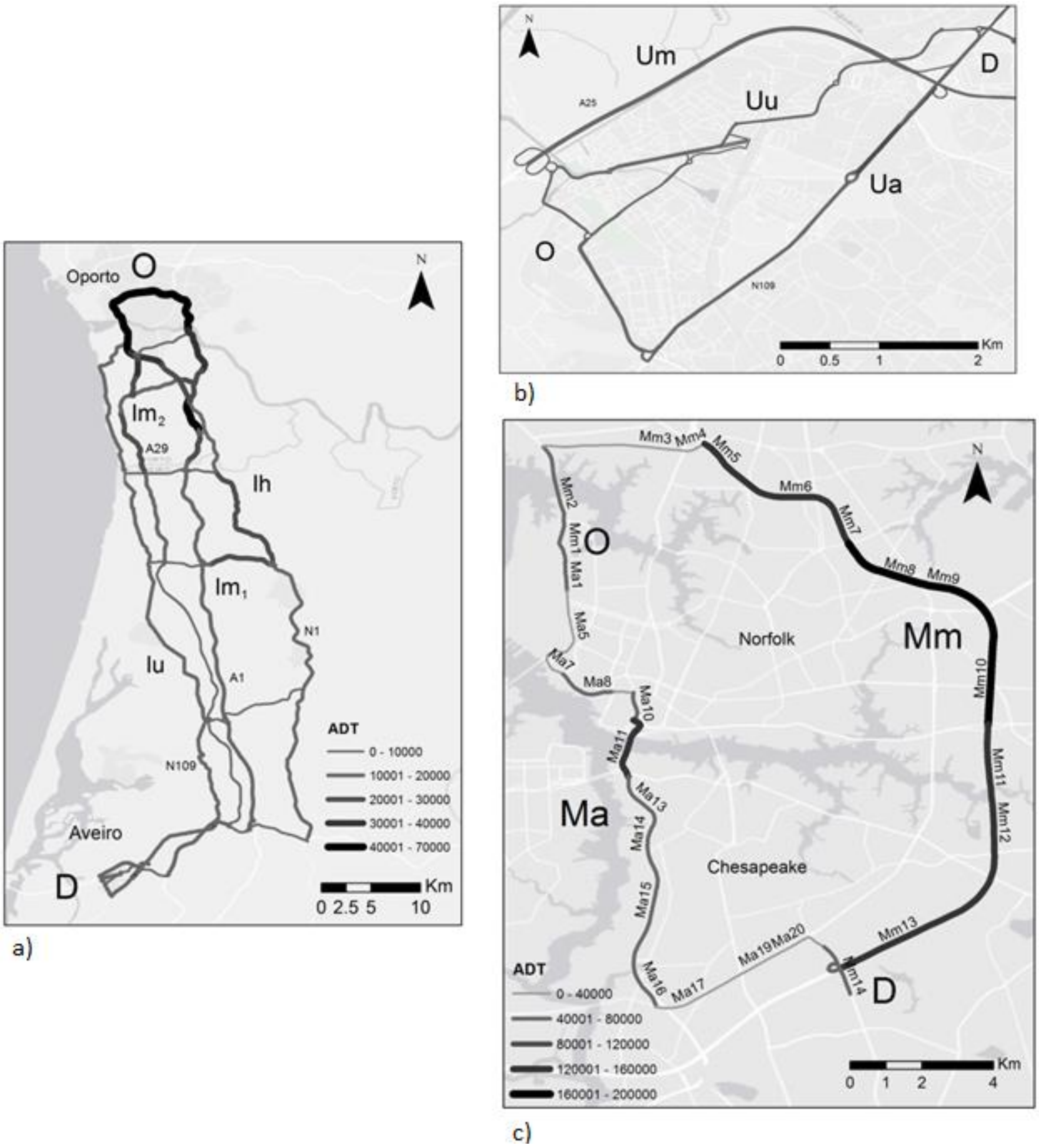


Figure 5 Study routes map and Average Daily Traffic (2012): a) intercity (Oporto-Aveiro): *Im₁*, *Im₂*, *Ih* and *Iu*; b) urban routes (Aveiro centre and suburbs): *Um*, *Ua* and *Uu* and c) Metropolitan (Norfolk-Chesapeake): *Ma* and *Mm*. Metropolitan routes are subdivide according VDOT segments.

Figure 6 Photos of representative sections of each route

To analyze the impacts of route choice decisions on an urban scale, three alternative routes (*Um, Ua, and Uu*) in Aveiro, Portugal were monitored. The city of Aveiro is a medium sized urban area (55,000 inhabitants) [123], in which urban traffic has demonstrated to be strongly connected with air pollutant levels [124]. All monitored routes, shown in Figure 5 , connect the city center (C) to a point located in the suburbs (S). A Origin-Destination (OD) survey [125] has shown that the main point of attraction during the morning peak hour is located in the south of the urban center (university). Thus, a significant part of the population living in the north of this area has to cross or bypass the urban core to reach this area. While Route *Ua* is predominantly (56%) on motorway A25, Route *Ua* essentially traverses arterial road N109. Finally, Route *Uu* is located entirely in a compact urban environment. All routes were tested and analyzed separately in both directions, Centre to

Suburbs (CS) and Suburbs to Centre (SC), because of the significant distance changes of each way related to traffic constrains.

In order to identify the energy and environmental impacts of route choice at the intercity level, GPS and video data of 4 parallel routes (Im_1, Im_2, *Ih and Iu*) were collected between Aveiro and Oporto, Portugal. Route Im_1 extends over 77 km and it consists virtually entirely of motorways. During the first period of field work, Motorway A1 was the only section where there was a toll of 3.15 €. This section had an average daily traffic (ADT) of approximately 20,000 vehicles [126] Route Im_2 is also 77 km long and traverses the A29 motorway that runs parallel to the A1. This option was widely used until September 2010, because this motorway had no tolls (unlike A1). The ADT on A29 ranges from around 33 000 vehicles in the southern sections to 73,000 in the northern sections. There are other distinctive features of A29 such as considerable areas of speed limit of 100 km/h, lower quality of pavement and more interchanges. After the introduction tolls the ADT has decreased approximately 50% [126].

Route *Ih* is the longest, 86 km in length, (34% of the distance is on motorways and 66% on the highway N1). Highway N1 runs north through towns and industrial zones with a considerable number of ramps and intersections, but some new 3-lane sections bypass the intermediate towns. Route *Iu* uses essentially N109 and the majority of the distance of the route (approximately 90%) is done on roads crossing built-up areas of towns and villages. All intercity routes have similar characteristics in both directions. To estimate the ADT on these routes, 7 hours of video data were collected at 6 key points of *Ih* and *Iu* during the evening rush hour. Using a peak hourly factor of 8.22% [127], it was estimated that *Iu* has an ADT of 11,500 and *Ih* of 17,500 vehicles per day (vpd).

With respect to the metropolitan area, two alternatives routes in Hampton Roads, VA, (Figure 5c) were considered. Route *Ma* is mostly performed on arterial roads crossing downtown Norfolk. Regarding route *Mm*, 70% of the route distance is done on a motorway. Although route *Mm* presents more intersections, the majority of them are accesses to residential neighbourhoods with little impact on the main road. The ADT are clearly higher on USA routes, reaching values higher than 180,000 vehicles per day in some sections [128]

(Figure 5c). These routes have high quality data on traffic volumes for all road segments and characteristics [128] which allows a detailed analysis of the traffic volume impact on emissions. Table 6 presents some key route characteristics, based on video data and satellite images (Google earth).

Table 6 Characteristics of the analysed routes.

Route	Length	Speed limit (km/h) (% of distance)				Nº of lanes (% of distance)					Intersections			Ramps	
	(km)	50 or 64	70 80	90 96	100 120	2	3	4	6	8	Total	Tl	R	On	Off
Im₁	77	2	-	7	91	2	-	83	7	8	9	1	3	26	26
Im₂	77	2	-	7	91	2	-	87	11	-	9	1	2	35	33
Ih	87	2	58	7	33	48	12	33	7	-	135	20	7	48	58
Iu	76	23	68	6	3	88	-	2	10	-	275	46	19	47	45
Um-CS	6.9	29	13	-	58	29	-	71	-	-	11	1	4	5	6
Um-SC	5.8	32	2	-	66	32	-	68	-	-	10	1	3	3	2
Ua-CS	6.4	66	34	-	-	45	-	55	-	-	10	1	5	11	15
Ua-SC	5.7	63	37	-	-	39	-	61	-	-	8	1	3	9	11
Uu-CS	4.3	100	-	-	-	60	-	40	-	-	15	3	5	6	5
Uu-SC	4.1	100	-	-	-	60	-	40	-	-	15	3	5	8	7
Ma	21	47	34	19	-	2	-	14	47	37	55	27	0	12	13
Mm	29	30	-	70	-	5	-	31	59	5	47	17	0	17	17

Note: Tl – Traffic lights; R - Roundabouts

3.3 RECORDING VEHICLE DYNAMICS AND ROUTE CHARACTERISTICS

Road tests were performed during weekdays under dry weather conditions during the months of February, March and April of 2010 and 2011. According to traffic volume data [124,128], the peak period in the Portugal (PT) site was considered between 7-9 AM and 5-7 PM while in USA the peak period was considered between 6-8 AM and 4-6 PM. Thus, all trips whose departure time was within this time range are defined as peak hour tests. The off peak tests occurred between 10 AM-5 PM (PT) and 9 AM-4 PM (USA). The USA tests were performed using a unique driver, while in the Portuguese case-studies, different drivers and vehicles were used (Table 7).

Table 7 Probe vehicles characteristics

Local	Probe Vehicle	Engine size (l)	power (cv)
Intercity/ Urban	*Toyota Prius*	1.5	77 + 58 (electric engine)
	OPEL Corsa	1.2	80
	VW Polo	1.2	70
	Toyota Yaris	1.4	90
Metropolitan	*Nissan versa*	1.8	110

As shown in Figure 7, GPS equipped-vehicles were employed to traverse the different routes to collect second-by-second trajectory data required for microscopic analysis. Simultaneously, route videotaping was performed, with the purpose of characterizing each route from various aspects and specific traffic events that can influence instantaneous emissions and fuel consumption.

Driving styles and behaviour were controlled to match the “average car” driving style [129] in which the test vehicle travels according to the driver’s judgement of the average speed of the traffic stream.

The GPS equipment used in this study has an active high sensitivity antenna with an accuracy of 1 to 5 m and a 5 Hz update rate. Speed and acceleration data were gathered directly from the GPS data logger. Altitude data were obtained through a Digital Elevation Model based on the geographic position (GPS Visualizer). Generally, the signal losses were not significant, so they did not affect the overall results. For 99% of cases, the horizontal dilution of precision (HDOT) was within 2 m.

Figure 7 Scheme used for routes videotaping and GPS data logger location

3.4 TRAFFIC MODELLING

VISSIM 5.4 model [55] was applied to simulate individual vehicle movements. This model was selected because of the possibility to define different road-user behavior parameters and sub-models for different vehicle types and traffic controls. Furthermore, it allows different vehicles performance such as desired maximum braking and acceleration per vehicle and class as well as to produce the requested data for the emission models [55]. Once the process of calibration and validation of the traffic model takes into account traffic some results obtained in Chapter 4, a more detailed description of the traffic modeling can be found in section 6.2.

3.5 EMISSIONS ESTIMATION

Micro-scale dynamic emissions models can be classified into load-based and regression based models. The vehicle specific power (VSP) methodology is an example of the latter. The computational efficiency of this type of models makes them more widely used in calculating energy and emissions factors associated with traffic planning projects [31].

3.5.1 Definition of vehicle specific power (VSP)

According to Palacios [32], VSP is defined as the instantaneous power per unit mass of the vehicle. The instantaneous power generated by the engine is used to defeat the rolling resistance and aerodynamic drag, and to increase the kinetic and potential energies (KE and PE) of the vehicle. It is equivalent to the product of speed and equivalent acceleration, including the effects of roadway grade and rolling resistance, plus a term for aerodynamic drag which is proportional to the cube of the instantaneous speed [32].

$$VSP = \frac{\frac{d}{dt}(KE + PE) + F_{rolling} \cdot v + F_{Aerodynimic} \cdot v}{m}$$

$$<=> VSP = \frac{\frac{d}{dt}\left(\frac{1}{2}m\cdot(1+\varepsilon_i).v^2 + mgh\right) + C_r mg \cdot v + \frac{1}{2}\rho_a C_D A (v+v_w)^2 \cdot v}{m} \qquad \text{Eq. 3}$$

$$<=> VSP = v(a(1+\varepsilon_i) + g \cdot \sin(\arctan(grade)) + gC_r) + \frac{1}{2}\rho_a \cdot \frac{C_D.A}{m}(v+v_w)^2 \cdot v \; 3$$

Where:

m - vehicle mass
v - vehicle speed
a – vehicle acceleration
ε_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 ε_i is gear-dependent).
h - altitude of the vehicle
grade - vertical rise/grade length
g - acceleration of gravity (9.8 m/s^2)
C_R - coefficient of rolling resistance (0.0135 -dimensionless)
C_D - drag coefficient (dimensionless)
A - frontal area of the vehicle
Pa - ambient air density (1.207 kg/m^3 at 20°C)
V_w - headwind into the vehicle

The units of VSP are power (W) per unit of mass (kg) equivalent to kW/ton (Eq. 4). Using characteristic values for all parameters, the Eq. 5 is obtained:

$$VSP\left(\frac{kW}{Ton} = \frac{W}{Kg} = \frac{m^2}{s^3}\right) \qquad \text{Eq. 4}$$

$$VSP = v(1.1a + 9.81\, sin(arctan(grade)) + 0{,}81 \cdot 0.0135) + \frac{1}{2}1.207 \cdot 0.0005 \cdot (v+v_w)^2 \cdot v <=>$$

$$VSP = v.1.1a + 9.81\, sin(arctan(grade)) + 0.132 + 3.02 \cdot 10^{-4} \cdot (v+v_w)^2 \qquad \text{Eq. 5}$$

Finally, ignoring the term *headwind into the vehicle* (v_w) the follow expression is achieved (Eq. 4).

$$VSP = v[1.1a + 9.81\,sin(arctan(grade)) + 0.132] + 0.000302 \times v^3 \qquad \text{Eq. 6}$$

The emission factors for LDGV used in this research were based on a modelling database consisting of about 232000 seconds of data from on-board and laboratory dynamometer measurements. Using these data, a conceptual modelling based on different VSP interval ranges was developed in order that each pollutant has a different sensitivity to each VSP mode. The categorization of VSP in 14 modes has been selected as being the most appropriate approach to facilitate the design of a modelling system [130]. Ideally, each mode should have a statistical significantly different average emission rate from any other mode. Furthermore, no single mode should explain more than approximately 10 % of total emissions. Table 8 shows VSP categorized into fourteen discrete modes.

Table 8 Definition of VSP mode (122)

VSP MODE	DEFINITION (KW/TON)		
1		VSP <	-2
2	-2	<=VSP<	0
3	0	<=VSP<	1
4	1	<=VSP<	4
5	4	<=VSP<	7
6	7	<=VSP<	10
7	10	<=VSP<	13
8	13	<=VSP<	16
9	16	<=VSP<	19
10	19	<=VSP<	23
11	23	<=VSP<	28
12	28	<=VSP<	33
13	33	<=VSP<	39
14		<=VSP<	39

Figure 8 shows the distribution of VSP modes according to different levels of acceleration. Negative VSP values are characteristic of descending roads or negative accelerations. VSP mode 3 corresponds to emissions in idling situations, whereas the higher levels of VSP correspond to a combination of the following factors, high-speed, hard acceleration and steep slopes.

For each road grade, the upper *plateau* represents all sets of speed and acceleration values (s,a) leading to VPS higher 39 kW/ton. In practice, these extreme VSP values are not commonly reported [18,38]. The bottom horizontal level corresponds to (s,a) pairs leading to VSP values lower than -2 kW/ton. The area of this level tends to increase with downward slopes while the opposite occurs with the upper level.

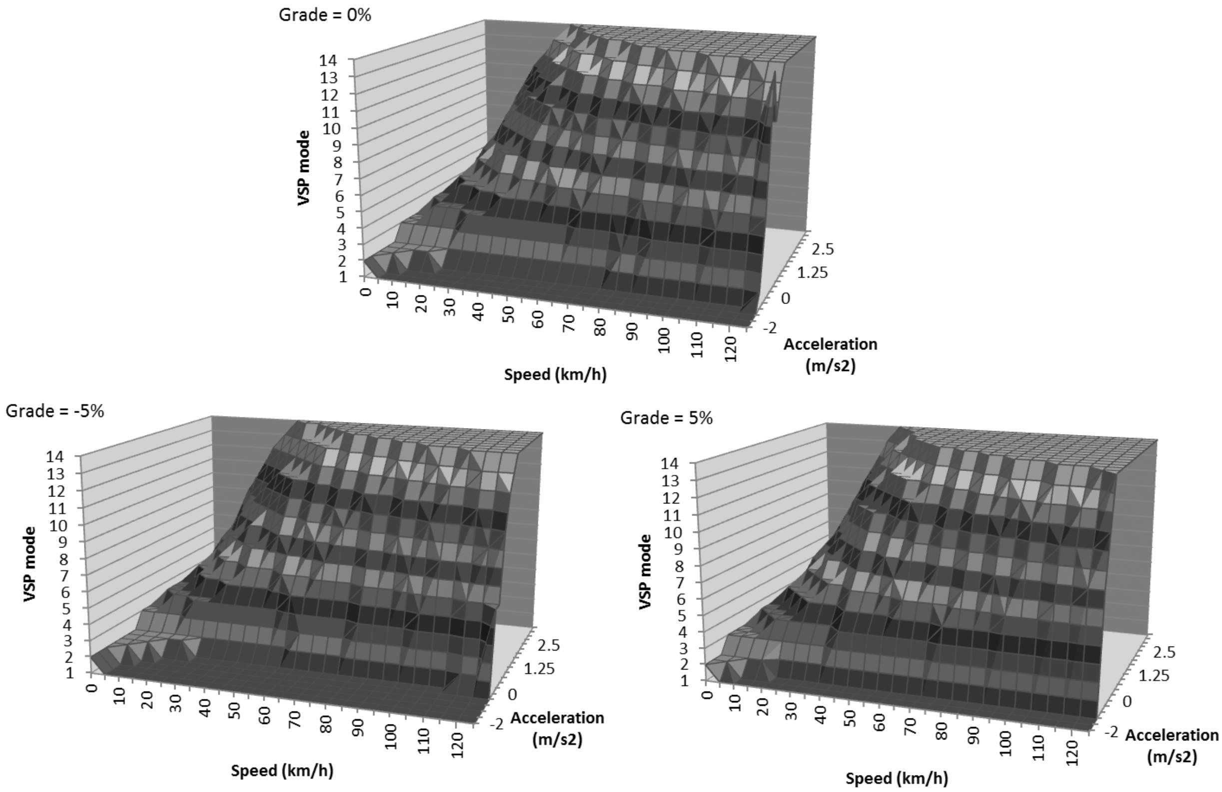


Figure 8 VSP modes according different levels of speed and acceleration and for road grad 0, -5 and +5%

3.5.2 Emission rates

This work focuses mainly on light duty vehicles (LDV). Figure 9 illustrates average modal emission rate in the VSP mode for LDGV with engine sizes smaller than 3.5 L [130]. Since each pollutant has a different sensitivity to the modal definition there are various situations in which a mode can contribute about 10 % of the total emissions of one pollutant but a considerably lower fraction of the total emissions for another pollutant, as demonstrated in Figure 9. For instance, the VSP bins 12, 13 and 14 represents about 30% of the total CO emissions and only 15 % or less of the total NO_X, HC, and CO_2 emissions.

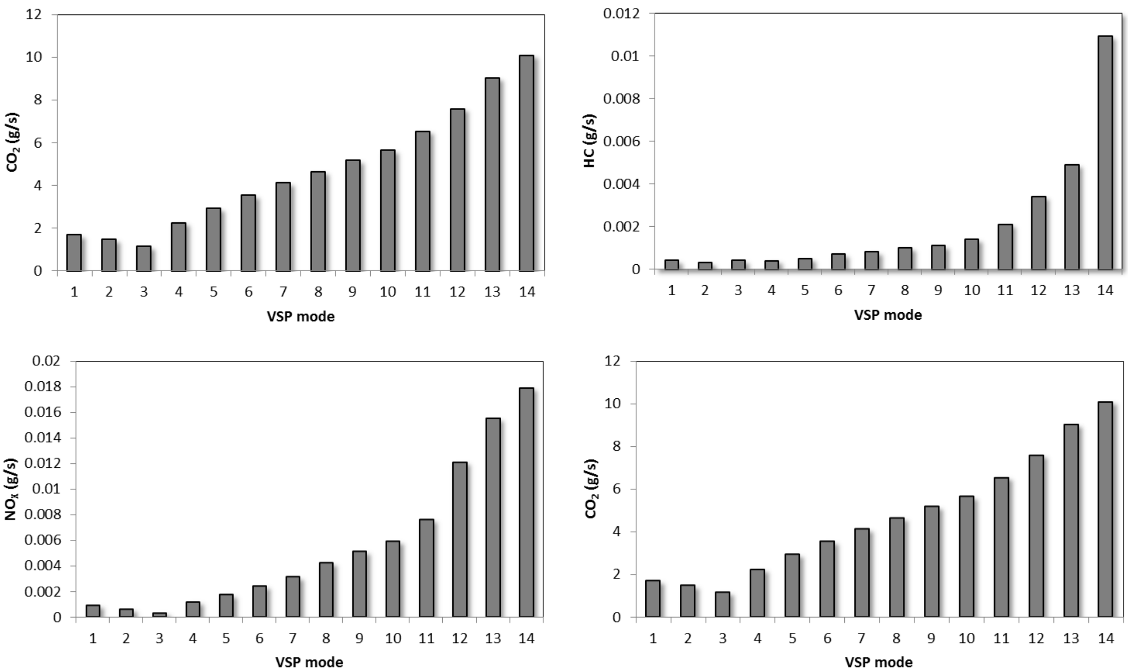


Figure 9 Emission rates for LDGV with engine displacement < 3.5 L [130]**.**

Recent research has demonstrated that VSP approach is also useful for modelling emissions from LDDV [18]. A quantification of average emission rates is presented in Figure 10.

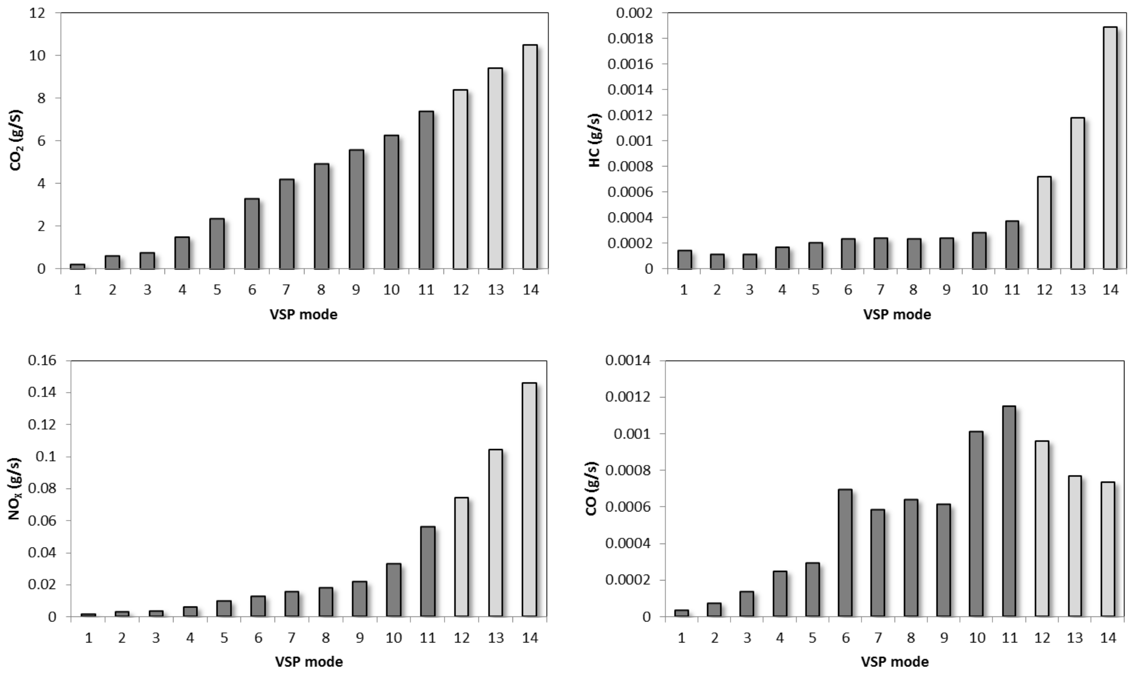


Figure 10 Emissions rates for LDDV with engine displacement =1.8 L [18,131]**.**

Since the sample sizes of the emission rates corresponding to VSP modes 12–14 was very small [18]; the resulting modal averages for these modes were estimated based on a quadratic regression [131]. Total emissions produced during a trip are estimated based on the average time spent in each VSP mode, multiplied by the respective emission factor (Eq. 7).

$$EP = \sum_{1}^{14} n_i XP_i \qquad \text{Eq. 7}$$

Where:
EP = Total emissions pollutant P (g)
i=VSP mode (1 to 14)
n= time spent on each VSP mode i (1 to 14) (s)
XP = Emissions rate (g/s) (of the pollutant P from a particular vehicle) for VSP mode i

Figure 11 shows the ratio between the emissions rate at each VSP mode and its corresponding emission rate for the VSP mode 14. Emission rates increase monotonically for positive VSP values. The only exception to the increase of emission rates with positive VSP are the CO emission rates for diesel vehicles. Coelho et al. [18] found that CO emissions seem to be more affected by speed changes and high accelerations compared to other pollutants. For the higher VSP modes CO emissions of LDGV increase considerably. This is because a high power demand often leads to a richer mixture, implying that there is insufficient oxygen to oxidize out CO (and HC) in the catalytic converter. In this situation, the tailpipe CO emissions can be very high which leads to a much higher average emission rate in mode 14 than for other modes [132]. Using different vehicle emissions databases the results can be easily updated for a different range of light vehicles based on the VSP distribution observed among the study routes.

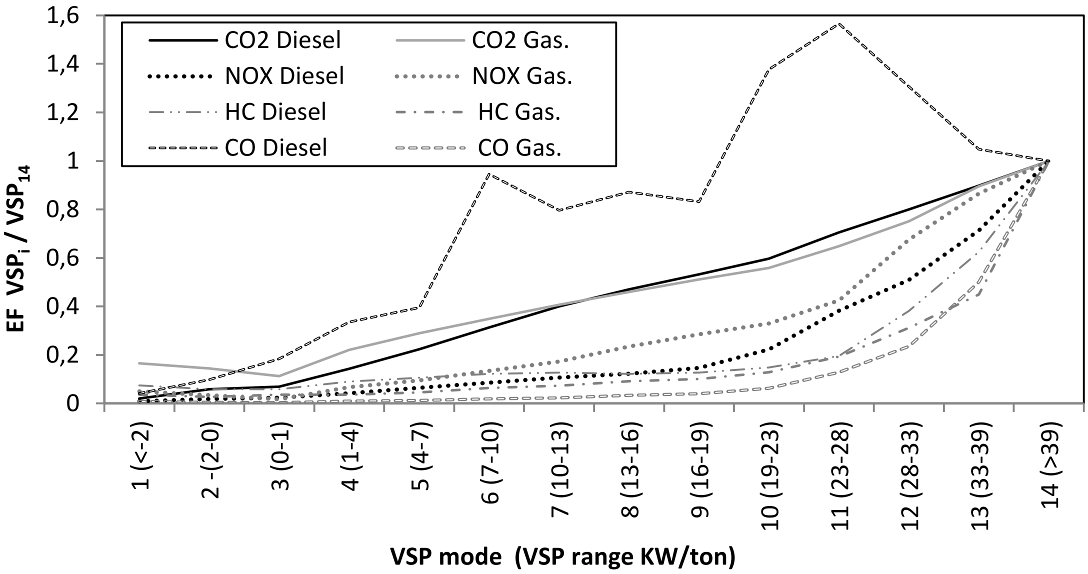


Figure 11 Normalized Emission Factors (EF) to VSP Mode 14 by pollutant and vehicle

VSP is a time-based model, i.e. emission factors are calculated per unit of time. Generally emissions factors increase monotonically with VSP values as demonstrated in Figure 11. However, emissions per unit of distance may follow an opposite pattern. To illustrate this, Figure 12 compares fuel consumption and CO emission factors per unit of time and distance. In the latter, speed and acceleration pairs VSP values outside the range considered (-2kW/ton, +39 kW / ton) - horizontal plateaus in the right figure) were excluded in order to avoid skewed results. For example, the emission factors (g/km) of all speed acceleration pairs with very high accelerations and a high speeds would present emissions factors lower than the actual values because the scale had been exceeded.

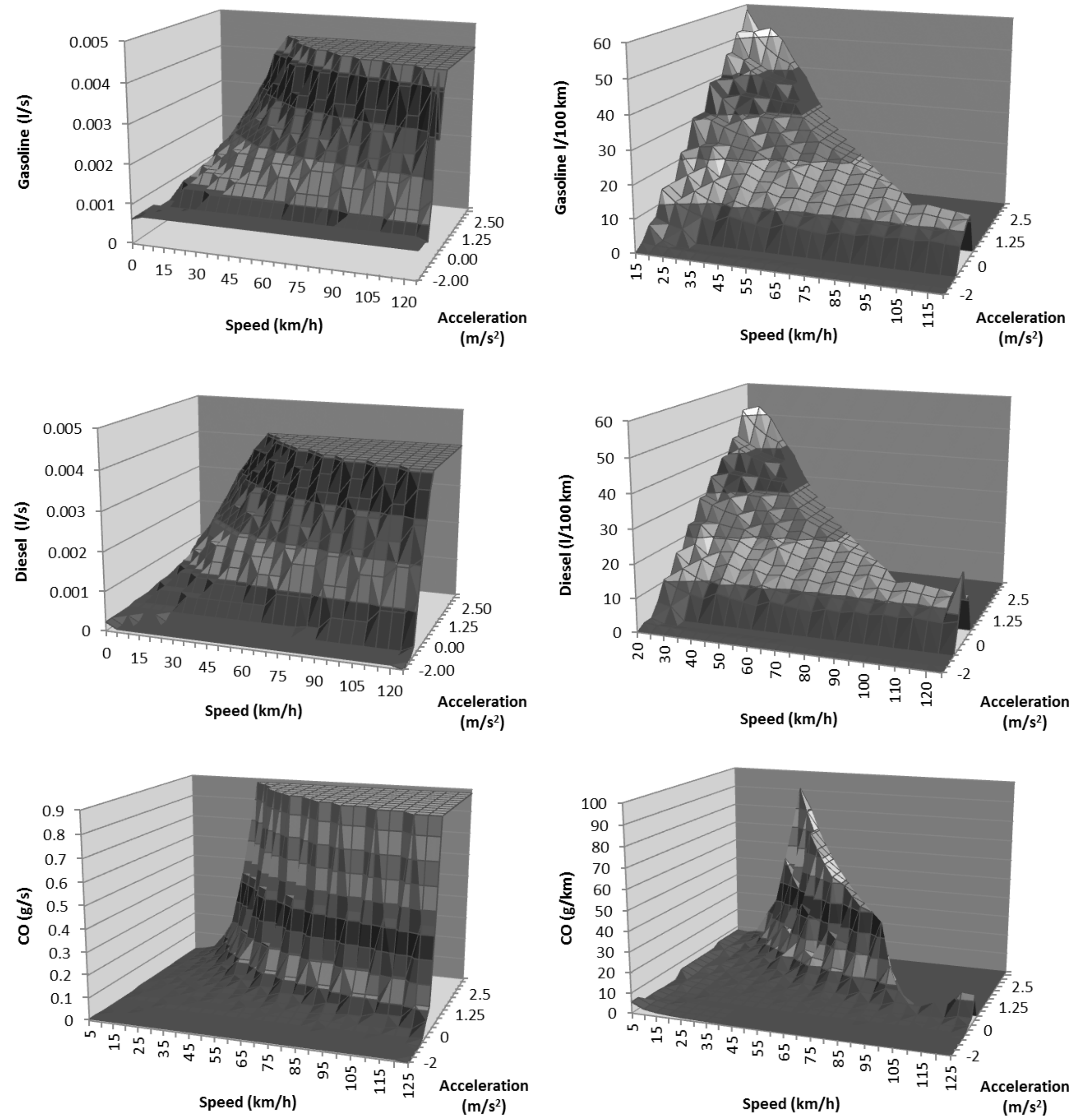


Figure 12 Fuel consumption (gasoline and Diesel) and emissions rates (CO from LDGV) per unit of time (left) and distance (right)

In relation to fuel consumption per distance, a tendency for decrease in fuel rates with speed is observed until certain speed values. Particularly, for a null acceleration, the speed which minimizes fuel the consumption is 80 km/h for LDGV and 60 km/h for LDDV. Regarding CO, the optimum speed is 59 km/h. However, both time-based and distance-based diagrams show that CO emissions are considerably more sensitive to accelerations.

3.5.3 Data processing

For each trip performed, second-by second data of speed, acceleration and altitude were incorporated into a spread sheet designed to calculate emissions and automatically provide some statistical data of each test performed. Data is automatically organized into a serious of tables allowing an easy export to more advanced statistical software (such as SPSS). Subsequently, new inter-route descriptive statistics and analyses of variance are performed in order to assess the significance of a number of variables such as route choice, driver, and test vehicle. These data will be discussed in detail throughout the next chapters. Overall emissions data across the study routes are presented by means of box plots in appendix B. Outliers have been removed from the analysis of route choice impacts under free flow and recurrent congestion.

3.6 NORMALIZATION OF EMISSIONS COSTS AND DEVELOPMENT OF AN ECO-FRIENDLY INDICATOR FOR ROUTE CHOICE

During the current research it was found that the optimization of different pollutants based on route choice can dictate different paths. In this context, different approaches for normalizing the emission impacts of each pollutant were assessed. Several sources [133–135] for assessing damage impacts per mass of pollutant emissions, at the national scale were considered (Table 9). Certainty, it would be more accurate to use data based on the effect of each pollutant at a higher spatial resolution. Thus, these methods must be considered as preliminary approaches to ponder the health and social impacts of emissions, and considering the full range of uncertainties specific of each method.

Table 9 Environmental costs and human health impacts caused by emissions.

	ECONOMIC COST		HEALTH IMPACT
	(2012 USD/g) [134]	(2000 €/g) [135]	(DALYs/kg) [133]
NO_X	0.02480	0.00540	1.7200
HC	0.00827	0.00070	0.0248
CO	0.00416	------	0.0141
CO_2	0.00007	0.000025	0.00406
PM	0.22920	0.220000	7.2600

The US Department of Transportation presented a framework for conducting benefit-cost analysis of real-time information systems [134] . The costs associated with each pollutant are available to HC, CO, NO_X, PM and CO_2. This approach applies different techniques based on social cost of carbon (for CO_2), social benefits (HC) and contingent valuation (NO_X, CO and PM). The monetary value changes over time in accordance with the source information's predicted values by year. In this work, data from 2012 were used.

A previous study [135] provides emissions cost information, by considering country-specific meteorological and national population densities (including Portugal). It should be noted that the suggested approaches are not per se absolute and adequate means of estimating local or regional air quality and health impacts. The atmospheric chemistry related to ambient concentrations of the above mentioned pollutants is very complex. A more complex simulation structure (such as full-scale photochemical modelling) is necessary to offer the required spatial and temporal detail to accurately estimate their associated health and welfare impacts [136].

A comprehensive study on human health impact of different pollutants is outlined in Eco-Indicator 99 report [133]. This study provides a method for assessing, normalizing and weighting a very extensive range of substances according to various damaging effects. To assess the human health effect of all studied pollutants in the present thesis the egalitarian perspective was selected. In this methodology each perspective is composed in three damage categories. The damage category "human health" is subdivided in six subcategories, such as carcinogenic effects, respiratory effects caused by organic substances, respiratory effects caused by organic substances, damages caused by climate change, by ionizing radiation and by ozone layer. The egalitarian perspective was chosen since it considers most of the pollutants analysed on human health impact category. The used data for assessing damage costs per mass of pollutant and GHG emissions is summarized in Table 9.

Depending of the selected cost criteria, the general equation to compute the Cost C of the amount of a certain set of pollutants P (g) according a particular weighting criterion ω_i associated to each pollutant (see Table 9) is given by (Eq. 8):

$$C = \sum_{i}^{i=n} P_i(\omega_i) \qquad \text{Eq. 8}$$

An additional method for weighing the impact of different pollutants has to do with real time conditions in the region of the trip. This can be an interesting approach if one want to give more importance to the most critical pollutants in a given region. Moreover. pollutant concentration limits have human health impacts implicit in their values [137]. This approach will be simulated by looking at the observed conditions of pollutants in a specific day (section 6.1.3). Accordingly, different weights to the vehicles' predicted emissions were assigned.

3.7 IMPLEMENTATION OF THE METHODOLOGY

All study areas described in section 3.2 will be evaluated empirically in chapters 4 and 5. In particular, a characterization of each route is done, and total emissions produced in each alternative route are estimated. In all routes, second-by-second vehicle dynamics were monitored using GPS-equipped vehicles as described in 3.3. GPS data recorded on urban and intercity routes will be in turn incorporated into computational models described in Chapters 6 and 7. Data recorded on metropolitan routes will be mainly used for describing emissions under different traffic demands (section 4.2), and in situations of unexpected congestion (section 4.3). Using the data collected in intercity and urban scenarios, a computational platform using historical data of emissions is presented in section 6.1. In

Section 6.2 the implementation of an integrated microsimulation traffic and emission modelling platform is described in detail.

All calculations of emissions (whether derived from GPS data (chapter 4) or from traffic model (chapter 7) have followed the methodology described in section 3.5. Different methodologies for weighting the impacts of emissions (section 3.6) were used throughout the various chapters.

4 EMPIRICAL EVIDENCES OF ROUTE CHOICE IMPACT ON EMISSIONS

This chapter describes second-by-second vehicle dynamic data recorded in the previously described study areas. Then, a methodology based on the Vehicle Specific Power (VSP) concept was used to estimate the emissions impact. On-board video footage recorded route features and traffic incidents.

Section 4.1 explores a way to generate information about emissions and other route characteristics for drivers faced with a choice of routes under free flow conditions. Two different vehicles and drivers traversed several urban and intercity routes to enable the consideration of the influence of driver variability and vehicle dynamics. A sensitivity analysis to assess the impact of road grade is also performed.

Although eco-routing has been shown as a promising strategy to reduce emissions, during peak-periods, with limited additional capacity, the eco-friendliness of various routes may change. Section 4.2 explores this issue empirically by comparing total emissions during peak on non-peak periods. In total, approximately 13,300 km of GPS data were considered in three different OD pairs.

Usually transportation studies on emissions are conducted over normal conditions of network operation, namely during free-flow or recurrent congestion. In Section 4.3 an analysis of emissions under unexpected and extreme congestion circumstances is performed.

4.1 ROUTE CHOICE IMPACTS UNDER FREE FLOW CONDITIONS

A lack of knowledge on driver variability and vehicle dynamics impacts among routes with different characteristics and scales (urban and intercity contexts) was found. Specifically, the impact of these factors on the development of future sustainable traffic guidance systems has not been addressed in depth.

Many of the devices allowing eco-friendly navigation that have emerged are based on fuel savings and lowering CO_2 emissions [138,139] , which is an important improvement with respect to the issue of global warming. However, current eco-routing devices do not for the most part consider the impact on local pollutants, which have direct effects on human health. Thus, it is necessary to improve the knowledge based on the role that driver variability or vehicle dynamics play in choosing an environmentally friendly route in an integrated way. Based on different case studies, this section examines how emissions vary across alternative routes.

This eco-information is intended to empower travellers who want to use emissions as an additional criterion for their route selection. It also can help traffic managers take into account environmental concerns. The pollutants considered in this study include CO, CO_2, HC, and NO_X.

Before the presentation of results, additional details on fieldwork and the development of a classification system of routes in several parameters are provided. Then a comparative analysis of the routes considering different criteria, including travel time, emissions per time and distance, and VSP modal distribution is described. Additionally, a classification system of routes considering a range of different criteria is presented. Finally, an analysis about the impact of driver and vehicle on emissions and travel time is performed and a classification system of routes is presented.

4.1.1 Methodological details

4.1.1.1 Field work campaign

This section consider field experiments during off-peak periods (10:30 AM - 1:00 PM and 2:30 PM – 5:00 PM), in order to analyse the inherent characteristics of the routes without the influence of significant changes in traffic. The use of minimum samples size guarantees that the average travel time obtained from the test vehicle is within a specified error range of the true average travel time for the entire vehicle population. The travel time data collection handbook from FHWA [129] presents typical minimum sample sizes for various combinations of confidence level and acceptable relative error in motorways (Table 10) and arterials (Table 11).

Table 10 Illustrative Test Vehicle Sample Sizes on Motorways [129].

ADT per lane	90% Confidence ± 10% Error	95% Confidence ± 10% Error	95% confidence ±- 5% Error
Less than 15000	5	6	15
15000 to 20000	6	**8**	21
Greater than 20000	10	14	47

Table 11 Illustrative Test Vehicle Sample Sizes on Arterial Streets [129].

Traffic Signal Density (nº. of signals per 1.61 km)	90% Confidence ± 10% Error	95% Confidence ± 10% Error	95% confidence ±- 5% Error
Less than 3	5	**6**	15
3 to 6	6	**8**	25
Greater than 6	9	12	37

Commonly specified relative errors are ± 10% for planning and policy-level studies [129]. Therefore, taking into account the ADT observed in the intercity and urban routes (<20.000 vpd/lane) and traffic signal density (<6 TL/1.6 km), the minimum sample size in each OD pair to ensure a 95 % confidence level with less of 10% error is 8 runs. In the urban and intercity routes 10 and 12 trips were performed respectively. Approximately 4000 km of road tests were covered during weekdays under dry weather conditions between March and April 201. In total three distinct data sets were considered: **DAV1** (**D**river **A** – **V**ehicle **1**); **DBV1** (**D**river **B** – **V**ehicle **1**); and **DAV2** (**D**river **A** – **V**ehicle **2**).

4.1.1.2 Route ranking characteristics

During the experimental phase, an important set of factors that can influence travellers' route choice were collected. To summarize this information, a classification system that is easily understood by users was developed.

For each factor a score of (0) was assigned to the worst route and a score of (1) was assigned to the best route. For the intermediate routes a linear interpolation was performed in order to assess their closeness to the extreme routes, by assigning each route a value between 0 and 1. Considering this score, a qualitative classification from 0 to 5 stars was developed.

4.1.2 Average speed and travel time

Considering the significant distance changes of each way related to traffic constrains, the results of travel time and average speed for urban routes will be analysed separately. For intercity routes, since these differences are not significant (and taking into consideration the purpose of this section) the data are analysed together. However, descriptive statistical analysis of travel times categorized by each OD pair and direction are provided in appendix A. Table 12 summarizes speed and travel time data observed during the fieldwork.

Table 12 Travel time and speed statistics

		Urban CS			Urban SC			Intercity			
		Um	**Ua**	**Uu**	**Um**	**Ua**	**Uu**	**Im_1**	**Im_2**	**Ih**	**Iu**
Travel time (min)	$\bar{X}$	7.2	8.1	8.4	5.4	7.0	8.0	48	51	80	97
	95th Percentile	7.7	8.8	10.0	6.0	7.5	9.0	51	63	89	104
	5th Percentile	6.6	7.5	7.0	5.0	6.3	7.1	45	45	74	91
	SD	0.5	0.5	1.3	0.4	0.5	1.3	1.8	4.2	5.0	2.4
	T-student-95th CI	±0.1	±0.1	±0.3	±0.1	±0.1	±0.2	±1.2	±4.2	±3.2	±2.4
Speed (km/h)	$\bar{X}$	56.4	47.1	29.4	63.2	48.9	28.4	96	91	65	46
	95th Percentile	61.5	50.5	33.6	67.5	44.9	31.8	101	100	70	49
	5th Percentile	52.9	43.7	24.6	57.7	44.9	25.4	91	73	59	43
	SD	4.2	3.4	4.8	5.9	3.8	2.0	4.8	5.5	5.0	4.2
	T-student-95th CI	±3.2	±2.6	±3.6	±4.4	±2.9	±1.5	±4.1	±4.6	±4.2	±3.5
	n (DAV1, DBVI, DAV2)	4,3,3	4,3,3	3,3,3	3,3,3	4,3,3	3,3,3	4,4,4	4,4,4	4,4,4	4.4.4
	$\bar{X}$ DAV1	56	47	28	63	47	28	99	95	66	46
	$\bar{X}$ DBV1	55	48	31	61	51	27	97	89	64	45
	$\bar{X}$ DAV2	60	48	32	67	67	32	94	89	66	47

$\bar{X}$ – mean, SD Standard Deviation, CI – Confidence Intervals, CS – Centre Suburbs, SC – Suburbs – Centre.

Despite being the longest route, *Um* is the fastest option allowing travel time savings of 33% and 23% (SC direction) when compared with Routes *Uu* and *Ua*, respectively. The travel time standard deviation and T-student confidence intervals suggest that there is more variability of travel time on Route *Uu.* Changes in average speed in relation to alternative drivers and vehicles were not found. In the opposite direction results are similar but with less difference between the routes.

Concerning intercity routes, the motorway options Im_1 and Im_2 are less time consuming than the alternative routes. Compared to the closer alternatives, Route Im_1 yields 40% time savings in relation to Route *Ih*, and Route *Im₂* yields 47% savings compared with Route *Iu*. The travel time standard deviation and 95th percentile confidence interval suggests that Routes Im_2 and *Ih* have lower reliability. Although Route *Iu* is the shortest, the travel time is higher than other routes. However, this route presents more uniform travel times compared with Route *Ih*. With the exception of motorways routes in which DBV1 shows a lower average speed comparing with DAV1 and the slight reduction of average speed for DAV2, no significant changes were observed.

4.1.3 Total emissions

Emissions of the monitored routes focused on CO_2, CO, and HC emissions from LDGVs, and NO_X from LDDVs (the major sources of each pollutant). Figure 13 provides a general description of average emissions according to driver and vehicle.

No significant changes in CO_2 are observed, mainly for routes driven towards the suburbs (CS); however, RC has the lowest emissions. Since the highest emission rates per distance were verified for this route, the shorter distance is a strong factor for total CO_2 emitted. Regarding intercity trips, the faster routes performed on motorways are more environmental friendly with respect to CO_2 emissions and fuel consumption.

Regarding NO_X emissions from LDDVs, the slower routes (Routes *Uu* and *Iu*) present average reductions of about 35%, compared with the fastest alternatives. However, for Route *Uu*, the reduction is related with the shortest distance, while for Route *Iu*, the difference lies primarily in the reduction of speed, since the distance is similar to Routes Im_1 and Im_2.

The analysis of total CO emissions suggests that there is a trade-off between travel time and CO emissions. Both urban and intercity routes show higher CO emissions if the route leads to faster driving. Although the travel times were approximately the same, a more aggressive driving style of Driver B yielded increased CO emissions by about 50 % for Route

RA. For intercity routes, combining a smoother driving style on a route with lower speeds enabled a two-thirds reduction of CO emissions.

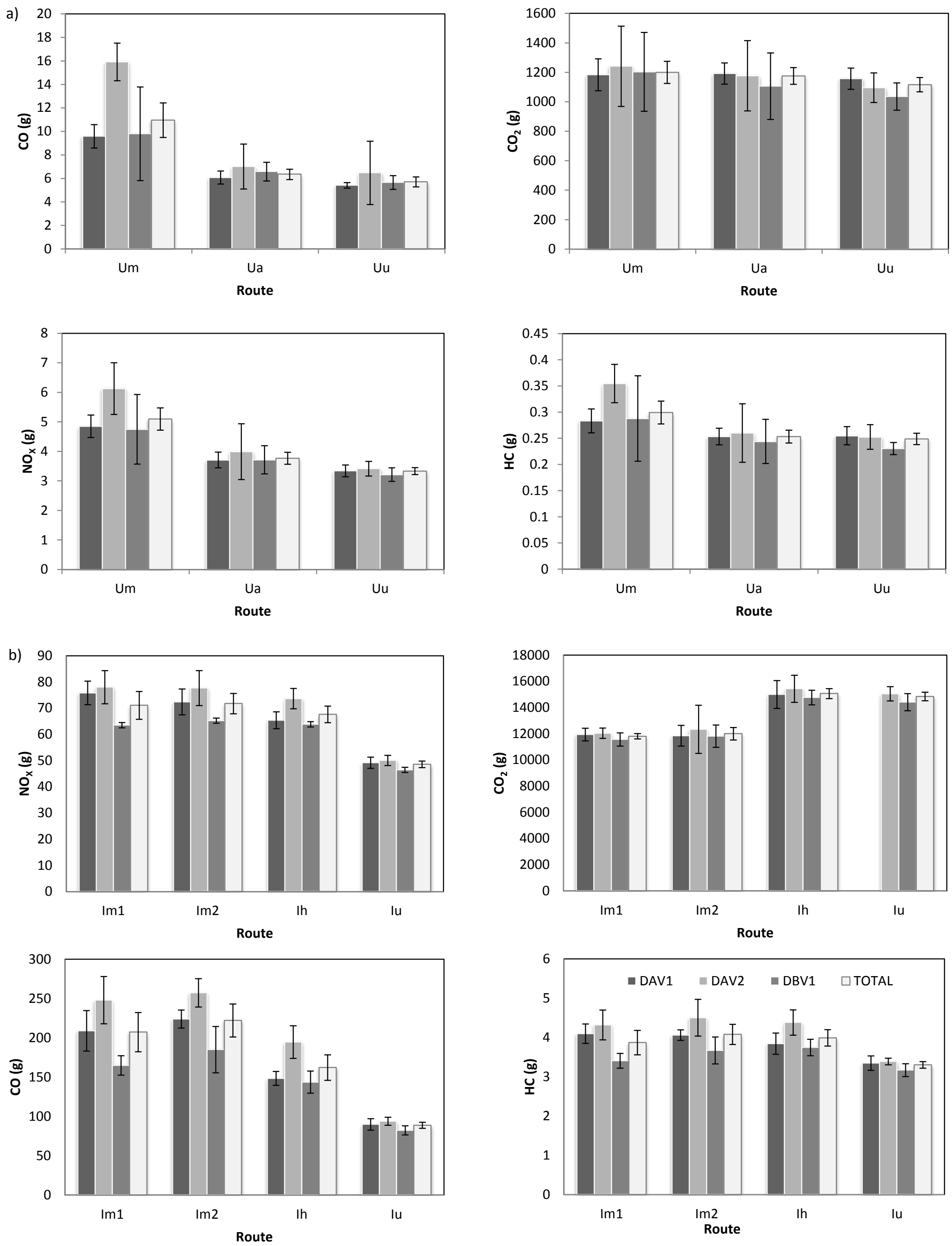


Figure 13 Total emissions per vehicle - a) urban b) intercity routes (Total Average; DAVI – Driver A Vehicle 1; DBV1 – Driver B Vehicle 1; DAV2 – Driver A Vehicle 2) - T-student 95% CI intervals.

In relation to HC emissions in the urban setting, Routes Ua and *Uu* show lower emissions, with slight variations depending on the travel direction (22% and 15%). Route R4 is the intercity route with the lowest HC emissions. Although the emission factors per distance for Routes R3 and R4 are quite similar, Route R3 is penalized because it is the longest.

Overall, under uncongested situations, a combination of an appropriate route and smoother driving styles can result in emissions reductions of CO_2-25%, CO-68%, NO_X-40% and HC-29%. At the intercity scale, quicker routes lead to fuel and CO_2 emissions savings. However, these options may considerably increase CO (150%), NO_X (46%) and HC (23%) emissions.

4.1.4 Emission rates analysis as a function of distance

To analyse emission rates profile, Route *Ih* was selected as a case study, due to its variability in road characteristics along the route. First the impact of road type on emissions is examined, and then the impact of road grade on different pollutants is assessed. Route *Ih* has been divided into 6 main sections corresponding to the following characteristics:

[S1], [S5] – Motorway at free flow speed
[S2], [S4] – 2-lanes highway crossing intermediate towns
[S3] – 2-3 lanes highway bypassing intermediate towns
[S6] – Motorway with high traffic volume - Oporto Ring

Figure 14 provides an example of speed, altitude and emission profiles for a trip performed on Route *Ih*. In addition to CO_2, the focus was on CO emissions from LDGVs and NO_X from LDDVs since they are main sources of these pollutants.

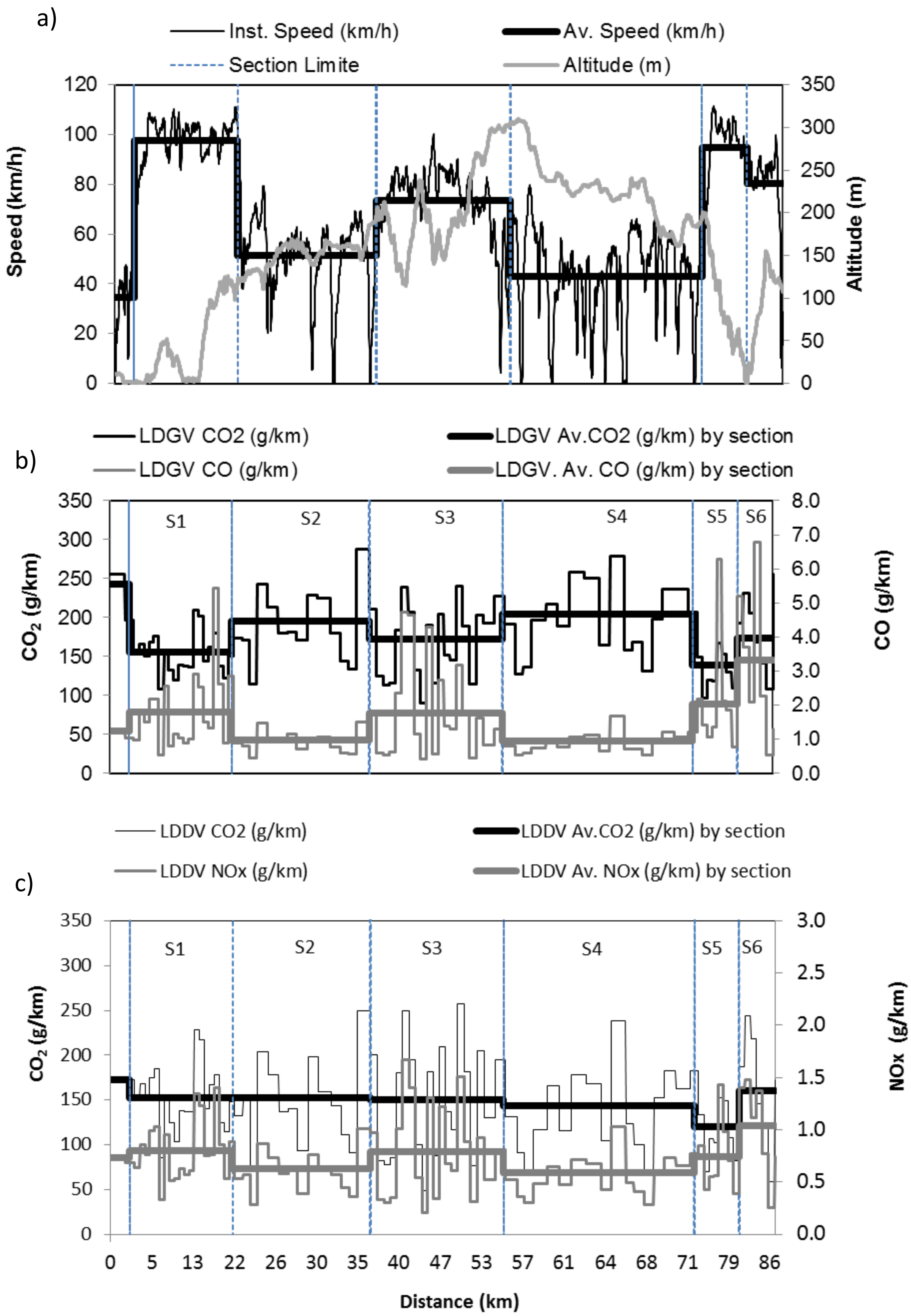


Figure 14 a) Average speed of a generic vehicle per km and section, and altitude profile, b) CO and CO_2 average emissions per km and section (LDGV), c) NO_X and CO_2 average emissions per km and section (LDDV).

As far as emissions from LDGVs, is concerned a complete opposite behaviour in CO_2 and CO emissions is observed. On motorways CO_2 emissions rates are lower, but the amount of CO emitted per kilometre in these sections is considerably higher. Regarding CO_2 emissions from LDDV, it should be emphasized two aspects: 1) emissions are consistently lower than those of gasoline vehicles, 2) there is less pronounced deviations along the various road sections. This confirms the well-known fact that accounting for the difference in energy density, the overall efficiency of the diesel engines is still greater than the gasoline engines. Regarding emissions from LDDV, NO_X emissions rates are lower in the slower sections [S2, S4]. As explained before NO_X emissions are mainly produced due to the increase of engine load especially at high temperatures.

A sensitivity analysis to assess the impact of road grade was performed. Thus, by artificially changing the altitude to a constant value (slope = 0%) the emissions from a hypothetical flat roadway surface scenario and from the real situation were compared (see Table 13). Assuming that the patterns of acceleration and speed remained constant, CO (+166%) and NO_X (+102%) are the pollutants most penalized by the positive road grade. For a LDGV the average positive slopes of 3.2% lead to an increase of CO_2 emissions, on the order of 38%. Diesel vehicles seem more sensitive to the road grade than gasoline vehicles. Considering emissions on the entire route, the distance of the descent sections is not enough to offset the increase in emissions caused by the positive grades.

Table 13 Percentage change in CO_2, CO and NO_X emissions relative to 0% grade for a generic LDDV and LDGV

			LDDV		LDGV	
	Av. Slope	**(% of distance)**	**CO_2**	**NO_X**	**CO_2**	**CO**
Downward	**-3.3%**	44%	-46%	-45%	-25%	-37%
Upward	**3.2%**	49%	63%	102%	38%	166%
Total	**0.1%**		8%	24%	6%	56%

In summary, the emission profiles vary considerably over the route, strongly depending on the characteristics of each roadway section. Opposing outcomes between CO_2 and CO emissions from LDGV were observed. Considering the sections S2 and S5, the road grade explains 34% and 62% of the difference between the emissions factors of CO_2 and CO, respectively. However, even ignoring the effect of the slope, the sections with higher traffic volume or lower capacity (e.g. S2) have the highest fuel consumption rates and thus higher CO_2 emissions.

4.1.5 Impact of Driver and Test Vehicle on emissions

In order to analyse the impact of driver variability, vehicle and route choice, linear regression models were estimated. These models predicted total emissions and average speed using dummy (0, 1) explanatory variables. Each dummy variable (route, driver, and vehicle) was compared to the reference base case, which was coded as “0". In this case, Route 1, Driver A and Vehicle 1 (DAV1) were considered the reference level.

The relevance of route choice, driver variability and vehicle are analysed over the intercity context. Linear regressions were performed to predict total emissions and average speed (Table 14), considering all trips performed for intercity routes. The adjusted R^2 parameter varied from 0.74 to 0.97. Route selection is the most important factor connected with emissions and speed (or travel time), and route Im_2 show no significant difference from Im_1. CO emissions from LDGV and NO_X emissions from LDDV appear to be dependent on the driver profile. CO_2 and HC emissions are not statistically significant with respect to driver (P values> 0.1). The emission patterns of these pollutants suggest that they are less sensitive to the driving variability than CO and NO_X. Average speed is confirmed to be independent of both vehicle and driver.

All local pollutant emission rates showed statistical significance regarding the vehicle used during the field tests. Since average speed, and hence travel time is shown to be independent of the driver and the vehicle, this dependency is likely a consequence of vehicle characteristics on driving behaviour affecting the profile of accelerations and decelerations. The presence of an automatic gearbox in Vehicle A and a manual transmission in Vehicle B could help to explain such variations.

Table 14 Regression Models Results

		Unstandardized Coefficients[1]		Standardized Coefficients[2]	t	Sig.	
		B	Std. Error	β			
Travel Time	(Constant)	48.5	2.241		21.661	0.000	
	Im_2	4.7	2.588	0.094	1.803	0.088	*
	Ih	33.5	2.588	0.678	12.946	0.000	**
	Iu	51.2	2.588	1.036	19.773	0.000	**
	DBV1	1.4	2.241	0.030	0.614	0.547	
	DAV2	-1.0	2.241	-0.022	-0.446	0.661	
LDGV CO_2	(Constant)	12029	189.683		63.414	0.000	
	Im_2	465	219.027	0.128	2.124	0.048	**
	Ih	3368	219.027	0.925	15.376	0.000	**
	Iu	3117	219.027	0.857	14.232	0.000	**
	DBV1	279	189.683	0.083	1.470	0.159	
	DAV2	-391	189.683	-0.117	-2.062	0.054	*
LDGV CO	(Constant)	198.3	13.197		15.029	0.000	
	Im_2	13.2	15.239	0.093	0.868	0.397	
	Ih	-38.8	15.239	-0.273	-2.545	0.020	**
	Iu	-118.0	15.239	-0.832	-7.746	0.000	**
	DBV1	40.1	13.197	0.307	3.036	0.007	**
	DAV2	-20.8	13.197	-0.160	-1.580	0.132	
LDGV HC	(Constant)	3.82	0.148		25.896	0.000	
	Im_2	0.22	0.171	0.189	1.290	0.213	
	Ih	0.20	0.171	0.170	1.163	0.260	
	Iu	-0.56	0.171	-0.478	-3.264	0.004	**
	DBV1	0.45	0.148	0.419	3.038	0.007	**
	DAV2	-0.28	0.148	-0.264	-1.913	0.072	*
LDGV NO_X	(Constant)	70.47	2.499		28.196	0.000	
	Im_2	2.02	2.886	0.075	0.701	0.492	
	Ih	-2.46	2.886	-0.092	-0.854	0.405	
	Iu	-22.43	2.886	-0.836	-7.771	0.000	**
	DBV1	6.73	2.499	0.273	2.694	0.015	**
	DAV2	-4.33	2.499	-0.176	-1.732	0.100	*

Note. Significance indicated by: *90% confidence. **95% confidence

4.1.6 Route ranking

[1] for a one-raw-unit increment on a predictor, the outcome variable increases (or if B is negative, decreases).
[2] for a one-standard deviation increment on a predictor, the outcome variable increasess (or decreases) by some number of SD's corresponding to what the β coefficient is .

A general rating of indicators for all intercity routes is presented in Table 15 that distinguishes between parameters that are usually known to the driver (such as travel time, distance, and cost) and other parameters that were analyzed during this research and may be disseminated through ATIS. The classification related to emissions assigned in Table 15 was developed considering the global average of total pollutant emissions, shown in white bars of Figure 13 for intercity routes.

The road safety indicator takes into consideration the available data which include the number of fatalities and serious injuries that occurred in the study routes over 2010 [140]. The Equivalent Property Damage Only (EPDO) crash rate was employed and adapted to address only accidents with fatalities and serious injuries. Thus, the annual number of crashes at each severity level was multiplied by a weighting factor (4 to deaths, and 1 to serious injuries) and divided by the average annual traffic to convert into the crash frequency – EPDO [141].

Table 15 Implementation of a route rating system to the study intercity routes

Routes	*Im₁*	*Im₂*	*Ih*	*Iu*
Travel time	*****	****	**	º
Distance	****	****	º	*****
Cost	º	*****	****	****
T. Time Variability	*****	º	**	***
Preservation	*****	****	**	º
Singularities	*****	****	**	º
Incidents	*****	****	**	*
Crash rate frequency (2010)	*****	***	º	*
CO_2 Emissions	*****	****	º	*
CO Emissions	º	*	**	*****
NO_X Emissions	***	º	****	*****
HC Emissions	*	º	*	*****

***** Best; º Worst

For those routes examined, the different rated parameters in Route *Im₁* establish a fairly regular pattern. This route is competitive for almost all categories as evidenced by the fact that 8 of its 11 parameters rate four or five stars, thus replicating the advantages of using the motorway: higher safety levels, high pavement quality, no interruptions from traffic lights or roundabouts, higher speed, and high reliability. Moreover, this route yields the lowest CO_2 emissions. By contrast, HC, NO_X, and particularly CO emissions take on their highest values. The presence of tolls is also negative for this route.

Route Im_2 yields almost the same advantages described for Route Im_1. Furthermore, this route also provided a key benefit in terms of cost since it had no tolls. However, compared to other alternatives, Route R2 has a greater variability of journey times as a result of the higher traffic volumes it serves. Like Route R1, this route has good ratings for CO_2, and poor classification for the other pollutants.

Route *Ih* receives an intermediate grade, meaning that it is a better option than Route *Iu*, but worse than the alternative motorway routes. This route presents the worst ratio of injury severity crashes normalized by traffic volume. Route *Iu* is advantageous for minimizing emissions of CO, HC, and NO_X. For CO_2 emissions and fuel consumption, Routes R3 and R4 are worse alternatives.

In summary, there is a trade-off between reductions of CO_2 and other pollutant emissions. Moreover, routes that reduce CO, HC, and NO_X emissions are characteristically unfavorable to the drivers, inviting slower speeds, high number of crossings and a higher density of incidents and crash frequencies.

4.2 ROUTE CHOICE IMPACTS UNDER RECURRENT TRAFFIC CONGESTION

Previous research studies indicate that it is not possible to generalize conclusions, considering limited study areas. Thus, more research is needed to evaluate a wider range of driving patterns conditions, namely at different periods of the day. A more extensive analysis including different scales, and different traffic volumes, as performed here, may better reflect the reality and improve the knowledge to develop further traffic management strategies.

In this section the impacts of route choice decision during peak and off peak periods are explored. The main objective is to evaluate the potential of eco-routing systems under situations of recurrent congestion and under saturated networks. Recurrent congestion is generally the consequence of factors that act regularly or periodically on the transportation system, such as daily commuting [142]. According the user equilibrium theory, travel times tend to be equal among the various alternatives as the network is becoming more congested. Thus, what could happen to the differences in emissions? Is there potential for significant emission reductions? This section focus on the following research questions:

- Is there a potential for significant emissions savings during traffic congestion periods and in different contexts?
- How do traffic volumes affect emissions on different types of roads?
- How does modal distribution of a microscopic emission model vary over different periods of time and in different contexts?
- Can recurrent congestion affect the choice of an eco-friendly route?

4.2.1 Methodological details

The following results were based on road tests performed during weekdays under dry weather conditions during the months of February, March and April of 2010 and 2011. In addition to the Urban (U), and intercity routes, the OD pair on the Metropolitan area of Hampton Roads, VA in USA is analysed.

According to traffic volume data [29,128], the peak period in the Portugal (PT) site was considered between 7-9 AM and 5-7 PM while in USA the peak period was considered between 6-8 AM and 4-6 PM. So, all trips whose departure time was within this time range are defined as peak hour tests. The off peak tests occurred between 10 AM-5 PM (PT) and 9 AM-4 PM (USA). The USA tests were performed using the same driver, while in the Portuguese case-studies, different drivers and vehicles (small family vehicles) were used.

A statistical test has been conducted to assess if VSP modal distribution between peak and off peak periods differed significantly on all routes performed. Since the number of data sets (number of seconds of the route) is higher than 30 the two-sample Kolmogorov-Smirnov test (K-S test) for a 95% confidence level is appropriate to assess if the probability distributions of two samples are different [143].

In order to normalize the emission impacts of each pollutant, both for Portugal [135] and USA routes [144], specific data on damage cost per mass of pollutant emissions, at the national scale was considered. Additional details and the values used to normalize the emission impacts can be found in section 3.6. An eco-friendly indicator for route choice bases on the predicted damage cost is presented.

4.2.2 Total emissions per route

In this section, the predicted emissions savings by pollutant that may occur by choosing an appropriate route are presented. The influence of the average speed on emissions is also examined.

Before analyzing the results in terms of emissions, a brief analysis of routes characteristics in terms of speed, and number of stops is performed. Table 16 presents the average and standard deviation of speed, the average time spent in different speed intervals and the average number of stops for off peak and peak periods.

Table 16 Observed average speed, percentage of time spent in specific speed intervals and typical numbers of stops during off peak and peak periods.

		Speed (km/h)		*Speed range (% of time)*				*Nº stops*	*Nº of stops*
		$\bar{X}$	SD	**0-20 km/h**	**21-50 km/h**	**51-90 km/h**	**91-130 km/h**	$\bar{X}$	**per km**
Im1	**Off peak**	96.4	3.4	4%	5%	16%	75%	6	0.07
	Peak	89.8	6.5	9%	7%	17%	67%	9	0.12
Im2	**Off peak**	94.7	6.2	3%	7%	20%	70%	4	0.06
	Peak	89.6	4.9	5%	9%	23%	63%	5	0.07
Ih	**Off peak**	65.4	3.7	8%	22%	48%	22%	11	0.13
	Peak	55.5	4.4	17%	28%	38%	17%	29	0.34
Iu	**Off peak**	46.0	1.8	14%	39%	46%	1%	31	0.41
	Peak	40.6	2.9	20%	42%	38%	0%	53	0.70
Um	**Off peak**	59.1	6.9	13%	36%	26%	25%	4	0.56
	Peak	48.7	6.7	27%	32%	21%	19%	5	0.75
Ua	**Off peak**	48.1	3.3	13%	32%	57%	0%	3	0.45
	Peak	38.9	4.1	29%	30%	41%	0%	6	1.00
Uu	**Off peak**	29.0	3.2	33%	52%	15%	0%	5	1.30
	Peak	26.0	3.7	42%	46%	12%	0%	8	1.90
Ma	**Off peak**	45.1	4.4	30%	21%	37%	12%	29	1.36
	Peak	42.6	8.2	36%	22%	31%	11%	44	2.04
Mm	**Off peak**	66.9	4.0	12%	11%	39%	38%	10	0.34
	Peak	56.1	7.7	21%	17%	45%	17%	14	0.48

$\bar{X}$ – mean, SD Standard Deviation.

As expected, average speed decreases for all routes during peak periods. The higher difference is observed at the routes *Ih*, Ua and *Mm*. Moreover the share of time traveling at lower speeds increases considerably in these routes, as well as the number of stops during peak period.

Table 17 presents the potential reductions/increases in emissions and environmental costs impact [135,144] for each OD pair. To address possible trade-offs between travel time and emissions minimization, each route is compared with the fastest route for each OD pair. Since results were relatively similar in both directions of each OD scenario, just one direction is presented. The data are split by vehicle type (LDDV and LDGV), OD pair/route, and time period (off peak and peak).

Table 17 Total emissions per vehicle (CO_2, CO, NO_X HC), estimated environmental damage cost (ED) and travel time (TT) per route during off peak and peak periods.

Vehicle	Route	Period	CO_2 (g)	CO (g)	NO_X (g)	HC (g)	ED ($)	TT (min)
LDDV	Im_1	Off peak	11543	1,54	73,90	0,928	0,688	48,8
		Peak	11704	1,55	74,78	0,938	0,697	49,2
	Im_2	Off peak	-3%	-3%	-2%	2%	-3%	50,9
		Peak	-2%	-2%	0%	6%	-1%	54,3
	Ih	Off peak	11%	18%	-9%	16%	0%	80,1
		Peak	12%	22%	-10%	22%	0%	90,9
	Iu	Off peak	-3%	10%	-34%	13%	-21%	97,2
		Peak	-1%	14%	-34%	20%	-20%	108,3
	Um	Off peak	1187	0,17	5,74	0,098	0,098	8,1
		Peak	1135	0,17	5,47	0,094	0,094	8,1
	Ua	Off peak	-16%	-12%	-28%	-10%	-22%	8,2
		Peak	-5%	-1%	-17%	7%	-11%	9,9
	Uu	Off peak	-25%	-21%	-35%	-12%	-30%	8,5
		Peak	-18%	-14%	-28%	2%	-23%	10,0
	Mm	Off peak	4378	0,636	21,355	0,357	0,842	28,4
		Peak	4778	0,681	25,426	0,431	0,971	33,7
	Ma	Off peak	-10%	-9%	-11%	0%	-10%	31,6
		Peak	-8%	-8%	-7%	2%	-7%	38,0
LDGV	Im1	Off peak	12072	217,03	12,57	4,014	0,372	48,8
		Peak	12203	220,20	12,71	4,053	0,377	49,2
	Im2	Off peak	-1%	3%	-3%	2%	2%	50,9
		Peak	2%	7%	-1%	6%	6%	54,3
	Ih	Off peak	25%	-25%	0%	-1%	20%	80,1
		Peak	30%	-29%	-1%	1%	24%	90,9
	Iu	Off peak	23%	-59%	-22%	-18%	14%	97,2
		Peak	29%	-61%	-21%	-14%	19%	108,3
	Um	Off peak	1429	11,60	1,12	0,340	0,042	8,1
		Peak	1377	10,66	1,05	0,329	0,040	8,1
	Ua	Off peak	-10%	-41%	-23%	-19%	-12%	8,2
		Peak	4%	-29%	-12%	-3%	2%	9,9
	Uu	Off peak	-15%	-47%	-31%	-22%	-17%	8,5
		Peak	-4%	-38%	-25%	-9%	-7%	10,0
	Mm	Off peak	5158	45,08	4,07	1,266	0,660	28,4
		Peak	5813	64,19	4,68	1,597	0,803	33,7
	Ma	Off peak	-5%	-12%	-12%	-2%	-8%	31,6
		Peak	-3%	-6%	-10%	0%	-5%	38,0

In the intercity routes (Aveiro-Porto), the motorway options (*Im_1* and *Im_2*) are clearly less time consuming than the alternative routes (*Ih* and *Iu*). Compared to the closer alternatives and during off peak periods, route *Ih* has a mean travel time 64% higher in relation to route *Im_1,* and route *Iu* has a mean travel time 90% higher than *Im_2*. During peak periods these differences are increased to 85% and 100% respectively. Taking into account the specific OD pair under analysis, it seems that the network is not going toward the user equilibrium. This can be explained by the local and regional traffic with different origin and destinations during peak periods, leading to higher travel time in these routes.

Regarding LDGV, CO_2 emissions data show that motorway routes (*Im_1* and *Im_2*) lead to less CO_2 emissions (thus, fuel consumption). However, as described in Chapter 2, NO_X and CO emissions are mainly generated during acceleration events at higher speeds such as observed on motorways. Therefore, in this case there is an evident trade-off between CO_2 and local pollutants minimization, since the routes that minimize local pollutants are the slower routes *Ih* and *Iu*. For local pollutants, the effect of peak demand is more obvious on the motorway routes *Im_1* and *Im_2.* For *Ih* and *Iu* the local pollutants emissions do not change significantly during the peak period.

Concerning urban routes, the peak demand effect is more evident on route *Uu* (center-suburbs), although it is still the best route considering the minimization of pollutants emissions. This route yields the highest emissions rate per distance but its shorter length leads to a reduction in total emissions of all pollutants. On route *Um* a high variability in NO_X emissions was noticed which can be to a certain extent explained by different driving behaviors. A detailed analysis of speed and emission profiles has shown that slight changes in driving behavior (frequent speed oscillations and more sudden accelerations) can produce significant differences in both NOx and CO emissions rates.

Regarding metropolitan routes (Norfolk-Chesapeake), *Mm* has the highest total emissions. Both at off peak and peak, *Ma* yielded CO_2 emissions saving from 7% up to 10% and CO savings of up to 12%. A more detailed analysis showed that on route *Ma*, CO emissions are mostly produced during the 6 km motorway section included in this route due to high engine-load conditions. Evaluating the average emission rates per distance CO_2 and CO emissions rates on *Ma* were found to be 1.27 and 1.18 times higher than route *Mm*. However, route *Mm* is 1.30 times longer than *Ma,* which makes this route more environmentally friendly in terms of total emissions produced.

Regarding the vehicle type, in terms of environmental damage (ED) costs, LDGV in Europe presents about 50% lower values than LDDV in the same routes. This is mainly explained by the lower NO_X emissions levels produced by the gasoline vehicles. In USA, this difference is reduced to approximately 20% because CO emissions (produced principally from LDGV) are more valued [144] than in the European approach for monetization of emissions [135]. For all OD pairs and both type of vehicles a slight decrease in the relative and environmental damage costs among the various routes during peak periods is observed. However, both costs and emissions savings are still significant.

Figure 15 shows the evolution in terms of emissions per kilometer of a global (CO_2) and local pollutant (CO) from LDGV as a function of average speed. Peak and off peak tests are displayed in solid and transparent background symbols, respectively. Motorway routes are displayed in blue squares and blue lozenges, arterial routes in red triangles and urban roads in golden circles.

For all OD pairs a general trend of decreasing CO_2 emissions (inter route and intra route) with average speed is clear. However, according to the literature [145] for average speeds values beyond the experimental range (>100 km.h-1), CO_2 emissions would tend to increase again. In the case of intercity routes, the increase between the routes *Iu* and *Ih* is caused by variations in slope most significant in the latter. It can be also observed that during the peak period, CO_2 total emissions show a higher increase on the national roads (*Ih*, *Iu*), due to higher congestion and travel times.

Although there is a higher variability in comparison to CO_2 emissions, it is visible a general trend to emissions increase with speed in the intercity and urban contexts (Figure 15a and Figure 15b). A higher variability for both pollutants emissions values is observed in metropolitan routes, namely in *Ma*, as can be confirmed by the dispersion of emissions data points in Figure 15c. This can be explained by the fact that a significant distance of *Ma* is travelled through downtown and covering more signalized intersections. This leads to a certain unpredictability in the speed profile.

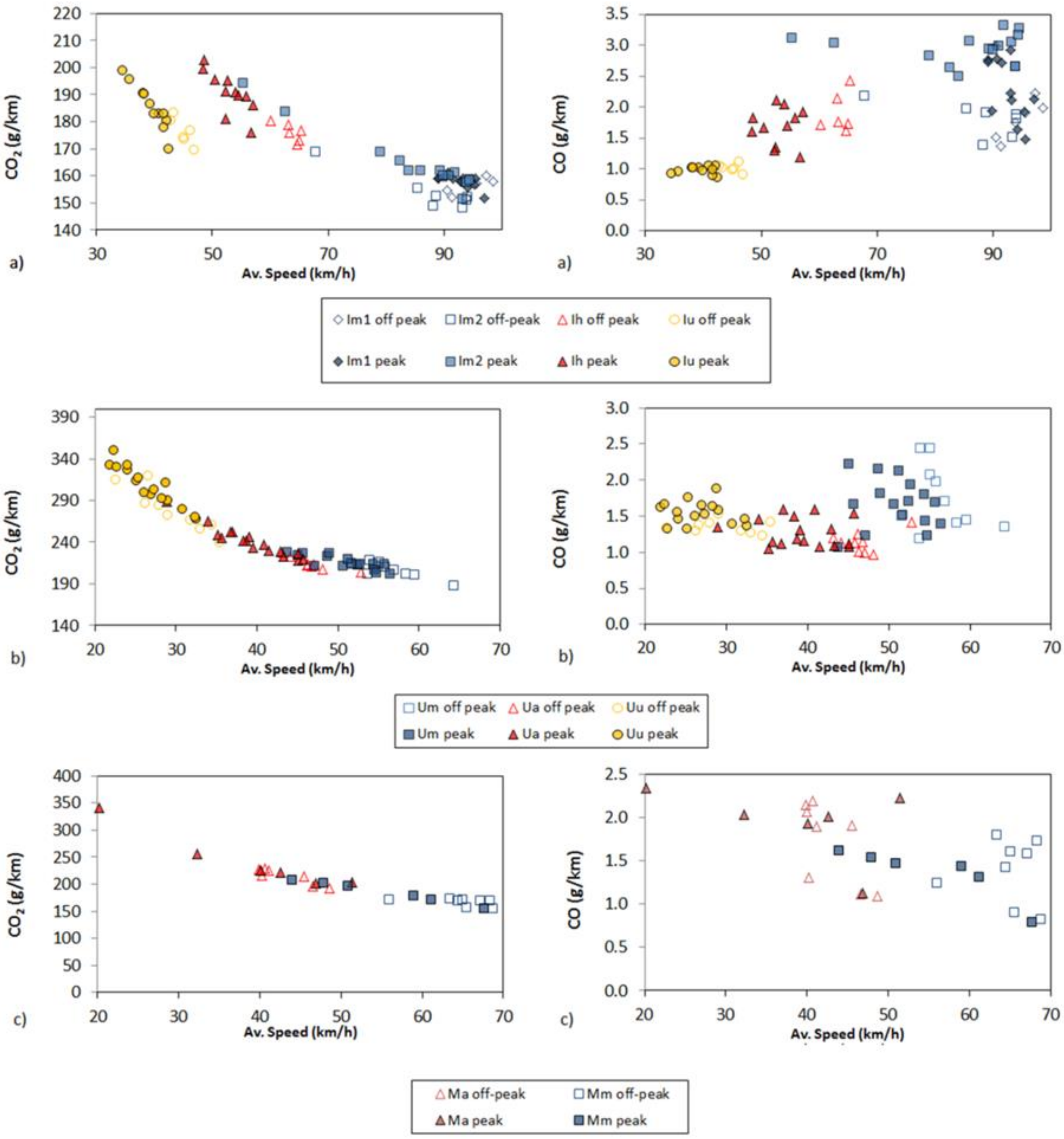


Figure 15 CO_2 and CO emissions factor (g/km) vs. average speed (km/h) for LDGV during off peak and peak periods for: a) Intercity routes (dir.: Oporto-Aveiro); b) Urban routes (dir.: centre-suburbs); c) Metropolitan routes (dir.: Norfolk-Chesapeake).

4.2.3 Eco-routing indicator

A suggestion for an eco-friendly route indicator summarizing the previous findings is presented in Table 18. Regarding intercity routes the most striking factor is that the best eco-friendly route depends on the type of vehicle. While for LDGV, route *Im*$_1$ is the best to minimize the environmental damage, for LDDV the most eco-friendly route is *Iu*. Two main reasons contribute for this: a) in this indicator (European context), CO emissions are not valued; b) in terms of CO_2 emissions (and fuel consumption), LDDV are not as penalized by stop and go situations as LDGV.

Table 18 Eco-friendly route indicator based on Environmental Damage costs.

	Im$_1$		Im$_2$		Ih		Iu		Um		Ua		Uu		Ma		Mm	
	NP	P	NP	P	NP	P	NP	P	NP	P	NP	P	NP	P	NP	P	NP	P
Travel time	○	○	◔	◑	◑	◕	●	●	○	◔	◑	●	◕	●	◔	●	○	◕
LDDV	!	✗	○	!	○	✗	✓	✓	✗	✗	○	!	✓	✓	✓	!	○	✗
LDGV	✓	○	✓	○	!	✗	!	✗	✗	!	✓	✗	✓	○	✓	!	○	✗

NP - Non-peak P - Peak

Travel time	Faster	○	◔	◑	◕	●	Slower
Emissions cost impact	Best	✓	○	!	✗		Worst

It is also possible to confirm that for all areas and for each type of vehicle, the eco-friendly route do not change between peaks and off peak. However, in the metropolitan area the most sustainable choice is to travel during off peak hours since during peak period both routes are always worse options than traveling during off peak. Finally, for almost cases, selecting a route with less environmental damages implies a higher travel time. The exception where this trade-off is avoided is for LDGV in the intercity context.

4.2.4 Link-based emissions

Link-based emissions were estimated for peak and off peak hours, using the second-by-second field data for all road segments on metropolitan routes, where detailed traffic data were available (Figure 16). Thus routes Ma and Mm have been subdivided in 23 and 15 sections according VDOT classification (Ma1 - Ma23; Mm1 –Mm 15). Although not statistically significant, in the majority of the sections, CO_2 emissions during peak are consistently higher than during off peak. *Mm*-4 and *Ma*-12 are the segments where the highest increase at peak hour is experienced. This can be explained by the frequent traffic jams that occur at peak hours since these links serve as connector to the belt roads I-64 and I-264/I-464, respectively. In I-464 segments (Ma13 to Ma17), there are no significant differences between peak and off peak, because even at peak period, a low volume/capacity ratio is maintained. On the other hand the I-64 segments (Mm5 to Mm14) are more vulnerable to higher traffic volumes, particularly on the northern sections Mm6 and Mm8. A slight decrease up to 8% (but not statistical significant) in emissions at peak period is observed in a small number of sections of route *Ma*. Furthermore, the average speed during peak is higher than during off peak periods. A detailed analysis of speed data has shown that this occurs due to the coordination of traffic lights, thus less time spent at the red lights in certain arterials during peak hours.

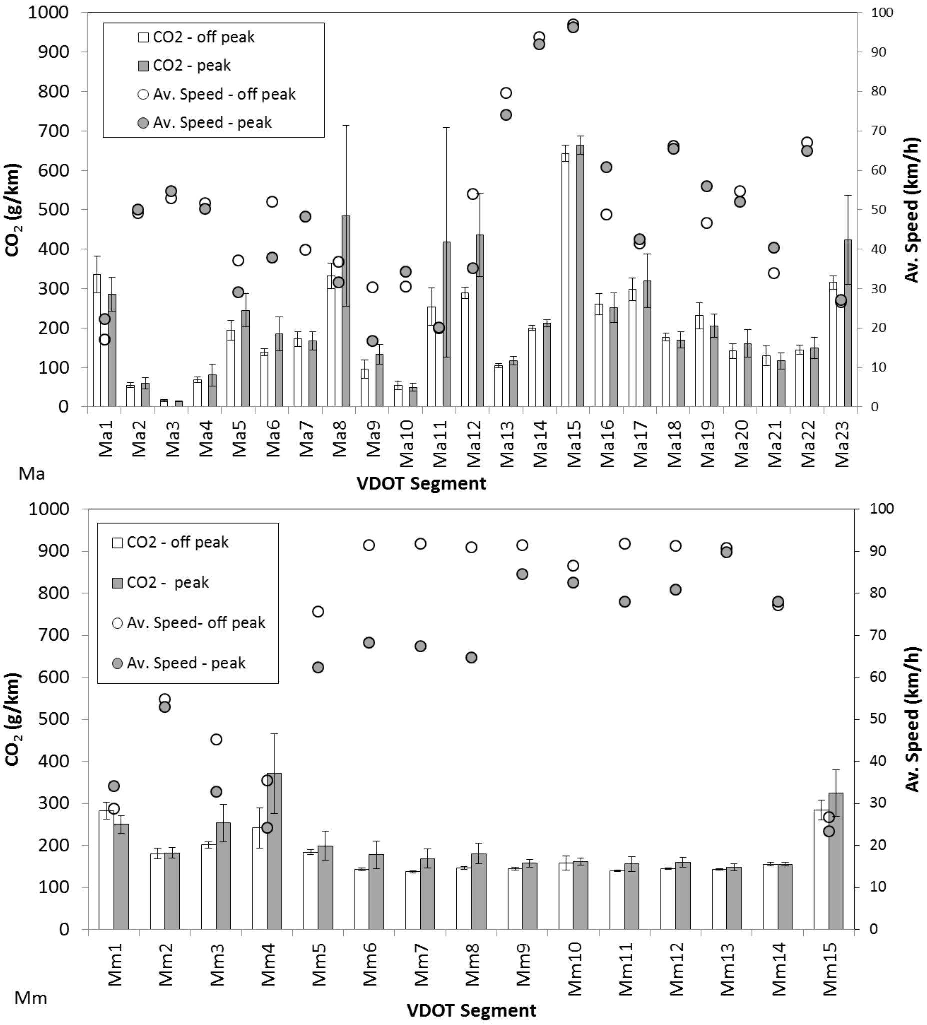


Figure 16 CO_2 emission factor (g/km) (CI 90%) and average speed (km/h) during off peak and at peak periods for *Ma* and *Mm* segments.

Figure 17 shows CO_2 and NO_X emissions under different traffic volumes on an arterial and a motorway. It was estimated that in each motorway lane, there is a capacity of 1,700 vehicles per hour (vph) and in each arterial lane, 850 vph (considering an average g/r ratio for through traffic of 0.50).

The analyzed arterial segment is a 4-lane road with 500 m long covering three signalized intersections, one of which is at the interchange with the motorway I-64 (Mm4). Figure 16 shows that this is the road segment of route *Mm* presenting a higher difference in CO_2 emissions between peak and off peak. Mm9 segment corresponds to a 3-lane I-64 section which extends over 2000 m. According to VDOT data, during the peak period both segments have been classified as operating in Level of Service (LOS) E.

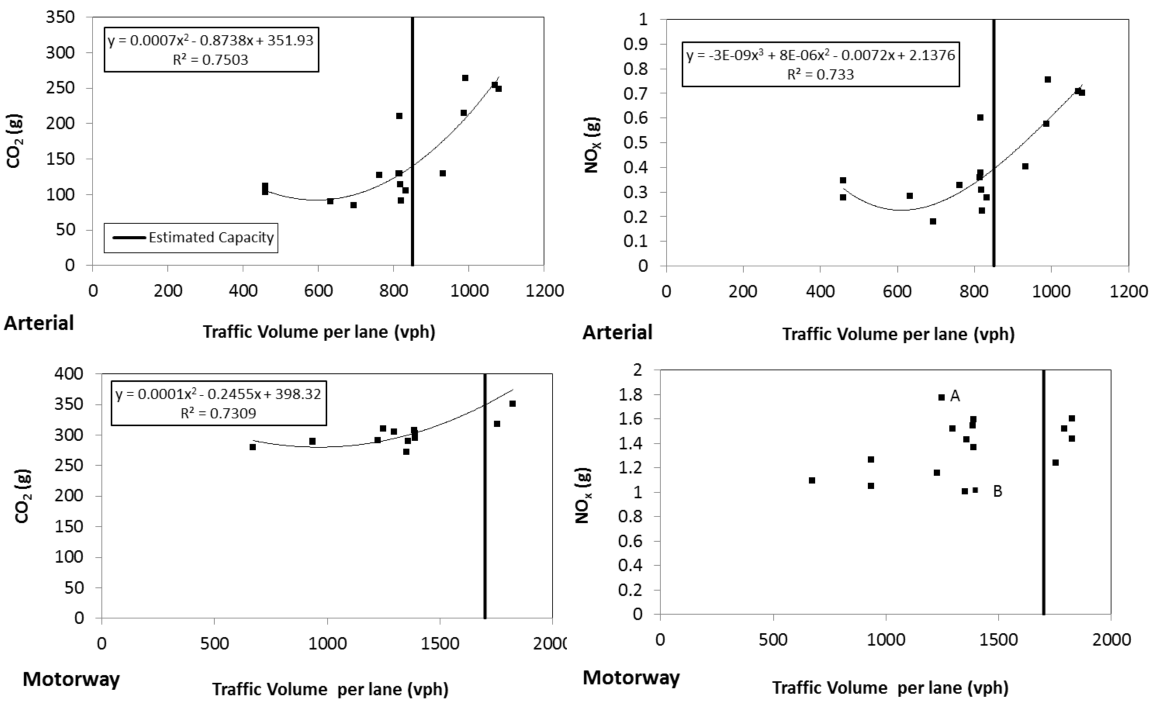


Figure 17 CO_2 (from LDGV) and NO_X (from LDDV) emissions (g) as function of traffic volume (vph) for an arterial and a motorway segment.

For the arterial segment, emissions and average speed remain relatively constant up to a certain traffic volume level. From that point emissions start to increase exponentially. A third-order polynomial was used to fit the data points, shown as solid lines in **Figure 17**.

Although more data points are needed to define a statistically valid trend, these results are consistent with previous research [92]. A detailed analysis of speed profiles have demonstrated that on Mm4 segment the emissions are strongly dependent of traffic congestion, namely the coordination between the traffic flow with the timing of traffic signals. Analyzing the ascending phase of the curve, for higher traffic volumes (>900 vph) it can be seen that the increase of one vehicle per hour generates an average increase in NO_X emissions of 0.1%.

On the motorway segments, relatively high correlations between CO_2, and traffic volumes were found and the same trend is observed. Thus, for traffic volume close to the capacity estimated, CO_2 emissions start to increase. Moreover, a strong correlation between average speed and CO_2 emissions was found which is consistent with previous research [145]. Nevertheless, correlations for local pollutants were not found. It has been shown shows that although the average speed remains relatively constant in free flow situations, NO and CO emissions show a higher variability. Figure 18 demonstrates that slight speed variations produce a significant impact on local pollutants, namely NO_X from LDDV. Thus, in similar sections the air quality could be improved significantly by minimizing high-emitting driving behavior.

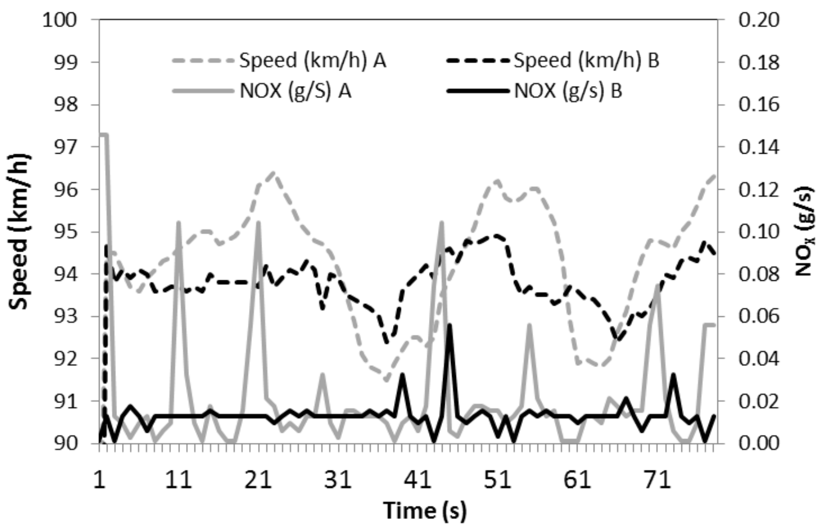


Figure 18 Speed and NO_X emissions profiles over time for two sample tests with similar average speed (94 km/h).

4.2.5 Analysis of speed data and VSP modal distributions

Since the frequency of occurrences of each VSP mode controls the total of emissions estimated, it is important to understand how VSP modes distribution varies across routes.

The columns charts shown in Figure 19 display the average time spent in each VSP mode during off peak and peak periods, with the respective standard deviation. The line charts above represent the relative contribution of each VSP mode for the total of CO_2, CO, and HC emissions from LDGV and NO_X from LDDV - the major sources of each pollutant. As described in section 3.5.1, Modes 1 and 2 represent deceleration modes (negative VSP values), whereas mode 3 represents idling or low speeds situations. Modes 4 to 14 describe different combinations of increasing and positive accelerations

For each OD pair, key route attributes are considered. *Ma* and *Mm* have comparable travel times but *Ma* is 27% shorter. Im_1 and *Iu* have a similar length, but during peak and off peak Im_1 allows more than 50% of time saving in relation to route *Iu*. Route *Um* is the longest urban route but with less travel time.

Regarding the VSP modes frequency, the routes *Um*, Im_1 and *Mm* (routes which are performed essentially on motorways) have a uniform VSP modes distribution compared with routes *Uu*, *Iu* and *Ma* predominantly driven on built-up areas. In the former cases, the reduction of speed shifts the distribution towards lower VSP modes. For instance, on *Iu* about 20% (during peak) and 14% (during off peak) of the time is consumed in idling or low speed situations and just 4% of the travel time is spent on VSP modes higher than 7.

The greatest difference between peak and off peak and the higher standard deviations intervals occur in VSP mode 3. This is more notorious in route *Uu*, *Iu*, and *Ma*, due to the higher number of intersections, illegal parking, work zones and other incidents leading to stop and go situations.

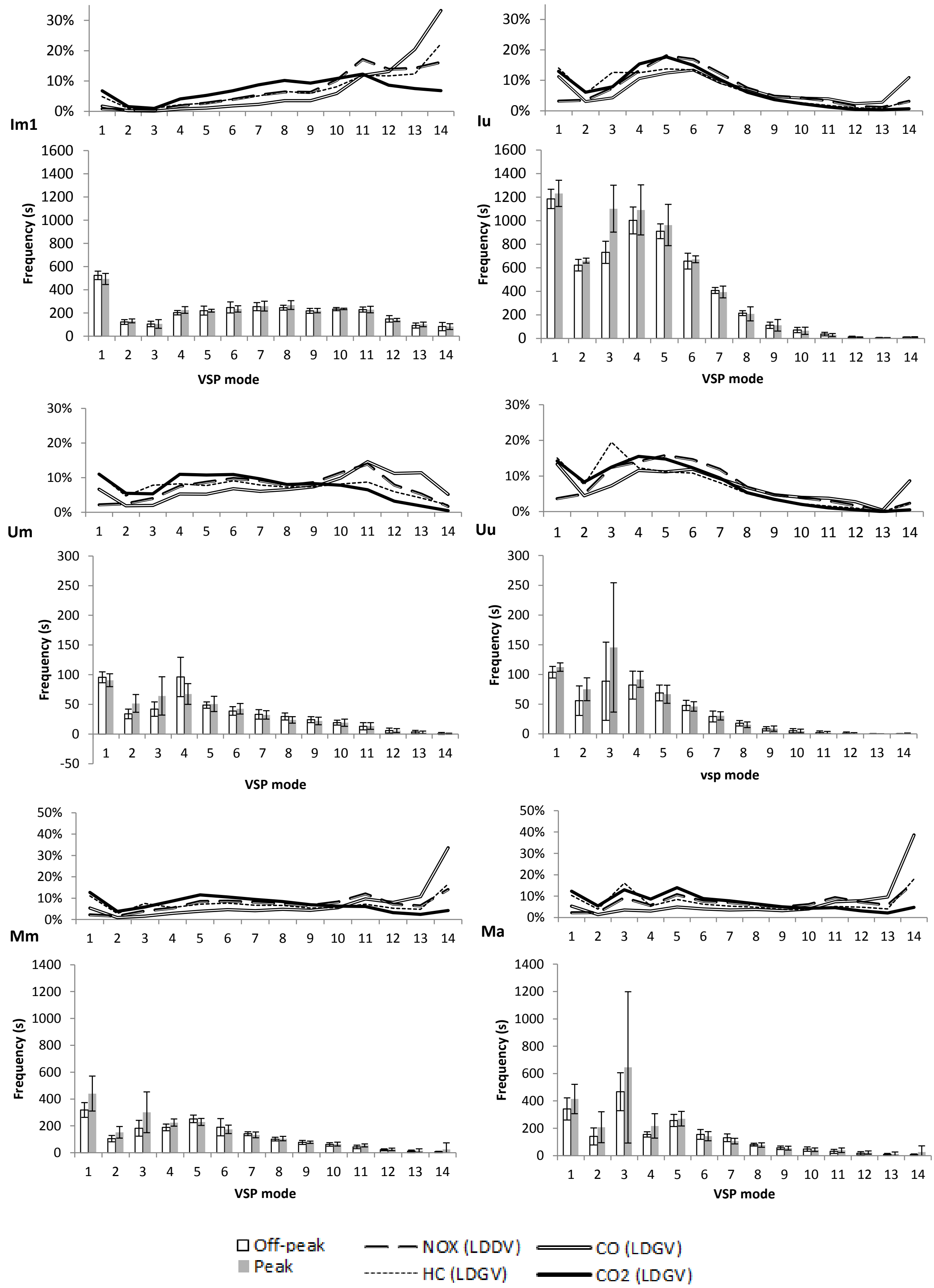


Figure 19 Relative contribution of each VSP mode for CO_2, CO, NO_X, and HC emissions at peak period (line charts) and VSP modes frequency (column charts) with SD intervals.

Each VSP mode contributes differently to the emission of the various pollutants. The distribution of CO_2 according to the VSP mode follows approximately the same trend of the relative frequency distribution of VSP modes. However, CO emissions are mostly generated during the occurrence of the higher VSP modes. For instance on *Ma*, more than 55% of CO emissions are generated during the occurrence of the VSP modes 12-14 which represent nearly 3% of the travel time. The contribution of each VSP mode for the remaining local pollutants (NO_X - LDDV, and HC - LDGV) showed a comparable behavior to CO emissions, but less sensitive to the higher modes.

For intercity routes, the D-value of K-S test to 95% confidence level indicated that routes Im_2, *Ih* and *Iu* have not the same distribution on the two periods evaluated (p-value of 0.0275, 0.0001, and 0.011). Im_1 did not present significant differences, since during off peak and peak an adequate capacity is available (p=0.999). Regarding the urban scenario, all routes have shown no significant differences (p-values ranged from 0.12 to 0.18). The metropolitan routes showed the highest difference on VSP modes distribution (p-value = 0,000). This can be justified by the higher traffic volumes and congestion situations that occur during the peak periods in both routes.

4.2.6 Implications for future eco-routing strategies

The results have shown that emissions can be considerably reduced if travelers choose eco-friendly routes. In the hypothetical extreme case of everyone choosing an eco-friendly route, a shift to all-or-nothing assignment from user equilibrium (UE) assignment may occur, producing an opposite result to the desired. However, although the results cannot be generalized for locations with different characteristics, the empirical results suggest that the route with lowest emissions during peak and off peak hours is the same and there is room for significant emissions savings during peak hour. Although some specific links of the analyzed networks were found to be close to saturation, the difference between total emissions produced in each route suggests that the designated eco-routes may accommodate a limited number of green routing users. Thus, for realistic market penetration scenarios of eco-friendly navigation systems, they might have sufficient capacity to accommodate demand without increasing emissions in the network.

On the other hand, the selection of the eco-friendly route is not always obvious. For example, the intercity routes that yield CO_2 savings might also lead to substantial increases in other pollutants, such as CO and NO_X. Furthermore, even during peak periods and for all case-studies, the routes that lead to a minimization of local pollutants are those that mainly cross urbanized areas, avoiding motorways. This fact will involve a careful assessment of potential externalities that may arise from a purely dedicated navigation system based on emissions minimization, since higher volumes of traffic crossing urban areas may lead to urban environmental degradation and worse levels of road safety.

Thus, in addition to the environmental information that can be provided to the drivers, some alternative traffic management strategies may be implemented to improve traffic operations. Moreover, the policies focused on eco-traffic assignment must necessarily be accompanied by efforts to promote eco-driving. The implementation of speed management/harmonization techniques on motorways aiming at reducing excessive high speeds and consequent high emissions levels can be helpful. It can also facilitate the minimization of the trade-off between the minimization of fuel/CO_2 emissions and other pollutants, and make less attractive (from the total emissions perspective) the routes that cross the urban centers.

When there is no real-time information, pre-trip planning programs can consider the variability of emissions on each link, based on different time periods and estimate the best route for a specific period. Clearly, this is only a valid option, assuming that the impact of these programs will not have a substantial impact on the equilibrium of the network. In a more advanced Intelligent Transportation System (ITS) scenario, in which vehicles are routed dynamically in the network, the changes in traffic volumes between the various routes can be significantly higher. In this scenario, one must consider the road segments capacity and the network configuration, in order to assess the system-wide impacts on emissions. Real-time or historical link based-emissions, such as the information generated in this study, can be incorporated in pre-trip planning software to determine the most eco-friendly route.

4.3 Unexpected Congestion

In previous sections, the behaviour of various pollutants in free-flow conditions and recurrent congestion were analysed. This information is useful for predicting the performance of the examined routes under normal operating conditions. In this section, the behaviour of various pollutants under a situation of unexpected congestion (UC) is analysed. The case study is the route *Mm*. Due to a security exercise at the military base of Norfolk (the world's largest naval station), one lane of the main arterial serving the military base was reserved. This change has caused considerable congestion in part of the metropolitan road network during the morning rush hour including several sections of route *Mm*. The test carried out in this period was analysed separately and compared with a regular test conducted during a similar period under recurrent congestion (RC) (7h30 AM).

4.3.1 Analysis of speed data and VSP modes distribution

Figure 20 shows a comparison of second-by-second speed data logs and VSP modes under RC and UC. Under RC there are three points in the vicinity of three interchanges where an increase in traffic density and lower speeds are observed (see yellow arrows in Figure 20). The red arrow indicates the local where the reduction of capacity took place during the event, while the white arrow indicates the point where the congestion shocking wave started. From that point, there is a significant increase in congestion levels and speed decreases sharply. It is also possible to verify the increase in the frequency of lower VSP modes over the traffic congestion zones. Figure 21 shows average speed over distance. The average speed was calculated in sections of 290, corresponding to one hundredth of route length).

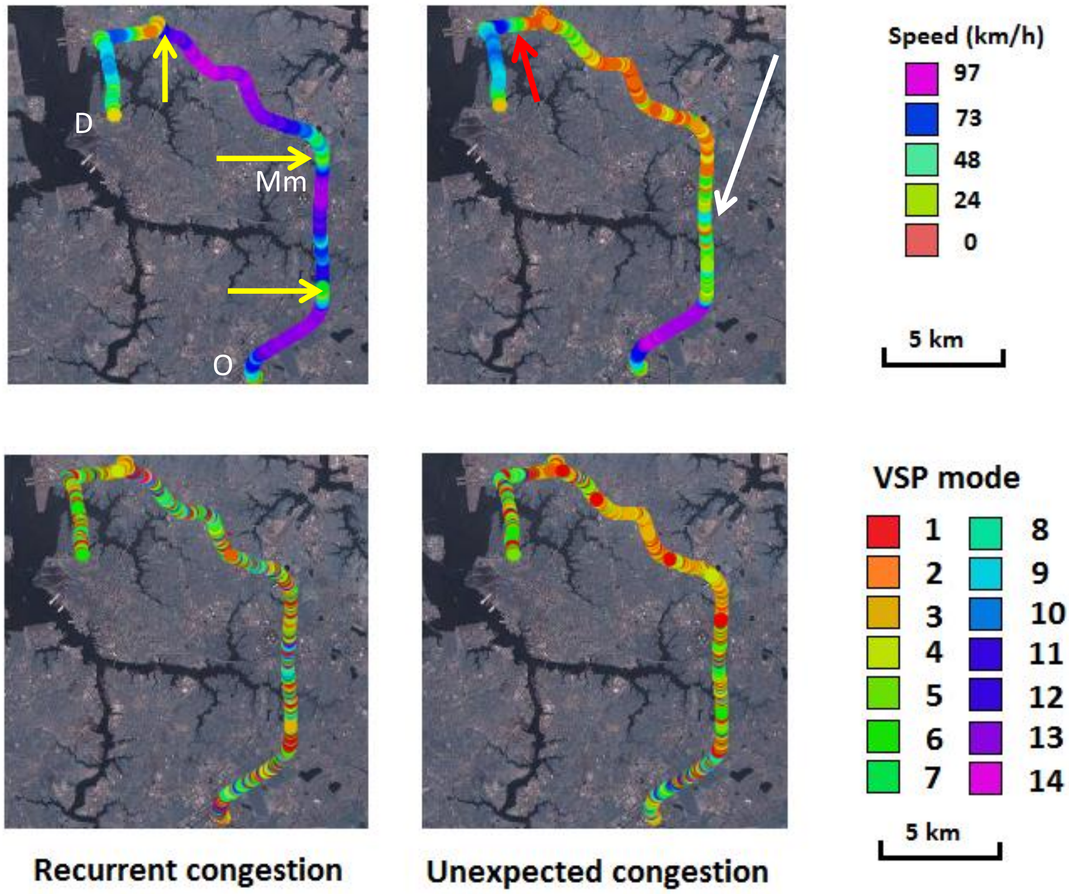


Figure 20 Second-by-second data point of speed and VSP modes under recurrent congestion and unexpected congestion

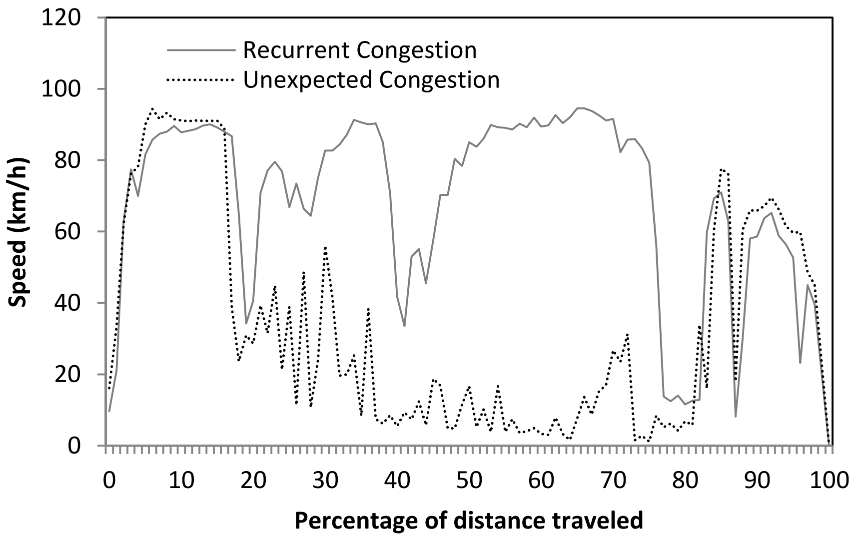


Figure 21 Average speed over recurrent and unexpected congestion scenarios.

4.3.2 Emissions behaviour

Figure 22 illustrates the cumulative difference of travel time over distance, and the relative difference in cumulative emissions between unexpected and recurrent congestion. At this stage, the analysis is focused on the emissions of CO_2, CO and HC from LDGV and NO_X from LDDV, the main sources for each pollutant. Delays compared to recurrent congestion situation had begun to be observed after 20% of the total distance had been covered. In the end, a delay of almost 144 min (travel time 388% higher than under RC) was observed. The bottleneck has caused a more significant impact on fuel consumption (and thus CO_2) and HC emissions. While the emissions of these pollutants have increased by 200%, CO and NO_X increased 36% and 110 %, respectively.

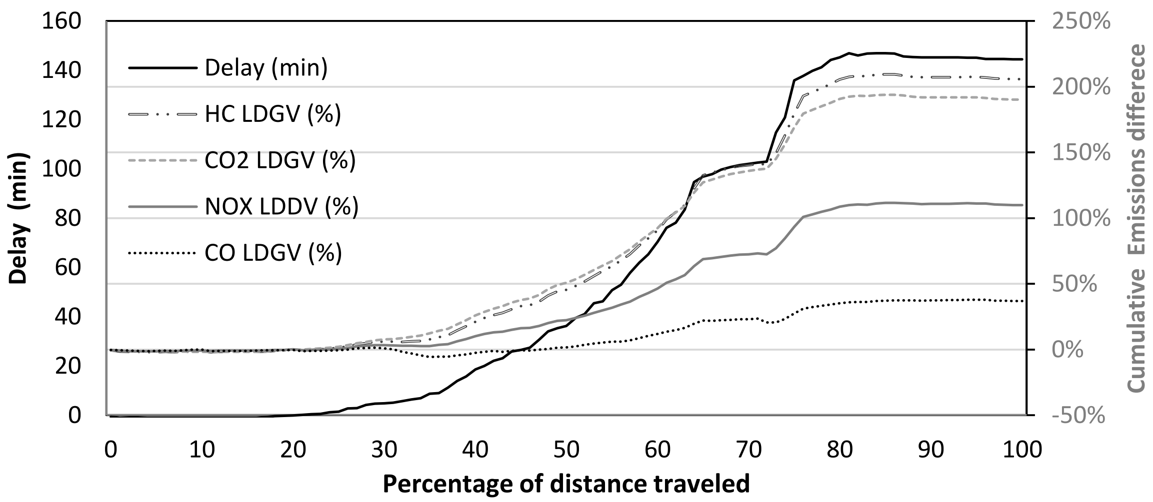


Figure 22 Cumulative delay over distance and relative difference in cumulative emissions between unexpected and recurrent congestion.

In order to examine the source of these differences, Figure 23 shows the relative change between the frequencies of VSP modes under UC and RC. Figure 24 indicates the contribution of each mode for each pollutant in both RC and UC tests.

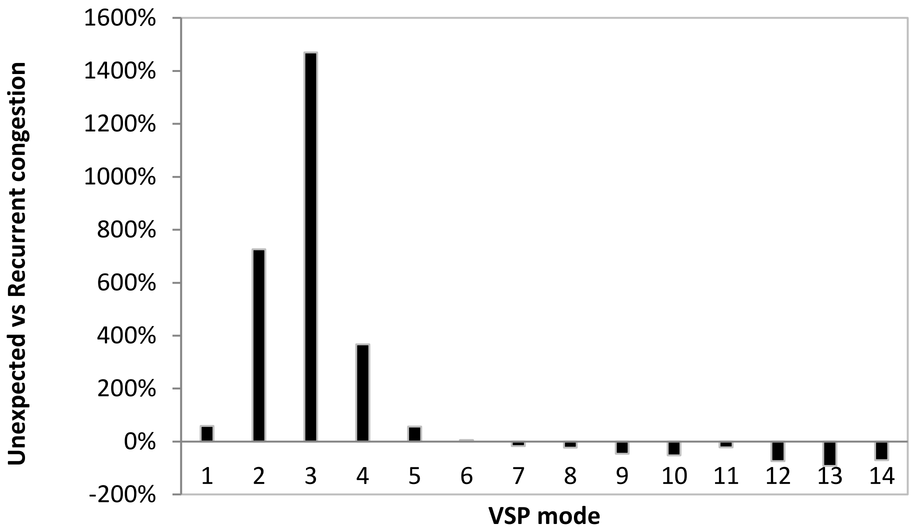


Figure 23 Difference of VSP modes distribution between unexpected and recurrent congestion.

The most striking feature is the exponential increase of lower VSP modes, particularly mode 3 (idling periods). Since more than half of the route was traversed at low speed, the occurrence of modes higher than 5 has declined significantly. Taking into account this scenario, Figure 24 clarifies the difference in the behaviour of the different pollutants. CO_2 and HC emissions are more affected in situations of extreme congestion because 40% and 53% of that pollutant emissions are generated during periods of idling - VSP mode 3. For NO_X from LDDV this value does not exceed 23%. Regarding CO emissions, a key reason for the less significant increase was the decline of VSP mode 14. VSP Mode 14 corresponds to 17% of CO emissions under RC and just 3% under UC.

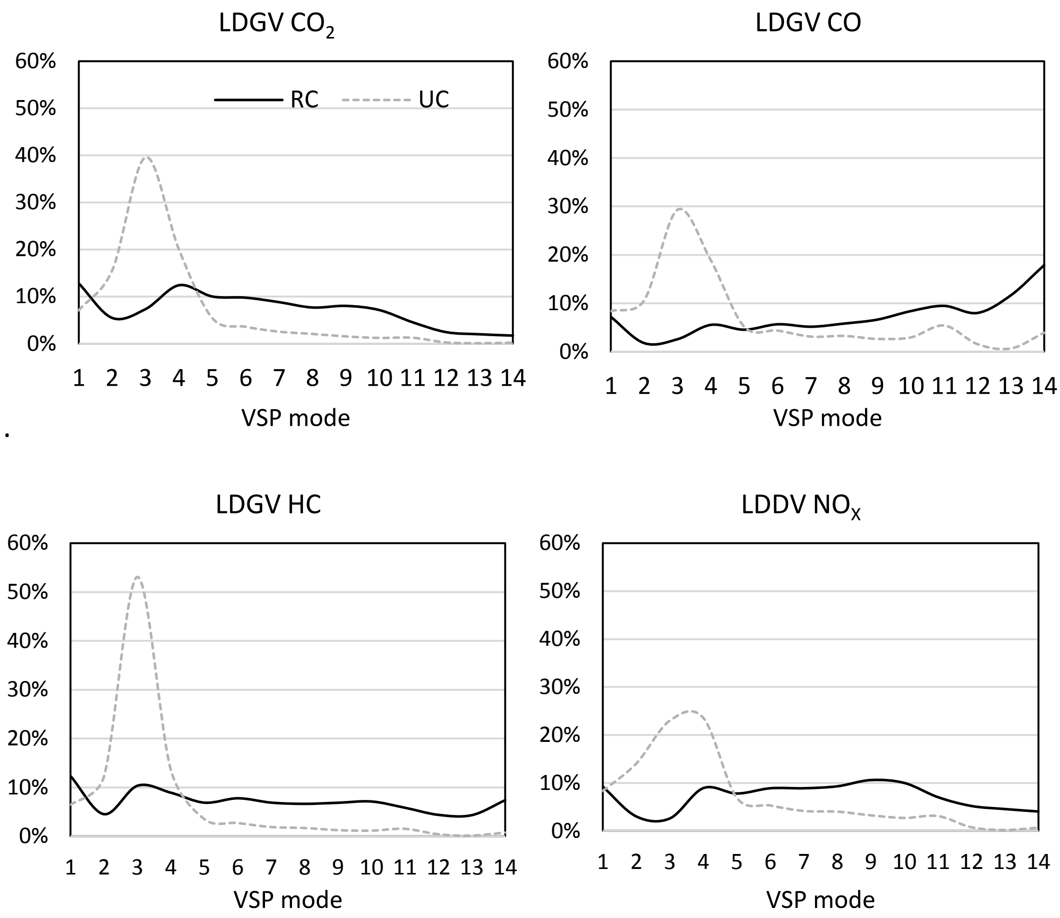


Figure 24 Relative amount of CO_2, CO, HC and NO_X emitted in each mode vsp under RC and UC.

Regarding the Influence of vehicle type under unexpected congestion LDGV presents a lower relative increase than LDDV for NO_X and HC. For CO_2 (and fuel use) there is a less significant variation in LDDV.

Regarding CO, LDDV present a considerable worse behaviour (more variation), however the absolute amount of emission is less than two orders of magnitude in comparison to LDGV. This can be explained because diesel engines produce lower amounts of carbon monoxide since they operate in excess air.

Overall, using a weighing factor based on economic costs [144] it appears there is a less significant variation in LDDV (Figure 25).

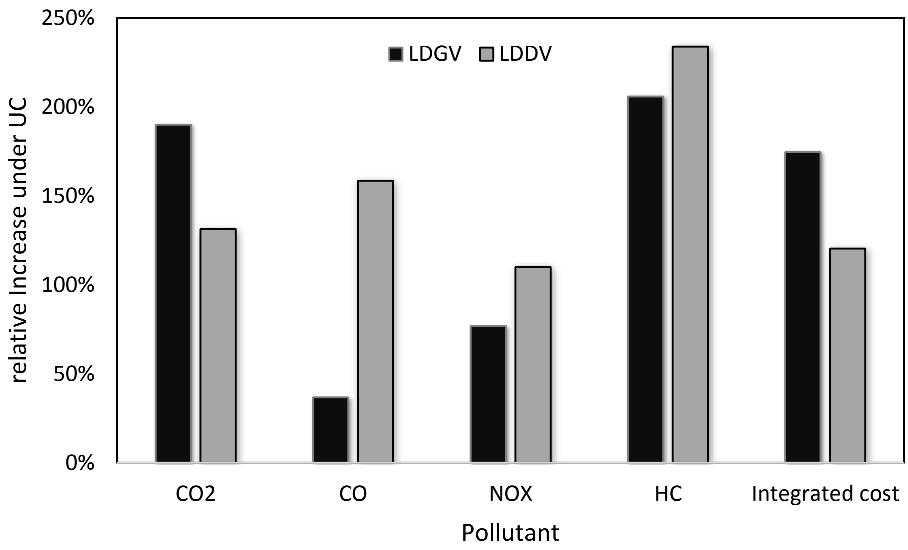


Figure 25 Variation in emissions under UC for LDGV and LDDV

4.4 CONCLUDING REMARKS

Section 4.1 addressed factors that may influence route choice in free-flow conditions, such as travel distance, cost, travel time, infrastructure quality, test vehicle and driving behaviour. A ranking system of competing pathways has also been established. Section 4.2 has attempted to assess whether eco-friendly routes change during peak hours. Section 4.3 studied the effect of extreme and unexpected congestion in different pollutants emissions. Overall 222 hours of GPS data have been considered to generate emissions information during off peak and peak periods. Although the absolute results in terms of emissions savings cannot be generalized, these empirical studies have reinforced the relevance of the eco-routing concept. It has been demonstrated that:

• Both during off peak and peak periods, the selection of an appropriate route can lead to significant emissions reduction: CO_2 up to 25% of and local pollutants up to 60%;

•A slight decrease in the differences of total emissions among the various routes during peak periods was observed. Moreover, for each OD pair, the eco-friendliness rating of routes was shown to be constant under different traffic volume levels. These facts suggest that the infrastructures analysed could have sufficient capacity to accommodate a limited extra demand of drivers who would like to select a route with lower emissions levels.

However, some limitations must be considered when implementing these systems. Namely, it was observed that the selection of an eco-friendly route selection is not always clear since:

- The eco-route could depend on the type of vehicle used;
- In some cases the routes that allow a minimization of pollutants can cross urbanized areas. This fact should involve a careful assessment of potential externalities that may arise from a purely dedicated navigation system based on emissions minimization;
- In the intercity OD pair, a trade-off between CO_2 vs. local pollutants minimization has been observed. Therefore, it must be emphasized, that the concept of "eco-friendly" should not be strictly confined to CO_2/fuel consumption.

Regarding the analysis of emissions behaviour under extreme situations of traffic congestion, HC and CO_2 have shown to be the pollutants more affected by extreme congestion.

This chapter has focussed on different parameters of route choice impacts under different traffic conditions. The next chapter will apply a similar methodology, based on second-by second GPS data and the VSP model, to explore the impact of the introduction of tolls on route choice and its consequences in terms of emissions and energy use on the road network.

5 USING EMPIRICAL DATA TO ASSESS THE IMPACT OF INTERCITY TOLLS ON EMISSIONS

Innovative road pricing schemes are suggested as a way to promote the use of public transportation and the gradual introduction of alternative propulsion systems [1]. However, the introduction of extensive, national road pricing systems should involve careful impact analysis [14]. Regarding sustainability impact assessment, the European Union (EU) requests a detailed evaluation of the full effects of a policy proposal that should comprise the estimation of economic, environmental and social consequences [1].

In the standard traffic network equilibrium model, a marginal-cost toll can drive a user equilibrium flow pattern to a system optimum [146]. In terms of environmental impacts, several studies have focused on the emissions impact assessment of cordon tolls introduction in urban areas [147–150] and it has been demonstrated that road pricing shows potential as an air quality management tool. However, limited research has been conducted to address the emissions impact of tolls introduction in intercity corridors.

Therefore, the introduction of tolls on a Portuguese motorway, and over the current intercity study domain, was a valuable opportunity to assess its consequences in different contexts. More specifically, this section aims to estimate the impact of tolls introduction in terms of:

- Traffic distribution changes on the network
- Speed performance in different segments during different periods
- CO_2, NO_X, CO and HC emissions and fuel consumption for light duty vehicles (using a micro-scale modeling approach)

5.1 STUDY AREA DESCRIPTION

A new electronic toll collecting system has been introduced on several motorways in Portugal (which were toll free before 15 October 2010). One of these cases is the A29 motorway (Im_2 route in the current work notation), which connects the cities of Aveiro and Oporto. To connect these cities, there are four parallel alternatives roads (A1-Im_1, A29-Im_2, N1-*Ih* and N109-*Iu*) that can be accessed via A25 (see Figure 26). In addition, a rail system with 50 daily connections is available as an alternative. The study area was divided into 6 sections (S0-S5), based on the latitude of the A1 interchanges and coinciding with the main East-West axes that cross the four main alternative routes (Figure 26). Figure 27 (left) shows the ADT on the motorways, before and after tolls introduction. Until September 2010, A29 was the favorite option for the majority of drivers because unlike A1, this motorway had no tolls. After the tolls were introduced on A29, about 50% decrease in the ADT was observed. Since A29 has a higher number of interchanges, the average traffic in each main section was estimated. As there was no traffic monitoring on the national roads, Figure 27 (right) provides an estimate of ADT on these routes. The ADT values before the introduction of tools were based on traffic volume data available in noise impact reports [151] (S1-S4 for N109 and S4 for N1). For the remaining sections without the availability of information, 7 h of video data at 6 key points of *Ih* and *Iu* hour were collected during the evening peak hour. Using a peak hourly factor of 8.22% (EP, 2010), the ADT was estimated.

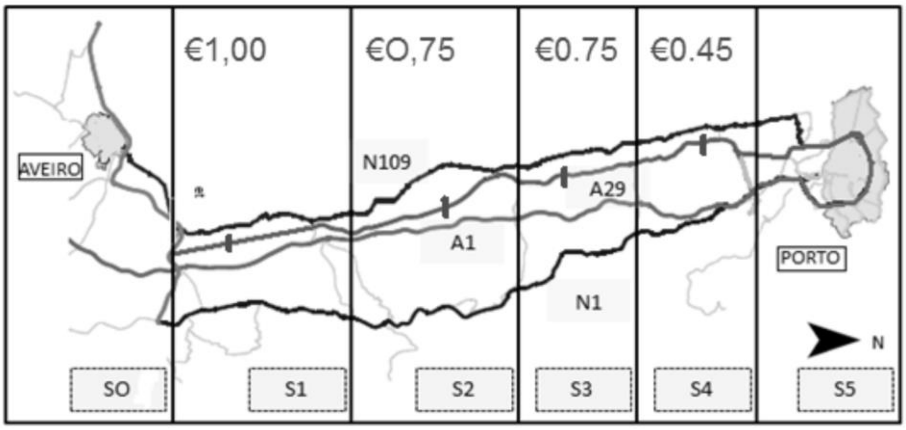


Figure 26 Study routes map, sections considered for analyses, and toll fees introduced on A29 (*Im2*)

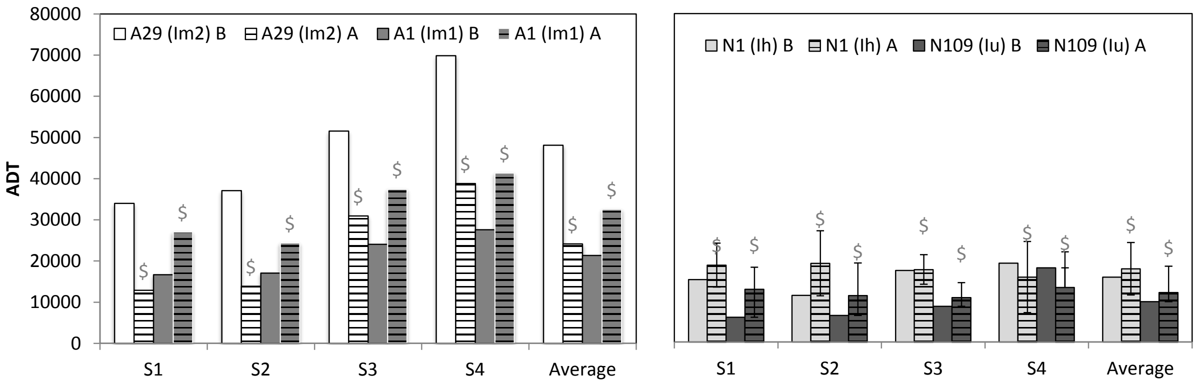
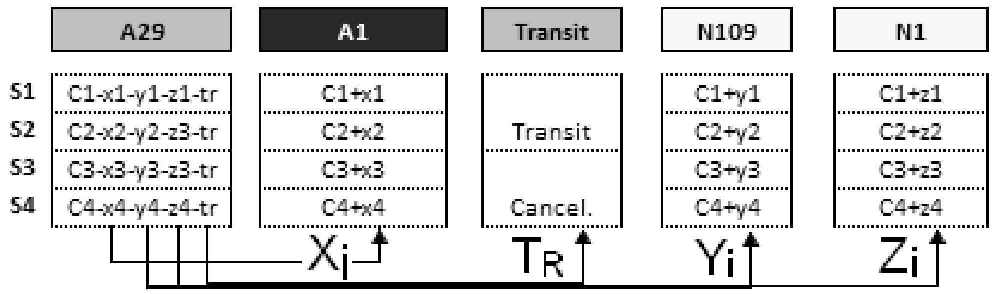


Figure 27 ADT traffic before (B) and after (A) tolls introduction on A29, A1, and c) estimated ADT in N109, N1 sections (based on EP, 2011 and noise reports) $ - After tolls introduction

After the introduction of tolls, it is still unknown the exact number of drivers that have abandoned the motorways and selected other options including the traffic diversion to alternative free-toll roads, changes for other modes or destinations and cancelled trips. Thus, the error bars sets the possible maximum and minimum range values of the ADT after the introduction of tolls.

Figure 28 provides a scheme of the traffic flows studied in this section. This research focused specifically on the impacts caused by the traffic diversion from A29 to the alternative roads, i.e., on the comparison of emissions and fuel consumption of the traffic flows “x”, “y” and “z” before and after tolls introduction on A29. Since no reliable traffic data on the N109 and the N1 were available, different scenarios of traffic distribution among the national roads were performed. The number of drivers that changed to the A1 after tolls introduction on A29 was calculated based on the traffic increase observed on the A1. This assumption is strengthened by the fact that, the ADT was relatively stable (before the introduction of tolls) and there were no significant changes in the transportation network. During the last quarter of 2010, a 4.5% increase in the number of passengers transported by rail was observed in the rail system parallel to the previous free motorway. However, the effect of the recent rises in public transportation fees and the reduction in demand caused by roadway tolls and fuel costs increase are still unknown. The literature provides values of elasticity of traffic volumes to tolls that vary typically from 0.1 to -0.45, depending on conditions (Spears et al. 2010). However, considering the high degree of uncertainty of these values, different scenarios considering several levels of traffic reduction are presented. It was assumed that the traffic fleet composition remains identical after tolls introduction.



X*i* *- ADT that used to travel on section* $s_{i\ of}$ *A29 and changed to A1,* Y_i *- ADT that used to travel on section* $s_{i\ of}$ *A29 and changed to N109,* Z_i *- ADT that used to travel on section* $s_{i\ of}$ *A29 and changed to N1, TR - ADT that used to travel on section* s_i *of A29 and changed to other modes/ cancelled the trip.*

Figure 28 Scheme of the studied traffic flows

To characterize fleet composition (namely diesel and gasoline passenger vehicles proportion), statistical data of Portuguese Automotive Commercial Association [152] were used. Thus, it was considered that light duty gasoline vehicles (LDGV) and light duty diesel vehicles (LDDV) represent 54.6% and 45.5% of the light duty fleet composition respectively. Since this research is focused on Light Duty Vehicles (LDV), heavy vehicles and motorcycles were not considered. According traffic data on a southern section of N1, LDV represent 80% of the fleet composition [127].

5.2 FIELD DATA COLLECTION AND EMISSIONS ESTIMATION

Three distinct data sets were collected for all routes in both directions - NPH tests (**N**on-**P**eak **H**our) - February, March, and April 2010, - PHB tests (**P**eak **H**our **B**efore tools introduction) - September, and October 2010, - PHA tests (**P**eak **H**our **A**fter tools introduction) - February, March, and April 2011. The peak period was considered to occur between 7:00-9:00 AM and 5:00-7:00 PM. The off-peak test runs were conducted between 10:00 AM-5:00 PM.

Table 19 indicates the number of tests as well as travel times and average speed data according to route and period. All field tests considered in the study were carried out during weekdays under dry weather conditions. Due to rainy weather, road works or road accidents the set of valid PHB tests on A1 and N1 was rather limited. It is possible to verify that the toll-free alternative roads N1 and N109 lead to a considerable increase in travel time. While the introduction of tolls has caused a reduction in travel times on A29, no significant changes were observed among the alternative routes. Although the data field collection took place between the Aveiro and Porto city centres, this analysis will focus essentially on sections S1 to S4 that contain A29 sections with new electronic tolls. Emissions estimation was based on VSP methodology which was described in previous sections.

Table 19 Number of test runs (n), speed and travel times during field data collection (m – mean; P95 - Percentile 95%)

				Travel time (min)						Average Speed (km/h)					
	NPH	PHB	PHA	NPH		PHB		PHA			3NPH	PHB		PHA	
	N	N	N	$\bar{X}$	P95	$\bar{X}$	P95	$\bar{X}$	P95	$\bar{X}$	P95	$\bar{X}$	P95	$\bar{X}$	P95
A1 (*Im_1*)	12	2	16	48	52	49	51	51	57	96	103	95	100	91	96
A29 (*Im_2*)	12	8	16	51	68	64	83	51	56	91	101	75	93	90	95
N1 (*Ih*)	12	3	16	80	90	97	103	94	108	65	71	54	57	56	62
N109 (*Iu*)	12	7	16	97	104	108	117	110	130	46	49	42	47	41	45

$N - \boldsymbol{Number\ of\ tests}, \bar{\mathbf{X}} - \mathbf{mean\ P95} - \mathbf{95th\ Percentil}$, NPH – Non Peak Hour, PHB, Peak Hour Before the introduction of tolls, PHA - Peak Hour Before the introduction of tolls

5.3 AVERAGE SPEED AND EMISSIONS PER SECTION

Figure 29 a) shows the average speed on two representative sections (S3 and S4), routes and time period in which the test run were carried out. Figure 29) b and c) shows the average total CO_2 and CO emissions produced for one generic LDGV. For both sections it is clear that the speed is mainly dependent on the route choice. However, a higher variability in section 4 was noticed due to higher congestion levels near Oporto suburbs. The average speed on A29 is higher after tolls introduction, due to the average 50% decrease in the traffic volume. During peak hour this difference is statistically significant (p=0.05) on section 4 of A29 where a higher reduction of traffic volume was detected. In fact, after the introduction of tolls, a free flow regime is observed on both motorways. On the other hand, a slight decrease in average speed (but not statistically significant) was observed on N109.

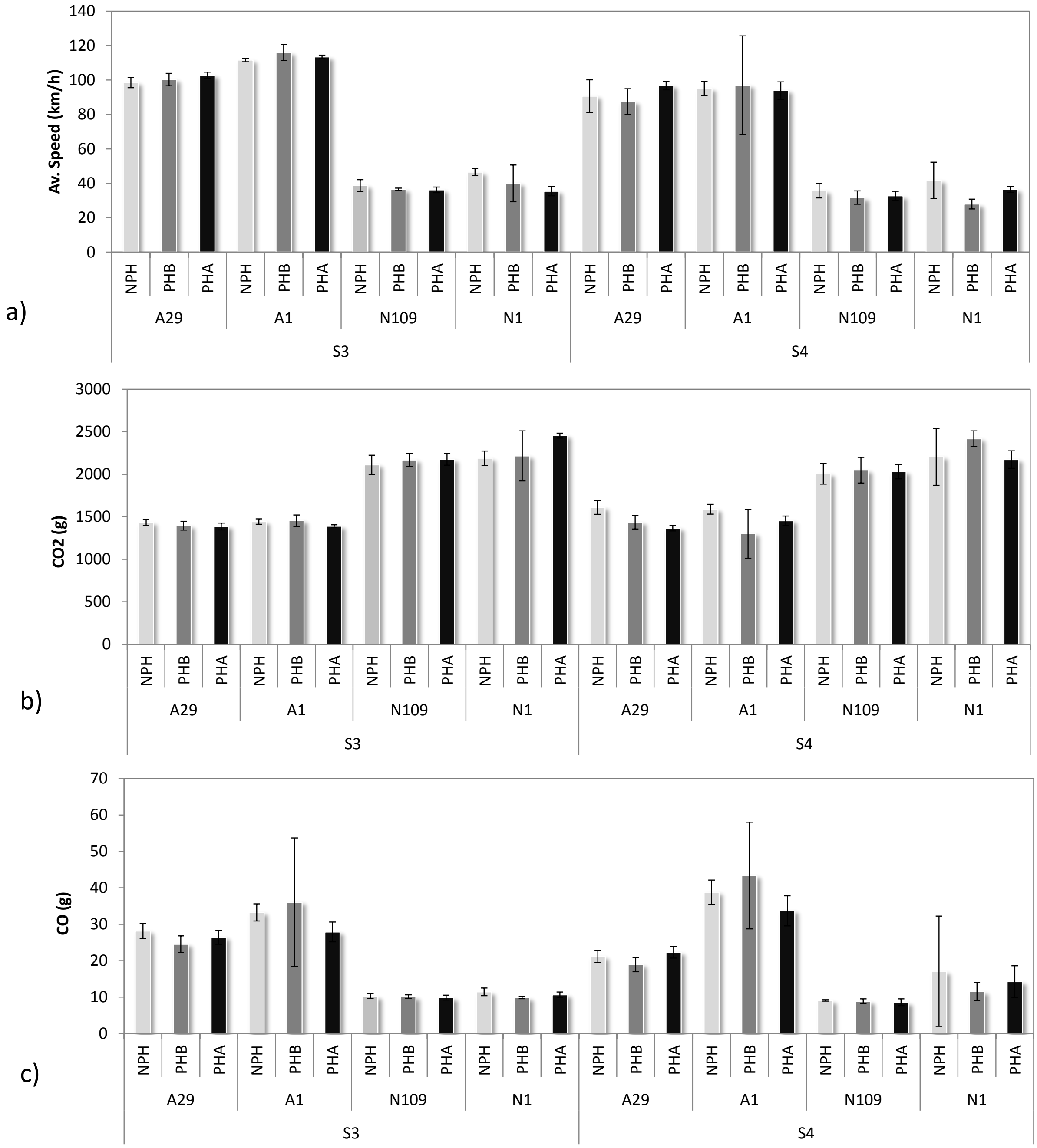


Figure 29 a) Average speed, b) CO_2 and c) CO emissions per vehicle (LDGV) according to section, route and period (includes T-student 95% confidence intervals).

It is clear that for all sections the motorway options (A1 and A29) lead to CO_2 savings when compared with the national roads (N1 and N109). However, regarding CO, NO_X and HC, emissions an opposite trend is observed. A comprehensive analysis of the time spent in each driving VSP mode showed that the higher frequency of high VSP modes on motorways leads to a significant increase in local pollutant emissions. On the other hand the higher travel time and a high occurrence of VSP modes 3 and 4 (caused by situations of idling and slow speeds) on national roads lead to an increase in fuel consumption and CO_2 emissions. Emissions factors per link are also primarily dependent on the route choice whereas the time period does not have a significant impact.

5.4 EMISSIONS AND FUEL CONSUMPTION IMPACT OF TOLLS INTRODUCTION

The impact of tolls introduction in terms of emissions and fuel consumption was analysed taking into account the traffic diversion from A29 to the alternative routes. It should be noted that on alternative routes, no statistically significant (95% level) differences in emissions factors were found regarding the introduction of tolls during peak hour periods. This can be explained because i) A1 motorway absorbed a substantial portion of the traffic and had enough capacity to accommodate the extra demand, ii) the remaining traffic was distributed evenly on alternative roads without significantly increasing traffic flows. A rough estimation of the traffic volumes per hour during the peak period was carried out. It was found that after the introduction of tolls, the traffic volumes per hour/lane may not exceed 1100 vehicles over the sections 1-4 of N1 and N109. This fact suggests that the capacity of the infrastructures is not clearly reached and consequently the speed and emission factors remain relatively stable.

Thus, it is reasonable to assume that, in terms of total emissions, the main impacts are related to the vehicles that previously used A29, but after the introduction of tolls may have moved to other routes with different emissions profiles. Table 20 shows the estimation of daily differences in total emissions after introduction of tolls, which is based on Eq. 9 for all pollutants. Since it is unclear how many drivers have diverted to national roads, emissions changes were calculated according distinct traffic reduction levels and considering that the traffic volume diversion from A29 was correspondingly distributed among N1 and N109.

$$DEC_i = DEA_i i - DEB_i \qquad \text{Eq. 9}$$

Where:

$$DEB_i = (x_i + y_i + z_i).k.E_{i/A29/PHB}{+}(x_i + y_i + z_i).(1-k)\,E_{i/A29/NPH} \qquad \text{Eq. 10}$$

$$DEA_i = \{x_i.k.E_{iA1\,PHA} + x_i(1-k).E_{iA1\,NPH+}\} \qquad \text{Eq. 11}$$

$$+(1-TR)\{y_i.k.E_{iN109\,PHA} + y_{i(1-k)}.E_{iN109\,NPH}{+}z_i.k.E_{iN1\,PHA} + z.E_{i\,1\,NPH}\}$$

Where:

i – Section i (S1 to S4)
DEB_i - Daily Emission before toll introduction on section i
DEA_i - Daily Emissions after toll introduction on section i
DEC_i - Daily Emission change on section i
Ei- Average total emissions on section "i" on Route A29/A1/ N1/N109 during NPH/ PHB/ PHA
k – Traffic Volume Ratio at Peak hour
TR- Traffic reduction (shift to public transportation and avoided trips)
x_i – Estimated ADT that used to travel on section s_i of A29 and changed to A1
y_i - Estimated ADT volume that used to travel on section s_i of A29 and changed to N1
z_i - Estimated ADT volume that used to travel on section s_i of A29 and changed to N1

Table 20 Estimated net changes in daily (system) emissions after the introduction of tolls by section according to different scenarios of traffic reduction

TR	CO_2 (TON/DAY)				NO_X (KG/DAY)				CO (KG/DAY)				HC (KG/DAY)				FUEL (10^6€/YEAR)
	S1	S2	S3	S4	S1	S2	S3	S4	S1	S2	S3	S4	S1	S2	S3	S4	Total
0%	**16**	**27**	**47**	**82**	-53	-9	0	4	-346	-541	-1	81	-4	-6	1	1	3.58
5%	**3**	**4**	**40**	**66**	-56	-86	-2	1	-352	-555	-3	75	-4	-6	1	1	2.32
10%	-10	-2	**34**	**5**	-59	-92	-3	-2	-358	-569	-5	69	-4	-7	0	0	1.06
20%	-35	-65	**20**	**18**	-65	-13	-6	-9	-38	-596	-9	56	-5	-7	0	0	-1.46

TR -Traffic reduction scenarios: **O%** - All traffic that diverted from motorways, shifted to the N1 and N109. **5% 10% 20%** - Percentage of drivers that diverted from A29 (section i) but did not select N1 or N109 (choose the shift to public transportation or avoided the trip)

Regarding CO_2 emissions and fuel consumption, the introduction of tolls has caused a negative impact on these parameters. In road sections 3 and 4 even with a hypothetical 20% decrease in traffic volume, the emissions would increase. These sections are particularly sensitive because there is a higher density of intersections and traffic lights leading to the increase of the fuel consumption and CO_2 emissions. The last column of Table

20 shows the estimation user's annual fuel costs related to the change in the traffic distribution. This estimation was based on the average gasoline and diesel prices in Portugal, on the October 21, 2013. It is clear that the introduction of tolls leads to the decrease of local pollutants emissions, namely NO_X and CO which is consequence of less traffic circulating on motorways. It should be noted that the differences in section 3 and 4 were minimized because a significant volume of traffic has changed to A1 where speed limit is higher than A29 (120km/h - A1; 100 km/h - A29) leading to an increase in local pollutants emissions. Figure 30 shows the relative impact of tolls introduction and different levels of traffic reductions (considering all sections).

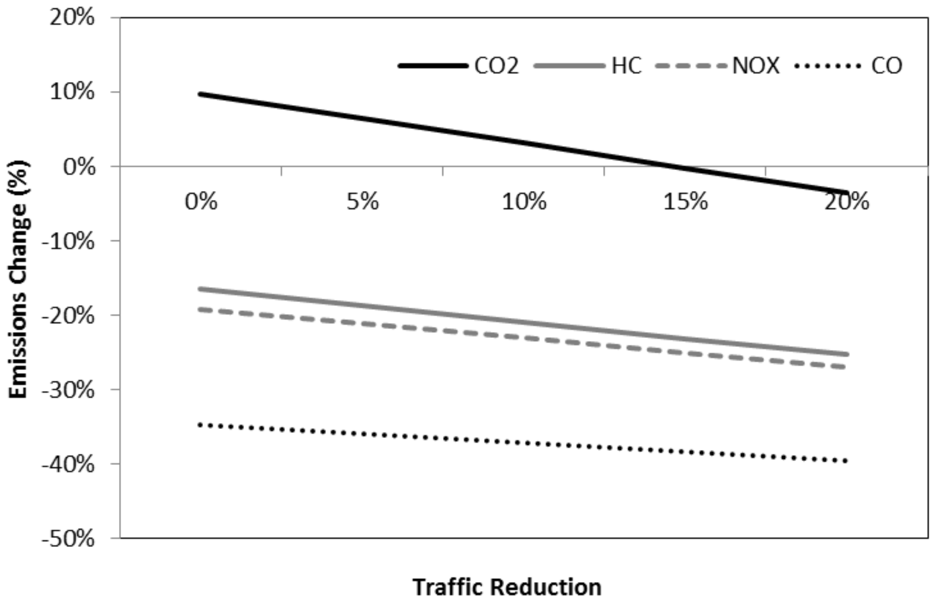


Figure 30 Relative changes in total (system) emissions (due to tolls) on all routes for different levels of traffic reduction.

Since it was demonstrated that at different periods (with different traffic volumes) emissions did not vary substantially, it was assumed that in the sections analysed, the emissions vary linearly with traffic volume. Regarding CO_2 emissions, only for traffic reduction values higher than 17%, it is possible to offset the emissions increase related to the traffic diversion from the A29 (Im_2) to the national roads (*Ih* and *Iu*). Concerning local pollutants, considerable reductions are achieved for all scenarios. A what if-analysis of different and extreme scenarios of traffic distribution among the national roads N1 and

N109 was performed. However, given that the emissions factors in N109 and N1 are relatively similar, a little impact on total emissions between the extreme cases (100% of traffic shifting to N109 and 0% for N1 and vice-versa) was observed (up to 3% for CO_2 and 5% for local pollutants).

5.5 CONCLUDING REMARKS

This chapter has provided an empirical assessment of the impact of tolls introduction on an intercity corridor. Based on second-by-second vehicle dynamics data collected immediately before and after tolls introduction, emissions and fuel consumption for a generic light passenger vehicle were estimated. Then, taking into account the ADT data from motorways, an extrapolation of total emissions change was done.

More than the period of the day (peak and non-peak) and the presence or absence of tolls, the selection of a specific route has shown to be the most important factor regarding the emissions factors on the analysed sections. Seemingly, although 25000 vehicles per day have shifted from A29 to alternative routes and modes, the new traffic distribution after the introduction of tolls had no significant impact on the performance of network in terms of speeds, travel times, and emissions factors. Thus in terms of total emissions the main changes are the result of the traffic deviation from A29 to the alternative routes. Since it is unclear the volume of traffic reduction caused by the introduction of tolls, different scenarios of traffic reduction were performed. It was found that unless there was a significant decrease in traffic volume (higher than 17%), CO_2 emissions and energy consumption may increase up to 10%. For local pollutants, a significant decrease (between 15% and 40%) is expected considering only the traffic volume that left the A29.

While in Chapters 4 and 5, the impacts of the choice of route have been based on a set of pre-defined routes, in chapter 6, empirical data will be incorporated into computational models in order include additional environmental criteria into existing routing algorithms.

6 INCORPORATING EMPIRICAL DATA ON COMPUTATIONAL METHODS FOR ROUTE IMPACTS ASSESSMENT

With the increased adoption of GPS and mobile computing, increasingly sophisticated routing solutions are becoming mainstream. Although research into adding environmental factors to route planning had been going on before the recent technological leap, current commercial applications usually just focus on shortest path or minimum travel time.

The main objectives of this chapter are: i) to investigate how empirical data can be exploited for developing eco-routing strategies; ii) to develop an integrated simulation platform of traffic and emissions, validated with real world data.

Section 6.1 focuses on the integration of multiple computational tools towards the objective of assessing emission impacts of different links and then compute optimal eco-routing solutions. Data from real life GPS tracks was integrated with traffic emission modelling for multiple pollutants (NO_X, HC, CO and PM_{10}) to investigate different routing strategies.

On the other hand, in Section 6.2 it is intended to employ GPS empirical data to calibrate and validate an integrated microsimulation platform of traffic and emissions. Figure 31 clarifies these conceptions. Fundamentally, this chapter establishes the link between the empirical assessment of route choice that have been performed in chapter 4, and the analytical approach that will be conducted in chapter 7 to analyse eco-traffic management strategies.

Both works presented in this study have been conducted under the scope of the SMARTDECISION project.

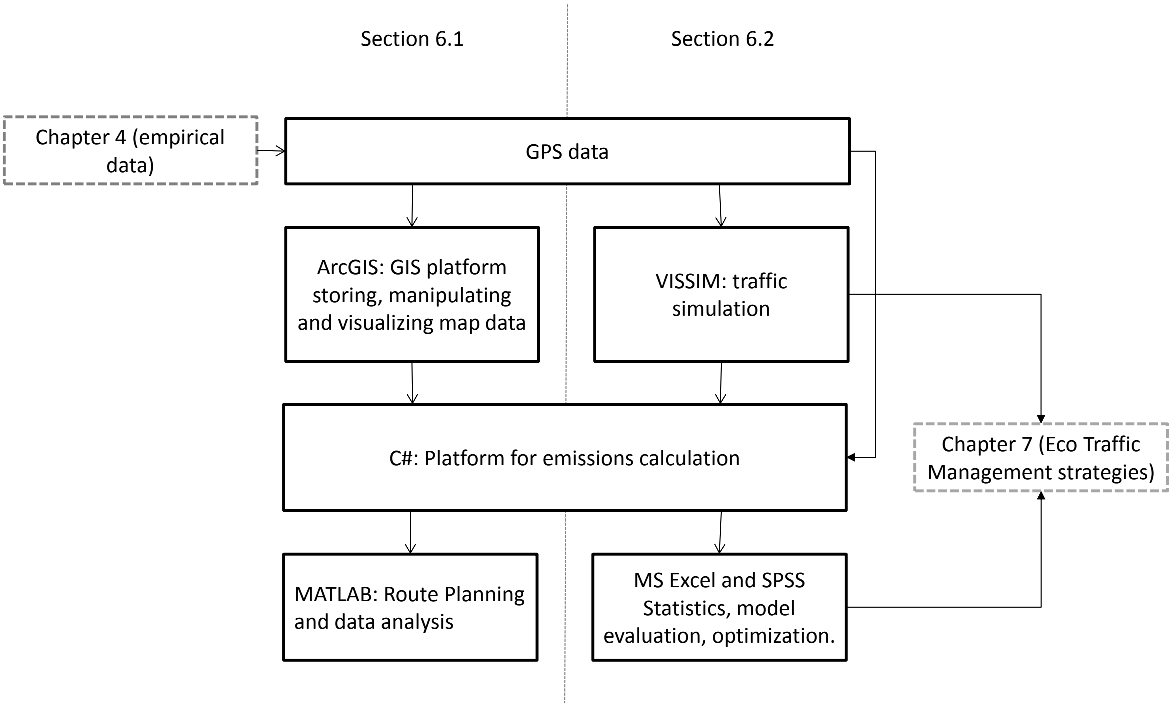


Figure 31 Integration of empirical data with different computational platforms used in chapter 5.

6.1 INTEGRATED COMPUTATIONAL METHODS FOR TRAFFIC EMISSIONS ASSESSMENT AND ECO-ROUTING INFORMATION

In previous chapters, empirical GPS data have been integrated with traffic emission models to investigate different route choice impacts in terms of emissions. This assessment was based on a set of pre-established paths. However, a real eco-navigation algorithm (focused on emissions minimization) should be based on environmental cost functions to generate a set of alternative paths. Additionally, one of the main conclusions is that different pollutants can dictate different best routes. Hence, strategies for assigning relative weights to pollutants are incorporated in the routing algorithm.

Real world GPS data from the intercity context has been processed on three different platforms: C# on Visual Studio, ArcGIS and MATLAB.

The post processing work has been allocated between the platforms as follows:

- ArcGIS: GIS platform for storing, manipulating and visualizing map data;

- C# (Visual Studio): numerical computing environment used to implement the emission calculations using VSP and CORINAIR [7] methodologies;
- MATLAB: numerical computing environment used for integration, route planning and data analysis.

6.1.1 Study domain and emissions estimation

In this section, second-by-second GPS data recorded in the urban and intercity contexts over peak and off peak periods (approximately 11550 km) have been considered. Additionally, in order to allow the switch between itineraries at various points of the network, four new road sections (N224, N223-N227, A41, A29) connecting the previous study routes (Im_1, Im_2, *Ih*, *Iu*) have been considered (see Figure 32). Vehicles equipped with GPS were driven in these roads, in both directions, totalling extra 650 km of GPS data.

Emissions modelling has been implemented using two different methods: a) VSP methodology for instantaneous speeds and b) the CORINAIR[3] methodology for average speeds [7]. To estimate average emissions per link, the VSP methodology was applied in 97% of this network, whereas the CORINAIR methodology was used in the remaining 3% where GPS data were not available. (These sections correspond to certain motorway and highway interchanges). CORINAIR methodology was also used to estimate PM emissions used due to the lack of accurate information on VSP emission factors for particulate matter (PM) from LDGV. Figure 33 outlines the methodologies used to estimate emissions.

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[3] Hot emissions (g/km) for Euro 1 and later gasoline and diesel passenger cars are calculated as a function of speed. The generic functions are:
Gasoline: $EF = (a + c * V + e * V^2)/(1 + b * V + d * V^2)$
Diesel: $EF = (a + c * V + e * V^2)/(1 + b * V + d * V^2) + f/V$
The values for the coefficients of the function can be found elsewhere [7].

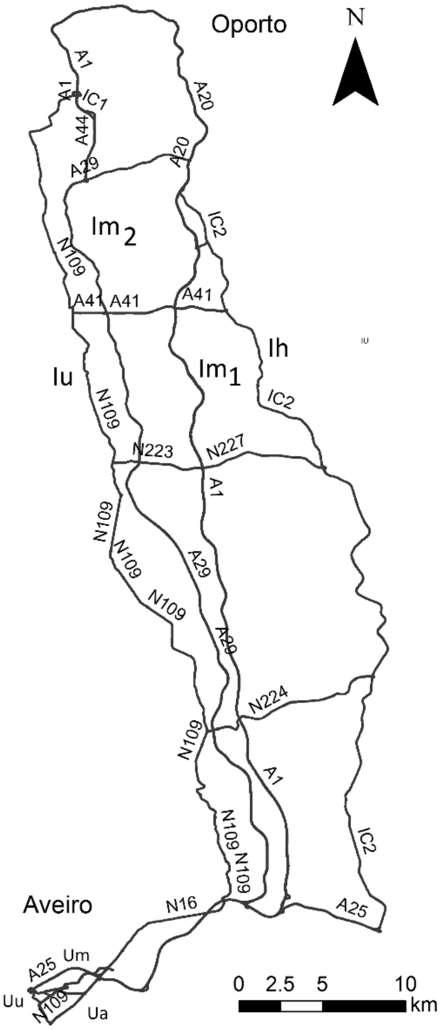


Figure 32 Study domain

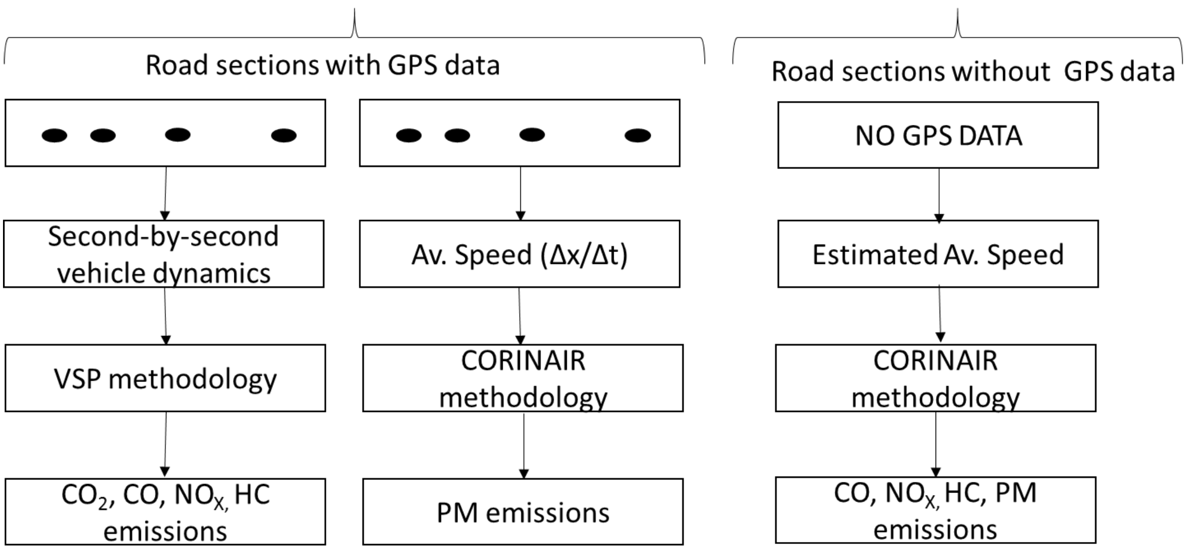


Figure 33 Layout of the methodologies used to estimate emissions

Under the R&D project SMARTDECISION, a C# code was developed to compute the second by-second data using GPS data, vehicle characteristics and to generate emissions information per link. Data is organised in terms of vehicle type with one data structure per type. Each type contains groups of two dimensional matrices, where each matrix corresponds to the weights of the map's graph. Once all the emission data have been calculated through the C# implementation of VSP and CORINAIR, each link of the network acquires new attributes.

The original geospatial map can be visualised as a weighted graph, the weights of whose edges correspond to the lengths of each road network segment. With the addition of the emission data, each link acquires multiple features; depending on the selected criterion for optimization (e.g. distance, time, pollutants or fuel consumption). Since GPS data have been recording during peak and off peak periods, these attributes can represent different periods of congestion according the time of day. All these criteria are integrated as shown in Figure 34.

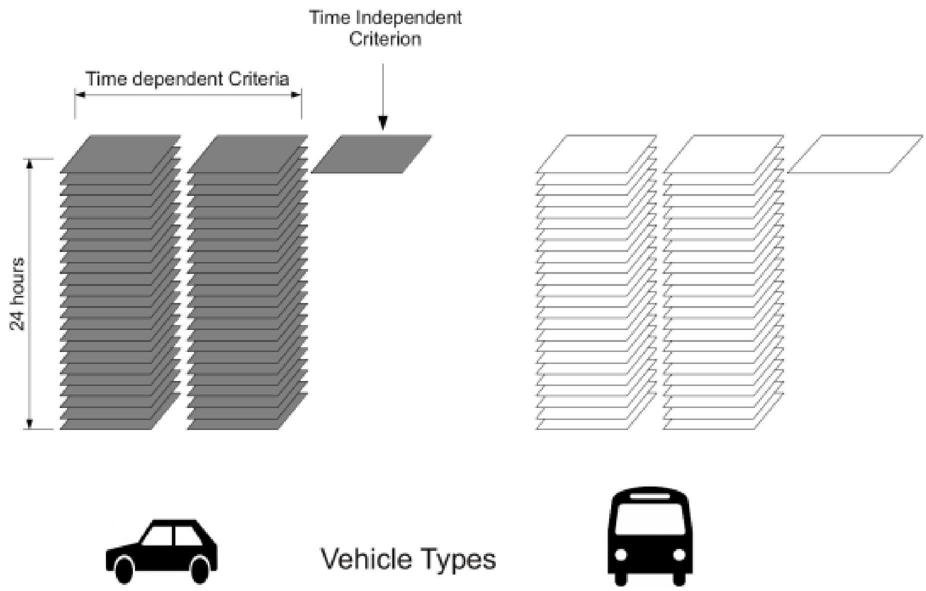


Figure 34 Overall structure of map data.

Data are organised in terms of vehicle type, which in turn contains groups of two dimensional matrices. Each matrix corresponds to the weights of the map's graph. Thus, all matrices code for the same topological map but each one contains different link attributes. Data are divided in two main categories, time independent (e.g. distance) and time dependent (Travel time, CO_2, NO_X, HC, PM). Time dependent data is organized in a set of 24 matrices (one per hour) for each criterion used.

In order for a route to be estimated, the data structure appropriate to the vehicle type in question is selected. Then, the appropriate criterion is chosen and, if time dependent, the matrix corresponding to the hour of day required is selected.

6.1.2 Route Planning

Once the data have been organised as described, route planning can be implemented using MATLAB. In this approach, a static matrix for each criterion is used. Thus, the route planning assumes that the following two conditions are satisfied: a) the eco-routing vehicles are not enough to change the conditions of the network operation, b) conditions are assumed to remain constant during the overall travel time of each eco-routing vehicle.

Taking into consideration the type of vehicle, time of day and a pair of origin/destination (O/D) nodes, the appropriate matrix is used, and a shortest path is calculated for each criterion graph search algorithm.

The *graphshortestpath* function of MATLAB's Bioinformatics Toolbox offers different graph theory tools and algorithms that can be used for purposed of route optimization, such as the Dijkstra [153] and Bellman-Ford [154]. Both algorithms have returned similar results in terms of minimizing the selected criteria. However, Bellman-Ford is slower than Dijkstra's algorithm for the same problem. In fact this algorithm is more suitable for handling graphs in which some of the edge weights are negative numbers, which is not the case of the current map structure. Previous research has demonstrated the feasibility of estimation optimal routes based on Dijkstra algorithm with extended data structure [100,155].

The Dijkstra algorithm calculates the shortest path between two points on a network using a graph made up of nodes and edges. It assigns to every node a cost value, set it to zero for source node and infinity for all other nodes.

The algorithm can be defined by the following steps [99]:

1. Start with the source node: the root of the tree.
2. Assign a cost of 0 to this node and make it the first permanent node.
3. Examine each neighbour node of the node that was the last permanent node.
4. Assign a cumulative cost to each node and make it tentative.
5. Among the list of tentative nodes:
i) Find the node with the smallest cumulative cost and mark it as permanent. A permanent node will not be
ii) Checked ever again, its cost recorded now is final.
iii) If a node can be reached from more than one direction, select the direction with the shortest cumulative cost.
6. Repeat steps 3 to 5 until every node becomes permanent

6.1.3 Case study – Assessing different criteria for minimizing local pollutants impacts

In this section different strategies for the minimization of pollutants with direct effect on human health are analysed. The paths calculated this way offer a different mix of criteria costs which can have very different value ranges. Two different approaches for assigning relative weights to each pollutant were considered: human health impact – based on eco-indicator 99 [133] and current atmospheric pollutant concentrations (see section 3.6 for further details about the eco-indicator 99 methodology).

The origin is in the city of Oporto and the destination in the city of Aveiro. Figure 35 shows the predicted emissions of the different pollutants for a light passenger gasoline vehicle at 9 AM. Thicker lines indicate higher predicted emissions of a pollutant for a given network segment.

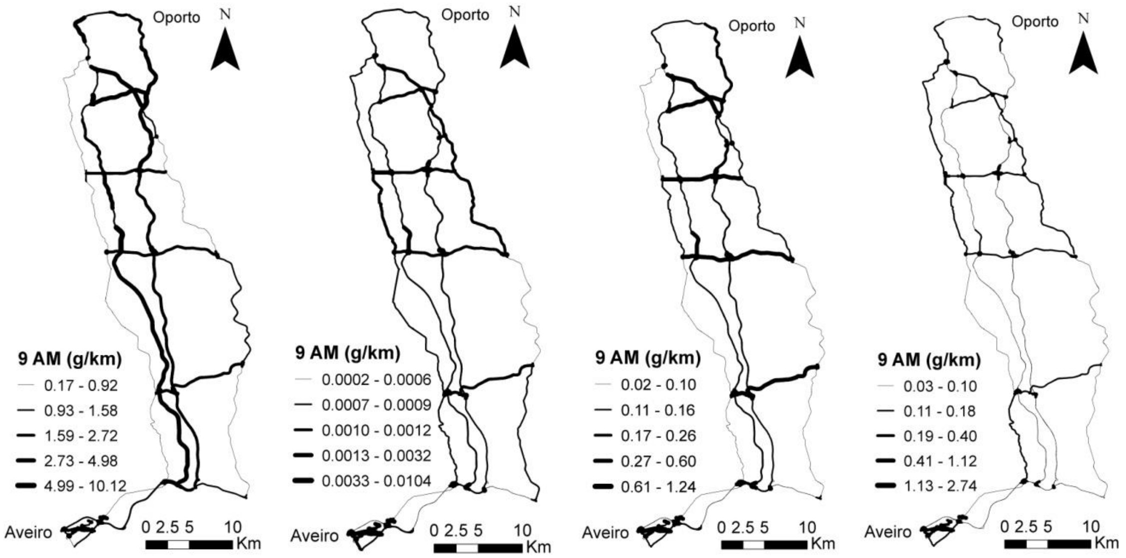


Figure 35 Pollutant estimations for NO_X, CO, HC and PM10 (from the left to right) at 9 AM.

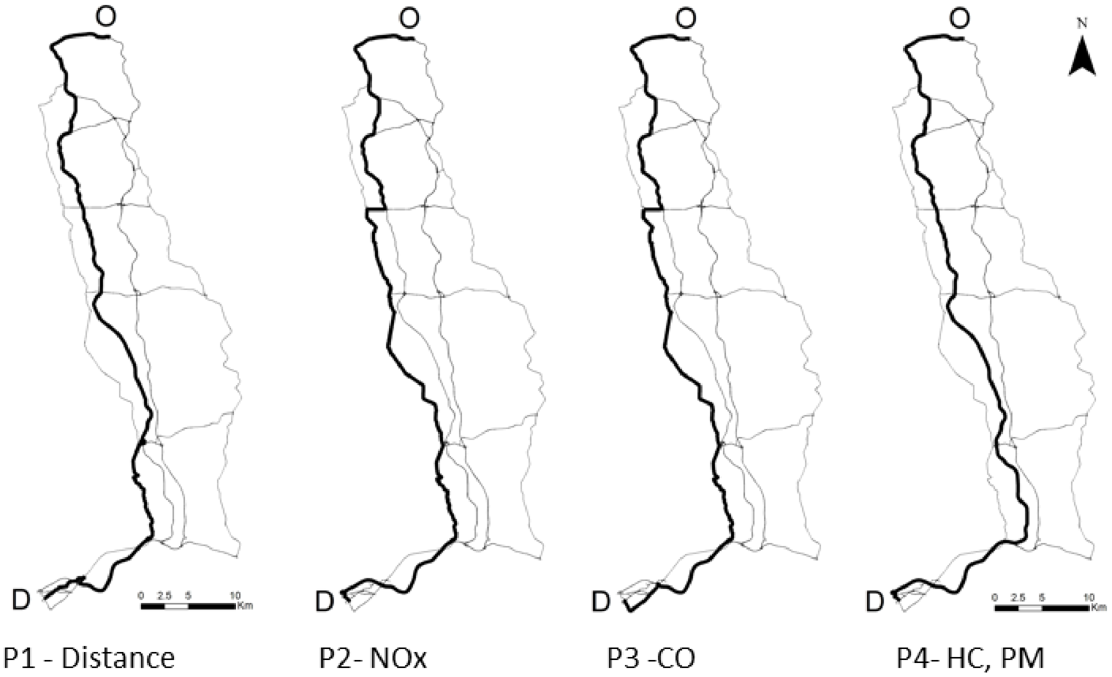


Figure 36 Best paths for various criteria at 9 AM.

Figure 36 shows the best paths for the different criteria. Note that, while there are 5 criteria (4 pollutants and distance), there are only 4 best paths. This is because HC and PM have the same best path (path 4), while the path for best distance (path 1) does not coincide with a best path for any pollutant.

The relative values for the criteria are shown in Figure 37 where each criterion is expressed as a percentage of its best (lowest) value. It can be observed that there is little variation in distance across the paths. The longest path (2) is only 3% longer than the shortest path (1). In contrast, the highest variability among the pollutants is exhibited by CO, whose worst value (at path 4) is 93% higher than its best (path 3). The lowest variability among the pollutants is exhibited by NO_X, whose worst value (path 1) is 10% higher than its best (path 2).

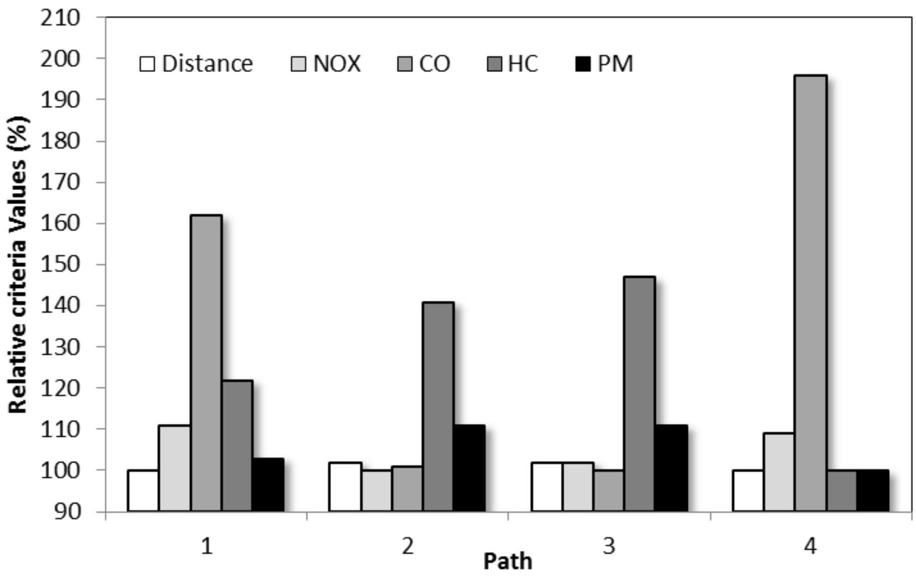


Figure 37 Relative values of the criteria expressed as percentages of their lowest value.

In order to assess which of these paths a vehicle should actually take, these results must somehow be compared.

The first comparison strategy is based on health impact as laid out in Eco-Indicator 99 (see section 3.6). The values for all pollutants and paths are shown in Figure 38. Since PM levels are much lower than the other pollutants, a log10 scale graph was selected in order to all pollutants emissions be shown more clearly.

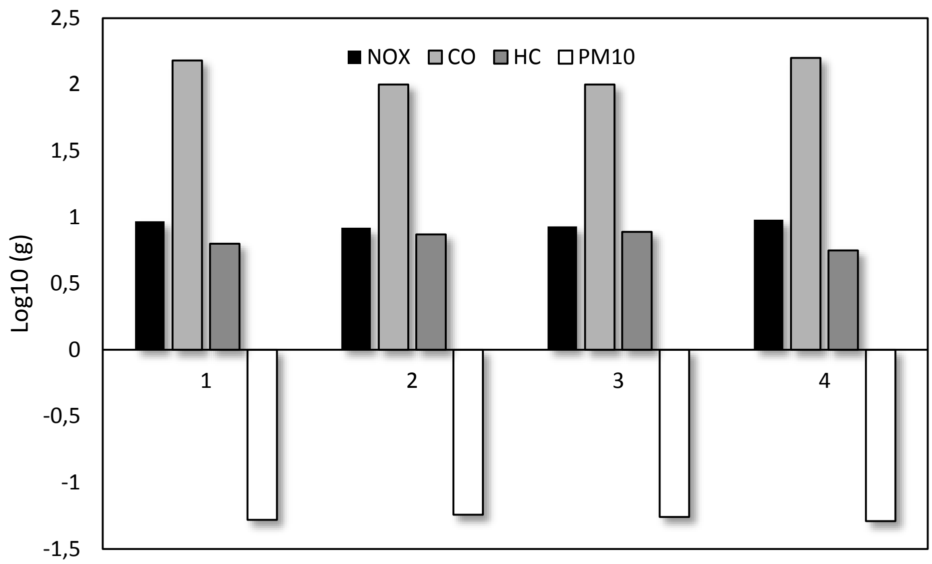


Figure 38 Absolute values for NO_X, CO, HC, and PM10 for different paths.

Using the weights of Table 9 (eco-indicator 99 [133]), the health impacts can be calculated by multiplying the mass value of each pollutant with the corresponding damage value (Figure 39). This methodology express the Damage to Human Health as the number of year life lost and the number of years lived disabled. These are combined as Disability Adjusted Life Years (DALYs) [133]. Taking into account the relative damage assigned to each pollutant, shows that this approach almost completely remove the dominance of CO and replace it with NO_X, while HC and PM become negligible. Because the variation in NO_X among the paths is lower than in CO, the overall variation among the paths is lowered. Considering this method for normalization of emissions impacts assessment, paths 2 and 3 outperform the others.

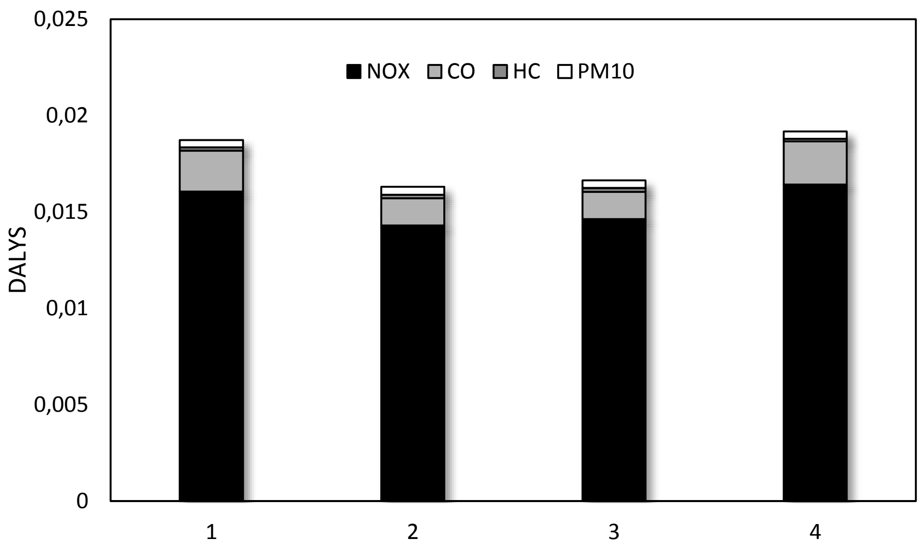


Figure 39 Health impact of NO_X, CO, HC, and PM10 for different paths.

The second strategy is related to current atmospheric pollutant levels. For this example, air pollution levels in the city of Aveiro on the 16th of July 2012 were selected. The historical data available in this case are NO_2[4], CO and PM_{10}. On this day, NO_2 was at 17% of its limit value, while CO and PM10 were at 2.8% and 68%, respectively.

Two straightforward weighting strategies have been explored here. In the first case (Figure 40a) the weights are taken directly from the limit value percentages (LVP) (e.g. 0.17, 0.028 and 0.68 for NO_2, CO and PM10 respectively). In this case, there is a slight increase in the importance of NO_x relative to CO, and PM10 becomes more noticeable. However, CO still dominates the sum, making paths 2&3 (corresponding to best NO_X and best CO respectively) the highest ranked.

However, a transport decision maker may want to prioritize the pollutants whose concentration in the atmosphere is closer to the legal limits. The optimal criteria for selecting a path can be more heavily biased towards the pollutants closer to their limit by raising the weights to some exponent. To illustrate this Figure 40 b-d shows the same scenario but, in these cases, the percentages have been raised from 2 to the 4th power. The effect of CO becomes negligible and PM_{10} becomes the dominant criterion as the

[4] Although the concentrations ratio NO / NO_2 can vary over time, for purposes of demonstration of the methodology, NO_X emissions are associated with values of concentration of NO_2.

exponent increases. In the extreme case (4th power) path 4 (best HC & PM10) becomes the highest ranked path.

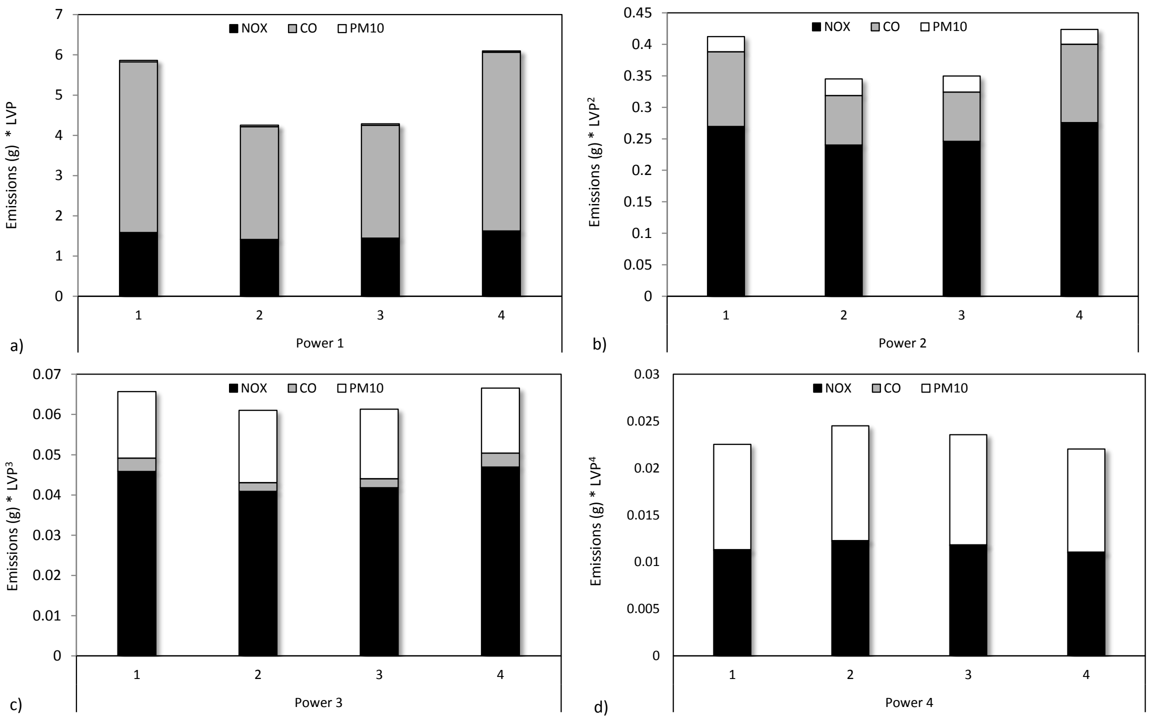


Figure 40 Relative impacts for different paths of NO_X, CO and PM10 with weights based on current concentrations and different exponents.

6.1.4 Discussion

The main objective of this section was to integrate different computational tools to identify the best routes based on multiple pollutants present in traffic emissions. This study was predominantly descriptive of the methodology, only investigating one type of vehicle, at one time of day (implying a particular congestion level) and one O/D pair. However, this structure can accommodate multiple O/D pair analysis, vehicle types and congestion levels.

Two different strategies of assigning weights to these pollutants have been analysed: i) based on health impacts according to Eco-Indicator 99 and ii) based on real time atmospheric pollutant concentration levels. The first strategy is more suited to an offline decision making application. In the absence of updated data for the region of interest, a lookup table of the impacts of a small number of pollutants can allow to identify a route based on reasonably realistic criteria. These results should be seen as a normalization method to assess different pollutants effects. The real effects of pollution depend on several factors including the built local environment of each link.

The second strategy is, in effect, a more general case, since information on air quality levels can updated in real time and legal limits for each region reflect health based standards built into them [137]. It should be noted that for this method to be used appropriately, the contribution of a pollutant specifically due to traffic has to be taken into account. Especially for large urban centres, pollution forecasting is already a reality, and air quality data can be straightforwardly exported to similar computational platforms.

6.2 Development of an integrated platform for microsimulation of traffic and emissions

The main objective of this section is to develop an integrated microscopic modeling platform calibrated with real world data to assess both traffic and emissions impacts of future ATMS. The empirical work based on traffic and road inventory data collection was used to calibrate and evaluate an integrated microscopic simulation platform.

The road network of Aveiro was selected to test the integrated simulation platform. Two main reasons support this choice: i) the network dimension and ii) data availability for calibration and validation. Moreover, studies conducted in medium-sized cities show that traffic problems are not just phenomena of the large metropolis [156]. One typical problem is that population densities are not high enough to support efficient public transportation, further increasing the demand for individual transportation. Therefore, ATMS are needed to increase the efficiency of these networks.

6.2.1 Data collection

To calibrate the traffic-emissions simulation platform, empirical data on vehicle dynamics, collected in the urban area have been considered. Additionally traffic volume and traffic signals timing have been monitored.

- Vehicles dynamics: 550 km over 15 hours of GPS data collection on Routes *Ua*, *Um* and *Uu* were covered (see section 413.3). Additional tests were performed in more 10 road segments (37 km) across the study network for the model validation in terms of total emissions.
- Traffic volume monitoring: traffic was counted in 14 strategic points of the study network. Based on these data, time dependent Origin/Destination (O/D) matrices were defined for each intersection;
- Traffic signals timing: cycle length and phasing were measured six times in the traffic lights

Figure 41 presents the simulation study domain, which covers an area of 3.9 x 4.5 km^2, and the main roads that were considered. VISSIM 5.30 model was applied to simulate individual vehicle movements. VSP methodology was used to estimate emissions based on real data from field tests and on the data provided by traffic model. In the framework of the SMARTDECISION project, a C# console application was developed to compute second-by-second vehicle dynamics data from VISSIM output for emissions estimate. Total emissions for passenger cars were calculated considering 57.5% of gasoline and 42.5% of diesel vehicles [152]. Data on vehicle dynamics from VISSIM and field tests were compared for the three urban routes. Due to the flat terrain, a road grade of zero was assumed. This approach generates a maximum error of 5% in the calculation of the emissions of all pollutants.

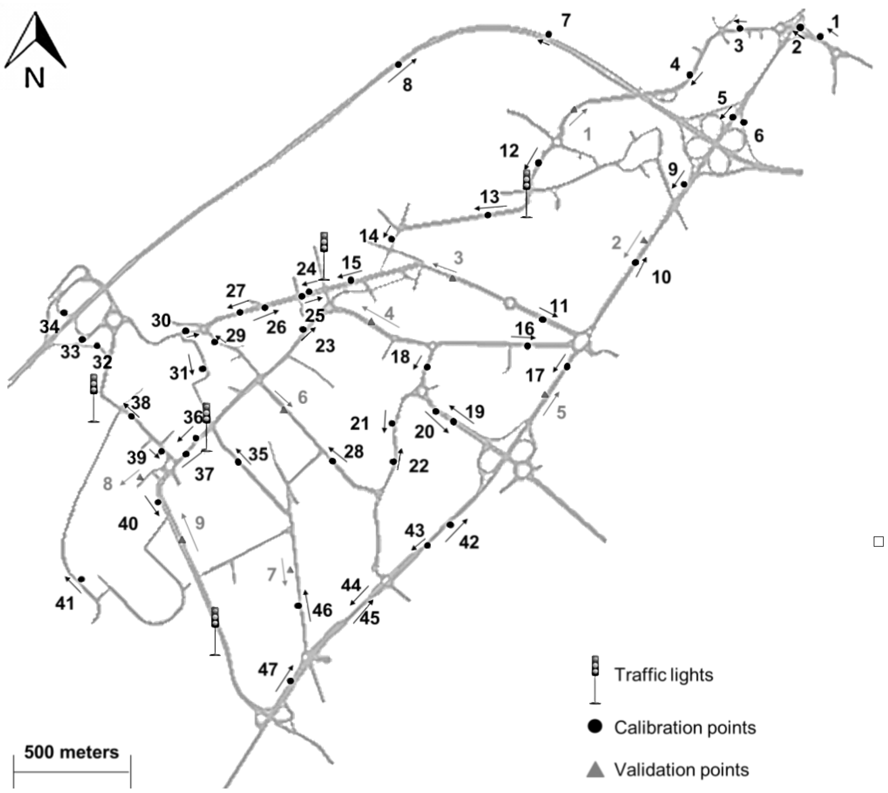


Figure 41 Study domain and data collection points (Aveiro, Portugal).

6.2.1.1 Calibration and validation

The model evaluation was made in two steps: calibration and validation. While the first step is focused on the driver behaviour parameters, the following step is related with traffic volumes, travel time, speed profile and VSP mode distributions. Calibration and validation were based on different datasets. Therefore, 47 points were used for calibration while the remaining points were used to validate traffic volumes, as illustrated on Figure 41. The same procedure was applied for travel times and average speeds.

In the calibration step a preliminary number of runs was selected applying the method suggest by Hale [157]. This method is based on the simulation results from a preliminary number of runs where the mean sample variance is compared to a predetermined confidence interval (CI) based on the t-distribution. As suggested by Hale [157], 10 initial random seeds runs were previously considered. Regarding simulation resolution, a fixed value was assumed (10 times steps/sim.sec) due to the input of VSP model (second-by-second).

For the calibration of driver behaviour parameters the strategy recommended by the FHWA [158] was adopted. Firstly, the driver behaviour parameters as car-following (average standstill distance, additive and multiple part of safety distance) and lane-change were tested in order to assess their effect on travel times and on speed rates. By an initial sensitivity analysis, no relationship was found between lane change parameters and those measures. To evaluate the goodness of fit, the Root Mean Square Error (RMSE) between observed travel times and simulated mean speed was applied. Several methods are suggested for finding the value of a single parameter that minimizes the squared error between the model and the observations [158]. Among these methods, the golden section search method (see appendix C1) was selected to obtain the optimal parameter value [158]. After several runs, the subsequent car-following parameters were obtained: additive and multiple part of safety distance by 1.95 m and 2.95 m, respectively, and a value of 1.60 m for the average standstill distance.

In the validation step, the estimated traffic volumes, travel times and speed profiles were compared with the observed data. To compare means and overall "goodness of fit" of those measures, the GEH Statistic test [158] and the Root-Mean-Square Error (RMSE) parameter were used. For this comparison 15 points of study domain were selected. For travel times and speed means, the "floating car runs" method suggested by the FHWA [158] was applied in order to guarantee an adequate number of data samples with a 95% confidence level.

The final step of the validation process was focused on the comparison between the relative frequency of observed and estimated VSP mode distributions. The VSP modes distribution was computed using the values collected during the field campaigns and using the VISSIM outputs. Since the number of data sets (number of seconds of the route) is roughly higher than 30, the two-sample Kolmogorov-Sminorv test (K-S test) for a 95% confidence level is appropriate to quantify the distance between empirical functions of those samples [159]. The null distribution of K-S test is calculated under the null hypothesis that the observed and simulated VSP modes are drawn from the same distribution.

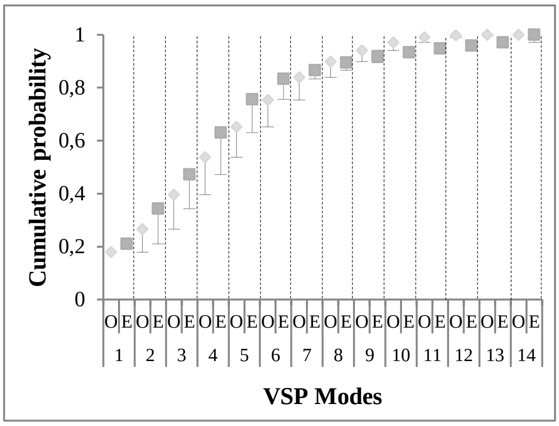
6.2.2 Model evaluation

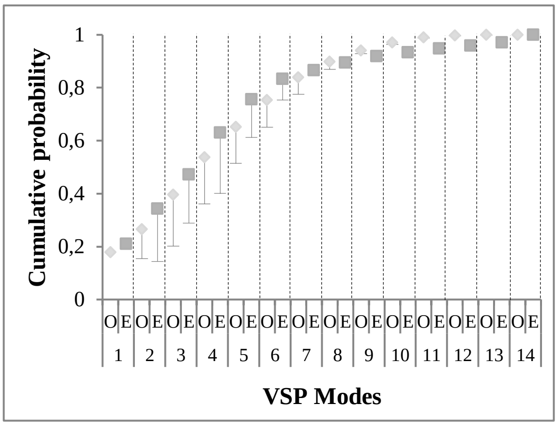
The statistical indicators of the integrated platform have shown valid results. The model performance is evaluated based on travel time, average speed and VSP mode distributions. Table 21 shows the comparison between observed and estimated means for travel times and speed. In this case, the GEH statistics test lower than 0.50 was yielded for both parameters on each route evaluated. The highest travel times differences between observed and estimated values were recorded on routes *Um* (C->S) and *Uu*. The results indicated that 10 runs per simulation were adequate.

Table 21 Observed and estimated values for travel times and speed means and number of floating car runs.

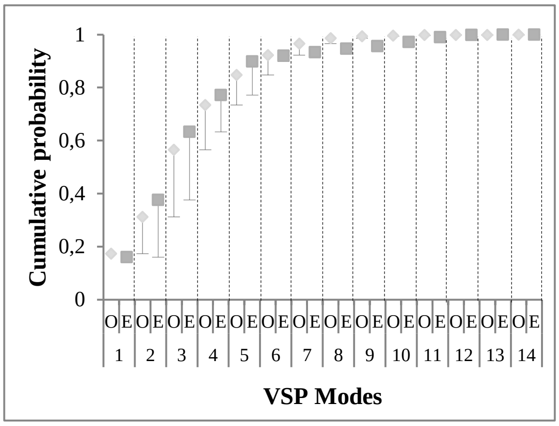
Route	N (N_{MIN})	Travel times (s)			Speed (km/h)		
		Observed (95%CI)	**Estimated (95%CI)**	**GEH**	**Observed (95%CI)**	**Estimated (95%CI)**	**GEH**
Um (C→S)	22 (3)	477.33 (±16.79)	480.64 (±10.82)	0.15	52.00 (±1.56)	51.35 (±1.26)	0.09
Ua (C→S)	16 (6)	597.59 (±32.81)	590.50 (±23.57)	0.29	38.50 (±2.11)	38.58 (±1.39)	0.01
Uu (C→S)	22 (5)	613.36 (±30.51)	604.18 (±19.06)	0.37	25.77 (±1.29)	27.33 (±1.08)	0.30
Um (S→C)	16 (4)	515.33 (±16.74)	528.38 (±16.74)	0.57	42.23 (±4.42)	40.50 (±1.23)	0.27
Ua (S→C)	18 (7)	565.88 (±20.50)	568.44 (±22.81)	0.11	38.65 (±1.85)	37.69 (±1.39)	0.16
Uu (S→C)	18 (3)	543.77 (±39.52)	551.67 (±11.99)	0.34	26.96 (±1.45)	26.59 (±0.99)	0.07

Notes: N_{MIN}: Minimum number of required floating car runs; 95%CI: Confidence Interval at 95%; GEH: Geoffrey E. Havers Statistics test.





(c)



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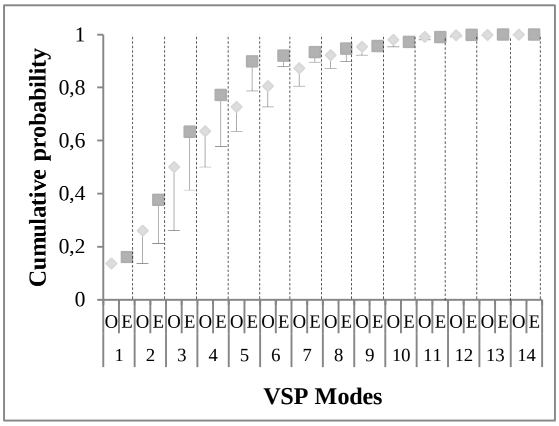
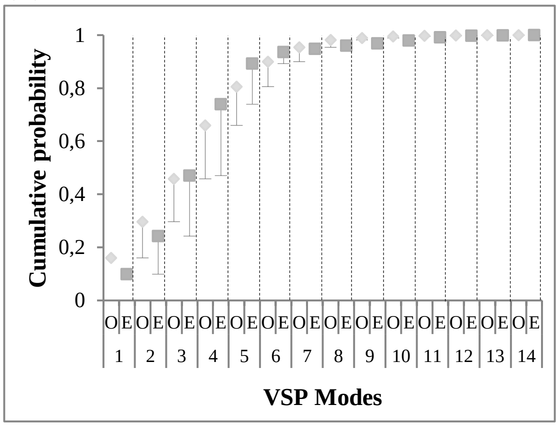
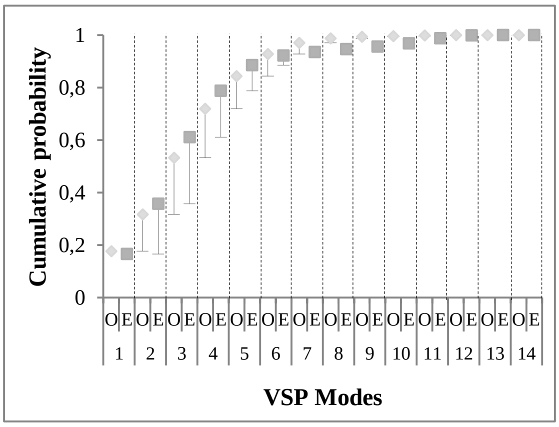


(e)



(f)



Observed (O) Estimated (E)

Figure 42 Cumulative probability in terms of discrete distributions for Observed and estimated VSP modes distribution (with standard deviation intervals) for: (a) Route *Um* (C->S); (b) Route *Ua* (C->S); (c) Route *Uu* (C-S); (d) Route *Um* (S-C); (e) Route *Ua* (S->C); (f) Route *Uu* (S->C).

Observed (O) Estimated (E)

Figure **42** displays the cumulative probability in terms of discrete distributions for observed and estimated VSP mode distributions, with the respective standard deviation among 6 different routes. Note that the two-sample test is one of the most useful and nonparametric methods for comparing two samples, as it is sensitive to differences in both location and shape of the empirical cumulative distribution functions of the two samples. VSP distributions followed the same trend in both approaches.

The highest absolute differences were found for modes 2 and 4 (modes with reduced speeds and decelerations or low accelerations) on routes A and B (C->S and S->C). This can be explained due to higher deceleration rates simulated in the traffic model confirming the findings of Song et al. [62]. Concerning mode 4, this difference arises from the fact that when the simulated vehicles reach the cruising speed they maintain a constant speed, while in reality there are more fluctuations in speed which enhance the occurrence of different VSP modes.

The two-sample K-S test (D-value) to a 95.0% confidence level indicated that routes *Uu* (C->S) and (S->C) have similar distributions. In these cases, D-values for these routes were 0.068 (D-critical = 0.078) and 0.078 (D-critical = 0.082), respectively. For a 97.5% confidence level, the observed and estimated VSP distributions of all routes did not show significant differences.

Additional GPS data in 10 different links of the network have been used to validate the model in terms of total emissions estimation. In terms of pollutants emissions, the maximum relative differences between observed (GPS data) and simulated (VISSIM) range between 8% for CO_2 and 9% for NO_X and CO.

6.3 CONCLUDING REMARKS

In section 6.1 multiple computational methods have been integrated to identify the best routes based on multiple pollutants present in traffic emissions. Emissions were estimated based on real life GPS data and emission models. Since the optimising of different pollutants can dictate different routes, two different strategies of assigning weights to these pollutants have been analysed: i) based on health impacts according to Eco-Indicator 99 and iii) based on atmospheric pollutant concentration levels.

While the simple inclusion of an additional cost factor is not very innovative in terms of routing algorithms, the developed computational modelling structure is an important contribution to i) understand the potential externalities of different routing strategies, ii) include methods for balancing emissions costs, and iii) host future real-time information.

Section 6.2 presented an integrated platform for modelling traffic and emissions calibrated with real world datasets, to assess future Traffic Management Strategies. After a rigorous calibration process, the model was validated in terms of speeds, volumes, travel time and VSP modal distribution.

The main purpose of this computational framework is to evaluate different policies for sustainable traffic management. Under the scope of the SMARTDECIOSION project the impact of introduction of eco-lanes in the urban network of Aveiro has been assessed [160]. The output of this platform has been incorporated into air quality models. (Dias et al.) On the other hand, this tool will allow extending the evaluation of route choice impacts from the individual to the system point of view. The next chapter will apply some results based on this platform.

7 ASSESSMENT OF ECO-TRAFFIC MANAGEMENT STRATEGIES

The introduction of eco-routing systems has been suggested as a promising strategy to reduce greenhouse gases and local pollutants emissions. While it would be utopic to achieve a system optimum scenario in a whole network, nowadays different Intelligent Transportation Systems and road pricing strategies have shown to be effective in optimizing traffic operations over certain corridors. Based on this assumption, section 7.1 seeks to analyse the impacts of eco-routing guidance strategies, operating for the origin-destination pair with higher demand in the urban network of Aveiro. The objective of this section is to answer the following questions: a) What are the most appropriate route guidance strategies to minimize fuel consumption and environmental damage costs; b) What are the potential environmental benefits in terms of emissions damage cost and CO_2 emissions; c) What is the extent of variations in system travel time.

Drivers routing decisions can be influenced to minimize environmental impacts by using, for instance, dynamic and intelligent road pricing schemes. In section 7.2, a tool for traffic assignment taking into account eco-routing purposes is presented. The main goal of this work is to identify the best traffic volume distribution that allows a minimization of environmental costs for a given corridor with predetermined different alternative routes. To achieve this, an integrated numerical computing platform was developed integrating microscopic traffic and emission models. The optimization tool employs non-linear techniques to perform different traffic assignment methods. The model was applied to representative sections of the intercity network, simulating three levels of traffic demand and three different strategies for traffic assignment.

7.1 ASSESSMENT OF ECO TRAFFIC MANAGEMENT STRATEGIES IN A URBAN CORRIDOR

Over the last decades, several empirical and modelling studies have been performed addressing the impact of route selection and traffic assignment in terms of emissions and fuel use. In chapter 2.3, a summary of important research on this topic is presented. Overall the majority of studies have identified a great potential for emissions reduction based on an appropriate route choice [38,58,92,93,100–104] and even during peak periods [161].

However, one of the main questions is how to put in practice the lessons learned from scientific research. In recent times, several ATMS are being proposed and implemented to reduce air pollution. In urban context, well-known examples are based on restrictions implemented by means of toll systems (such as in London). Other cities such as Lisbon have implemented limited traffic zones to vehicles that have an European Emissions Standard lower than EURO 2 [162]. However, minimizing overall emissions based on an appropriate route choice has proved to be a difficult process to implement.

What has arisen from the literature review is that a considerable number of studies have reinforced the relevance of the eco-routing concept since the selection of an appropriate route can lead to significant emissions reduction. However, frequently the route optimization with environmental constraints can lead to contradictory results [163]. Regarding eco-traffic assignment systems, the first studies assessing the implementation of eco-navigation in large scale have found that these systems may lead to the occurrence of unexpected results such as increased fuel consumption [164]. Although there is a considerable number of patented technologies on eco-navigation solutions [28,117–120,165,166], and patented systems to encourage drivers choosing more sustainable routes [116], there is a lack of knowledge on eco-routing systems impacts.

Therefore, the main objective of this section is to evaluate the environmental impacts and network performance of the implementation of an eco-traffic assignment in an urban corridor. Hypothetically, to increase the acceptance of this program, commuters could receive an electronic card bonus transferable to use in different contexts such was suggested in a patent application [116].

7.1.1 Methodological details

Figure 43 shows the main steps of the methodology which consists of two distinct phases: 1) at link level - traffic and road inventory data collection and development volume-emission-functions by using an integrated and calibrated platform of micro simulation; 2) at network level - traffic flow optimization and evaluation of scenarios. The integrated traffic-emission microsimulation platform (presented in section 6.2) has been used to evaluate the baseline scenario and to develop link performance functions. The process of calibration and validation of this platform is described in 6.2.1.1 .Then; several scenarios related with the implementation of eco-routing strategies were evaluated to compare the efficiency of these ATMS under different levels of acceptance and network saturation.

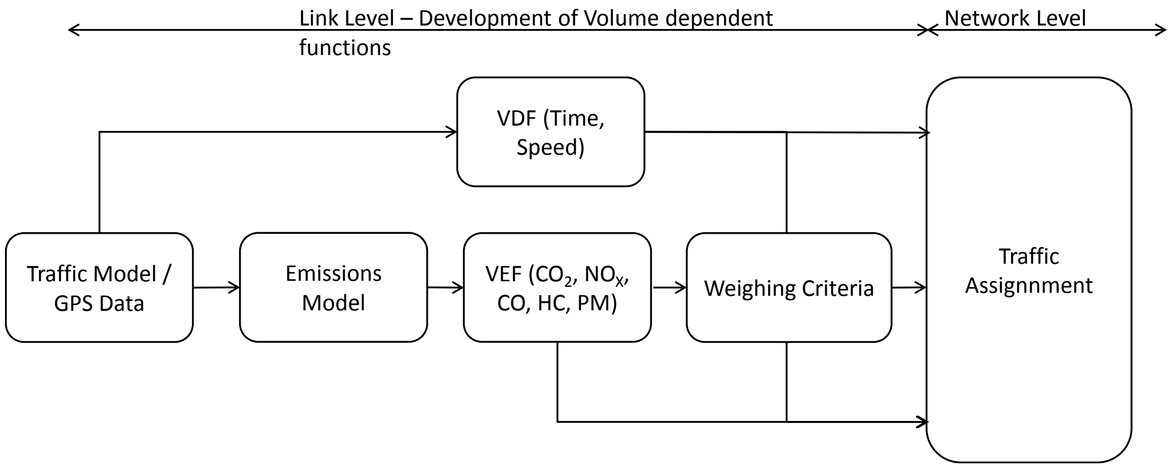


Figure 43 Overall methodology for traffic assignment

Section 7.1.2 provides additional details about the study domain. Then, the process for generating link performance functions is presented in 7.1.3. The process of optimization of traffic flow is described in 7.1.4.

7.1.2 Study domain and field campaigns

The urban network of Aveiro was used as case-study. Previous research conducted in this area has empirically addressed the impact of individual route choice in terms of emissions (chapter 4). Later an integrated platform for traffic and emissions simulation was developed to assess the effectiveness of implementing ATMS (section 6.2). This work uses this modelling platform, to assess the impacts of implementing an eco-traffic assignment system.

A Origin-Destination (OD) survey [125] has revealed that the key point of attraction during the morning peak hour is situated *in the* south of the urban centre *(university). C*onsequently, drivers commuting from the northern area have to cross or bypass the urban core to reach this area. Figure 44 shows the network map, the main alternative routes and key characteristics of the main links (volume during peak hour q, capacity C and distance).

The network under analysis contains the three routes studied previously namely: *Um* (O-A-D), *Ua* (O-C-E-D), and *Um* (O-A-D). However, an additional link connecting route *Ua* and Uu was added. This new connection has created a fourth alternative route. This route *comprises* a section (OC) which is common to route *U*a, and another section (BD) which match route *Uu*. Given this mix of typologies, this route will be referred as Umx.

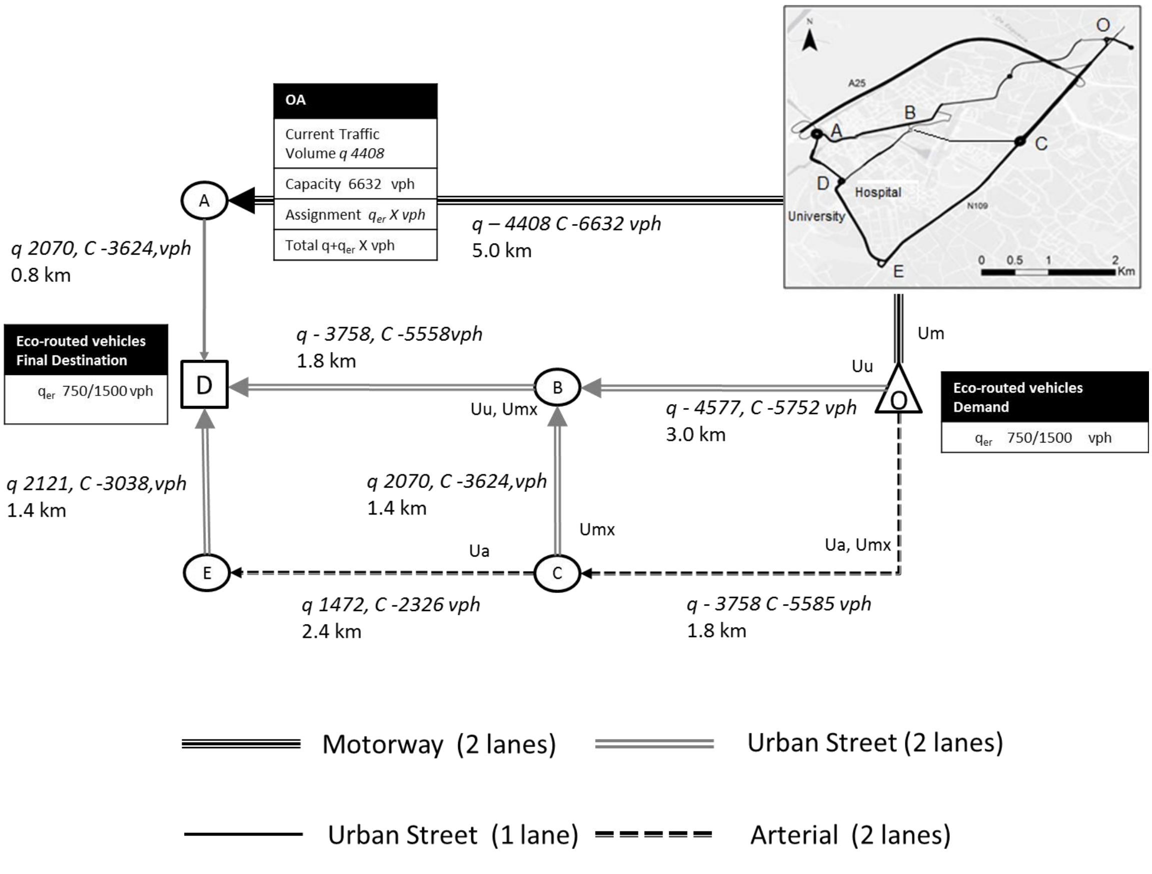


Figure 44 Study network area (top right) and simplified network for the assignment optimization process.

7.1.3 Link performance analysis - Traffic and emissions simulation

The integrated traffic-emission microsimulation platform presented in section 6.2 has been used. This platform allows estimating second-by-second emissions based on vehicle's dynamics (speed, acceleration/deceleration and road grade).

VISSIM was used to simulate the traffic dynamics of light duty vehicles and light commercial vehicles which were found to represent 97% of all vehicle types operating on the network [29]. Total emissions were calculated considering 45% of light duty gasoline vehicles (LDGV), 35 % of light duty diesel vehicles (LDDV) and 20% of light commercial Diesel vehicles (LCDV) [152]. Due to the flat topography of the network, a road grade of zero was assumed.

NO_X, CO, HC, and CO_2 total emissions by link can be derived based on the time spent in each VSP mode multiplied by its respective emission factor (Eq. 12).

$$P_{link\ l} = \sum_{i=1}^{14} n_i \left\{ \left(f \times e_{P,i}\right)_{LDGV} + \left(f \times e_{P,i}\right)_{LDDV} + \left(f \times e_{p,i}\right)_{LCDV} \right\} \qquad \text{Eq. 12}$$

Where:
f - Share of vehicle types in the fleet (%);
e_p - Emissions factor of pollutant p for VSP mode i according each vehicle type, (g/s).
P – Total (NO_X, or CO, HC, and CO_2) emissions generated on link l (g) for a given period of time.
n_i - time (seconds) spent on mode i for all vehicles using the link l.

Due to the lack of accurate information on VSP emission factors for particulate matter (PM) from LDGV, the CORINAIR methodology [167] was used.

7.1.3.1 Environmental cost functions

To minimize the problem of environmental contradictory objectives in optimizing routes, a method to weigh the cost of each pollutant is presented (i). Then the process for generating VEF and Volume Damage Functions (VDmF) is described (ii).

i) Monetization of emissions costs

In addition to the estimation of emissions individually, a strategy to consider the relative impact of each pollutant was followed. The monetization of emissions externalities (environmental impact of emissions) was based in the AERIS report [134] (see further details in chapter 3.6). This approach is suggested for the assessment of different ATMS such as dynamic Emission Pricing and dynamic eco-routing [134]. However, it should be noted that a hypothetical implementation of these policies would require further research to adjust the actual costs of each pollutant according to the characteristics of the study area.

VSP methodology was adapted to calculate directly the emission damage costs based on VSP modes frequency. Thus, for each VSP mode, and for a set of pollutants P, a general cost factor was calculated considering the fraction of each vehicle type (*f)*, the respective emission factor *(e_p)* and the specific cost for each pollutant/gas *(c_p)* (see Eq. 13). Figure 45 shows the estimated environmental damage cost according to the VSP mode with the respective contribution each pollutant. Total emissions were calculated considering 45% of gasoline passenger vehicles (LDGV), 35 % of diesel passenger vehicles (LDDV) and 20% of light commercial Diesel vehicles (LCDV).

$$D_{vsp_i} = \sum_{p=1}^{P} c_p \left\{ \left(f \times e_{p,i}\right)_{LDGV} + \left(f \times e_{p,i}\right)_{LDDV} + \left(f \times e_{p,i}\right)_{LCDV} \right\} \qquad \text{Eq. 13}$$

$\boldsymbol{D_{vsp,i}}$ - Damage cost of VSP mode i (\$/s);
c_p - Cost factor for the associated with the emission of the pollutant p (\$/g);
f - Share of vehicles in the fleet;
e_p - Emissions factor for a vehicle type, pollutant p and VSP mode i (g/s);

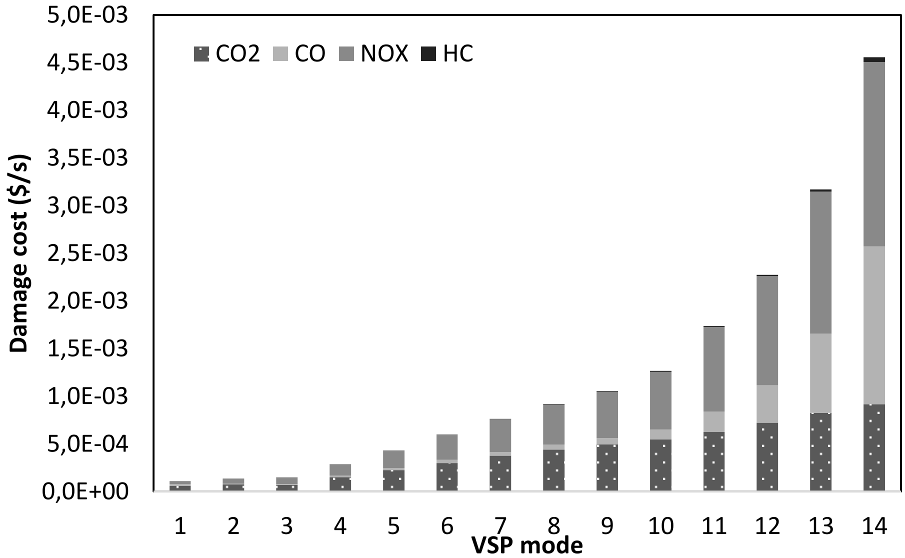


Figure 45 Total Environmental Damage for each VSP mode and respective contribution of pollutants.

The Environmental Damage (*ED*) cost in a particular link and over a certain period of time is given by Eq. 14.

$$ED_{link\ l} = \sum_{i}^{14} \left(n_i \times D_{VSP_i}\right) + PM \times C_{PM} \quad \text{Eq. 14}$$

Where:
ED – Total Environmental damage on link l (USD)
n_i - time spent on mode i for all vehicles using the link l (s);
$D_{vsp,i}$ - Damage cost of VSP mode i (USD/s);
PM – Estimated PM emissions (g) based on CORINAIR methodology (g) for all vehicles using the link l
C_{PM} - Cost factor for PM emissions (USD/g)
.

ii) Development of Volume-Delay-functions and Volume- Emissions-Functions

Traffic control approaches based on on-line optimization require fast and accurate models for traffic flow [168]. Once the traffic model was validated, Volume-Delay-Functions (VDF), Volume-Emissions-Functions (VEF) and Volume-Damage-Functions (VDmF) for each main road segment were defined. The main objective is to develop accurate relationships which can be straightforwardly applied in the traffic flow optimization under environmental concerns.

These functions use the traffic volume as an independent variable and travel time (VDF), emissions (VEF), and damage costs (VDmF) as dependent variables. It should be emphasized that VDF were only used to estimate the equilibrium conditions on the network. VEF and VDmF were applied to optimize the flow distribution of eco-routing vehicles among the four alternative routes (see Figure 44). For developing these functions, different traffic demands scenarios (progressive increments of 20 vph using 5 random seed runs) over each main link of the network were performed.

For VDF the widely used Bureau of Public Roads (BPR) [169] functions were applied (Eq. 15). The equation parameters were optimized to get a deeper insight of each link performance. This optimization is conducted by minimizing the Root Mean Square Error between observed/simulated and predicted values of travel time. Please see appendix C2 for a more detailed explanation.

$$t = t_0 \left(1 + \alpha \left(\frac{Q}{C}\right)^{\beta}\right) \qquad \text{Eq. 15}$$

Where: t - Travel time for traffic flow Q, ; t_0 - travel time at free flow; C – Capacity; α; β - dimensionless parameters.

By conducting a regression analysis, a cubic polynomial function was shown to be appropriated to interpolate the traffic volume with total ED costs and CO_2 emissions over the eight segments analysed ($R^2 > 0.94$ p-value < 0.05).

Figure 46 shows an example of a VDmF for the segment AD. Additional VDmF for the remaining sections can be found in Appendix D.

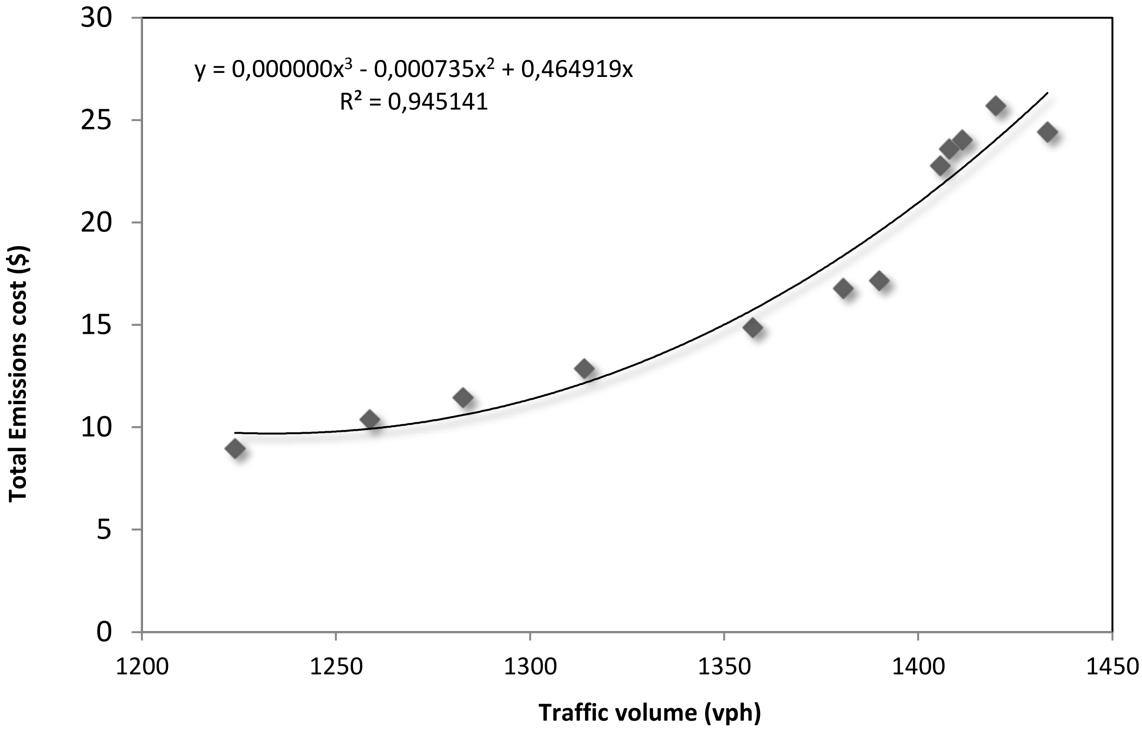


Figure 46 Volume Damage Function for link AD

It should be noted that in practice, such high correlations will be not easy to find (as demonstrated in section 4.2.4). Although VISSIM is a stochastic model, a higher homogeneity in emissions generated over different traffic volumes is observed. However, both empirical tests and traffic simulation approaches have shown that for the considered ranges of volume/capacity ratios, a polynomial cubic equation is the best model (higher coefficient of determination) relating the effect of the volume and emissions change. However, it must be noted that this solution may be not necessarily convex for all set of pollutants analysed.

7.1.4 Traffic flow optimization

The integrated platform for traffic and emissions microsimulation has allowed describing in detail the environmental performance of each link according to different traffic demands. The traffic assignment process is programmed independently in a spread sheet-based format (Microsoft Excel ®). For networks of similar size such as the one considered in this study, this method allows greater flexibility, speed data processing, and it is user-friendly for potential practitioners.

The main idea behind this system is to focus on the optimization of the traffic on key urban routes that converge to the zone of higher activity in morning peak hour. In such scenario, the commuters to the selected area would receive voluntarily the indication of which route they should follow during the commute, to minimize the emission impacts in these corridors. Hypothetically, to increase the acceptance of this program, commuters could receive an electronic card bonus transferable to use in different contexts such was suggested in [116].

For traffic assignment under UE, an iterative process based on the Wardrop's first principle [170] [5] was followed i.e., for each iteration, only the path with minimal costs, has a vheicle assigned to it. Thus, according to the purpose of each traffic assignment scneario, VDF (travel time), VED (CO_2) (which is directly correlated to fuel consumption) and VDmF (ED) were used to determine which route enables the minimization of individual impacts of each additional eco-driver approaching the network. Under this eco-routing guidance system no driver can unilatereally reduce his travel impacts (ED costs or CO_2 by shifting to a diiferent route. For an OD pair, the equilibrium can be solved incremntally, step-by-step, for each upcoming eco-routing vehicle (Eq. 16). After each step, link-based impacts (ED costs or CO_2 emissions) are recalculated based on link volumes.

$$q_{er}^{l} = \begin{Bmatrix} 1, if\ link\ l \in u \ \forall \ C_l \in u > 0 \\ 0, otherwise \end{Bmatrix} \qquad \text{Eq. 16}$$

Where:

q_{er}^{l} is the number of eco-routing vehicles guided to link *l* belonging to the route *u* that minimizes user impacts (ED cost or CO_2), and containing all links with available capacity *C* higher than 0.

[5] *The journey times (or costs) in all routes actually used are equal and less than those which would be experienced by a single vehicle on any unused route*

The minimization of the system environmental damage (SED) is achieved by assigning the eco-routers (q_{er}) on the network in such a way that the sum of total ED cost caused by eco routing vehicles and non-eco-routing vehicles ($q+q_{er}$) in all links (L) of the network is minimized (Eq. 17). The constraints ensure that the maximum capacity on each link is not reached (Eq. 18), the non-negativity of traffic flow (Eq. 19) and conservation of eco-routers flow (Eq. 20) for each node of the network.

$$Minimize\ f_{SED}(q_{er}) = \sum_{l}^{L} ED_{link\ l} \qquad \text{Eq. 17}$$

Subject to:

$$\sum_{l}^{L} q_{er} + q \leq C_l \qquad \text{Eq. 18}$$

$$\boldsymbol{q_{er,l}} \geq \mathbf{0} \qquad \text{Eq. 19}$$

For a set on notes

$$\sum_{\boldsymbol{into\ N}} \boldsymbol{q_{er}} = \sum_{\boldsymbol{out\ of\ N}} \boldsymbol{q_{er}} \qquad \text{Eq. 20}$$

Where:
q_{er} - Traffic volume of eco-routing vehicles (vph);
q - General traffic flow (vph);
C_l - Estimated maximum capacity for link i (vph).

The minimization of CO_2 emissions of the system follows the same procedure used for SED but considering specific VEF for CO_2 adjusted to each link. Since fuel consumption is directly related with CO_2 emissions, the flow patterns that minimize fuel consumption minimize CO_2 as well.

A Genetic Algorithm (GA) was chosen to solve the ED and CO_2 network problem. Previous research found that GA outperform several optimization strategies to solve continuous similar problems [94,171]. Even though this approach is a random search technique, it exploits the historical information to find a new search point with expected enhanced performance. Because of its simplicity, minimal problem restrictions and minimal assumptions on search space, global-approach, and implicit parallelism, GA can be straightforwardly applied to assignment traffic problems. An additional advantage is that GA approach yields the use of any mathematical form for the cost functions. Moreover, this approach allows for explicitly imposing capacity constraints on each link [172].

The optimization was performed in Solver with MSOffice which employs multiple variations of four different cross-over strategies. To solve the design model, mutation rate was set to 0.01, and the population was set to 100. The number the iterations is set such that the objective function was no longer improving in each scenario. Recent literature demonstrated that these parameters work well in analogous problems [94]. A more detailed description of the structure of GA and its implementation can be found the appendix C3.

7.1.5 Scenarios

The simulated scenarios include:

a) Two different levels of eco-routing vehicles (750 and 1500 vph - corresponding to approximately 50 and 100% of the traffic with this OD pair, respectively)

b) two different levels of network saturation (average volume/capacity (V/C) of 50% and 80%).

Under these circumstances, two routing guidance strategies (UE and system Optimum (SO)) with two different objectives (minimization of ED costs and CO_2) were tested.

UE scenarios assume that each eco-routing vehicle approaching the network is routed to the path that minimizes its individual costs in terms of travel time, ED and CO_2. Therefore, the traditional concept of UE is adjusted for considering either ED costs or CO_2 and it is simulated that all eco-drivers are routed to minimize their own environmental impacts. As stated previously, under this system no eco-driver may lower his impacts by changing his recommended route.

SO scenarios are based on the assumption that the population of eco-routing vehicles is controlled by the system and these vehicles are routed to minimize system ED costs and system CO_2. Therefore, possibly these drivers would have different available routes with lower costs and impacts. Although one can consider the SO assignment unrealistic, theoretically , variable speed limits, road pricing systems, or different types of incentives, can be implemented to optimize (or at least move towards a better direction) the traffic flow distribution in a certain corridors.

Table 22 summarizes the objectives and assumption of each scenario.

Table 22 Assumptions, application and objectives of each scenario

	UE_{TT*}	**UE_{ED} UE_{CO2}**	**SO_{TT} SO_{CO2}**
ASSUMPTIONS	Users have perfect knowledge of Travel time - Travel time on a given link is a function of the flow on this link.	- Users are informed to follow the route that minimizes their impacts (ED costs or CO_2) - ED costs and CO_2 are function of the flow on each link	- Users are informed to follow the route that minimizes overall network impacts (ED costs or CO_2). -ED costs and CO_2 are function of the flow on each link.
APPLICATION	Non-eco routing vehicles	Eco-routing vehicles	Eco-routing vehicles
OBJECTIVE	Minimize individual User Travel Time	Minimize the ED cost / CO_2 emissions of each eco-driver.	Minimize system ED costs / CO_2 emissions.

- Reference scenario

The UE_{TT} scenario will be considered as reference due to several reasons. First of all, a key assumption of user equilibrium is that travellers have perfect information about road conditions, which indeed can be considered generally true for commuters. It should be highlighted that this work is focussed on an OD pair mainly used by commuters on a weekday. Secondly, this work assumes the existence of real time traffic monitoring stations, so in drivers could be informed (for ex. using VMS) on real time traffic conditions. Finally, similar studies also use UE_{TT} as reference scenario [84,164].

Different equilibrium flow distributions are presented in section 7.1.6. In section 0, an overall evaluation of different traffic assignment strategies on network performance, emissions and ED costs will be conducted. Finally, the main results and their implications are discussed in section 7.1.8.

7.1.6 Equilibrium distribution

In this section, UE distribution based on travel time (TT), ED costs and CO_2 is presented. Figure 47a presents the traffic distribution over the 4 alternative routes considering the travel time as the decision factor for traffic assignment. If demand is less than 600 vph, all vehicles are assigned to the *Um* (motorway route OAD), then R4 (OCBD) is becoming competitive, and for more than 850 vph, *Ua* (OCED) begins to be chosen. Until 1500 vph Route *Uu* (OBD) is not considered as it entails more travel time that the remaining routes.

Figure 47b illustrates the traffic distribution assuming that all incoming eco-routing vehicles are informed of environmental impacts on each route. Accordingly, eco-routing vehicles are suggested to the route which allows reducing their own impacts. In this case, *Uu* would be the selected for all eco-drivers until a demand of approximately 800 vph. At this moment, *Um* turns into a valid option for eco-routing vehicles. *Ua* and *Umx* are not eligible since under the considered demand levels, the ED costs are always higher than *Um* and *Uu*.

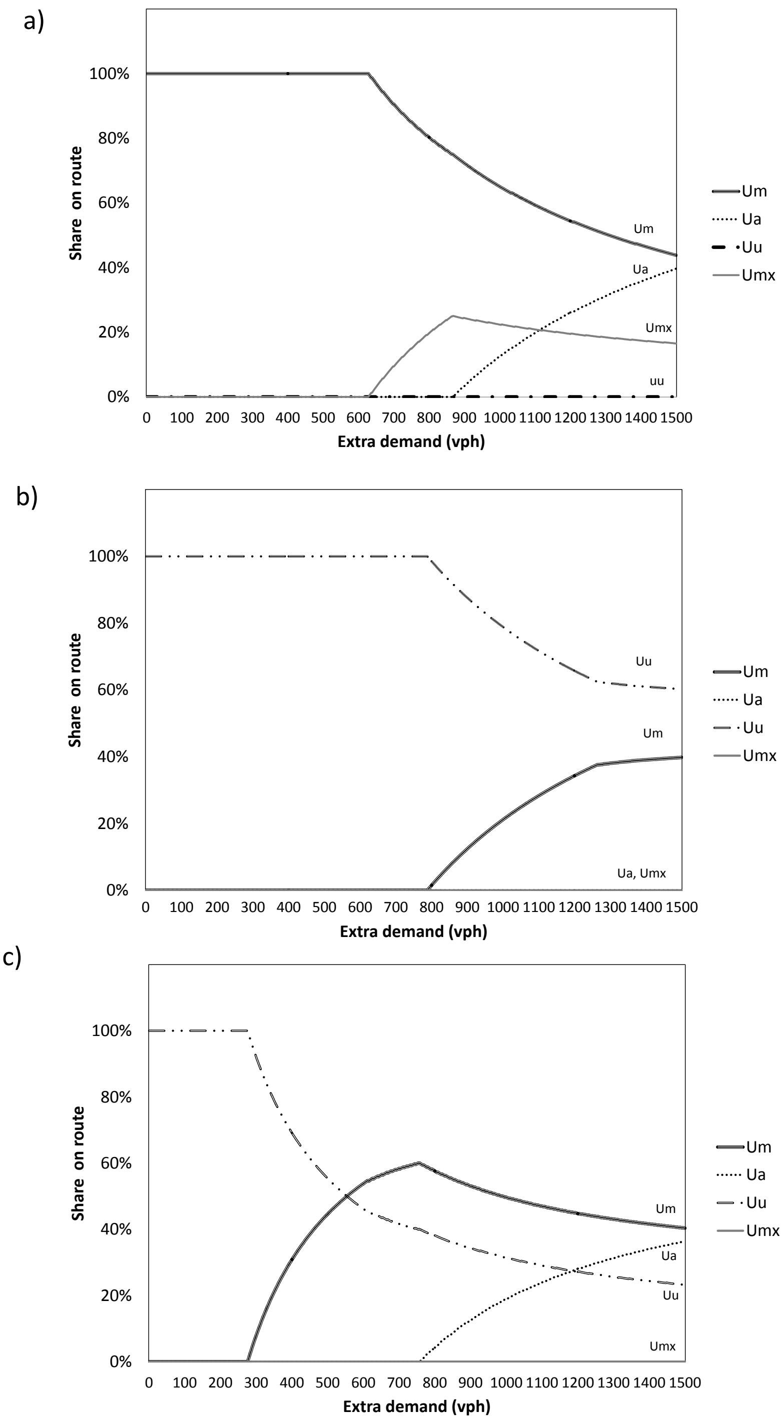


Figure 47 Distribution of equilibrium traffic flow under different parameters: a) travel time, b) environmental damage costs, c) CO_2.

In Figure 47c it is assumed that eco-drivers will choose the route that minimizes their CO_2 emissions. Until a traffic demand of 250 vph, the urban route *Uu* is the alternative with lowest CO_2 levels. For a traffic demand higher than 250 vph, fuel consumption rises considerably and *Um* presents a more competitive alternative. The arterial route Ua is competitive for demands higher than 750 vph, while Umx is never considered.

These results are in line with the empirical assessment in which has been demonstrated that in spite of the fact that route *Uu* is the slower route, this is the alternative that enables emissions savings for all pollutants, principally for NO_X and CO. Furthermore, since the relative differences in CO_2 emissions (compared with the remaining pollutants) were also lower), as it would be expected, this route becomes less competitive from lower demand levels, when CO_2 is the unique criterion for route assignment.

7.1.7 Assessment of traffic assignment strategies on network performance, emissions and environmental damage costs

In this section, the overall impacts in terms of system travel time, travel time of eco-routing vehicles, total ED costs and CO_2, according to different traffic assignment strategies are presented. Table 23 shows the overall impacts for different levels of network saturation and eco-routing vehicles. Assuming that user's route choice behaviour is primarily affected by travel time (TT), each traffic assignment strategy will be compared to UE_{TT} scenario.

For moderate levels of network saturation (V/C-50%), SO traffic assignment based on ED costs yields a reduction up to 5% in total ED costs and SO CO_2 assignment allows a reduction of 12% in CO_2 emissions compared to UE_{TT} scenario. Moreover, the total system travel time for SO CO_2, is lower than under UE_{TT}. This is a classic example that there may be traffic flow patterns with lower travel times than the UE_{TT} [173]. This paradox is not only true for travel time. Interestingly, under UE_{TT}, system ED costs and system CO_2 emissions are lower than under UE_{ED} and UE_{CO2}. An explanation for this is the fact that if when an eco-routed vehicle changes to a specific route, their own improvement is lower than the additional costs inflicted on the other travellers. For these network conditions, SO_{CO2} demonstrated satisfactory performance for all parameters tested.

Table 23 Overall impacts for different levels of network saturation and eco-routed vehicles (lines) under different traffic assignment strategies (columns).

			Route guidance strategies				
				UE		SO	
Network Saturation	**Eco routing acceptance**		**TT**	**ED**	**CO_2**	**ED**	**CO_2**
50%	1500 vph	**System TT (h)**	514	532	531	532	**477**
		Travel Time $q_{er\,(h)}$	92.9	95.9	96.7	95.4	**90.3**
		System ED (USD)	168.9	175	183.6	**160.2**	161.1
		System CO_2 (ton)	3.8	4.4	4.3	3.5	**3.4**
80%	1500 vph	**System TT (h)**	726	881	**711**	690	718
		Travel Time $q_{er\,(h)}$	94.9	149	94.3	**93.5**	94.3
		System ED (USD)	239	235.1	224.7	**214.5**	245
		System CO_2 (ton)	6.5	9.1	6.4	7.1	**6.1**
80%	750 vph	**System TT (h)**	726	810	730	**720**	737
		Travel Time $q_{er\,(h)}$	**46.0**	75.0	44.0	50.1	47.9
		System ED (USD)	239	232.4	226.7	**226**	244.6
		System CO_2 (ton)	6.5	9.8	8.1	7.1	**6.2**

For higher levels of network saturation (80%), SO ED yield 11% reduction in ED costs, but an increase in system CO_2 emissions of 8% is observed. Instead SO_{CO2} assignment allows a decrease of 7% in CO_2 emissions but leads to an increase in ED costs of 2%. The optimization of traffic distribution to minimize CO_2 and ED costs presents different solutions. For all traffic assignment strategies based on CO_2 the travel time is not increased compared with UE_{TT}.

The last scenario simulates that 50% of drivers follow an eco-route recommendation, and the remaining 50% are distributed according UE_{TT}. SO assignment results show the same pattern of the previous network circumstances. However, ED costs reduction is decreased to 6% and CO_2 reduction to 5 %. It should be noted that for optimizing ED costs the travel time of eco-routers is considerably increased.

Figure 48 presents the evolution of a) SED costs, and b) system CO_2 emissions, under different UE assignment strategies for an average network saturation of 80%.

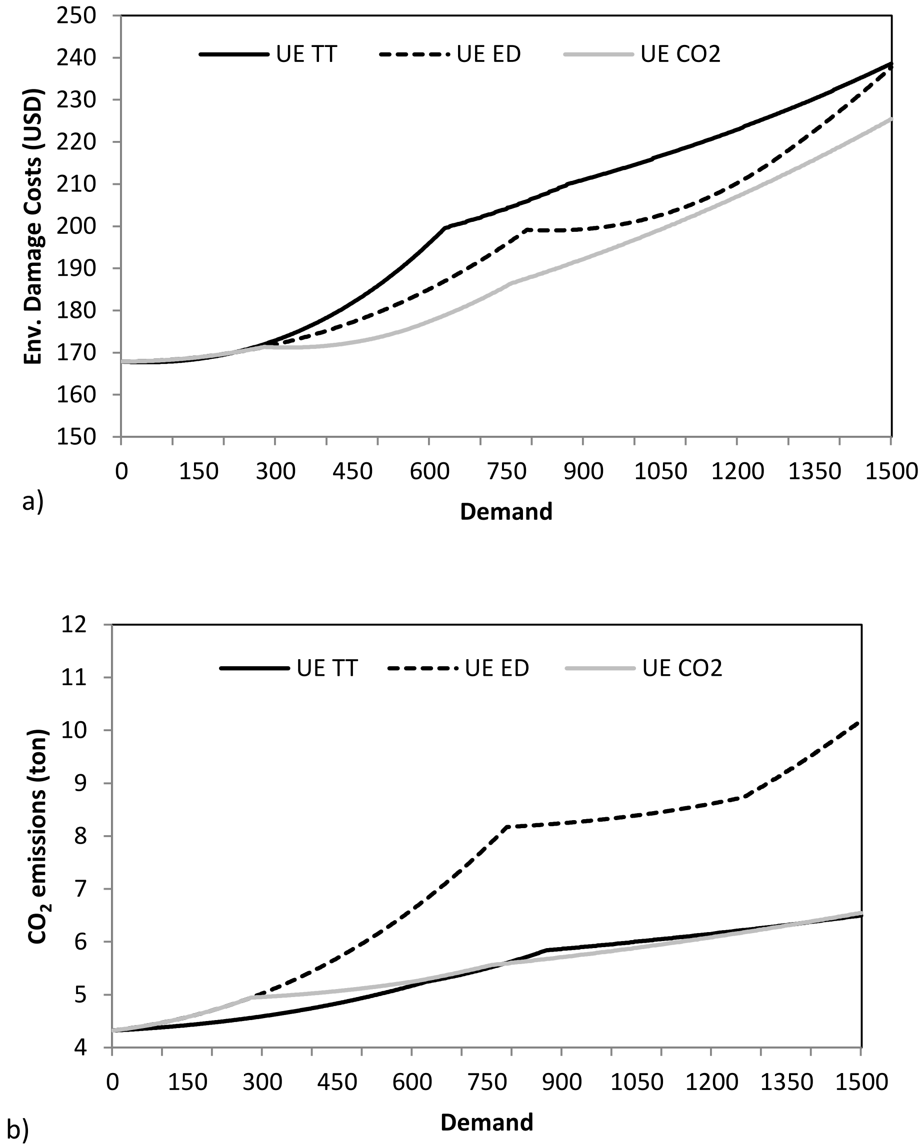


Figure 48 Evolution of a) environmental damage costs and b) CO_2 emissions under different UE assignment strategies.

Regarding ED costs it is interesting to note that for a demand higher that 300 vph, total ED costs of eco-drivers would be lower than if drivers selected their route based on CO_2 information (Figure 48a). With respect to CO_2 emissions, drivers routed based on travel time or CO_2 information present similar results. However, if drivers are routed based on ED costs information, CO_2 emissions are considerably increased (Figure 48b). This can be explained because the first vehicles approaching the network minimize their individual ED costs by selecting the urban route R3 (which leads to less local pollutant emissions due to lower speeds and lower frequency of high VSP modes. However, when this route becomes more congested, CO_2 emissions increase faster than ED costs.

Figure 49 shows the relative difference of system travel time (STT) under U_{ED} and UE_{CO2} routing strategies compared with UE_{TT}.

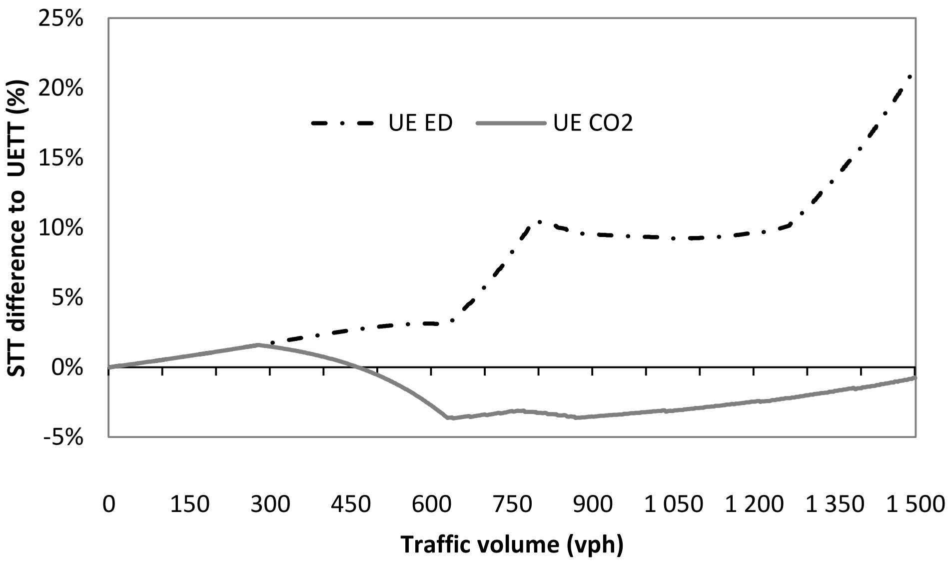


Figure 49 Evolution of the relative difference of system travel time (STT) of UE_{ED} and UE C_{O2} compared with UE_{TT}

Regarding the UE_{CO2} strategy and for different levels of demand there are no significant differences in the STT compared with UE_{TT}. In all cases the relative difference to UE_{TT} is less than 5%, so the network would be constantly operating close to the normal UE conditions in terms of travel time. Regarding the eco-routing scenario based ED costs, it is possible to verify that for demand levels higher than 700 vph, there are more significant differences between STT of UE_{ED}, and STT of UE_{TT}. This difference increases progressively to approximately 25% to 1,500 vph.

7.1.8 Discussion

In a Nash equilibrium network, drivers have no incentive to change their routes (41). Basically in this study, these circumstances are changed since a specific subpopulation of vehicles (with a common destination) receives an incentive to improve the environmental performance of the main corridors in a medium-sized city. The previous results showed that it is easier to keep a network under equilibrium in (terms of travel time) if the objective is focused on reducing CO_2 emissions of each individual driver. By contrast if the aim is the integrated reduction of ED costs, it has been demonstrated that for demand higher than 700 vph networks becomes instable in terms of the travel time.

The overall impacts on the network according to the traffic assignment strategy suggest that SO assignment yields a higher reduction on emissions compared with UE. Although this fact is not surprising, it is interesting to note that under UE distribution, providing information of different parameters can help minimizing others goals. For instance, Table 23 (see 80%, 1500 q_{er} case) shows that if every eco-routing vehicles followed the route that allows minimizing their CO_2, the total system TT could be reduced. Instead SED can be higher if drivers are routed with the objective of minimizing their own ED costs. These findings are in line with previous work [105] which demonstrated that for certain levels of market penetration of eco-routing vehicles, fuel use can be higher than under the standard UE travel time.

An extrapolation of these results suggests that a sustainable traffic management will be more efficient if it is addressed macroscopically (e.g. dynamic road-pricing schemes) than by providing eco-routing devices based on the individual cost minimization. However, this fact must be supported by a stronger theoretical framework and tested in more case-studies.

7.2 ECO-TRAFFIC MANAGEMENT SYSTEMS IN AN INTERCITY CORRIDOR

7.2.1 Introduction

A more efficient management of existing infrastructures has been identified as a key strategy to reduce emissions. In previous sections it has been demonstrated that these strategies may include behavioural changes in the operation of vehicles (eco-driving) as well as route selection with lower emissions impacts associated.

In a more realistic picture, a more efficient (environmentally) traffic distribution could be performed in certain corridors wherever is possible to implement intelligent toll systems that may lead to a better allocation of traffic. Yin and Lawphongpanich [174] demonstrated that there always exists a (non-negative) tolling system that leads to a traffic distribution with minimum emissions. Recently an optimal emission pricing model to reduce emissions in a given transportation network was proposed by Sharma & Mishra [90].

This section presents an eco-traffic assignment tool used to define the most sustainable traffic distribution, given a total demand provided by the user, among n routes linking an Origin/Destination pair (OD). This optimization can be performed using different criteria and assignment methods. In a further step this optimal distribution may be integrated with previous research such as [90,174], to estimate optimal emission pricing schemes under different levels of traffic demand. A case study is presented based on a simplification of the intercity OD pair presented before. It should be noted that this methodology can be extended to larger networks, provided that there are human and computer resources to develop equations applied to each link of the network.

7.2.2 Methodological details

This section presents the methodology for the development of an eco-traffic assignment tool. First, a brief description of the case-study network is provided. Then, the process for the development explanation on the development of Volume-Delay functions (VDF) and Volume-Emission functions (VEF) is explained. Finally, the optimization methods and the criteria available for eco-friendly traffic assignment strategies are described.

7.2.2.1 Network characteristics

The case study is based on a stylized road network that consists of four sections of one kilometre of length with different capacities. Four representative sections of the intercity routes network were simulated in a microscopic traffic simulator. Specifically, four routes were analysed:

Rm_1 - Motorway with three lanes and with an average toll cost of €0.08/km;

Rm_2 -Motorway with two lanes and one interchange, with a toll cost of €0.064/km;

Rh - Highway with one and two lanes sections and one interchange;

Ru -Road in an urban environment with one lane in each direction, five intersections and one traffic light.

It should be highlighted these segments do not represent any particular section. However, they simulate typical characteristics (number of interchanges, intersections, number of traffic lights, number of lanes, toll price per km) observed in the analysed routes Im_1, Im_2, *Iu* and *Iu*. The purpose of this section is not to provide absolute information about the routes studied, but rather explain the methodology that may be extended to a larger scale in further research. Figure 50 presents the links configuration of the simulated network.

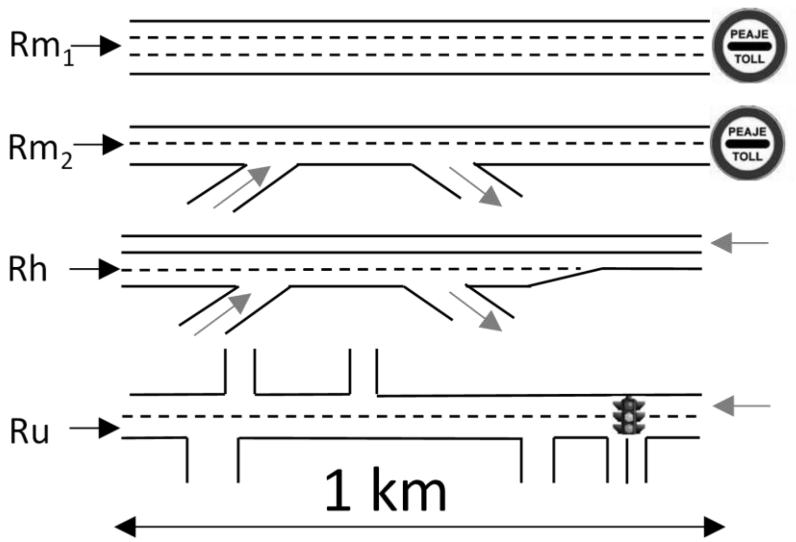


Figure 50 Layout of alternative routes.

7.2.2.2 Volume-Delay and Volume- Emission functions

The evaluation of traffic performance under different traffic demand levels was performed using the platform micro-simulation previously described. VDF and VEF for each link must be defined before the optimization process is started. These functions use the traffic volume as an independent variable and both travel time (VDF) and emissions (VEF) as dependent variables. Following the same procedure described in the previous section, different scenarios of traffic volumes using different links can be performed using commercial microscopic traffic models or real world GPS data using probe vehicles.

By conducting a regression analysis a cubic polynomial function was shown to be appropriated to interpolate the traffic volume with total pollutant emissions and other traffic parameters (P). Figure 51 outlines a VEF for a local pollutant (NO_X) and Figure 52 GHG (CO_2) respectively. Table 24 presents the respective regression parameters.

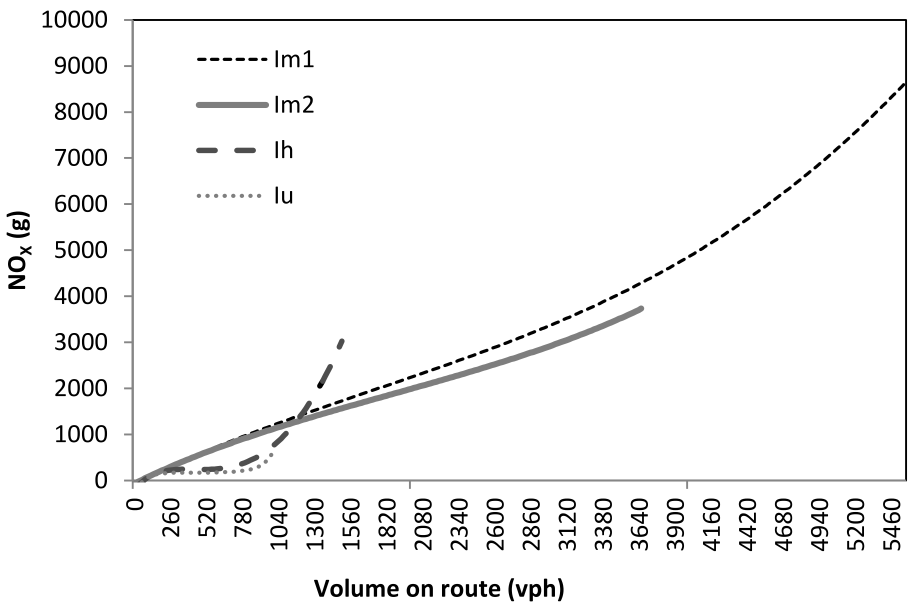


Figure 51 Volume Emission Functions for NO_X

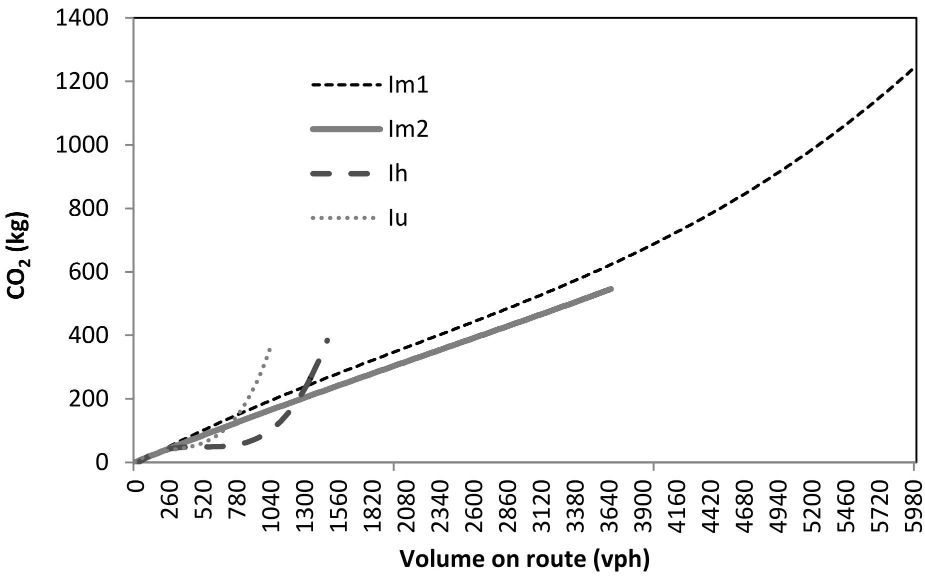


Figure 52 Volume Emission Functions for CO_2

Table 24 Regression Parameters of NO_X and CO_2 VEF

NO_X	r^2	F	sig
Rm_1	0.996	576	<0.001
Rm_2	0.999	112495	<0.001
Rh	0.959	55	<0.001
Ru	0.997	762	<0.001

CO_2	r^2	F	sig
Rm_1	0.998	1123	<0.001
Rm_2	0.999	219682	<0.001
Rh	0.951	45	<0.001
Ru	0.997	739	<0.001

Regarding NO_X emissions, Rh and Ru routes have lower emission levels than the motorway routes. Although these segments do not simulate any specific section, this trend is in line with overall emission values estimated from experimental data (GPS data) in intercity routes. For higher demands (>1000 vph) these routes exceed the emissions levels observed on motorways. As regards CO_2 emissions, there is an equilibrium among the various routes. However, for higher demands, total emissions produced on motorways are less than on Rh and Ru.

The likely traffic distribution in the network can be assessed through the traditional volume-delay (or cost) functions and the User Equilibrium (UE) model formulation. In this platform, an additional tool to optimize the most widely used VDF parameters of the BPR

[169] (Eq. 15), and Conical [175] (Eq. 21) functions is available. This optimization is conducted by minimizing the Root Mean Square Error between observed/simulated and predicted values of travel time (see further details in appendixC2). Figure 53 outlines 53 the estimated Volume-cost functions for the alternative routes.

$$t = t_0 \left(1 + \alpha \left(\frac{V}{C}\right)^{\beta}\right) \qquad \text{Eq. 15}$$

$$t\frac{t}{t_0} = 2 + \sqrt{\left(1 - \frac{V}{C}\right) + \beta^2 - \alpha\left(1 - \frac{V}{C}\right)} - \beta \qquad \text{Eq. 21}$$

Where:

t - Travel time for volume V;
t_0 - travel time at free flow;
C – Capacity;
α; β - dimensionless parameters.

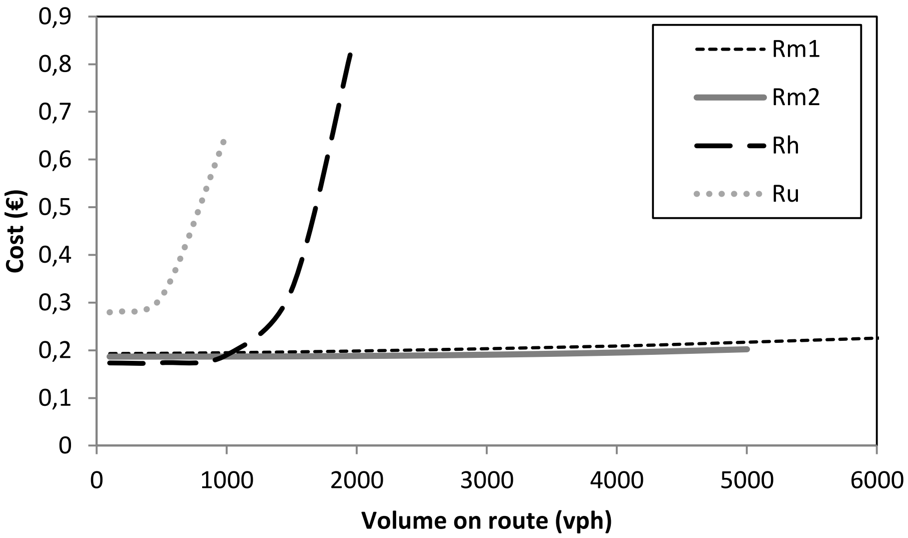


Figure 53 Estimated Volume-cost functions for the alternative routes.

7.2.2.3 Criteria and Assignment method

A wide range of criteria is available to optimize the traffic distribution among alternative routes in a corridor, according to criteria and methods selected by the user. In addition to traffic performance parameters (travel time, speed, and traffic density), individual pollutants (CO, NO_X, HC, PM), and Greenhouse Gases (CO_2), three integrated optimization approaches are available based on: a) economic cost; b) health impacts; and c) air quality levels. A more detailed explanation on the methodology for normalization of emissions impacts can be found in section 3.6. By default, the parameters for weighting pollutants effects (economic cost and health impacts-indicator) are based on literature [133,134], and are shown in Table 9, page 52.

In this analysis it is assumed that all drivers have the same attributes and the same access to information. Consequently the standard user equilibrium (UE) techniques will be used for modelling the drivers that select their routes on the basis of their own objectives. In addition to the traditional UE approach, two different optimization goals are considered: System Equitable (SE) and System Optimum assignment (SO). In the first case, the traffic distribution between the OD pair is achieved at the same cost for all routes. This concept was introduced by Rilett and Benedek [99] in 1994 and has as main goal to distribute equitably the negative effects of traffic among the alternative routes. Moreover, a maximum amount of pollution in the total network or in a specific link can be defined first. This objective is attained by minimizing the standard deviation (among the alternative routes) of the cost associated with the selected criterion. Both Eq. 22 and Eq. 23 exemplify the optimization process taking into account the criterion “Integrated Environmental Damage Cost”.

In the second method, the traffic assignment is performed with the aim of maximizing the overall benefit of the whole network (Eq. 23). This objective is attained by minimizing the total of the system environmental damage costs. This approach indicates a lower bound for the amount of pollution impacts possible, and allows the planners to identify how close to the optimum scenario they are. The constraint functions ensure that the overall and the specific capacity of each link is not exceeded, the non-negativity and the user-defined total demand is met (Eq. 27 -Eq. 29)

$$\text{Min} \sqrt{\frac{\sum_{i-1}^{n}(\,[\![ED_i-\overline{ED})]\!]^2}{n-1}}$$ Eq. 22

$$\text{Min} \sum_{\text{i}}^{\text{n}} ED_i$$ Eq. 23

Where:

$$\text{ED} = \sum_{\text{i}}^{\text{n}} \sum_{\text{j}}^{\text{m}} \text{P}_\text{j}\text{CP}_\text{j}$$ Eq. 24

$$P_{ji(Vi)=}(constant_{ji} + b1_{ji}Q_i + b2_{ji}{Q_i}^2 \ + b3_{ji}{Q_i}^3)$$ Eq. 25

$$Q_i = QT\ x_i$$ Eq. 26

Subject to:

$$\sum_{\text{i}}^{\text{n routes}} Q_\text{i} = \text{QT}$$ Eq. 27

$$\sum_{\text{i}}^{\text{n routes}} x_1 \ = 1$$ Eq. 28

$$Q_\text{i} \leq \text{C}_\text{i}$$ Eq. 29

Where:

b_{ij} – *Estimated Parameters of the model equation*
C_i - Capacity of route *i* (vph);
CP_j - Cost of the pollutant *j* released in the air (€/g);
ED - Economic Damage cost (€);
m - Nº of pollutants considered;
n - Nº of alternative routes;
P_{ji} - Total emissions of the pollutant *j* produced on route *i* (g);
Q_i - Total traffic volume on route *i* (vph); QT - Total Demand (vph); x_i - Relative flow on route *i*.

Depending on the complexity of the optimization process two optimization strategies can be selected. The Generalized Reduced Gradient (GRG) Nonlinear Solving based on Lasdon and Waren's code [176], selects a basis, determines a search direction, and performs a line search on each major iteration – solving systems of nonlinear equations at each step to maintain feasibility. For more complex problems (non-convex), MS Excel provides an evolutionary algorithm to optimize the relative flows (x_i) that minimize the selected objective function. The use of a population of solutions helps the optimization processes algorithm avoid becoming "trapped" in a local optimum (Frontline Systems Inc., 2013).

7.2.2.4 Scenarios

Three traffic assignment scenarios were assessed. The first one simulates the likely traffic distribution using the user equilibrium formulation (UE). In this scenario each user seeks to minimize his costs without considering environmental issues. The second scenario simulates an optimized traffic distribution scenario (SO) with the aim of minimizing the overall cost of emissions produced on the network. In the third scenario, a SE assignment is performed. Here, the pollution impacts are equally distributed over the various routes. For each scenario, three distinct traffic demands are analysed: low demand, 1,000 vph; moderate demand, 4,000 vph; and high demand 10,500vph.

7.2.3 Results and discussion

In this section, examples of model outputs are discussed. Firstly, the relative contribution of each pollutant for the total environmental economic costs and the eco-indicator is analysed. Then, the evaluation of an optimization based on environmental costs is conducted.

7.2.3.1 Optimization parameters

Different approaches were tested to solve the non-linear problem, the GRG method, and genetic algorithms (GA) using a set of recommended settings [177,178], Table 25 exemplifies the optimization time and the objective function value. It can be seen that the GRG method is considerably faster than the use of evolutionary algorithms, since this non-linear problem was convex. For non-convex problems, the employ of GA can produce more reliable results and avoid be trapped in a local minimum.

Table 25 Optimization time and objective function result (total integrated cost using different optimization tools).

Assignment strategy		System Equitable (SE)			System Optimum (SO)		
Optimization method		GA [177]	GA [178]	GRG	GA [177]	GA [178]	GRG [176]
Optimization time (s)		67	65	2	104	63	9
Relative flow	R1	25.3%	25.3%	25.4%	27.8%	30.4%	29.8%
	R2	17.3%	17.5%	17.4%	11.8%	10.4%	10.7%
	R3	13.1%	13.4%	13.1%	6.7%	6.3%	6.6%
	R4	25.3%	25.3%	25.4%	27.8%	30.4%	29.8%
Final result ($)		0	0	0	652	653	669

7.2.3.2 Relative impact of pollutants under UE

Figure 54 and Figure 55 and present the environmental impact costs and the health impacts related with each pollutant among the alternative routes. In this case the total impacts were estimated using the traditional UE assignment for a total traffic demand of 4,000 vph. Each bar is an alternative route and each pollutant a different segment of the bar.

In terms of mass, all pollutants exhibit very distinct orders of magnitude and CO_2 is by far the most abundant. However, when translated in economic terms, the weight of CO is considerable higher. Considering the health impact, the influence of PM and CO_2 are comparable but in this case NO_X is clearly the pollutant with major impacts. Considering this perspective, HC and CO are negligible.

It should again be emphasized that these figures are based on different studies and adopted for different realities. Regional factors such as population densities or land use type influence the environmental costs impact factors, but this is beyond the scope of this thesis.

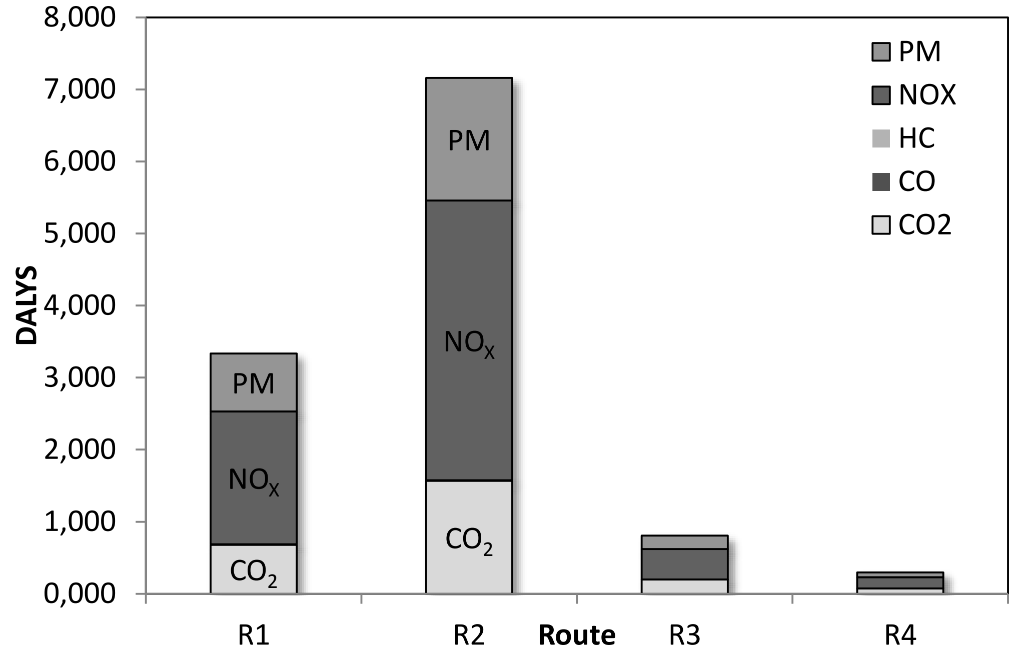


Figure 54 Health impact of pollutants (DALYS) over different routes under UE distribution (4000 vph)

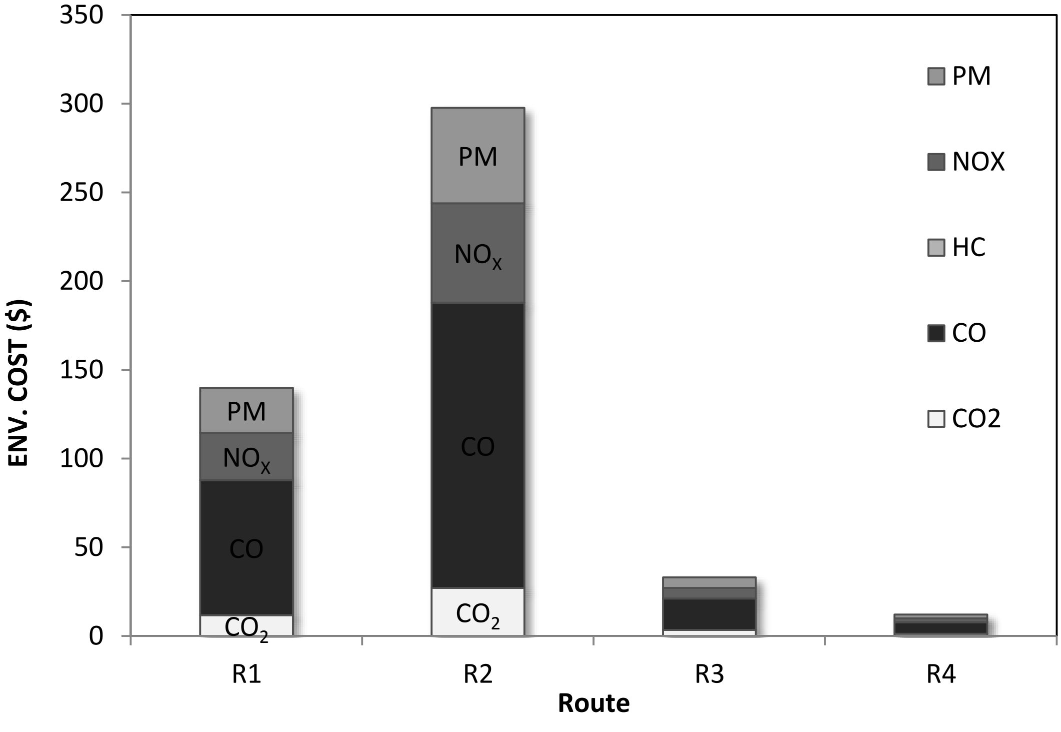
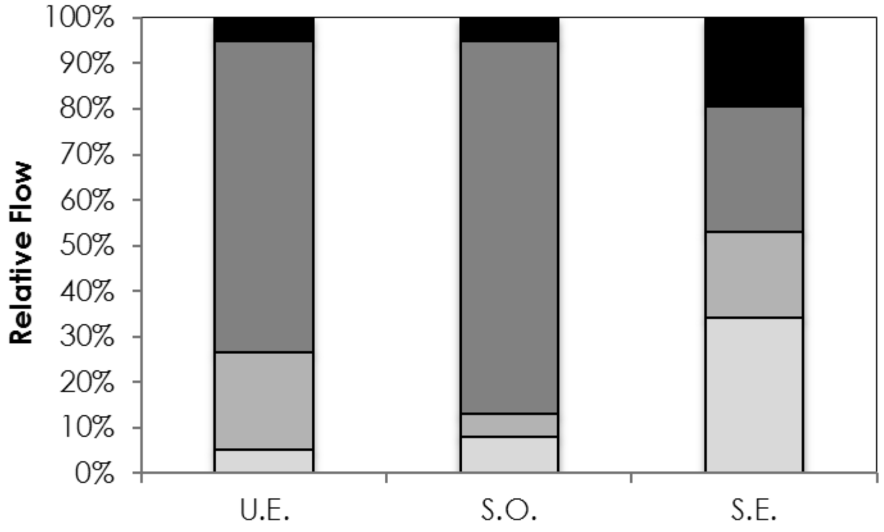


Figure 55 Environmental costs of pollutants over different routes under UE distribution (4000 vph)

7.2.3.3 Optimization of environmental costs under different levels of demand

In order to exemplify the implementation of the proposed method, an analysis of various scenarios to minimize the environmental costs under different demands are presented. Figure 56 to Figure 58 show the traffic distribution for each scenario according different growing demands and the total cost of pollution over similar conditions. Each bar is a different traffic assignment scenario and the contribution of each route is shown in a different coloured segment. The relative change (%) of users' total costs between SE or SO assignments and the UE scenario is shown by the grey triangles.

Regarding the low congestion scenario, (Figure 56) an optimized traffic distribution would allow about 18% reduction of emissions impacts with a marginal impact in the users cost (1%). This situation occurs because the alternative Rh offers a good alternative in terms of environmental costs without a considerable increase of travel time. On the other hand, the S.E. assignment would imply an increase in both SED costs (32%) users costs (16%). This increase is driven by the diversion of traffic to the route Iu.



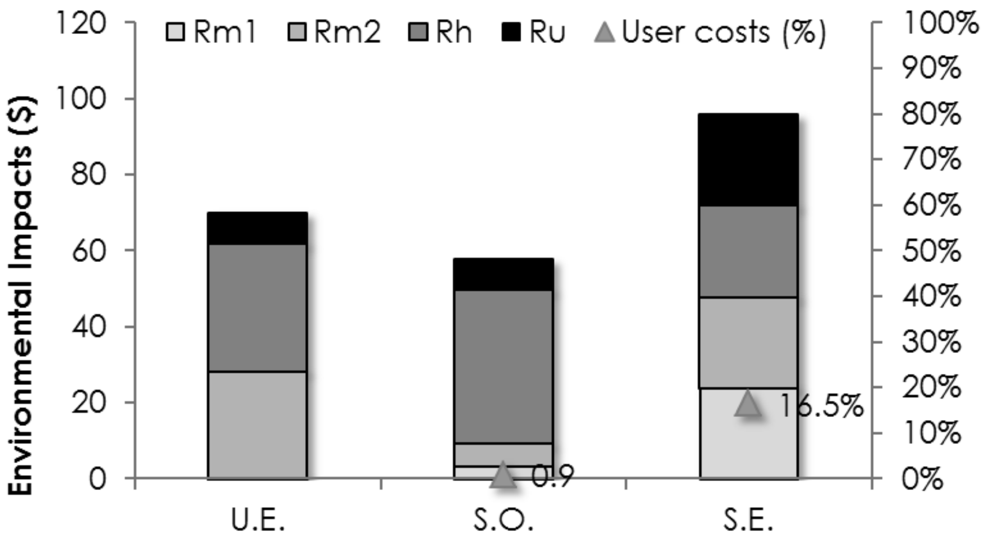


Figure 56 Flow distribution (%) for each traffic assignment under low demand (top) and Environmental costs and relative increase in total users cost in comparison to UE (bottom)

Under moderate demand (57), the SO assignment yields 33% reduction of pollution costs with 5% increase in total users cost compared with the UE assignment. This situation occurs by shifting a considerable amount of traffic from Rm_2 to Rm_1 with higher road capacity but higher toll costs. The SE scenario would allow a slight reduction (-2%) in the total environmental costs (compared with UE assignment) but an increase in user costs of 24%.

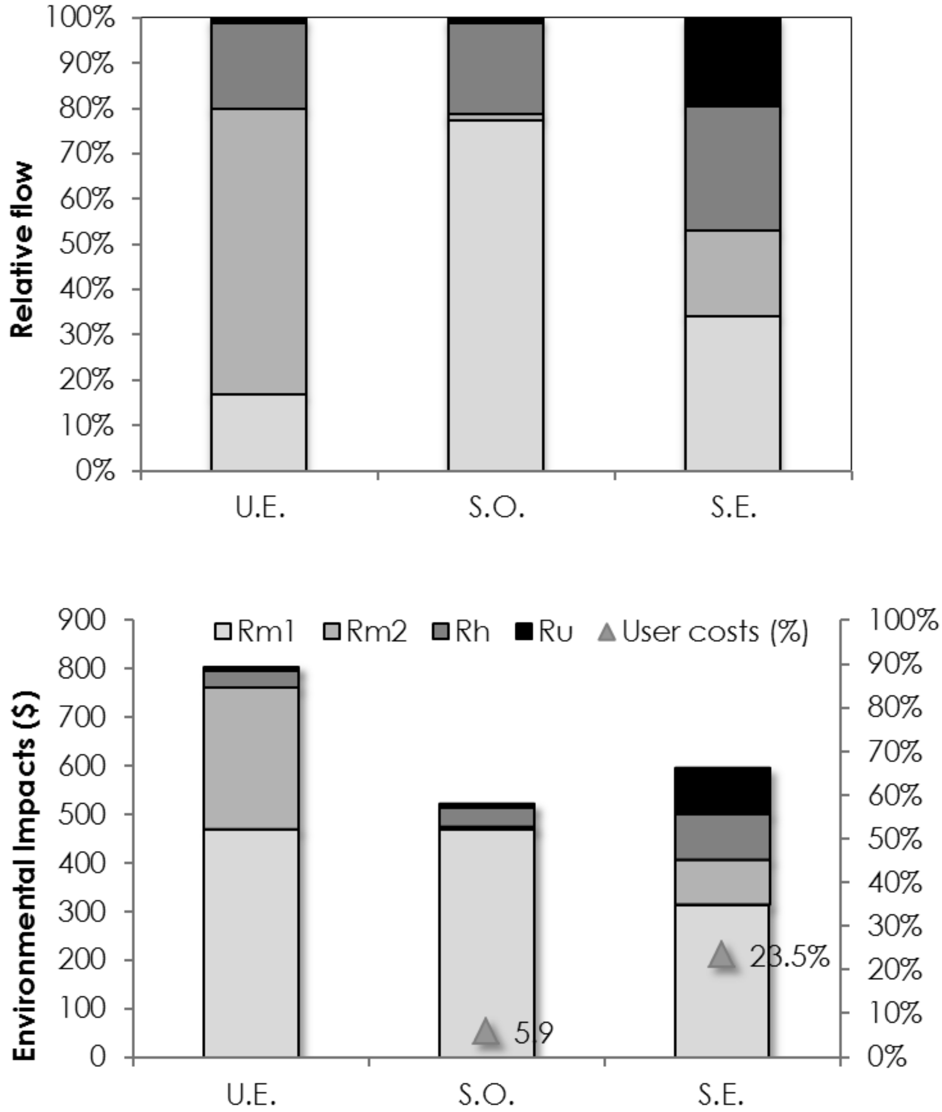


Figure 57 Flow distribution (%) for each traffic assignment under moderate demand (top) and Environmental costs and relative increase in total users cost in comparison to UE (bottom)

Considering the higher congestion scenario (Figure 58), there is no significant road capacity to allow considerable improvements in emissions reduction. In this case, the SO assignment has a similar distribution with the UE case. Naturally, the potential of minimizing costs associated with pollution decreases when the V/C ratio for the OD pair is close to 1.

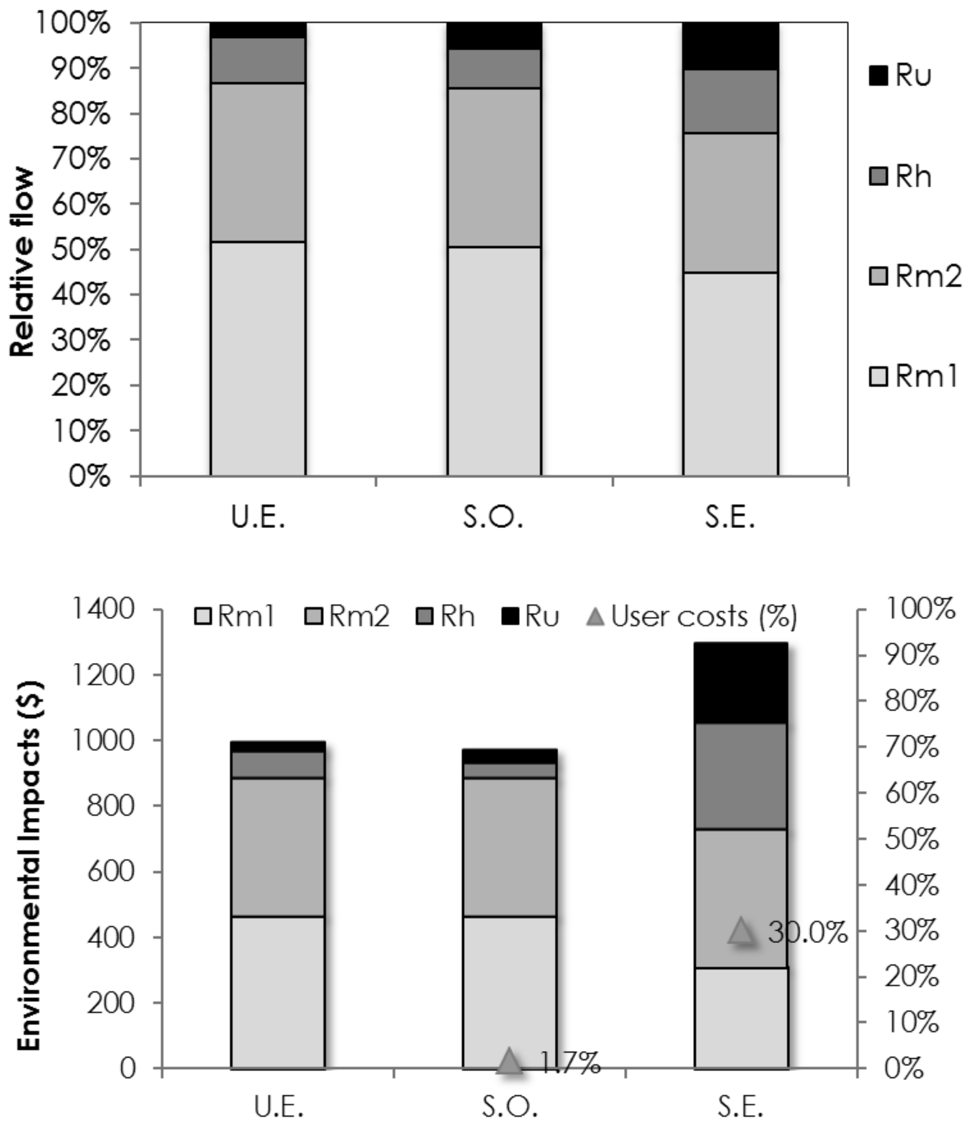


Figure 58 Flow distribution (%) for each traffic assignment under high demand (top) and Environmental costs and relative increase in total users cost in comparison to UE (bottom)

In general, an optimization of environmental impacts requires an extra effort in terms of users' cost. Accordingly, it can be concluded that the toll rates scheme can be improved taking into account environmental criteria.

7.3 CONCLUDING REMARKS

The main objective of this chapter was to explore different approaches to bring environmental issues into the standard traffic assignment techniques.

In section 7.1, an integrated micro-simulation platform based on state of the art traffic and emissions simulations was used to generate volume-delay functions and volume-emissions-functions. Then, these functions were used to explore eco-strategies that are appropriate for emissions reduction over a critical OD pair in an urban network. Two traffic assignment procedures were tested: 1) minimize the individual impacts of each eco-routing vehicle approaching the network, 2) minimize the overall impacts of the network based on an optimization of the flow patterns of a subpopulation of eco-routing vehicles.

Regarding the first approach, it was demonstrated that under certain conditions (traffic congestion levels, density of eco-routing vehicles, and characteristics of the eco-friendly route) the optimization focused on updated information on ED costs and CO_2 can lead to worse results than the traditional UE_{TT} approach. In these circumstances the eco-routing information should only be provided ensuring that individual savings outweigh the total potential increases of the remaining vehicles.

For a network operating at moderate levels of saturation, 100% of eco-routing vehicles could generate an overall reduction of 11% system CO_2 emissions when compared with the standard UE travel time. This value tends to be lower (4-6%) as the number of eco-routing vehicles is reduced to half or the network is becoming more congested respectively. Both for eco-routing vehicles, and for general traffic, the travel time is not affected significantly. If the objective is to minimize the system environmental damage (SED) costs, the traffic optimization would allow a reduction of approximately 10% in SED costs. However, this scenario may lead to considerable increases in travel time of eco-routing vehicles and non-eco-routing vehicles.

The proposed SO traffic assignment may force the network to a permanent state of instability, since the population of eco-routed vehicles would select their route based on updated traffic data. Even if assuming that UE is the likely state, it is useful to describe what such an ED or fuel consumption-minimizing state might look like. This methodology and the generated information can be applied to other regions to quantify the impacts of the implementation of eco-routing strategies, and therefore help decision-makers better implement intelligent road traffic management policies.

In section 7.2 a tool to help the traffic assignment in a certain corridor more efficiently and environmentally friendly has been developed. The most innovative factor of this tool is the ability to include the impacts of major pollutants in an integrated form according to user's needs. This instrument is not intended to replace the traditional traffic assignment models but rather complement them and contribute to a more effective management of traffic.

The output of this model can be the basis for implementing intelligent traffic management measures. It is common knowledge that SO assignment is an unrealistic scenario since it assumes that drivers will collaborate in making their route choices considering the overall benefit of the complete network, instead of their own benefits. However, new traffic advanced information systems and smart road-pricing schemes may lead to a more efficient allocation of traffic in certain corridors by dynamically change the equilibrium conditions. The case study has demonstrated that it is possible to significantly reduce environmental costs (30%) by changing the flow distribution along a corridor with 4 alternative routes.

Further research is needed to evaluate driver’s response to new eco-routing systems. Moreover, a methodology to adjust and estimate more accurately the effective impact of pollutant emissions according to the characteristics of specific links should be developed in future work. Then, the optimization procedure could be further improved by adjusting the capacity constraints; for instance, the maximum capacity of each link could be defined by considering the maximum amount permissible of environmental damage costs produced by a certain number vehicles.

8 CONCLUSIONS

Firstly, this chapter summarizes the contribution of the research and provides answers to the main research questions raised at the beginning of this thesis. Section 8.2 address transferability issues and work limitation and finally some unresolved issues that deserve future research attention are identified in section 8.3.

8.1 CONTRIBUTIONS (METHODOLOGY AND RESEARCH QUESTIONS)

A major contribution of this work has been the development of methods to analyze the impact of route choice under different energy and environmental criteria. A unique database from approximately 13,300 km of road coverage over the course of 222 h has been developed by considering a wide range of driving patterns conditions, namely at different periods of the day (peak vs. non-peak hour) and different scales (city, urban, and metropolitan). These data have been used to generate emissions information based on the instantaneous emissions model VSP. This method is more accurate since it reflects the transient emission rates under different operating modes, thus yielding a better estimate of vehicle emissions than speed-based emission models.

In a second phase, emissions estimations based on GPS data were incorporated into Geographic Information Systems and state-of-the-art routing algorithms. Different approaches to consider the specific impacts of several pollutants were suggested. Subsequently, an integrated traffic-emission microsimulation platform has been developed and validated with real world data including the distribution of vehicle's operational modes. This modelling platform has been used to establish accurate models based on link-based volume emissions functions. This original approach allows one to estimate with higher accuracy the performance of different links, under different demands and simultaneously enabling greater operational flexibility and speed data processing for evaluating different traffic assignment and route guidance strategies. Similar computational structures may become a user-friendly solution for assessing the sustainability of different ATMS.

Overall this research contributes by comprehensively exploring and quantifying the potential environmental benefits of providing additional travel information to drivers. Furthermore, the insights gained from this study can also serve as the basis for implementing ATMS under environmental and traffic performance constraints. The main research questions addressed in chapter 1 are summarized below.

8.1.1 How can route selection influence the emissions output in different spatial and temporal contexts?

Empirical tests have demonstrated that route choice can play a very important role in reducing fuel consumption and emissions. Regarding LDDV, from a strictly individual perspective, and for specific pollutants, empirical tests have shown that it is possible to reduce CO_2 emissions by 10% in intercity and metropolitan routes and 25% in urban routes. Regarding NO_X emissions, reductions of 35% in the urban and intercity scenarios and 11% in the metropolitan routes were observed.

Regarding LDGV, the selection of an appropriate route has been shown to yield the reduction of 5% of fuel consumption (and CO_2 emissions) in metropolitan routes, 15% in urban routes and 25% in the intercity context. The variations in CO range from 12% in metropolitan routes to 60% in the intercity corridor.

For all OD pairs, the differences in emissions among all routes differences are to some extent reduced during peak hour. However, for both types of vehicle, and in the large majority of cases, emissions are statistically significantly different between the routes with the highest emission levels the routes yielding lower emissions.

Despite the positive results in terms of potential for emissions reduction based on an appropriate route choice, the overall results exhibit a number of important trade-offs that should be discussed.

i) Fuel consumption and CO_2 vs. local pollutants.

This trade-off was particularly evident in intercity routes for LDGVs. This conflict would be more problematic in regions where high concentrations of local pollutants such as CO are usually observed. However, this conflict could be reduced with an increasing market penetration of cleaner vehicles. Figure 59 shows the relative evolution of emissions factors since 1992. It can be seen that since 1992 the reduction rate of average emissions factors of local pollutants (due to the application of end-of-line technologies) has been considerable higher than CO_2 emissions [179]. Thus, the contribution of the transportation sector to local pollutants emissions will be reduced considerably in the medium term. Additionally local pollutants emissions can be reduced by applying speed management/harmonization techniques on motorways aiming at reducing higher speeds and consequent high emissions levels.

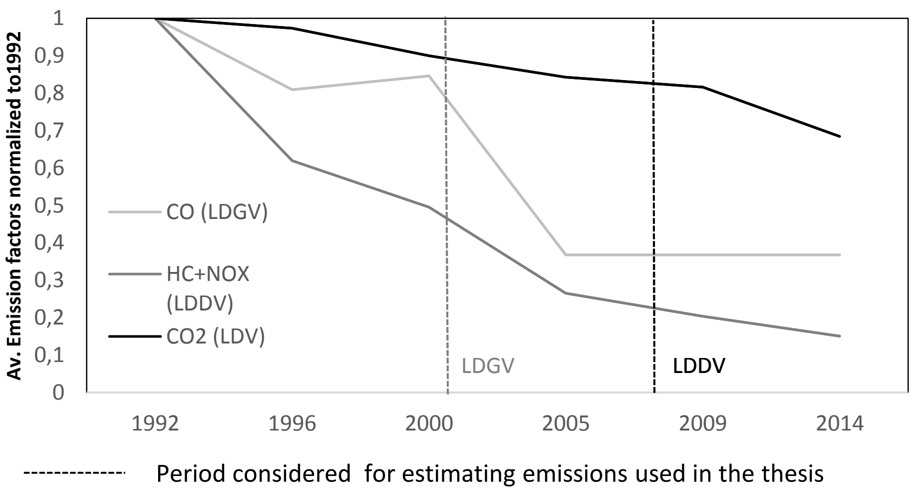


Figure 59 Relative reduction of average emissions factors since 1992. CO, NO_X and HC - data based on European emission standards) CO_2 – data based on new vehicles sold in UE.

ii) Eco-friendly route vs. travel time

Considering an eco-indicator for route choice based on economic cost of each pollutant, it was found that generally, the selection of an eco-friendly route leads to higher travel time. This fact could seriously limit the acceptance of eco-routing suggestions to a considerable number of drivers. However, if the eco-routing strategy is predominantly focused on CO_2, this conflict would tend to decrease. Additionally, by reducing CO_2 emissions drivers will reduce their fuel consumption, and therefore their travel costs.

iii) Eco-friendly route vs. local impacts

In some circumstances the routes that yield a minimization of pollutants cross densely populated areas. This fact suggests that a careful assessment of potential externalities that may arise from a purely dedicated navigation system based on the minimization of total emissions is needed.

iv) Eco-friendly route vs. Vehicle type

Depending on the characteristics of the routes linking a certain OD pair, the eco-friendly route may differ according to the type of vehicle. For individual navigation devices, this issue can be easily resolved, by including specific information on different types of vehicle into routing algorithms. For a centralized network management, the average fleet composition must be considered in order to maximize the effectiveness of advanced traffic management systems.

8.1.2 How can Intelligent Transportation Systems be used to provide eco-routing information?

Figure 60 outlines an ideal network equipped with different ITS to clarify where some of the research findings and methodologies can be applied.

Several methods can be used to collect real time information on traffic performance and air quality indicators. Given the potential of smart vehicles, either through the use of nomadic devices and vehicle to infrastructure technologies (V2I), online traffic data could be fed into modelling systems, which will help traffic engineering's forecast traffic emissions. Alternatively or simultaneously, traffic monitoring stations (TMS) (A) could transmit to a Traffic Management Center TMC (B), information on traffic speed and traffic volumes. At the same time, air quality stations (AQS) (C) broadcast real time information on air pollutants concentrations to the TMC, allowing to prioritize the most critical pollutants such as has been performed in chapter 6.1.

A methodology based on VSP data such as demonstrated in section 6.1.3. (or an alternative modelling tool) can be employed to calculate real-time emissions across several road segments using the (speed, acceleration and road grade) data transmitted by probe vehicles. This information can be constantly updated and incorporated in routing algorithms such as was demonstrated in section 6.1.

On the other hand, similar models to the one presented in sections 4.2.4, 7.1.3.1, 7.2.2.2 (Volume-Emissions Functions) can be used to estimate real time emission information based on real time data on traffic volume.

Real time or historical average emissions per road segment may be incorporated in pre-trip planning software in order to determine the most eco-friendly route. This information could be available on navigation routing systems such as GPS devices (D) and pre-trip planning software available online (E). Using innovative traffic assignment methods such as described in chapter 7, dynamic road pricing schemes (F) can be used to improve the energy and environmental performance of the network. Additional route information could be summarized into different rating systems such as presented in section 4.1.6 and 4.2.3.

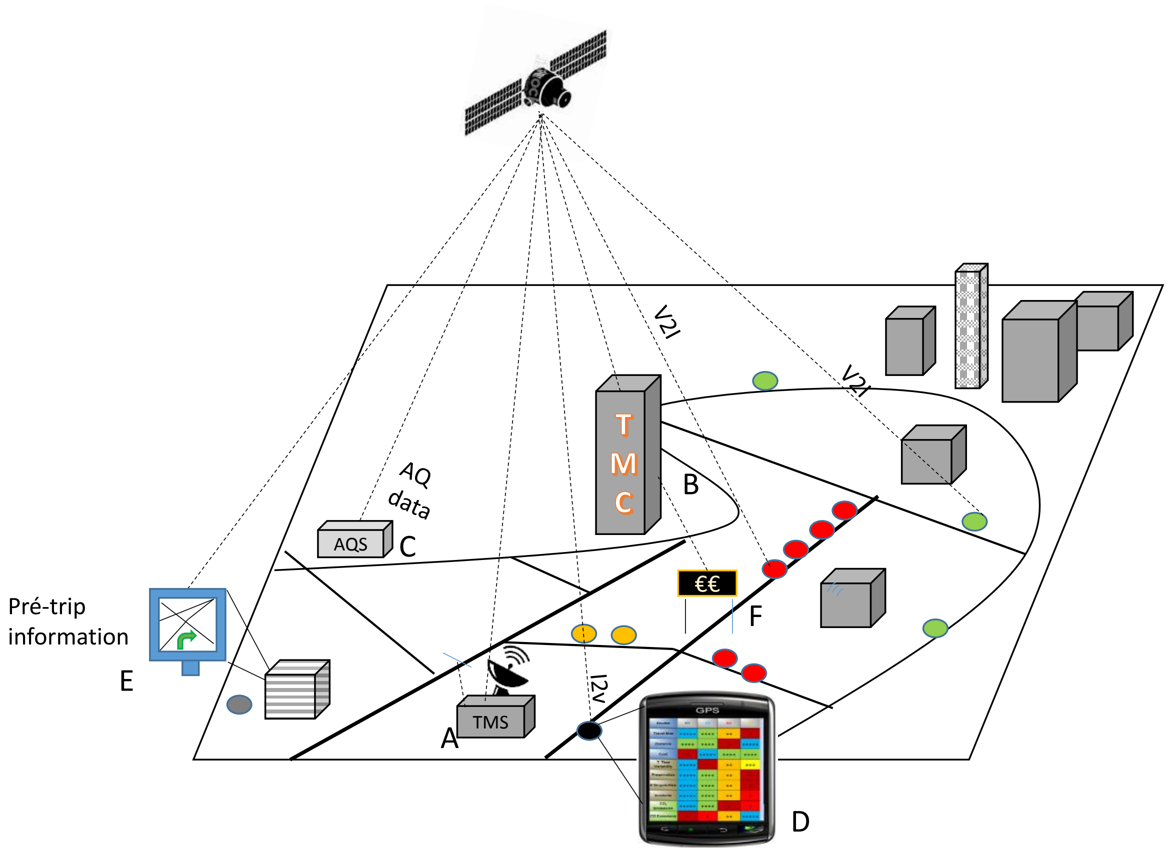


Figure 60 Integration of the methodology in an ideal network equipped with different ITS

8.1.3 What strategies of traffic management can be applied to improve the efficiency of road infrastructure in terms of traffic performance, energy consumption and emissions?

Both empirical and analytical results have shown that for limited levels of acceptance, the eco-routing strategies have significant potential to reduce emissions. However, for higher demands of eco-routing vehicles, the overall network performance can be deteriorated.

In fact, system environmental impacts can be higher if drivers are routed with the objective of minimizing their own ED costs. The degradation in network performance caused by the self-interested behaviour of network users is being studied over the last decades by a considerable number of researchers. The Price of Anarchy (term introduced by

Koutsoupias and Papadimitrio [180]) measures the ratio between average travel time under system optimum (centralized) and user equilibrium (decentralized system).

In this study, it has been demonstrated that the deterioration of the network performance may be even more notorious when drivers are routed to reduce their individual environmental impacts as demonstrated in the case-study shown in Chapter 7.1. This may be connected to the fact that when drivers are routed with the purpose of minimizing their own travel time, they are conducted to motorways with higher capacity. On the other hand, when drivers seek routes for minimizing their own environmental impacts, they can be routed to slower roads, with less capacity, where the impact inflicted on other users is significantly higher, even for lower traffic volumes.

An alternative solution to overcome this issue would be to address the routing problem macroscopically i.e. by changing the equilibrium costs of routes (e.g. dynamic road-pricing schemes) towards more a more sustainable traffic distribution. The analysis carried out in section 7.2 has demonstrated that significant emissions reduction can be achieved by changing the network equilibrium in terms of perceived user' costs. However, it is necessary to conduct further behavioural research to strengthen understanding of driver's feedback to dynamic tolling systems.

8.2 LIMITATIONS AND TRANSFERABILITY ISSUES

Several limitations must be taken into account. All emission results presented in this report are tailpipe exhaust emissions that were based on emission factors that represent generic light passenger vehicles (gasoline and diesel). Although there is no consensus about which model is the most appropriated to use in traffic planning projects, VSP methodology has proven to be very useful in estimating micro-scale emissions [18,37,40]. One of the disadvantages found in literature review section, is that a finer categorization of emission rates is needed with regard to engine size, and vehicles mileages. However, this handicap could be overcome with the predictable updates and more detailed emissions rates that should be available in the short term. Moreover it should be noted that the data collected in the experimental tests could allow future assimilation of another microscale models such as VT-micro [181] or CMEM [47]. The absolute values can be significantly different if one considers vehicles of different categories and mileages. Since the main objective was the development of a methodology rather than an exhaustive database of on-board emission rates for different patterns of vehicle dynamics, it was not necessary to consider all vehicles of the Portuguese fleet. Yet, more than calculating absolute values, the main objective of this work was to assess the relative impact of different operational aspects of networks performance in terms of emissions.

Field tests were conducted based on the driver's judgement of the average speed of the traffic stream. During free flow conditions the speed limits were respected. Logically, the study results can only be extrapolated assuming similar driving behaviours.

Several strategies for weighting the impact of different pollutants appear throughout the various chapters. It is not possible to determine which is more correct, since it depends on the main purpose of the study and the circumstances of each site. However, more research is clearly needed to develop more detailed and dynamic measures to assess the real impacts (health, environmental and socio-economic impacts) of different pollutants.

One of the limitations of a primarily empirical study and based on specific study areas, is the ability to generalize from the field data on which the study has been conducted to a larger population. However, the applied methodology (use of test vehicles, microsimulation, statistical analysis and systematization of information) can be applied to provide eco-routing information in different OD pairs. Given the diversity and heterogeneity of the analysed scenarios, it may be expected that some conclusions of this study can be extrapolated to other contexts. Specifically the following findings can be generalized beyond the case study:

1) The presented method on implementation of eco-routing information.

2) The evidences of significant potential emission savings for eco-routing even during peak periods.

3) The assessment of the potential to accurately predict emissions of various pollutants in different types of roads based on GPS measurements and traffic volumes data (Volume-emissions functions). In Future, these VEF can be incorporated in routing and traffic assignment algorithms.

4) The identification of drawbacks associated with eco-routing systems which have rarely been considered so far.

8.3 FUTURE WORK

The implementation of environmental policies in the transportation sector should consider the level of contribution of each externality and the geographical scale; otherwise some isolated measures may just move the problems elsewhere. Thus, a future crucial research topic would be to explore the nature of these dynamic externalities, in order to manage efficiently current road networks. Further research should focus on developing a platform to estimate and standardize the major impacts of road traffic, and support a sustainable use of existing infrastructures. Transportation related impacts can be integrated and continuously updated database supported by Geographic Information Systems (GIS) - Figure 61.

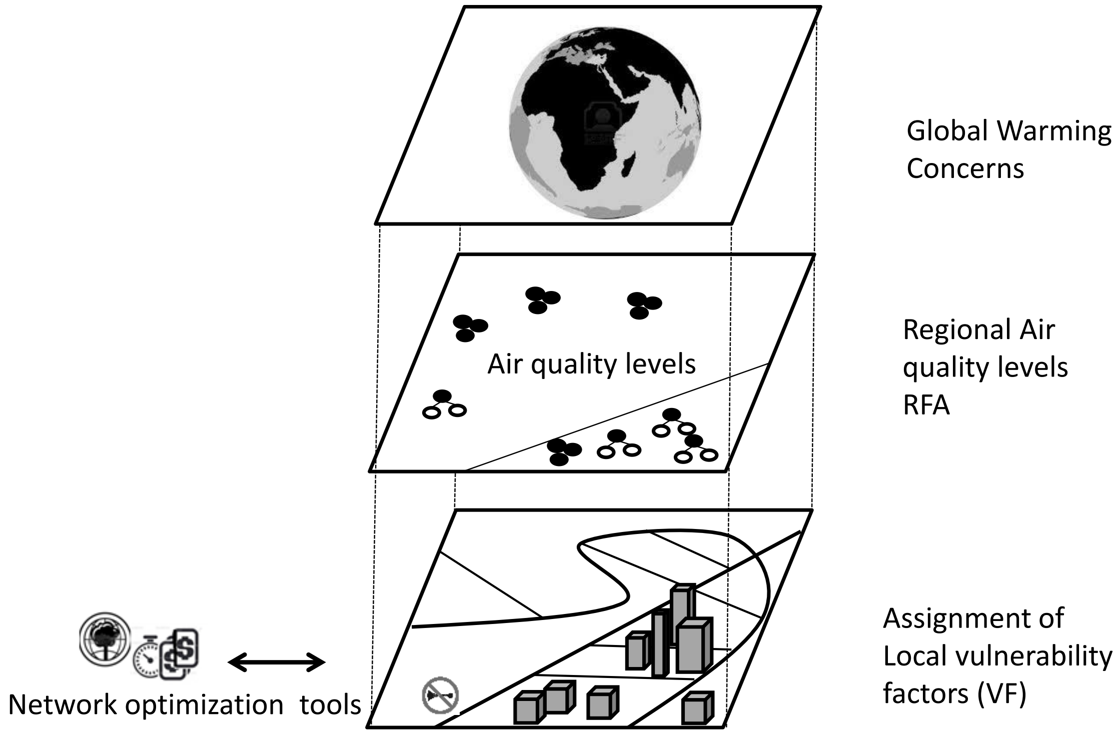


Figure 61 Integration of optimization tools with different layers of transportation-related impacts

However, such platform should consider improved weighing criteria and new measures for assessing different transportation-related impacts (GHG, local pollutants, noise, and safety). Taking into account that some of the recommended eco-routes cross densely populated areas, further eco-routing algorithms needs to consider the real impacts of traffic by means of weighting factors assigned to each link, according to specific local vulnerability factors. This method would allow considering additional objectives such as minimizing the number of homes exposed to high levels of traffic-related externalities such as pollutants and noise.

Under the framework of the SMARTDECISION project, the emissions data was integrated into different air quality models, according to the scale of analysis. One of the main objectives was to assess if potential improvements on regional air quality modelling related with the implementation of a more comprehensive methodology for traffic emission estimation would be obtained [182]. It has been found that improvements in air quality results have been achieved by applying a detailed methodology for emission estimation (using VSP), mainly for PM10, CO and O_3. However, further improvements can be made by increasing the detail in vehicle categories and testing alternative emissions modelling tools.

The integrated traffic-emission modelling platform was validated in terms of speeds, volumes, travel time and VSP modal distribution. Despite this rigorous process of calibration and validation, it would be interesting to conduct a retrospective analysis of the models to predict link-based emissions over different traffic demands.

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APPENDIXES

A DESCRIPTIVE STATISTICS FOR TRAVEL TIME

A1 Urban routes

		Um CS		Ua CS		Uu CS	
Statistics		**Statistic**	**Std. Error**	**Statistic**	**Std. Error**	**Statistic**	**Std. Error**
Mean		464	13	532	14	538	19
95% Confidence Interval for Mean	Lower Bound	436		501		495	
	Upper Bound	492		563		582	
5% Trimmed Mean		463		530		537	
Median		451		522		524	
Variance		1774		2119		4180	
Std. Deviation		42		46		65	
Minimum		407		476		428	
Maximum		541		623		672	
Range		134		147		244	
Interquartile Range		60		65		93	
Skewness		0.535	0.661	0.844	0.661	0.530	0.661
Kurtosis		-0.497	1.279	-0.092	1.279	1.073	1.279

		Um SC		Ua SC		Uu SC	
Statistics		**Statistic**	**Std. Error**	**Statistic**	**Std. Error**	**Statistic**	**Std. Error**
Mean		404	16	479	16	520	16
95% Confidence Interval for Mean	Lower Bound	368		443		485	
	Upper Bound	440		515		555	
5% Trimmed Mean		406		477		518	
Median		427		458		507	
Variance		2864		2866		2692	
Std. Deviation		54		54		52	
Minimum		295		415		443	
Maximum		479		575		621	
Range		184		160		178	
Interquartile Range		80		90		80	
Skewness		-0.762	0.661	0.511	0.661	0.561	0.661
Kurtosis		0.189	1.279	-1.148	1.279	-0.069	1.279

A2 Intercity routes

		***Im₁* AP**		***Im₂* AP**		***Ih* AP**		***Iu* AP**	
Statistics		**Statistic**	**Std. Error**	**Statistic**	**Std. Error**	**Statistic**	**Std. Error**	**Statistic**	**Std. Error**
Mean		2965	21	3319	148	5707	177	6408	142
95% Confidence Interval for Mean	Lower Bound	2917		2977		5300		6079	
	Upper Bound	3014		3661		6115		6736	
5% Trimmed Mean		2964		3281		5713		6397	
Median		2955		3185		5805		6308	
Variance		3965		198225		280645		182678	
Std. Deviation		63		445		530		427	
Minimum		2897		2922		4847		5866	
Maximum		3056		4403		6465		7139	
Range		159		1481		1618		1273	
Interquartile Range		132		386		843		682	
Skewness		0.420	0.717	2.137	0.717	-0.457	0.717	1	.717
Kurtosis		-1.527	1.400	5.111	1.400	-0.550	1.400	0	1.400

		***Im₁* PA**		***Im₂* PA**		***Ih* PA**		***Iu* PA**	
Statistics		**Statistic**	**Std. Error**	**Statistic**	**Std. Error**	**Statistic**	**Std. Error**	**Statistic**	**Std. Error**
Mean		2921	56	2995	53	5175	112	6266	151
95% Confidence Interval for Mean	Lower Bound	2793		2872		4916		5918	
	Upper Bound	3050		3117		5434		6614	
5% Trimmed Mean		2910		2990		5186		6262	
Median		2882		2972		5195		6225	
Variance		27988		25289		113585		205535	
Std. Deviation		167		159		337		453	
Minimum		2763		2749		4514		5590	
Maximum		3278		3317		5644		7014	
Range		515		568		1130		1424	
Interquartile Range		223		176		436		731	
Skewness		1.431	.717	.709	.717	-.699	.717	.177	.717
Kurtosis		1.678	1.400	1.609	1.400	.933	1.400	-.507	1.400

A3 Metropolitan routes

		Mm NC		Ma NC		Mm CN		Ma CN	
		Statistic	Std. Error	Statistic	Std. Error	Statistic	Std. Error	Statistic	Std. Error
Mean		28	2	31	1	27	1	26	1
95% Confidence Interval for Mean	Lower Bound	23		28		25		25	
	Upper Bound	32		33		30		28	
5% Trimmed Mean		29		30		27		26	
Median		28		31		26		26	
Variance		76		16		13		4	
Std. Deviation		9		4		4		2	
Minimum		0		25		24		23	
Maximum		40		40		37		30	
Range		40		15		14		7	
Interquartile Range		5		4		3		3	
Skewness		-2.262	0.580	0.884	0.616	1.977	0.616	0.177	0.580
Kurtosis		7.863	1.121	1.009	1.191	4.575	1.191	-0.824	1.121

B TRAVEL TIME AND EMISSIONS DATA BOXPLOTS

Table B1 Explanation of Box-and-Whisker Plots

Group Summary Statistic	Feature of Box-and-Whisker Plot
Maximum	Endpoint of upper whisker
Third quartile (75 th percentile)	Upper edge of box
Median (50 th percentile)	Line inside box
First quartile (25 th percentile)	Lower edge of box
Minimum	Endpoint of lower whisker
Outlier - less than or equal to the first quartile minus 1.5 times the interquartile range, or is greater than or equal to the third quartile plus 1.5 times the interquartile range.	circle
Outlier - less than or equal to the first quartile minus 3 times the interquartile range or greater than the third quartile plus 3 times the interquartile range, it is characterized as a far outlier	star

B1 Travel time

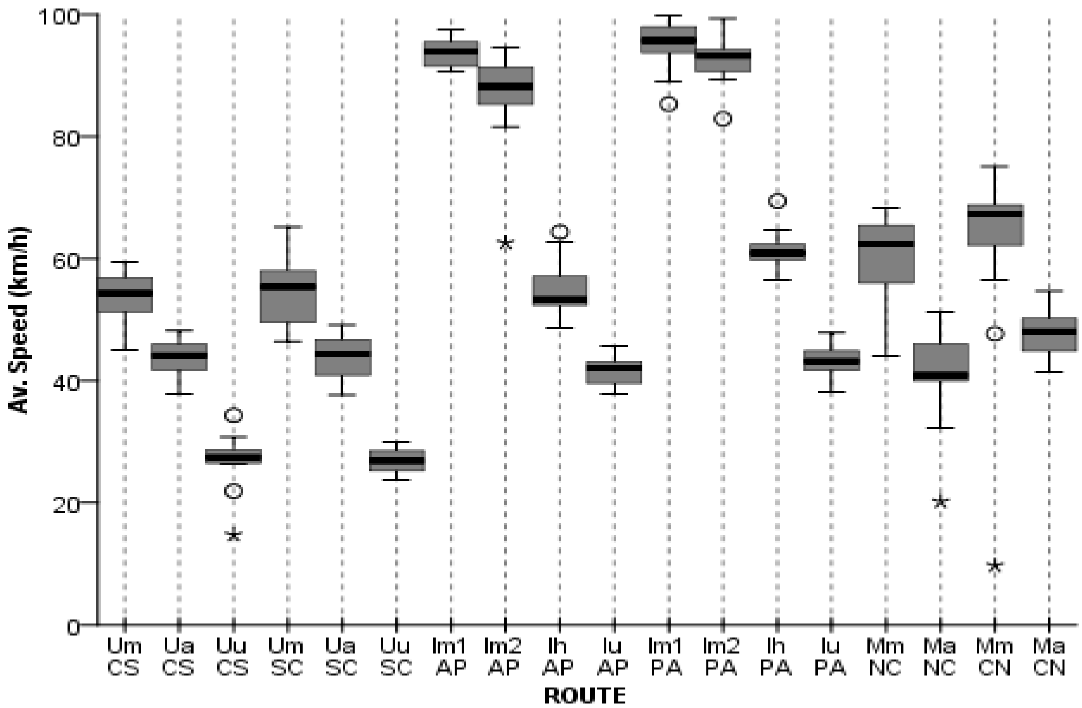
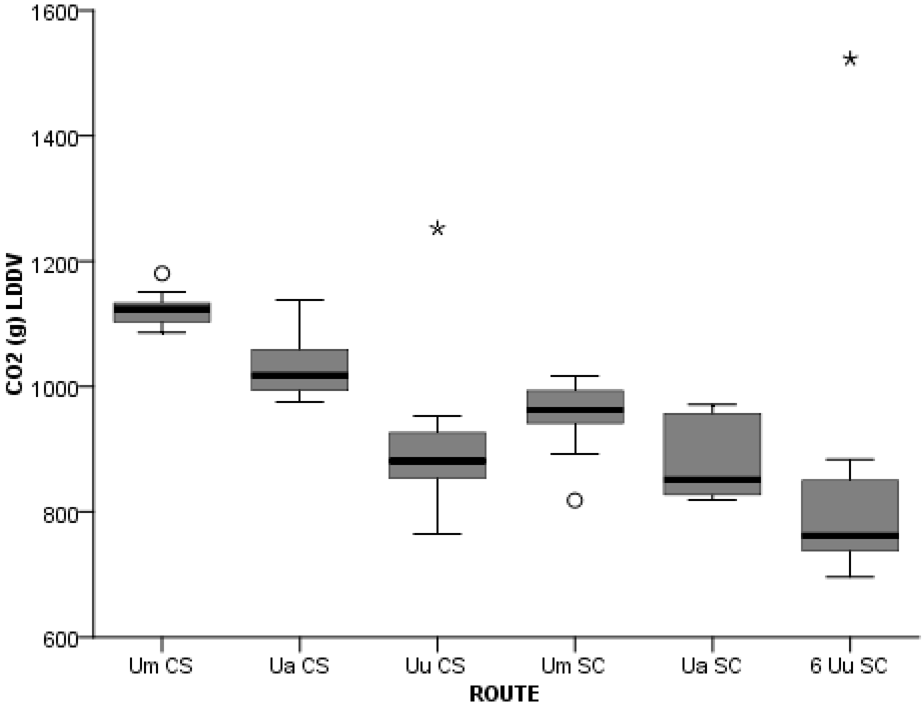
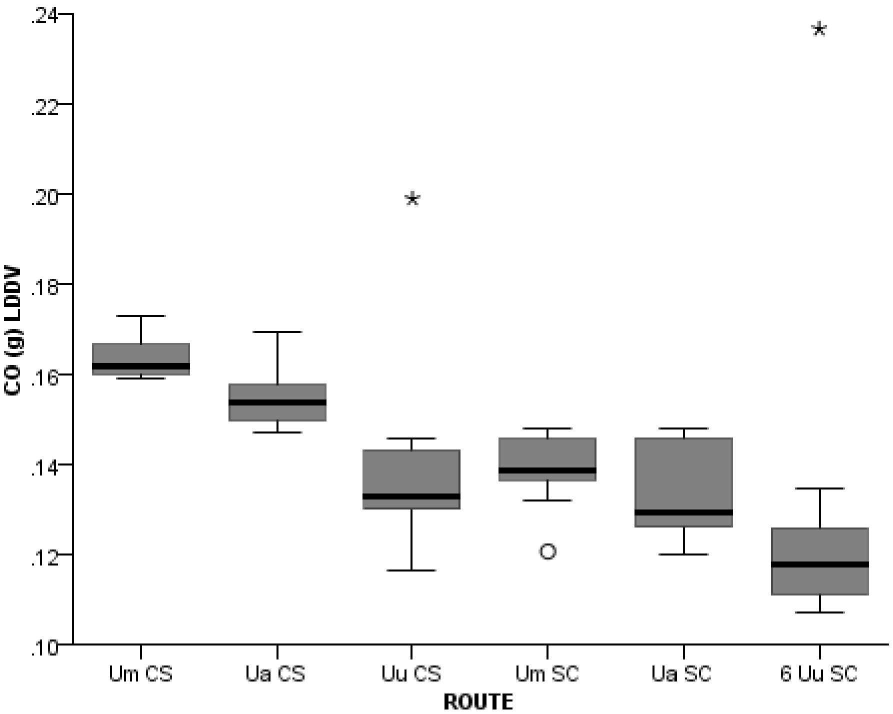
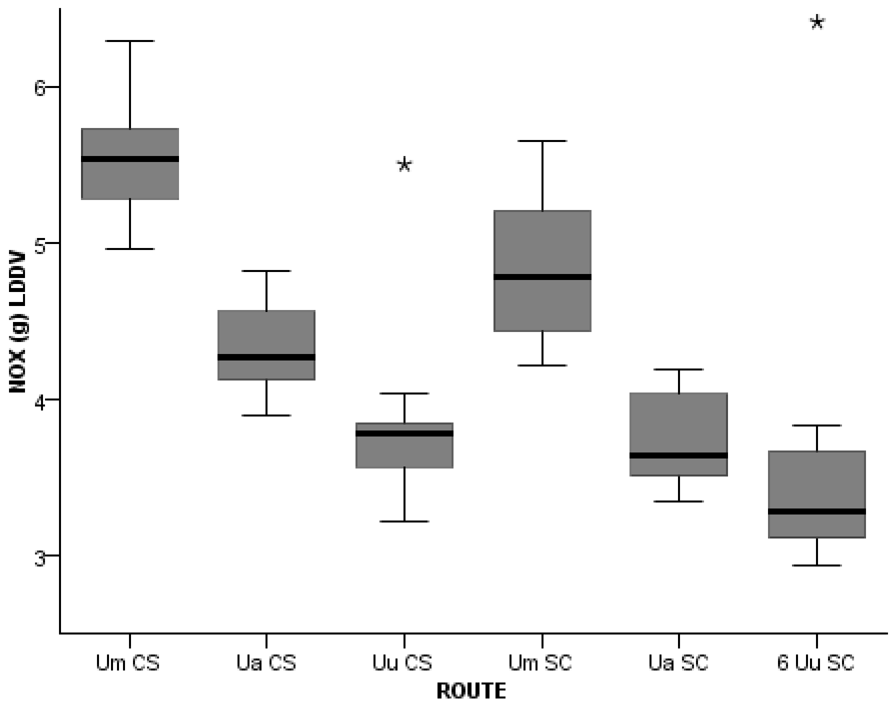


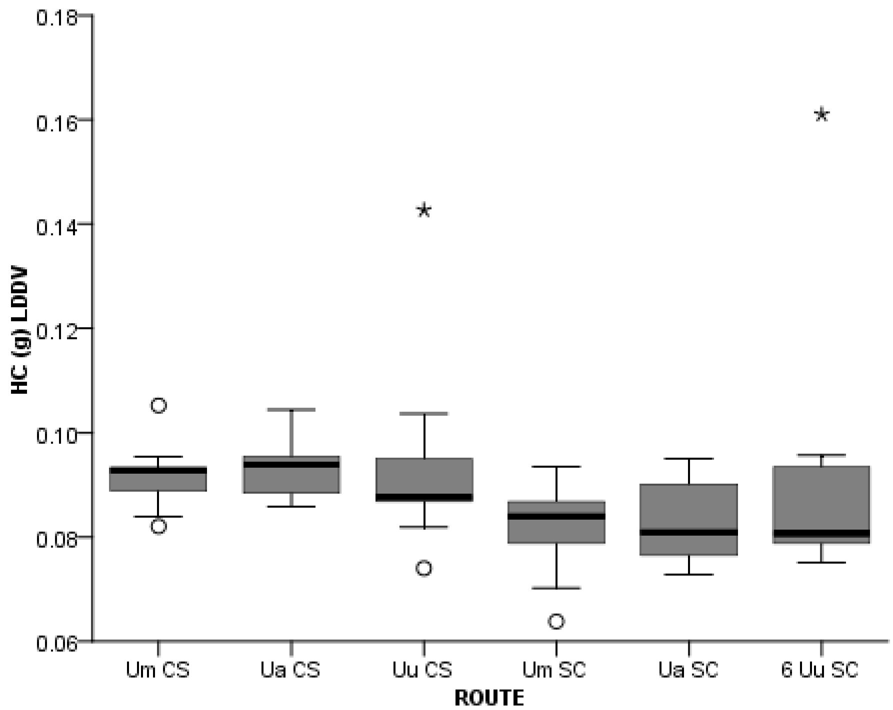
Figure A1 Boxplots for Average speed in all routers

B2 Urban routes - CO_2, CO, NO_X and HC from LDDV

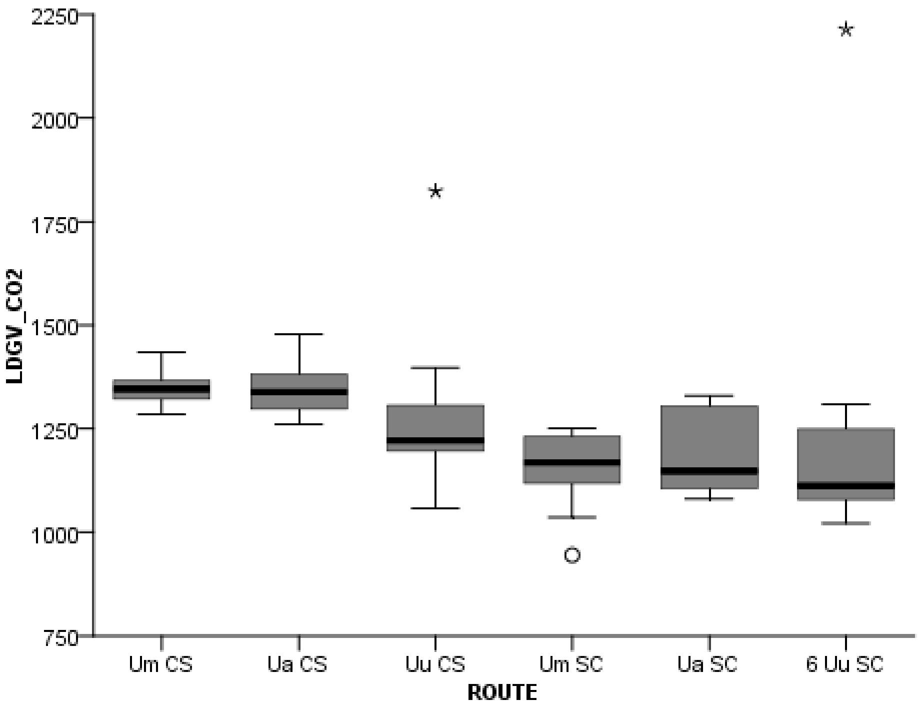


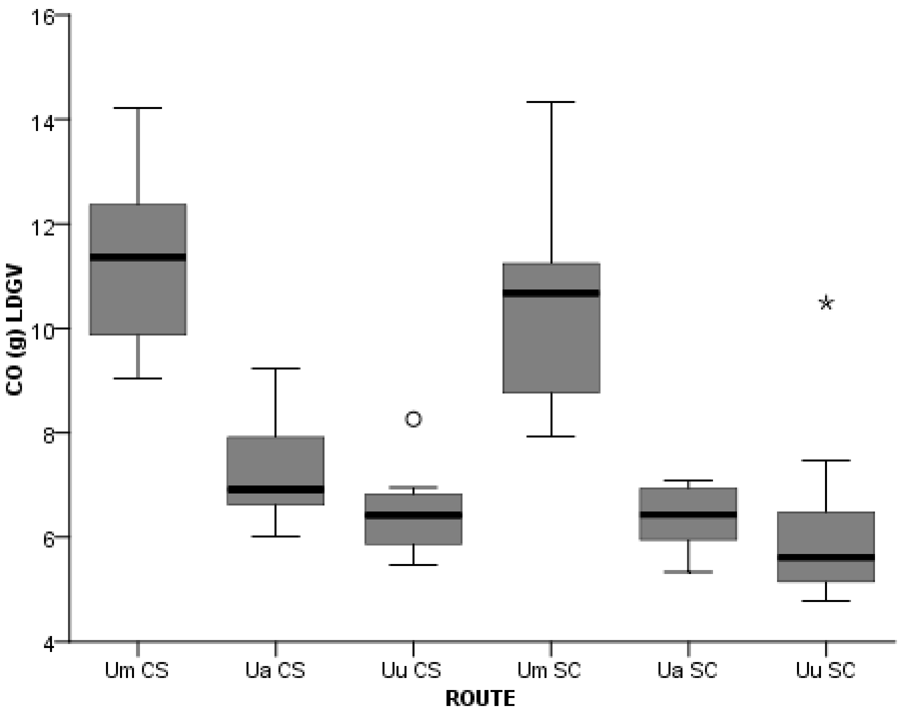


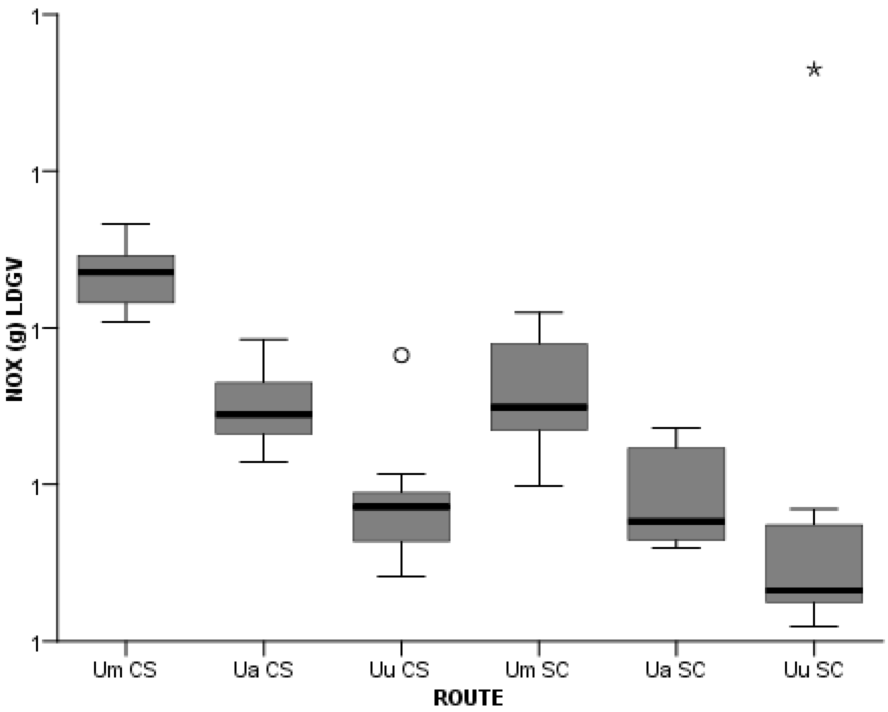

NOX (g) LDDV
6
5
4
3
Um CS
Ua CS
Uu CS
Um SC
Ua SC
6 Uu SC
ROUTE

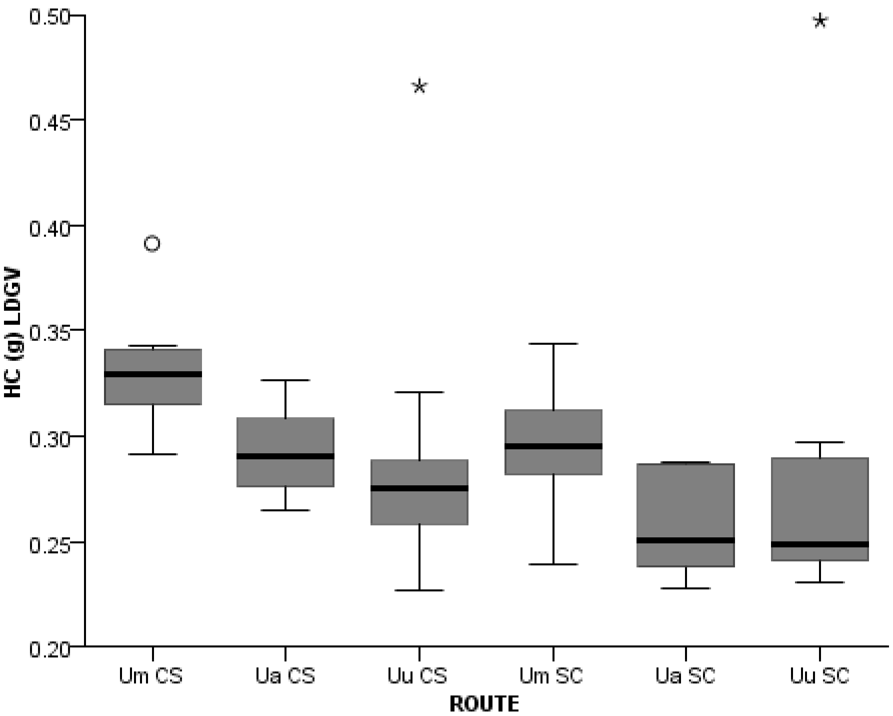

HC (g) LDDV
0.18
0.16
0.14
0.12
0.10
0.08
0.06
Um CS
Ua CS
Uu CS
Um SC
Ua SC
6 Uu SC
ROUTE

B3 *Urban routes - CO_2, CO, NO_X and HC from LDGV*

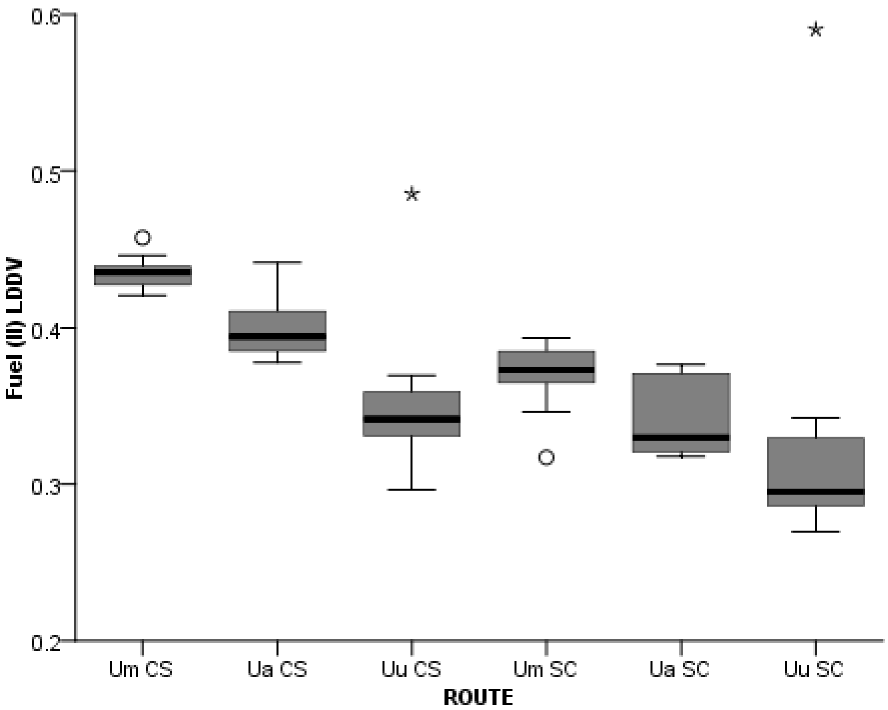


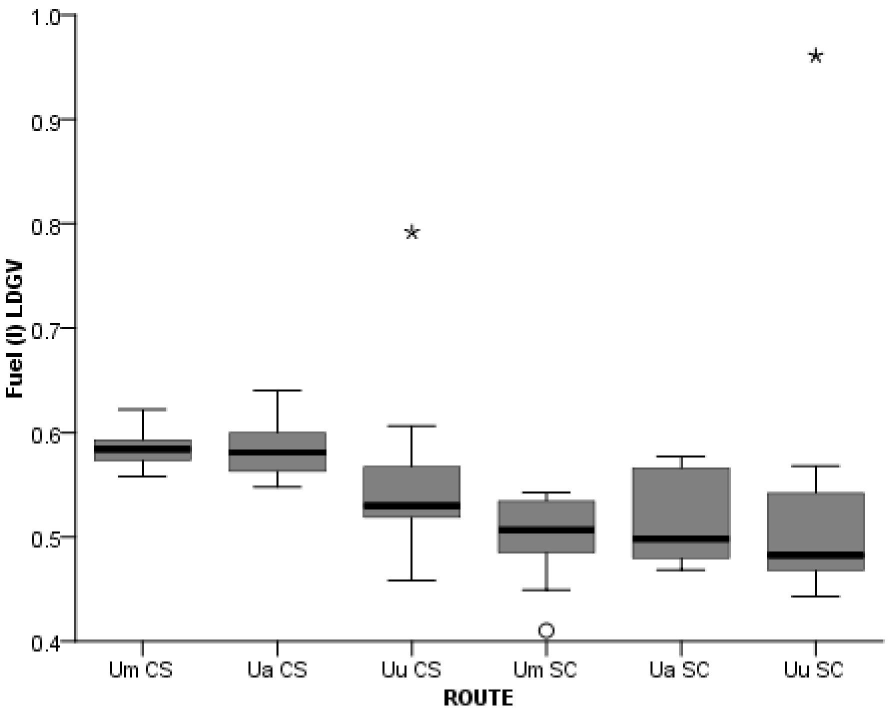



NOX (g) LDGV
1
1
1
1
1
Um CS
Ua CS
Uu CS
Um SC
Ua SC
Uu SC
ROUTE

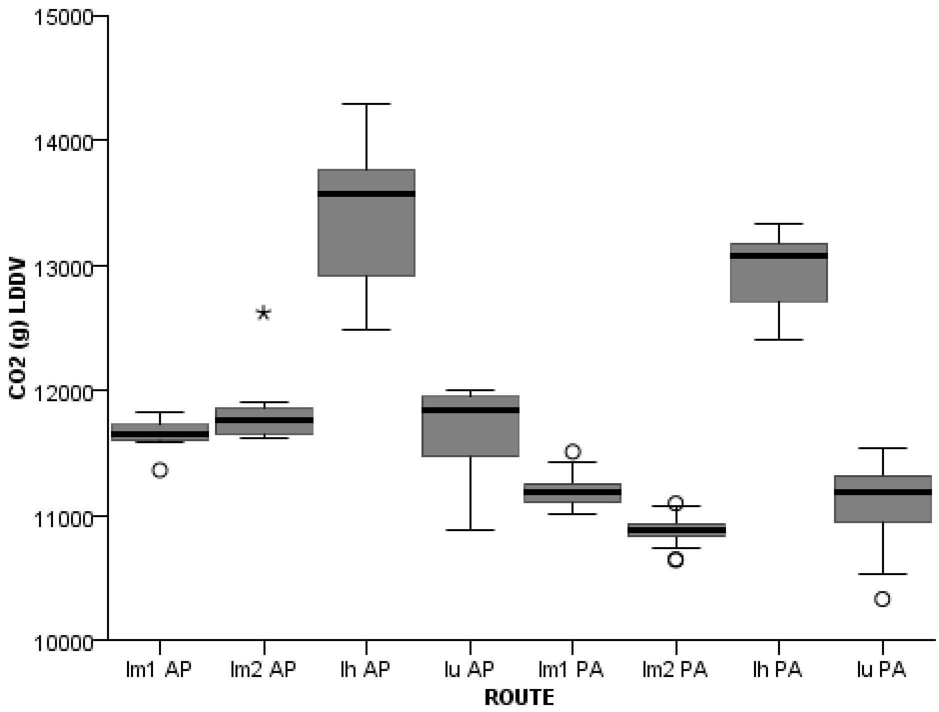

HC (g) LDGV
0.50
0.45
0.40
0.35
0.30
0.25
0.20
Um CS
Ua CS
Uu CS
Um SC
Ua SC
Uu SC
ROUTE

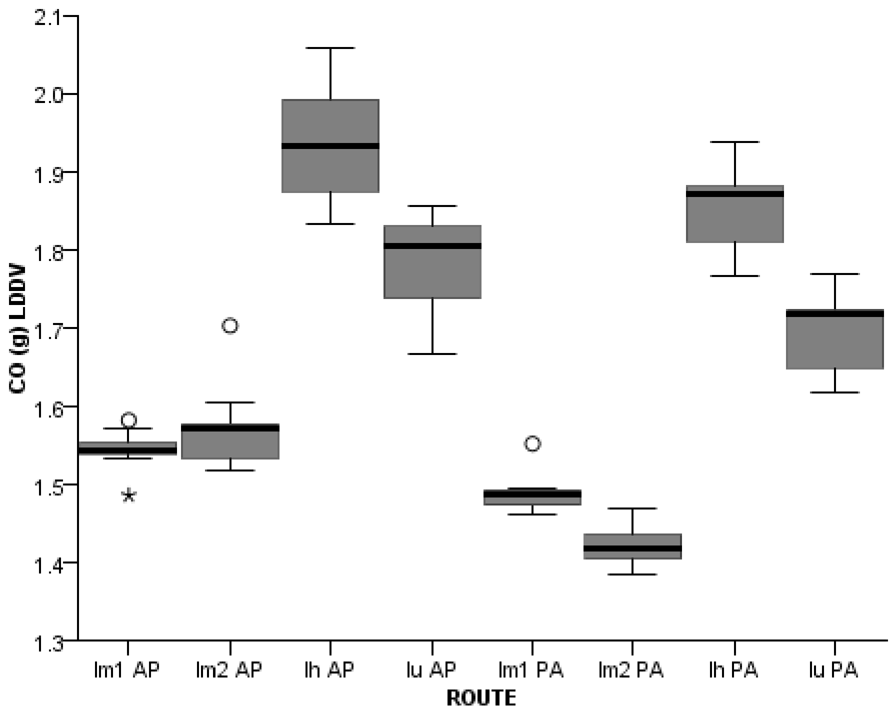
B4 Urban routes – Fuel consumption from LDDV and LDGV

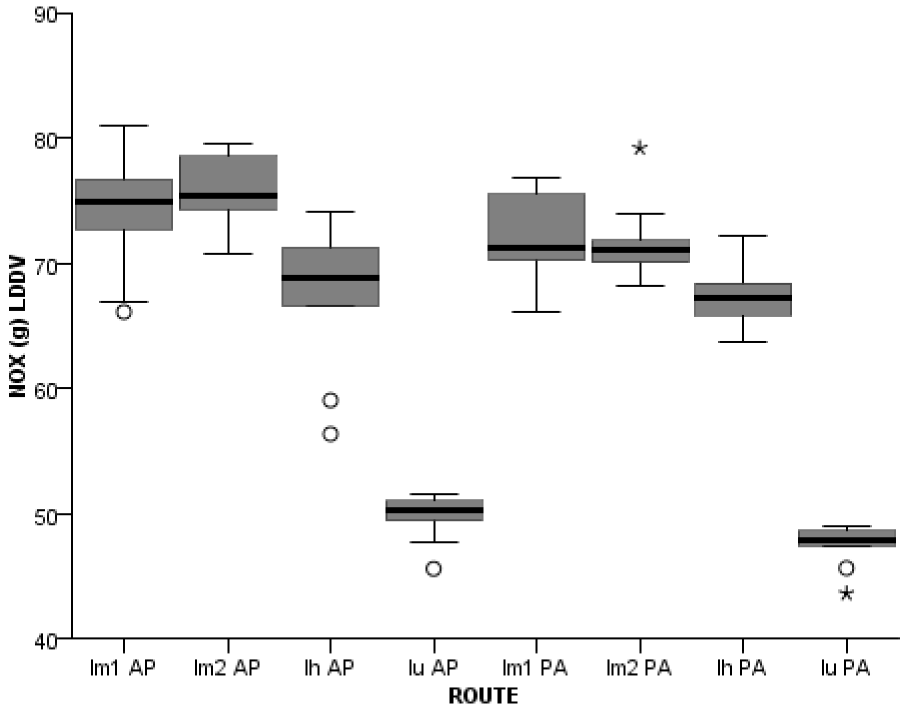


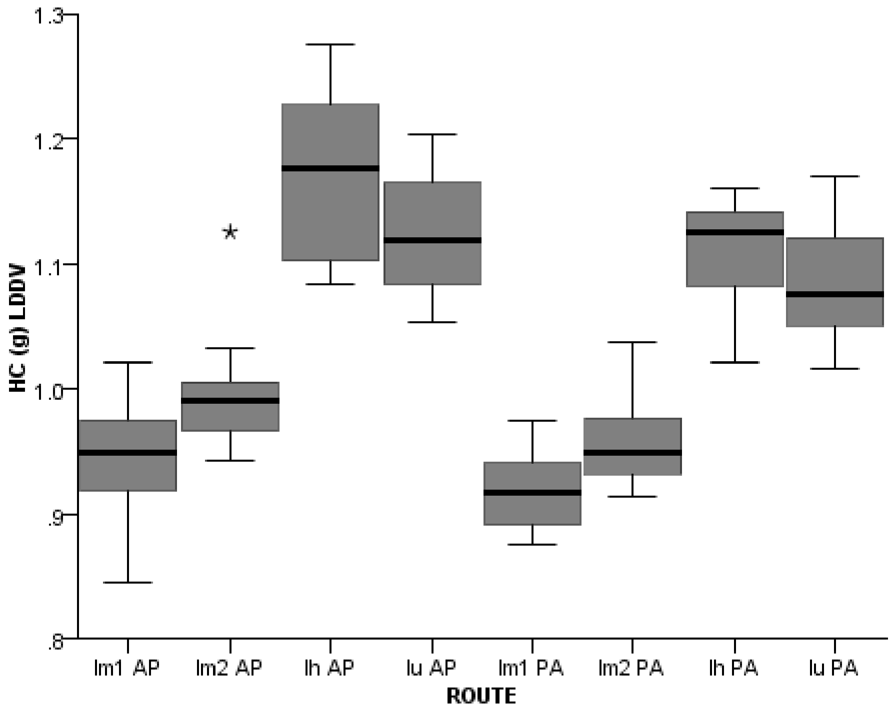


B5 *Intercity routes - CO_2, CO, NO_X and HC from LDDV*

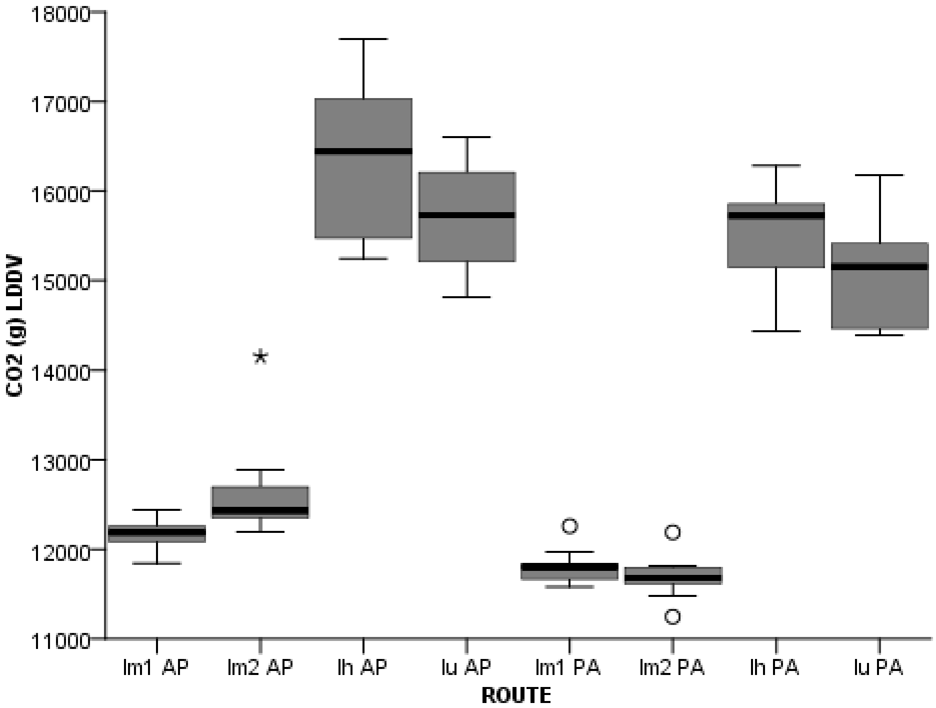


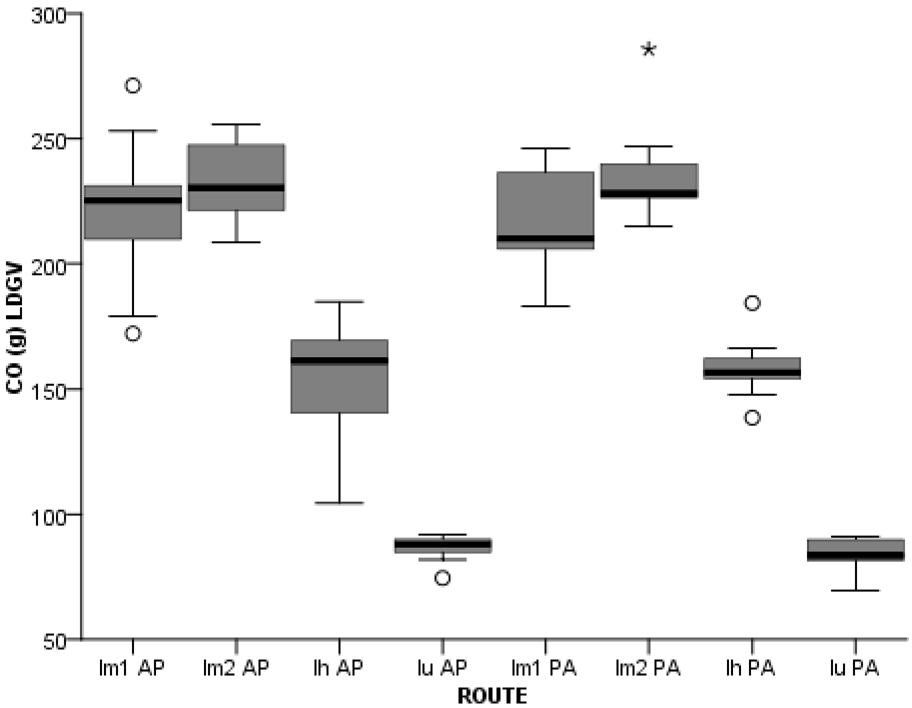


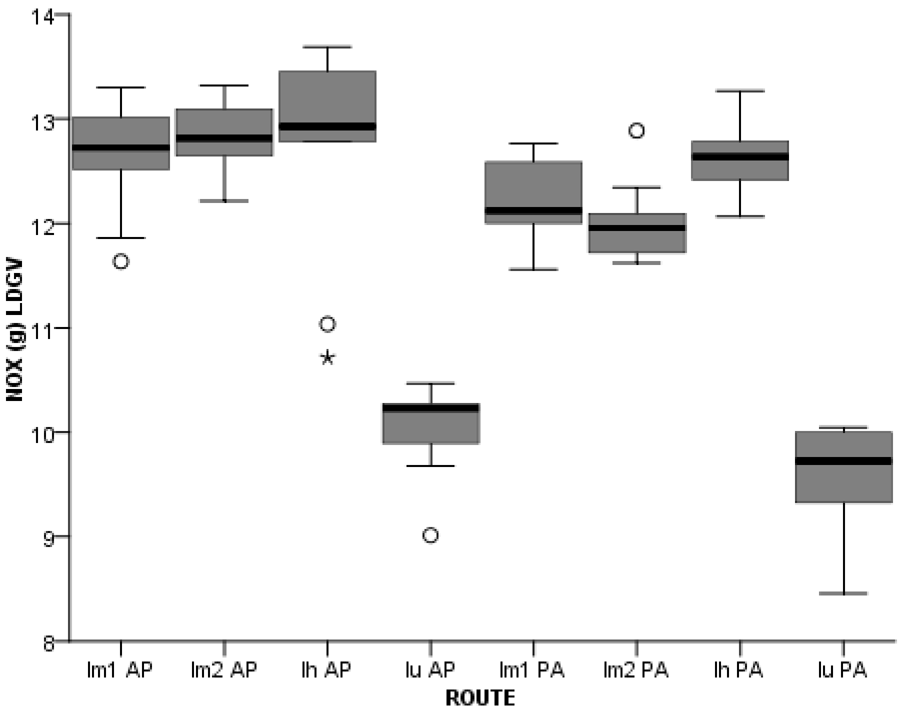

90
80
70
60
50
40
NOX (g) LDDV
lm1 AP
lm2 AP
lh AP
lu AP
lm1 PA
lm2 PA
lh PA
lu PA
ROUTE

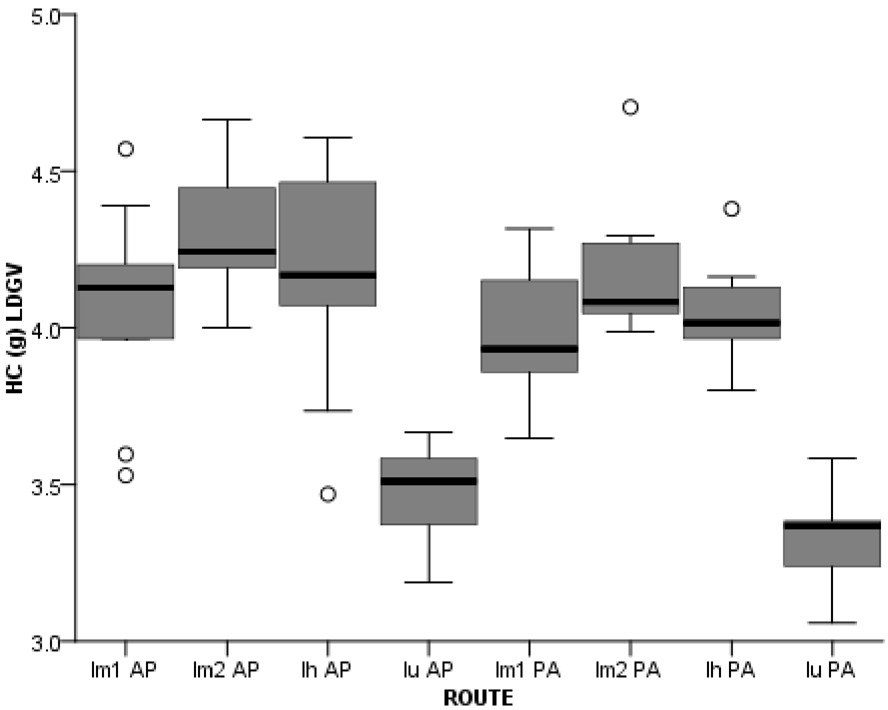

1.3
1.2
1.1
1.0
.9
.8
HC (g) LDDV
lm1 AP
lm2 AP
lh AP
lu AP
lm1 PA
lm2 PA
lh PA
lu PA
ROUTE

B6 *Intercity routes - CO_2, CO, NO_X and HC from LDGV*

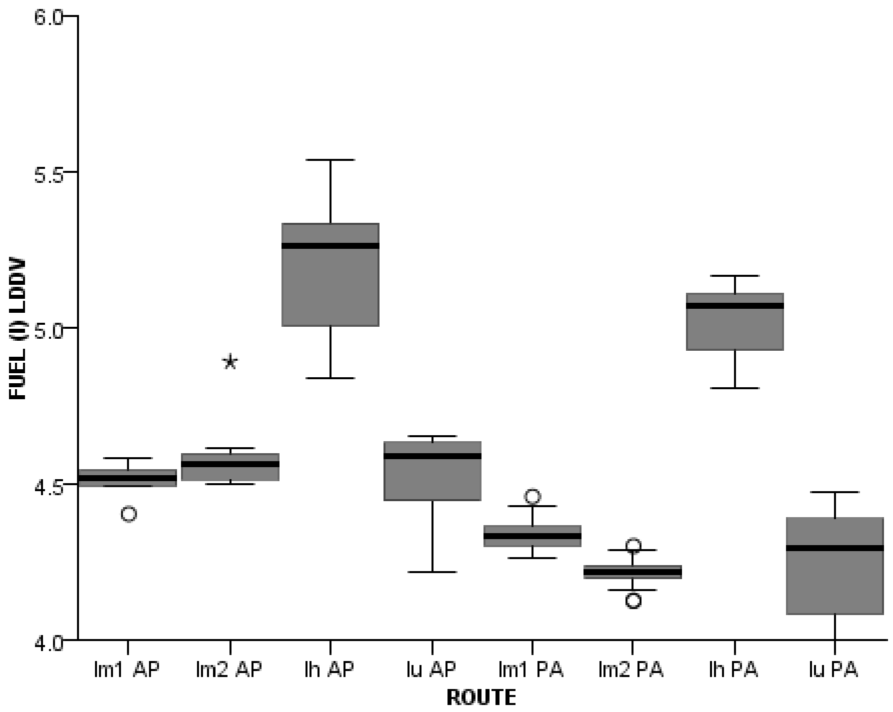


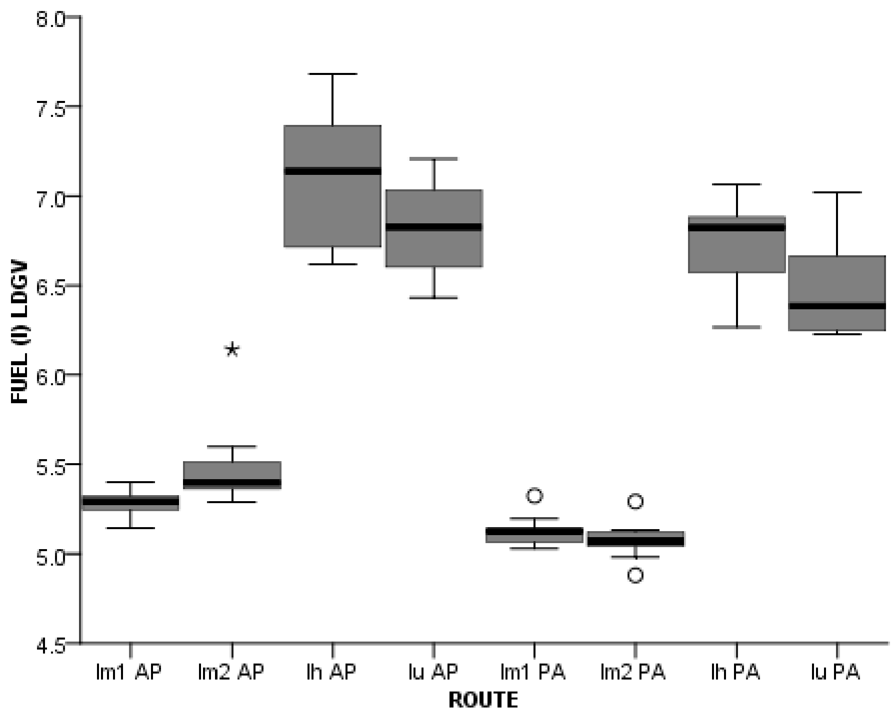



NOX (g) LDGV
14
13
12
11
10
9
8
lm1 AP
lm2 AP
lh AP
lu AP
lm1 PA
lm2 PA
lh PA
lu PA
ROUTE

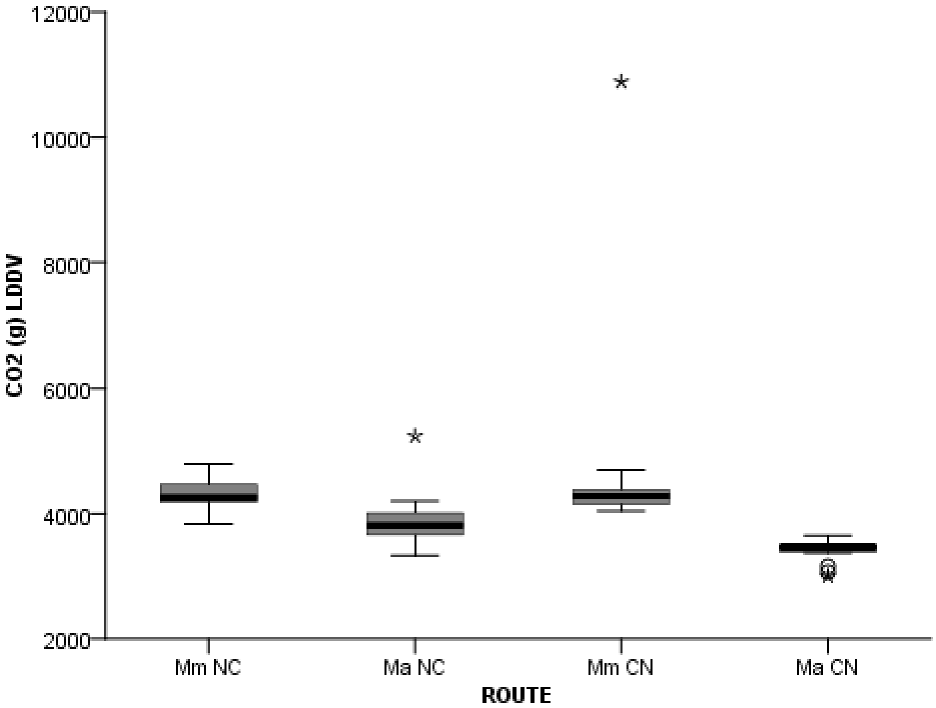

HC (g) LDGV
5.0
4.5
4.0
3.5
3.0
lm1 AP
lm2 AP
lh AP
lu AP
lm1 PA
lm2 PA
lh PA
lu PA
ROUTE

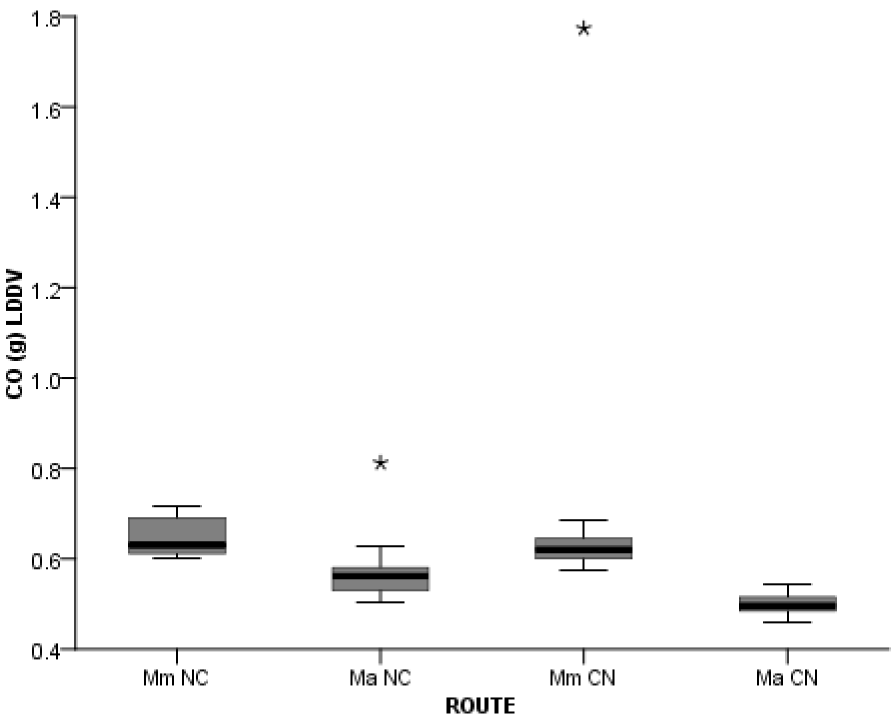
B7 *Intercity routes – Fuel consumption from LDDV and LDGV*

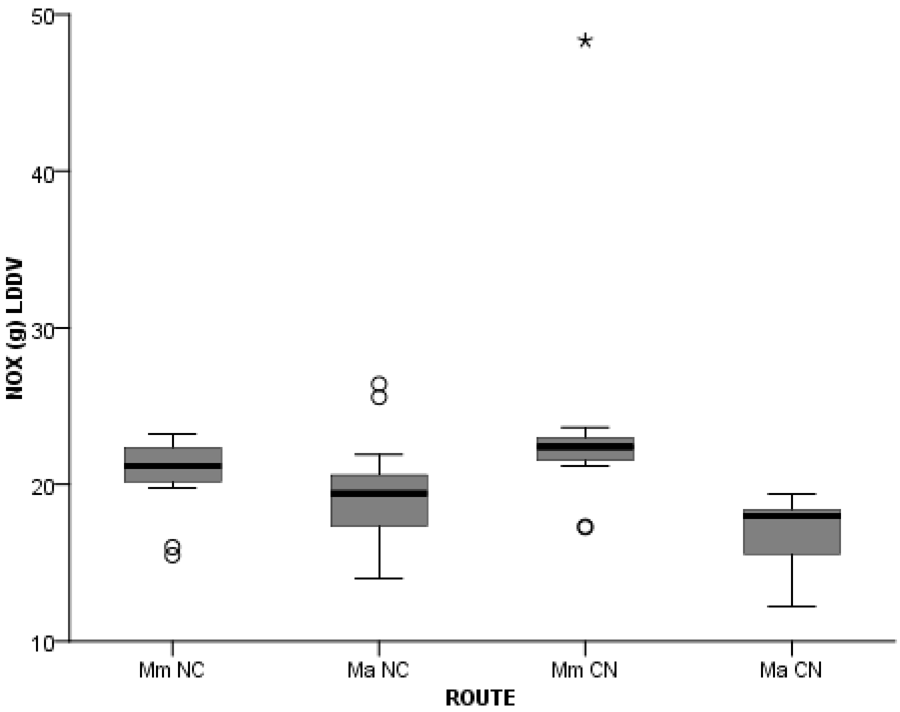




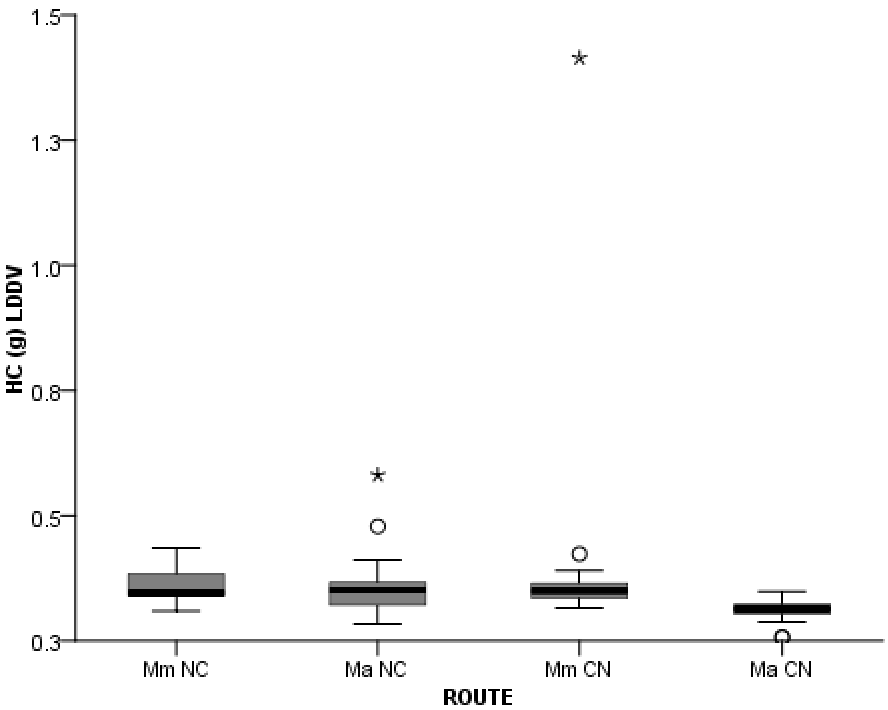
B8 *Metropolitan routes - CO_2, CO, NO_X and HC from LDDV*





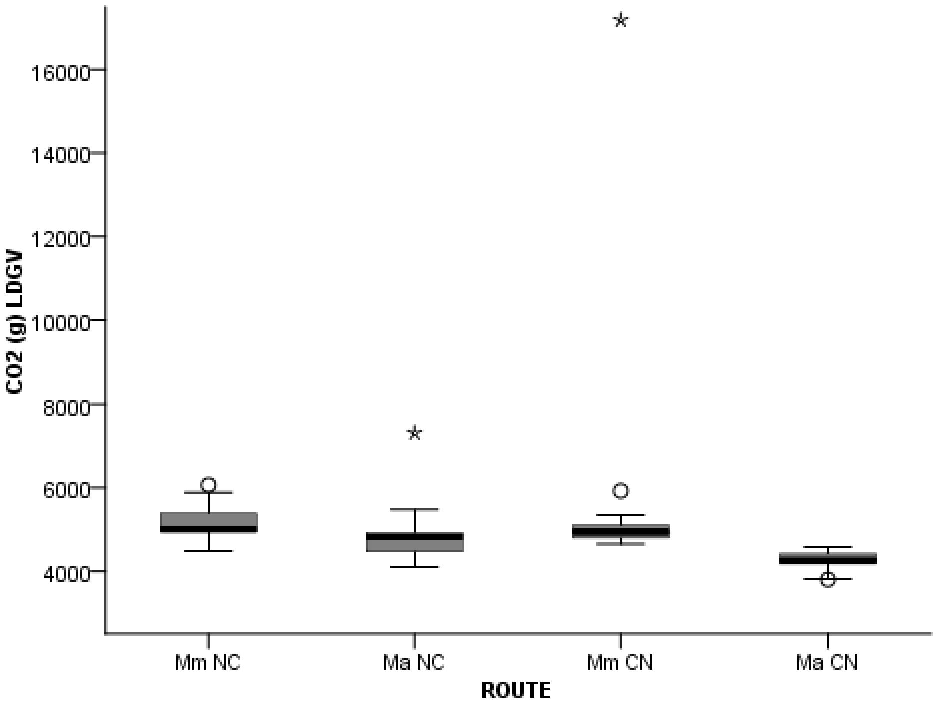


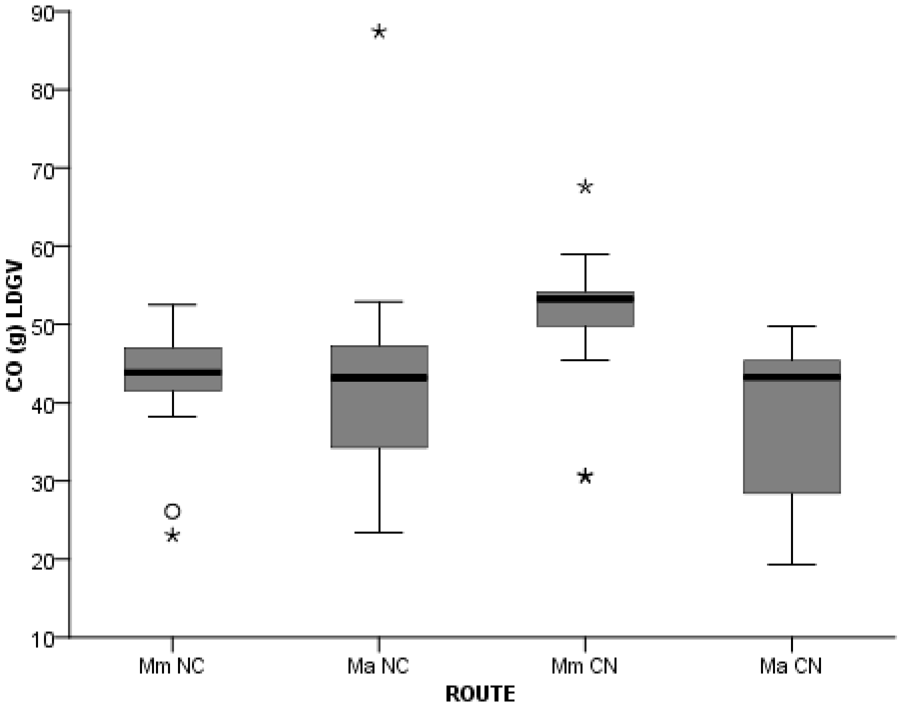
50
40
30
20
10
NOX (g) LDDV
Mm NC
Ma NC
Mm CN
Ma CN
ROUTE

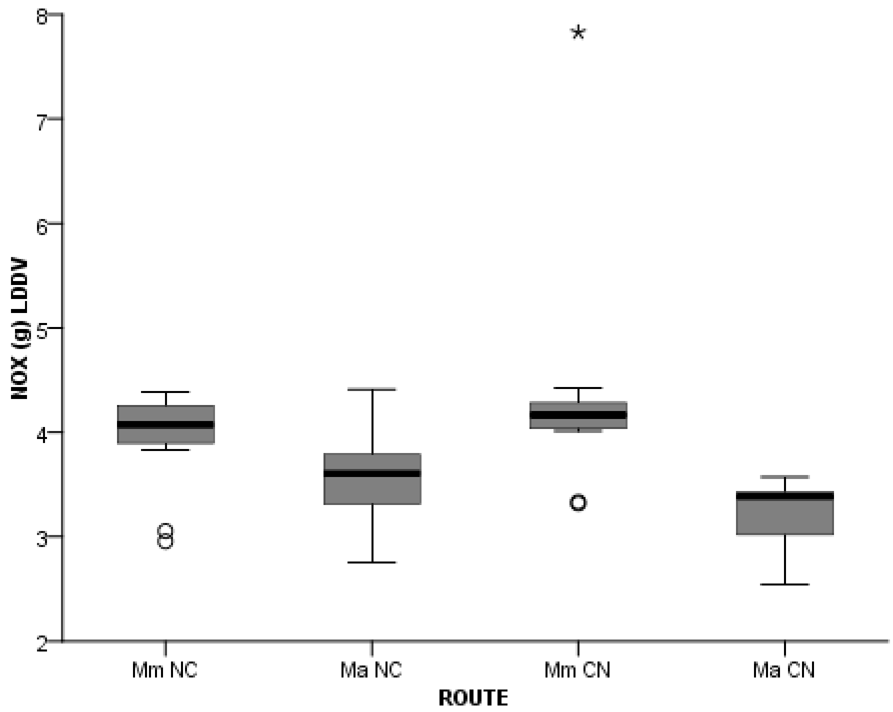


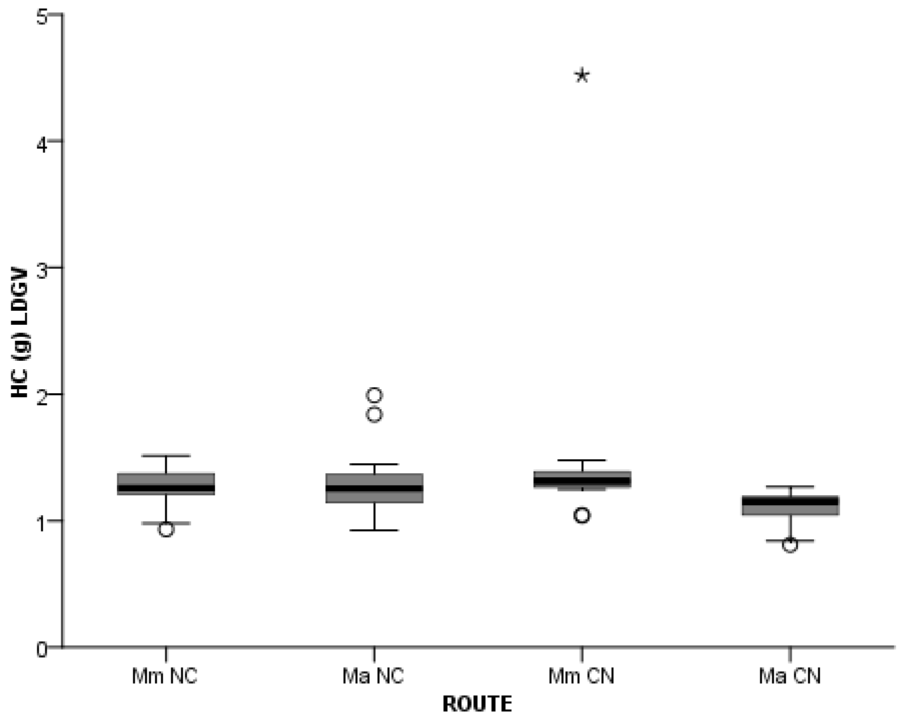
1.5
1.3
1.0
0.8
0.5
0.3
HC (g) LDDV
Mm NC
Ma NC
Mm CN
Ma CN
ROUTE

B9 Metropolitan routes - CO_2, CO, NO_X and HC from LDGV

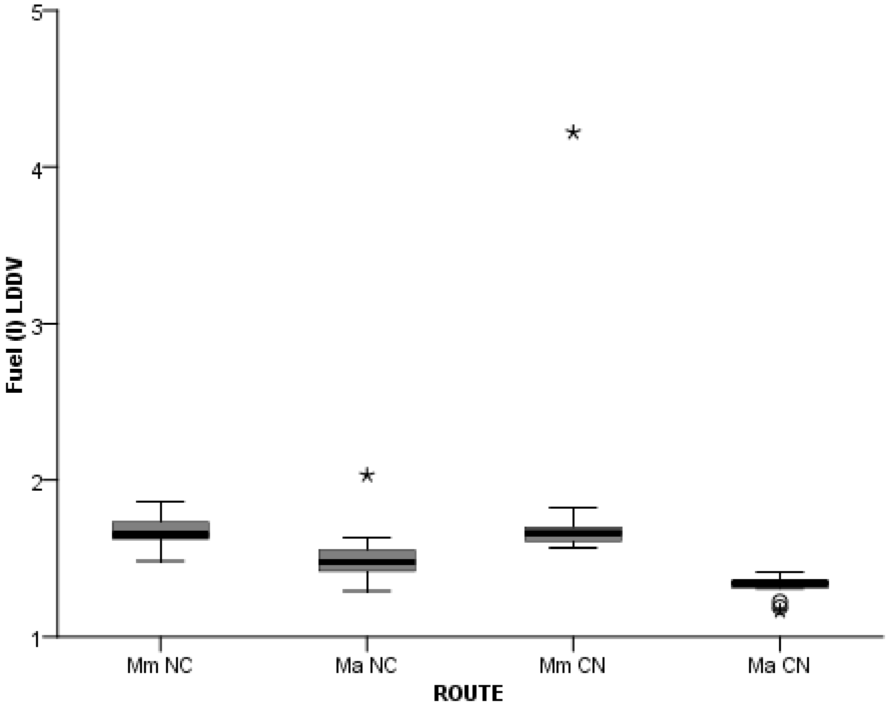


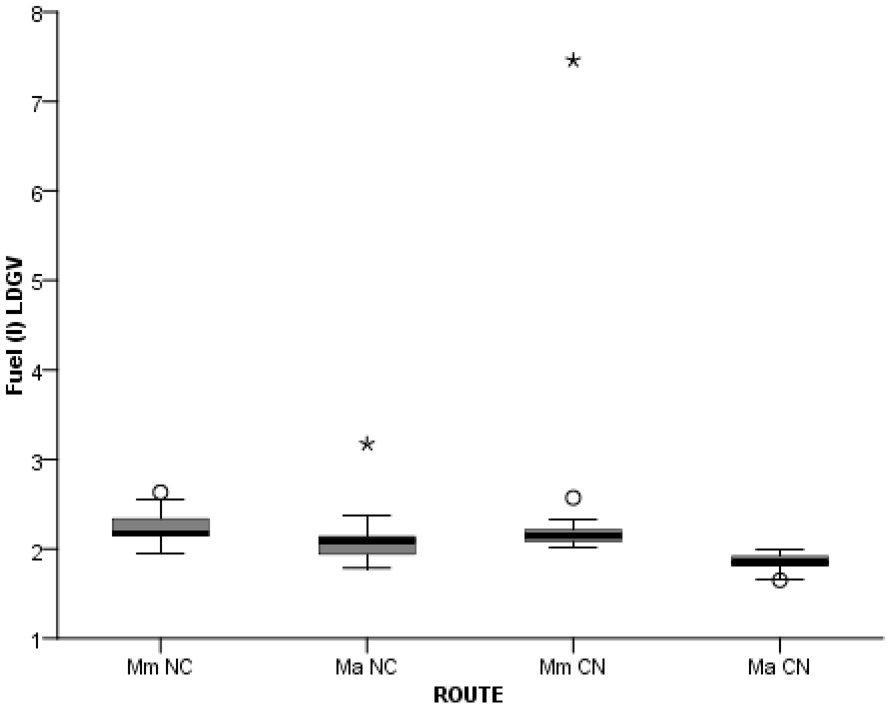



NOX (g) LDDV
8
7
6
5
4
3
2
Mm NC
Ma NC
Mm CN
Ma CN
ROUTE


HC (g) LDGV
5
4
3
2
1
0
Mm NC
Ma NC
Mm CN
Ma CN
ROUTE

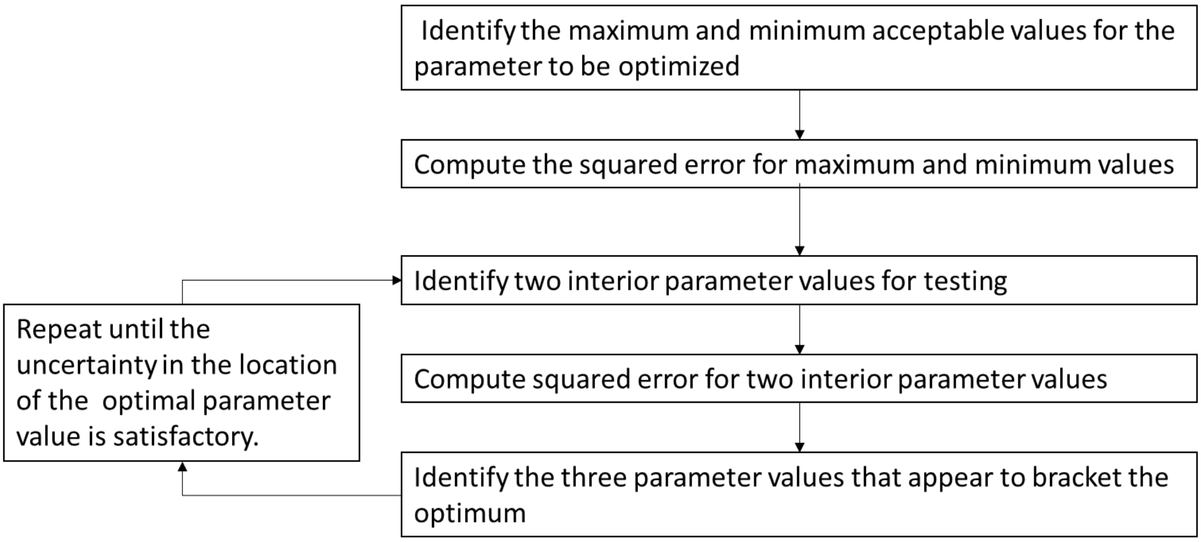
B10 Metropolitan routes – Fuel consumption from LDDV and LDGV





C IMPLEMENTATION OF ALGORITHMS

C1 GOLDEN METHOD SEARCH FOR MODEL CALIBRATION



C2 Calibration of Volume Delay Functions

Although the Highway Capacity Manual [16] provides default parameters VDF functions according the type of road classification, often is not easy to find the correct parameters for a particular region with limited data. For example, if there are 4 road classes there will be 8 parameters to be found. Nevertheless, If there are 10 possible discrete values to test then, 10^8 runs would be needed to be perform [9].

Thus, an optimization method is desirable to find the best VDF parameters. In this context, previous research has demonstrated that algorithms based on intelligent techniques have been efficiently employed. Particularly, genetic algorithms (GA) have become an increasingly used approach [17-19]. A comparative study suggested that GA shows equivalent or better performance than other approaches like the sensitive based analysis (SBA) and the simulated annealing approach [20, 21].

Regarding the calibration parameters, the root-mean-square error (RMSE) is commonly used to compare the experimental observations with the estimated observations [22]. The Equation (1) shows how RMSE is determined where “O” denotes the observed vehicle counts, “E” symbolizes the estimated counts by the travel demand model and “N” represents the number of segments that contain observed counts. Acceptable RMSE values can vary between 30% to 40%, according the network size [23].

$$RMSE = \sqrt{\frac{\sum (O_i - E_i)^2}{N}} \bigg/ \frac{\sum O_i}{N} \tag{1}$$

C3 Basic structure of genetic algorithms

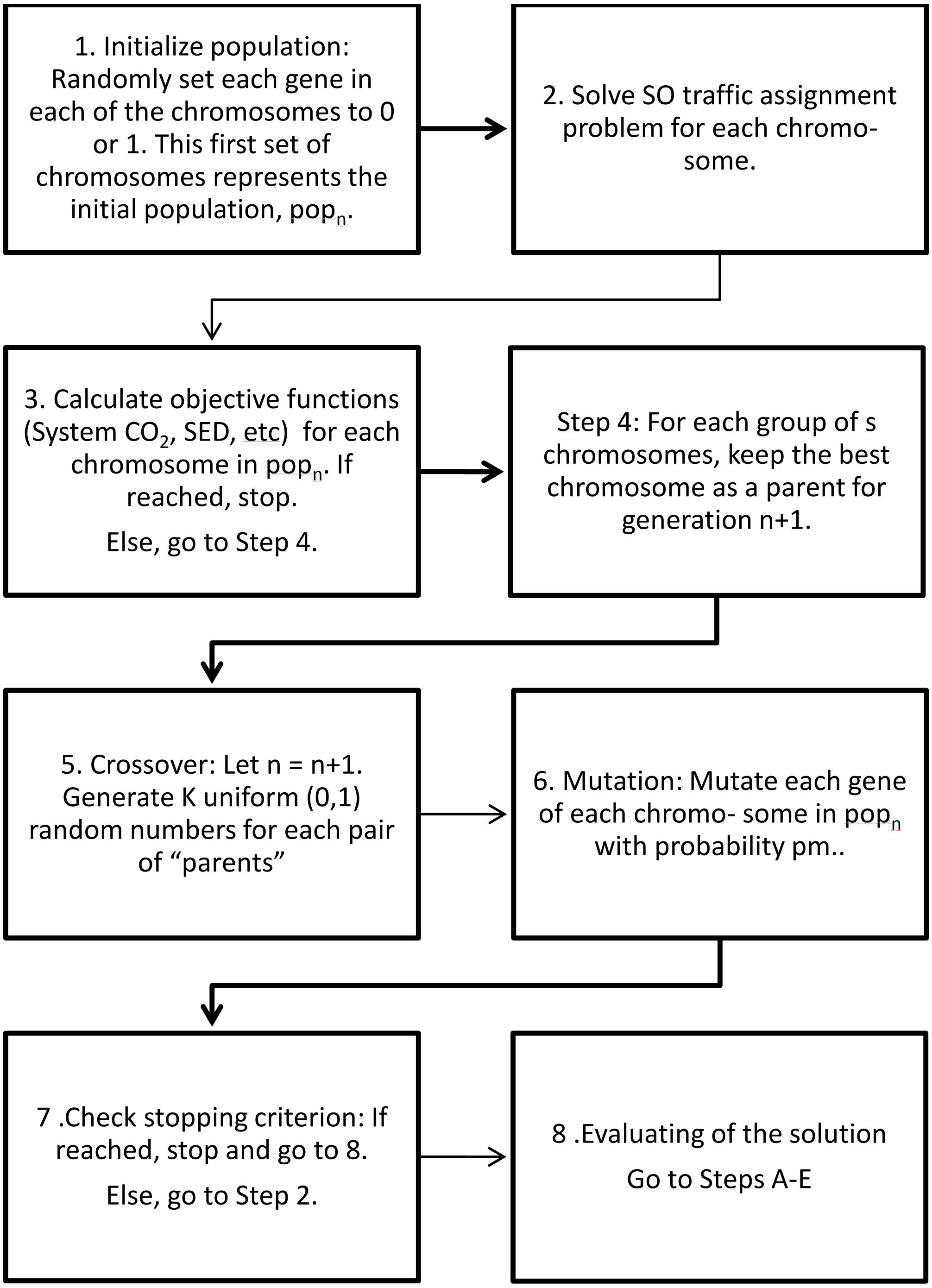
Genetic algorithms are adaptive procedures to find the global optimum solution for an optimization problem. The population members are strings or chromosomes, which as originally conceived are binary representations of solution vectors. GA undertakes to select subsets of solutions from a population [183].

In order to set up the use of a genetic algorithm it is necessary to outline a representation of the problem genome, a means of scoring a fitness, and a means of reproduction [184]. Additional possibilities are to provide means of mutation and crossover to offer more flexibility to the algorithm. GA need a way to score its population which usually is also referred to as fitness. Numerous genetic algorithms preserve the strongest or highest scored genome, a strategy frequently denoted as elitism. The scoring and fitness operation within the GA also allow for removal of the unfit genomes. This is important, since the upcoming generations must derive from the higher scored or the more fit genomes [185].

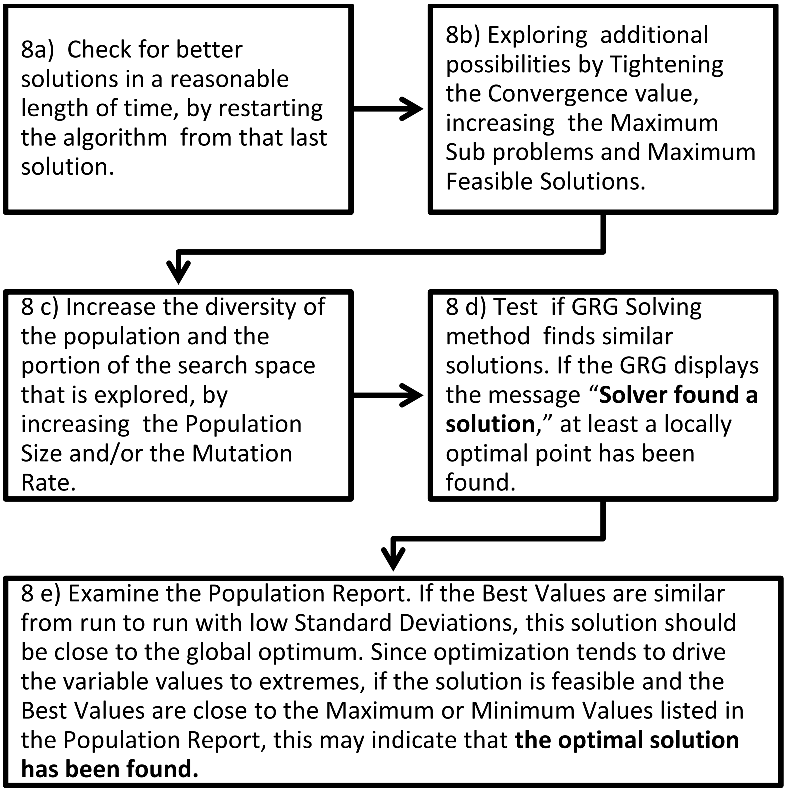
Reproduction is another essential operation required for a genetic algorithm. Reproduction should incorporate two genomes within the population. The two parents should produce a number of descendants (off spring) that should be based on the two parent's data. Often off spring is a binary mix of the parent's values, but can be also new random values within a range of the parents. Relationship to the parents is important because this is what locates the local minimums of the problem space [9].

Genetic mutation and crossover operations are also very convenient. These processes are designed to change offspring in a way that may possibly allow finding the local minimum area of the problem space. Often mutations are random changes to a genome that are unpredictable, for example a random gene's binary value would be flipped, or would be set to a new random number. Crossover is analogous processes to reproduction where two genomes swap values to produce a crossed genome in hopes that the better genes of one genome will be incorporated with another to yield better results [185]. Eventually if mutation or crossover is not executed the results could end up locking onto a local minimum and the GA would not be able to break away from this solution to find the global minimum [185].

A disadvantage of any evolutionary algorithm is that a solution is "better" only in comparison to other, currently identified solutions; such an algorithm actually has no concept of an "optimal solution," or any method to check whether a solution is optimal. This also means that an evolutionary algorithm never knows when to stop, aside from the length of time, or the number of iterations or candidate solutions [186]. Figure 1 shows the application of a genetic algorithm for of a network optimization based on environmental criteria [94]. Appendix Figure 2 outlines several procedures for evaluating the quality of the solutions given by the evolutionary algorithm.

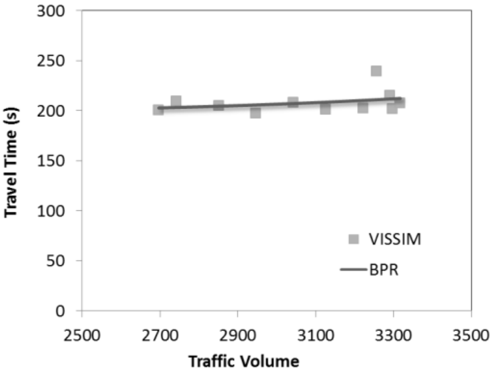


Appendix Figure 1 Step by step procedure regarding the implementation of an evolutionary algorithm for solving the network optimization problem with environmental cost functions (adapted from [94]**).**

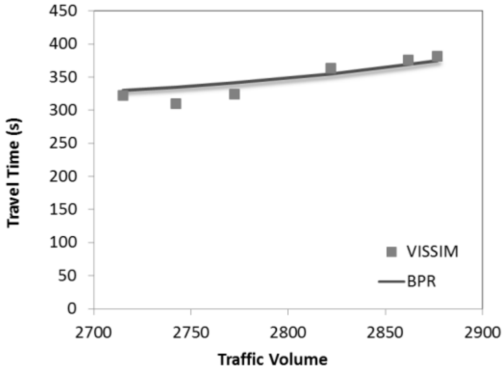


Appendix Figure 2 Procedure for assessing the quality of the solution given by the evolutionary algorithm (adapted from [186]**) .**

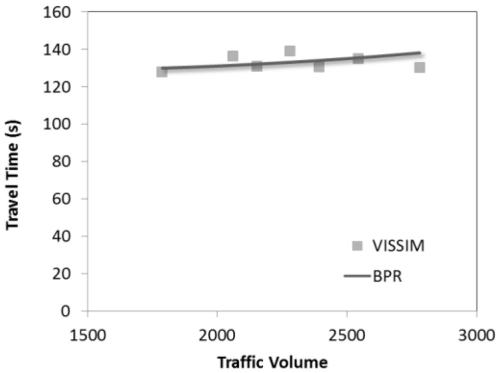
D LINK PERFORMANCE FUNCTIONS – TRAVEL TIME, ENVIRONMENTAL DAMAGE, AND CO_2 COSTS


Travel Time (s)
Traffic Volume
VISSIM
BPR

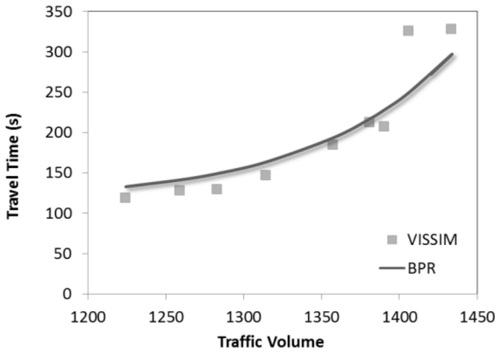
OA


Travel Time (s)
Traffic Volume
VISSIM
BPR

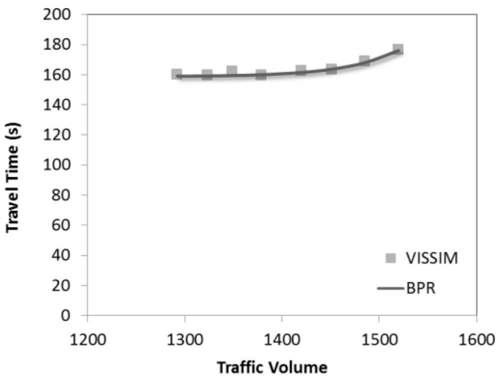
OB


Travel Time (s)
Traffic Volume
VISSIM
BPR

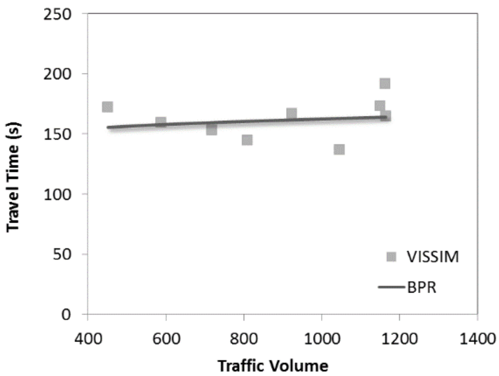
OC

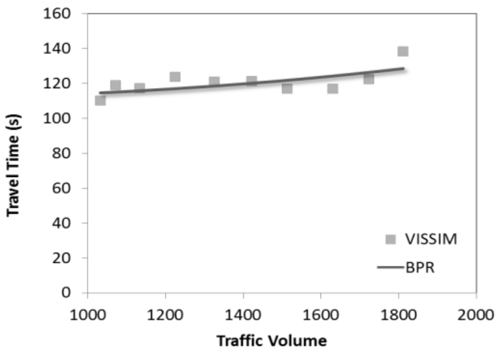

Travel Time (s)
Traffic Volume
VISSIM
BPR

AD

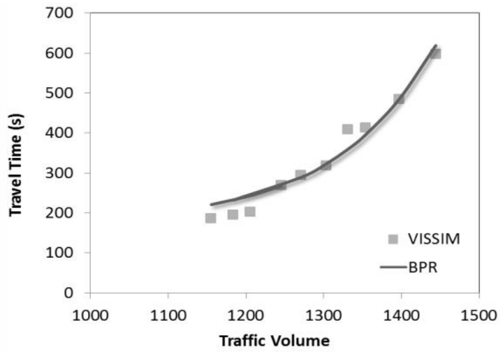

Travel Time (s)
Traffic Volume
VISSIM
BPR

ED


Travel Time (s)
Traffic Volume
VISSIM
BPR

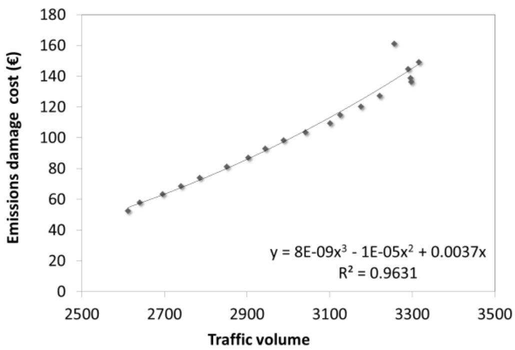


CB

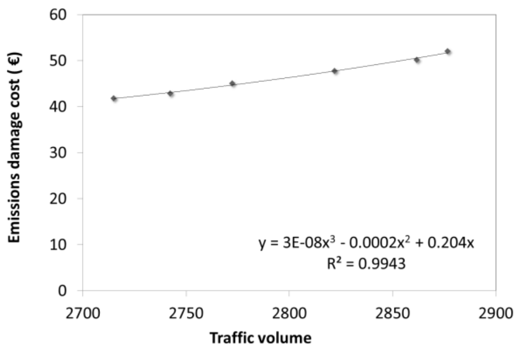


BD

Appendix Figure 3 Volume Env. Damage Cost Functions for the main links of the urban network



OA



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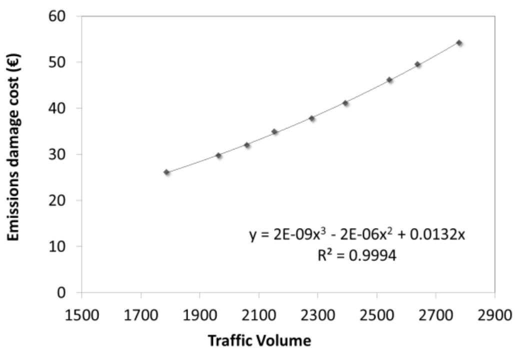

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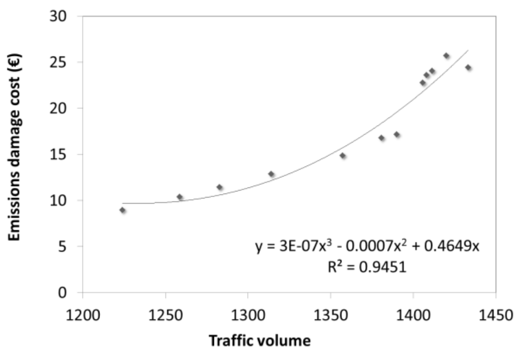

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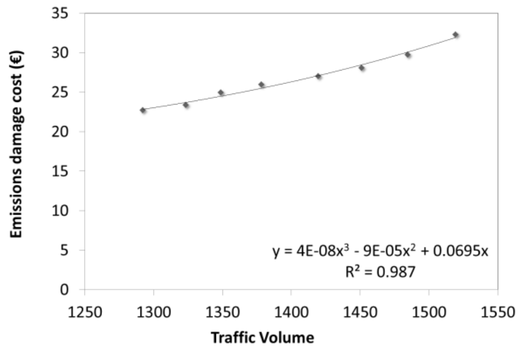

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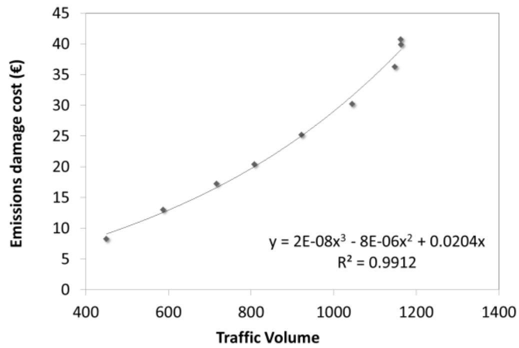
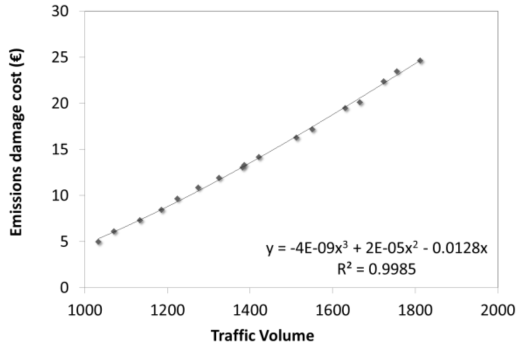


CE



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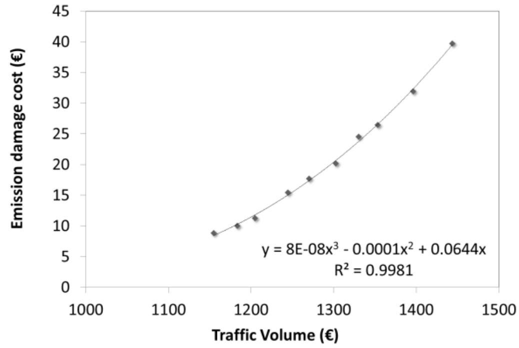
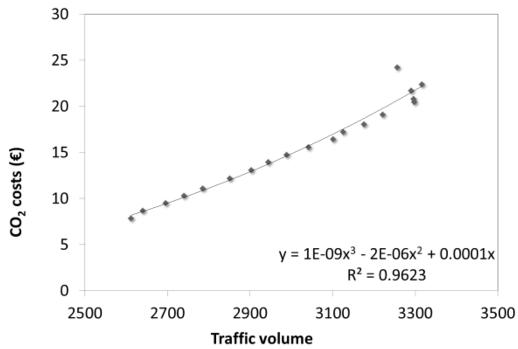
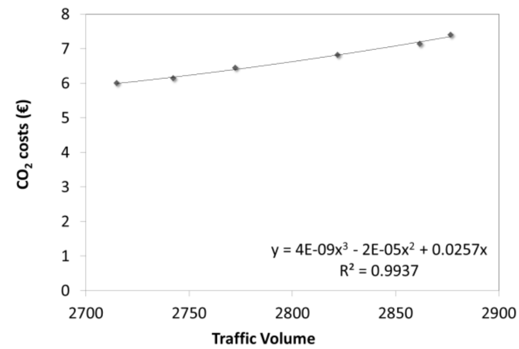


BD

Appendix Figure 4 **Volume Damage Cost Functions for the main links of the urban network**



OA



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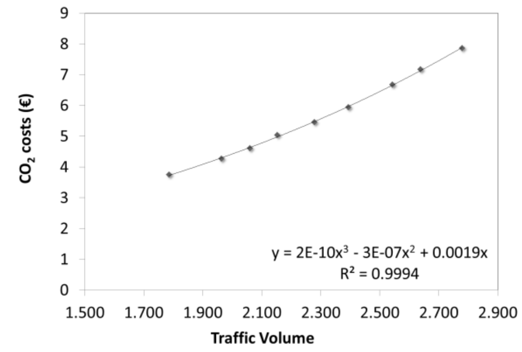
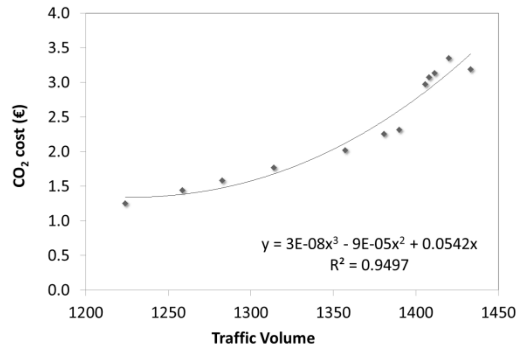


OC



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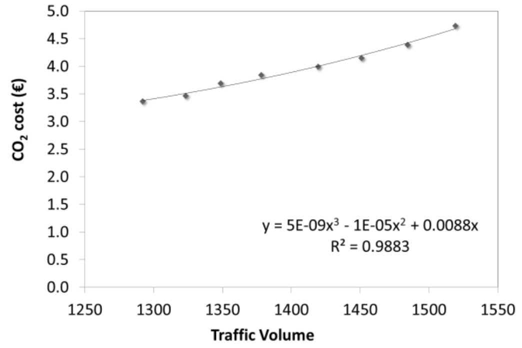
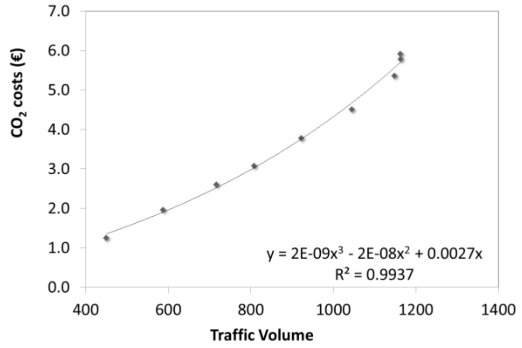
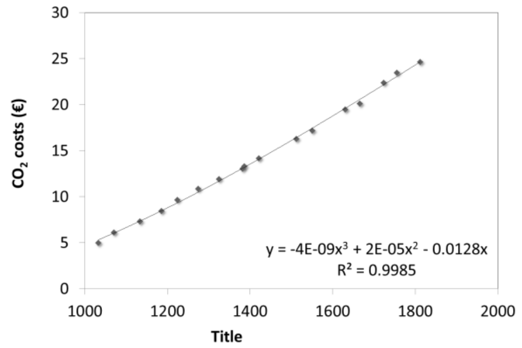


ED



CE



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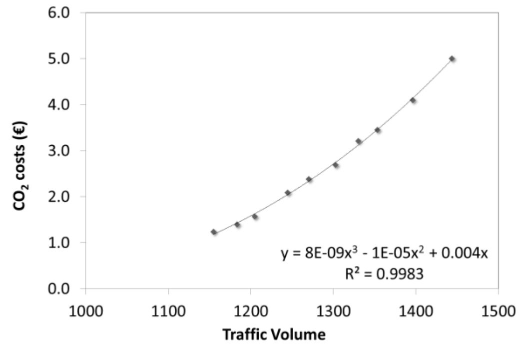

BD

Appendix Figure 5 Volume-CO_2 Cost Functions for the main links of the urban network