UNIVERSIDAD POLITÉCNICA DE MADRID
ESCUELA TÉCNICA SUPERIOR DE INGENIEROS
DE CAMINOS, CANALES Y PUERTOS

DOCTORAL THESIS

Understanding how to reduce road
transport emissions. Modelling the
impact of eco-driving

ÁLVARO GARCÍA CASTRO
M.Sc. Civil Engineer

SUPERVISORS

ANDRÉS MONZÓN DE CÁCERES, Ph.D.
MANUEL ROMANA GARCÍA, Ph.D.

Patience is a tree with bitter roots that bears sweet fruits.

Persian proverb

La paciencia es un árbol de raíz amarga pero de frutos muy dulces.

Proverbio persa

AGRADECIMIENTOS

Con estas líneas quiero agradecer a todas las personas que de algún u otro modo han contribuido a la consecución de esta tesis.

En primer lugar a mi director Andrés Monzón, por la oportunidad de formarme y realizar esta tesis doctoral. Hago extensivo mi agradecimiento a Manuel Romana por su colaboración en la tesis y en la estancia en la University of Florida.

A mis compañeros de proyecto ICT-Emissions Cristina, Andrés y Fiamma, por todas sus horas, viajes y teleconferencias juntos. A toda la gente de TRANSyT, por hacer estos años agradables y divertidos y compartir conmigo cafés, comidas y buenos momentos.

A todos mis amigos por seguir soportándome después de tantos años juntos y aguantar estoicamente mis explicaciones, aunque puedan provocar somnolencia.

A mi familia, grande en todos los sentidos.

A ti, por todo, por ser y por estar.

Álvaro

ABSTRACT

Climate change and the reduced air quality in our metropolitan areas are two of the main environmental problems that the society is addressing currently. Being road transportation one of the main contributors, public administrations are facing these problems from different points of view: shift to cleaner modes, new fuels and vehicle technologies, demand management and the use of information and communication technologies (ICT) applied to transportation.

The first objective of this thesis is to understand how certain ICT measures affect traffic, emissions and vehicle dynamics. The study is based on a data collection campaign with floating vehicles to evaluate the impact of four specific measures: section speed control, variable speed limits, cruise control and eco-driving.

The second objective of the study focuses on eco-driving, as it is one of the measures that present the largest fuel savings at an individual level. Although these savings are well documented in the literature, few studies focus on how eco-drivers affect the surrounding vehicles and the traffic, and what would be the impact in case of different eco-drivers percentage.

Using a traffic micro-simulation tool, four models in urban context have been built, corresponding to urban motorway, urban arterial, urban collector and a local street. Both the base-case and the parameters setting to simulate eco-driving have been calibrated with the data collected through floating vehicles.

In total 72 scenarios were simulated, varying the type of road, traffic demand and the percentage of eco-drivers. Then, the CO₂ and NO_x emissions have been estimated through the use of an emission model at microscopic level.

The results show that in scenarios with high percentage of eco-drivers and high traffic demand the emissions rise. Higher headways and smooth acceleration and decelerations increase congestion, producing higher emissions globally.

RESUMEN

Entre los problemas medioambientales más trascendentales para la sociedad, se encuentra el del cambio climático así como el de la calidad del aire en nuestras áreas metropolitanas. El transporte por carretera es uno de los principales causantes, y como tal, las administraciones públicas se enfrentan a estos problemas desde varios ángulos: Cambios a modos de transporte más limpios, nuevas tecnologías y combustibles en los vehículos, gestión de la demanda y el uso de tecnologías de la información y la comunicación (ICT) aplicadas al transporte.

En esta tesis doctoral se plantea como primer objetivo el profundizar en la comprensión de cómo ciertas medidas ICT afectan al tráfico, las emisiones y la propia dinámica de los vehículos. El estudio se basa en una campaña de recogida de datos con vehículos flotantes para evaluar los impactos de cuatro medidas concretas: Control de velocidad por tramo, límites variables de velocidad, limitador de velocidad (control de crucero) y conducción eficiente (eco-driving).

Como segundo objetivo, el estudio se centra en la conducción eficiente, ya que es una de las medidas que más ahorros de combustible presenta a nivel individual. Aunque estas reducciones están suficientemente documentadas en la literatura, muy pocos estudios se centran en estudiar el efecto que los conductores eficientes pueden tener en el flujo de tráfico, y cuál sería el impacto si se fuera aumentando el porcentaje de este tipo de conductores.

A través de una herramienta de microsimulación de tráfico, se han construido cuatro modelos de vías urbanas que se corresponden con una autopista urbana, una arteria, un colector y una vía local. Gracias a los datos recogidos en la campaña de vehículos flotantes, se ha calibrado el modelo, tanto el escenario base como el ajuste de parámetros de conducción para simular la conducción eficiente.

En total se han simulado 72 escenarios, variando el tipo de vía, la demanda de tráfico y el porcentaje de conductores eficientes. A continuación se han calculado las emisiones de CO₂ and NO_x mediante un modelo de emisiones a nivel microscópico.

Los resultados muestran que en escenarios con alto porcentaje de conductores eficientes y altas demandas de tráfico las emisiones aumentan. Esto se debe a que las mayores distancias de seguridad y las aceleraciones y frenadas suaves hacen que aumente la congestión, produciendo así mayores emisiones a nivel global.

INDEX

PART I – RESEARCH FRAMEWORK AND METHODOLOGY	15
1. INTRODUCTION. POSING THE PROBLEM	17
1.1. Posing the problem.....	18
1.2. Thesis structure	20
2. LITERATURE REVIEW. RESEARCH OBJECTIVES AND METHODOLOGY	23
2.1. Measures to reduce emissions in road transportation. Eco-driving.....	24
2.1.1. Road transportation – Energy consumption, emission of Greenhouse Gases and pollutants	24
2.1.2. Speed management.....	27
2.1.3. ICT measures to reduce emissions	33
2.1.4. Eco-driving. Previous research.....	38
2.1.5. Traffic and emissions simulation.....	51
2.2. Research objectives and methodology.....	55
2.2.1. Research objectives	55
2.2.2. Research methodology.....	56
PART II – ICT MEASURES. DATA COLLECTION.....	61
3. CASE STUDY DEFINITION – DATA COLLECTION.....	63
3.1. The ICT-Emissions project	64
3.2. Madrid metropolitan area	66
3.3. Preliminary study. Variable Speed Limits	68
3.3.1. Methodology to evaluate VSL systems using an aggregate effectiveness indicator	68
3.3.2. Preliminary analysis: West section of Madrid M30 motorway	71
3.3.3. Analysis of results	74

3.4. Main data collection campaign.....	81
PART III – DATA ANALYSIS. ICT MEASURES, CONGESTION AND DRIVING DYNAMICS	89
4. IMPACTS OF ICT MEASURES AND ECO-DRIVING ON FUEL CONSUMPTION AND DRIVING DYNAMICS	91
4.1. Evaluation variables	92
4.2. Section Speed Control	96
4.3. Variable Speed Limits	99
4.4. Cruise Control.....	102
4.5. Eco-Driving.....	104
5. CONGESTION EFFECTS ON FUEL CONSUMPTION	107
5.1. Traffic congestion in energy and emission models.....	108
5.2. Congestion indicators and data processing.....	110
5.3. Results. Fuel consumption as a function of delay	113
5.4. Conclusions on fuel consumption and congestion	119
6. FUEL CONSUMPTION EXPLANATORY VARIABLES	121
6.1. Reducing the number of variables. Factor Analysis.....	122
6.1.1. Definitions and theoretical background	122
6.1.2. Application to the case study of Madrid.....	124
6.2. Explaining the fuel consumption variation. Multiple regression model..	132
6.3. Consideration on the slope of the itineraries	135
PART IV – NETWORK WIDE SIMULATION OF ECO-DRIVING.....	137
7. ECO-DRIVING SIMULATION IN DIFFERENT TYPES OF ROADS	139
7.1. Selection of itineraries to model	140
7.1.1. Urban motorway	141

7.1.2.	Urban arterial.....	143
7.1.3.	Urban collector	144
7.1.4.	Local street.....	145
7.2.	Model construction and calibration of the basecase.....	148
7.2.1.	Urban Motorway.....	151
7.2.2.	Urban arterial.....	157
7.2.3.	Urban collector	163
7.2.4.	Local street.....	168
7.3.	Adjustment of micro simulation tool parameters to reproduce eco-driving behavior	173
7.3.1.	Eco-driving effects on speed profiles.....	173
7.3.2.	Eco-driving simulation in VISSIM.....	174
7.4.	Scenarios to simulate.....	179
8.	IMPACTS OF DIFFERENT ECO-DRIVING PENETRATION RATES ON TRAFFIC AND EMISSIONS.....	185
8.1.	Simulation results for the base-case scenarios	186
8.2.	Eco-driving impacts. Results	189
8.3.	Analysis of eco-driving impacts in each type of road	193
8.3.1.	Urban motorway.....	193
8.3.2.	Urban arterial.....	195
8.3.3.	Urban collector	198
8.3.4.	Local streets.....	201
8.4.	Aggregation of eco-driving impacts in an urban area	204
8.5.	Eco-driving impacts. Time aggregation	208
8.6.	Summary of results.....	212
8.7.	Answers to research questions	214

8.8. Results compared to previous research.....	217
PART V – CONCLUSIONS, FURTHER RESEARCH AND REFERENCES	219
9. CONCLUSIONS AND FURTHER RESEARCH.....	221
9.1. Objectives compliance review	222
9.2. Main findings	225
9.3. Limitations and future research lines	227
10. REFERENCES.....	229
ANNEX I- SCIENTIFIC PUBLICATIONS	241

INDEX of FIGURES

Figure 1. Structure of the thesis.....	20
Figure 2. Integrated approach to reduce road transportation emissions. Source: Samaras et al. (2012).....	27
Figure 3. Changing to eco-driving behavior strategies	40
Figure 4. Scheme of scenarios and impacts of different eco-driving penetration rates.....	58
Figure 5. Research methodology steps and relationships.....	59
Figure 6. Location of Madrid, Spain.....	66
Figure 7. Madrid motorway network. Source: Valdes, 2012.....	67
Figure 8. Regression fit for CO emissions as a function of speed and acceleration rates. Source: Rakha et al. (2000)	69
Figure 9. Graphic representation of PAA indicator from an acceleration function.	70
Figure 10. Daily Traffic profile in the west section of the M30 motorway. Southbound.....	71
Figure 11. West Madrid motorway ring-road and the 5.8 km. test section (from A to B) with the location of the Variable Message Signs (VMS). The bottleneck junction where the congestion usually starts (M-500) is highlighted.....	72
Figure 12. PAA indicator values in free flow. Obtained in the morning hours of 5 and 6 June.	74
Figure 13. Comparison of the effectiveness indicator (PAA) on Tuesday 5 and 12 June.....	75
Figure 14. Comparison of speed profiles for trips with VSL activated and deactivated.....	76
Figure 15. PAA values and travel times	78
Figure 16. PAA values and CO ₂ emissions	79
Figure 17. PAA values and NO _x emissions.....	80
Figure 18. Data collection calendar and schedule.....	84
Figure 19. Monitored itineraries in the data collection campaign in Madrid	85
Figure 20. Data collection process.....	86
Figure 21. Section Speed Control system in operation	96

Figure 22. Madrid case study. Traffic intensities on a weekday at M30 East section northbound.....	97
Figure 23. Madrid case study. Traffic intensities on a weekday at M30 West section southbound.....	99
Figure 24. Madrid case study. M30 West section southbound with detail of the bottleneck junction	100
Figure 25. Recommended Variable Speed Limit in operation at the M30 West Section	100
Figure 26. Entrance to the M30 tunnel section limited to 70 km/h	102
Figure 27. Urban itinerary for eco-driving testing.....	105
Figure 28. Urban and ring motorway itineraries with the same average speed but with different fuel consumption.....	109
Figure 29. Relation between fuel consumption and delay rate - Example of two itineraries in M30 Ring Motorway	113
Figure 30. Fitting curve of fuel consumption for delay rates close to free flow conditions (LOS A and LOS B)	115
Figure 31. Example of Positive Accumulated Acceleration and fuel consumption as a function of delay, for an itinerary of M30 urban motorway	116
Figure 32. Fuel consumption as a function of the delay rate in urban itinerary	117
Figure 33. Regression lines of fuel consumption and positive accumulated acceleration as a function of the delay rate in urban itinerary	118
Figure 34. Box-and-whisker plot for the variable fuel consumption, differentiating among vehicles.....	125
Figure 35. Results of reliability analysis for the first set of considered variables.....	125
Figure 36. Reliability test of the final 30 variables.....	126
Figure 37. Scree plot with the tendency lanes crossing in 3 factors.....	129
Figure 38. Madrid case study. Traffic intensities on a weekday at M30 West section southbound.....	142
Figure 39. Urban Motorway Itinerary. M30 west section	142
Figure 40. Aerial view of the west section of the M30 ring motorway and the M500 junction.....	143

Figure 41. Urban arterial from Lopez de Hoyos to Cuatro Caminos.....	144
Figure 42. Aerial view of the urban arterial segment.....	144
Figure 43. Urban Collector from Principe Pio to San Pol.....	145
Figure 44. Aerial view of Paseo de la Florida to San Pol.....	145
Figure 45. Local streets from Padre Claret to Lopez de Hoyos	146
Figure 46. Aerial view of crossing of Padre Claret with Luis de Salazar	147
Figure 47. Scheme of Wiedemann car-following model (PTV, 2014)	149
Figure 48. Model construction based on Calle30 cartography.....	152
Figure 49. Maximum acceleration as a function of instantaneous speed	155
Figure 50. Travel time calibration for 4 hours of simulation	157
Figure 51. Arterial model designed based on Bing Maps.....	158
Figure 52. Frame of one the videos recorded to count vehicles, pedestrians and adjust the traffic signal programs	159
Figure 53. Traffic signal program of the urban arterial.....	159
Figure 54. Instant speed and position. Urban arterial	160
Figure 55. Collector model based on Bing Maps.....	163
Figure 56. Frame of one the videos recorded to count vehicle, pedestrian and adjust the traffic signal programs	164
Figure 57. Instant speed and position. Urban collector.....	165
Figure 58. Local street model based on Bing Maps	168
Figure 59. Frame of one the videos recorded to count vehicle, pedestrian and adjust the traffic signal programs	169
Figure 60. Instant speed and position. Local street.....	170
Figure 61. Driving behavior parameters in Wiedemann 99.....	175
Figure 62. Daily traffic distribution in M30 East. The peak, off-peak and night hour selected are highlighted.....	179
Figure 63. Passenger Car settings in the VERSIT+ emissions model.....	181
Figure 64. Average speed for the base-case scenarios.....	186
Figure 65. CO ₂ emissions per kilometer for the base-case scenarios.....	187
Figure 66. NO _x emissions per kilometer for the base-case scenarios.....	187
Figure 67. Average speed values for each scenario in the urban motorway model	193

Figure 68. CO ₂ variation with reference to base-case per traffic situation and eco-driving penetration rates. Urban motorway	194
Figure 69. NO _x variation with reference to base-case per traffic situation and eco-driving penetration rates. Urban motorway	195
Figure 70. Average speed values for each scenario in the urban motorway model	196
Figure 71. CO ₂ variation with reference to base-case per traffic situation and eco-driving penetration rates. Urban arterial.....	197
Figure 72. NO _x variation with reference to base-case per traffic situation and eco-driving penetration rates. Urban arterial.....	198
Figure 73. Average speed values for each scenario in the urban collector model	199
Figure 74. CO ₂ variation with reference to base-case per traffic situation and eco-driving penetration rates. Urban collector	200
Figure 75. NO _x variation with reference to base-case per traffic situation and eco-driving penetration rates. Urban collector	201
Figure 76. Average speed values for each scenario in the local street model	202
Figure 77. CO ₂ variation with reference to base-case per traffic situation and eco-driving penetration rates. Local street.....	202
Figure 78. NO _x variation with reference to base-case per traffic situation and eco-driving penetration rates. Local street.....	203
Figure 79. Madrid highways and urban consolidated areas	204
Figure 80. Aggregated average speeds for Madrid area under different scenarios	205
Figure 81. CO ₂ variation with reference to base-case per traffic situation and eco-driving penetration rates. Aggregated values for Madrid area.....	206
Figure 82. NO _x variation with reference to base-case per traffic situation and eco-driving penetration rates. Aggregated values for Madrid area.....	207
Figure 83. Daily traffic distribution. Peak, off-peak and night periods in Madrid.	208
Figure 84. Average speed per type of road and eco-driving penetration rate	209
Figure 85. CO ₂ variation with reference to base-case per traffic situation and eco-driving penetration rates. Daily aggregation.....	210

Figure 86. NO _x variation with reference to base-case per traffic situation and eco-driving penetration rates. Daily aggregation	210
---	-----

INDEX of TABLES

Table 1. Summary of evaluation variables used in different research studies.....	32
Table 2. Summary of eco-driving research studies	49
Table 3 Madrid's first campaign: dates and time periods.....	73
Table 4 Traffic flow intensities upstream (Measuring point PM 22421)	73
Table 5. Values obtained for PAA effectiveness indicator. Congested trips	74
Table 6. Traffic throughput relation downstream/upstream the test section	76
Table 7. Trip travel time per day (activated/deactivated).....	77
Table 8. Emissions per trip (activated/deactivated).....	78
Table 9 Emissions savings comparing the scenarios activated vs. deactivated.....	79
Table 10. Data collection campaign. Trips description.....	83
Table 11. Variables calculated in the data collection campaign	86
Table 12. Variables extracted from the recorded driving profiles and their correspondence with VISSIM and AIMSUM parameters.....	94
Table 13. Changes in vehicle trajectory variables produced by the activation of a section speed control system.....	97
Table 14. Changes in vehicle trajectory variables produced by the activation of a Variable Speed Limit system	101
Table 15. Changes in vehicle trajectory variables produced by the use of a Cruise Control system.....	102
Table 16. Changes in vehicle trajectory variables produced by eco-driving behavior in motorway itineraries.....	104
Table 17. Changes in vehicle trajectory variables produced by eco-driving behavior in urban itineraries.....	105
Table 18. Number of Analyzed Trips According to Itinerary ID Number and Vehicle	111
Table 19. Slope and Goodness-of-Fit of the Regression Line for each Motorway Itinerary and Vehicle	114
Table 20. Slope and Goodness-of-Fit of the Regression Line in Service Levels and Sublevels A and B, for each Itinerary and Vehicle.....	114

Table 21. Goodness-of-Fit of the second degree polynomial in Service Levels and Sublevels A and B, for each Itinerary and Vehicle	115
Table 22. Slope and Goodness-of-Fit of the Regression Line for each Urban Itinerary and Vehicle	117
Table 23. Results of Kaiser-Meyer-Olkin and Barlett's test.....	126
Table 24. Total variance explained by factors with eigenvalue > 1. Extraction Method: Principal Component Analysis.....	128
Table 25. Pattern Matrix and variable loadings to each component.....	130
Table 26. Descriptive statistics of the dependent and independent variables	132
Table 27. Variable correlation matrix.....	133
Table 28. Summary values of the regression model.....	133
Table 29. Multiple regression model coefficients.....	134
Table 30. Trips average slope.....	135
Table 31. Summary of the regression model including slope as predictor	136
Table 32. Multiple regression model coefficients.....	136
Table 33. Vissim input. Relative flow per vehicle type in M30 Motorway.....	154
Table 34. Comparison of real and simulated intensities in 5 different measuring points of the M30 West section	156
Table 35. Travel time calibration for 15 replications	157
Table 36. Vissim input. Relative flow per vehicle type in M30 Motorway.....	161
Table 37. Comparison of real and simulated intensities in 5 different measuring points of the selected urban arterial	162
Table 38. Travel time calibration for 15 replications. Urban arterial.....	162
Table 39. VISSIM input. Relative flow per vehicle type in the area within the M30 motorway	166
Table 40. Comparison of real and simulated intensities in 5 different measuring points of the selected urban collector.....	167
Table 41. Travel time calibration for 15 replications. Urban arterial.....	167
Table 42. VISSIM input. Relative flow per vehicle type in the area within the M30 motorway	171
Table 43. Comparison of real and simulated intensities in 5 different measuring points of the selected local streets	172

Table 44. Travel time calibration for 15 replications. Urban arterial	172
Table 45. Percentage of variation when applying eco-driving.....	173
Table 46. Meaning of the driving behavior parameters of the Wiedemann 99 car following model. Source: PTV (2014).....	175
Table 47. Maximum values of the acceleration functions in VISSIM for motorway and urban trips.....	177
Table 48. Final calibration values of car following parameters.....	177
Table 49. Real fuel consumption and simulated CO ₂ emissions variation after applying eco-driving.....	178
Table 50. Volume to capacity ratio for each scenario.....	180
Table 51. Summary of simulated scenarios	182
Table 52. Emission and traffic simulation results per traffic situation and eco-driving penetration rate. Urban motorway	189
Table 53. Emission and traffic simulation results per traffic situation and eco-driving penetration rate. Urban arterial	190
Table 54. Emission and traffic simulation results per traffic situation and eco-driving penetration rate. Urban collector.....	191
Table 55. Emission and traffic simulation results per traffic situation and eco-driving penetration rate. Local Street.....	192
Table 56. Traffic distribution per type of road inside Madrid second ring road (M40)	205
Table 57. Summary of eco-driving effects per type of road.....	212
Table 58. Summary of eco-driving effects per traffic situation.....	213

PART I – RESEARCH FRAMEWORK AND METHODOLOGY

1. INTRODUCTION. POSING THE PROBLEM

“Men argue. Nature acts”

Voltaire

This first chapter presents the introduction to the document. It starts briefly posing the problem of climate change and pollutant emissions caused by road transportation, deeper developed on Chapter 2. At the end of this introductory chapter the structure of the thesis is explained in detail.

1.1. Posing the problem

Greenhouse gases (GHG) emissions and overconsumption of energy resources represent a global problem, which concerns both their causes and consequences (Ramanathan and Feng, 2009). Changes in the atmospheric presence of greenhouse gases and aerosols alter the energy balance of the climate system. *“Warming of the climate system is unequivocal, as is now evident from observations of increases in global average air and ocean temperatures, widespread melting of snow and ice, and rising global average sea level”* (Intergovernmental Panel on Climate, 2007).

The transportation sector is one of the largest emitters despite the advances in the field of engine technology. According to statistics provided by the European Environment Agency (2013), GHG emissions from the road transportation sector have started to decline, but still account for about 93% of the emissions attributable to the transportation sector, and approximately 20.4% of total emissions. This value is slightly higher than reported for other developed countries such as Japan (Greenhouse Gas Inventory Office of Japan, 2012). In the United States, the contribution of road transportation to total GHG emissions is even higher, reaching almost 22% (United States Environmental Protection Agency, 2013). The transport sector accounted for 26% of global energy consumption in 2010, and transportation energy use is expected to increase by 1.1% every year from 2010 to 2040 according to the International Energy Outlook 2013 Reference case (Energy Information Administration, 2013).

In addition to the global problem of GHG emissions, another current major public concern is air quality in urban areas. According to the European Environment Agency (2010), during the period 1997–2008 up to 62% of the European population living in cities (70% of the total population) may have been exposed to concentrations of particulate matter, ozone or nitrogen dioxide above European Union established air quality limits. This constitutes an alarming health problem as recent studies have led to increase the importance of traffic-related air pollution in respiratory diseases (Laumbach and Kipen, 2012).

Transportation is widely recognized to be a significant source of air pollution, specially in metropolitan areas where urban transportation accounts for 70% of pollutants (European Environment Agency, 2010).

In this context, much of the effort dedicated to reducing energy consumption and emissions has focused on the road transportation sector. The European Commission (2009) proposes an integrated policy to tackle the problem from different approaches; these include particularly demand management, a shift to cleaner modes, improving vehicle technologies, traffic management, and the use of information and communication technologies (ICT). ICT applied to transportation (Intelligent Transportation Systems, or ITS) is a broad field that has the potential for producing positive effects on efficiency, safety, comfort and the environment (European Commission, 2008).

Toffolo et al. (2014) classified the ICT measures in five different groups, including traffic management, driver behavior change or advanced driver assistance systems (ADAS).

Focusing on one of these measures, eco-driving has shown a great potential in reducing energy consumption and emissions in individual test. According to Barkenbus (2010), eco-driving is the efficient operation of a vehicle following specific rules such as using the vehicle inertia, accelerating and braking smoothly, maintaining a steady speed, etc.

In spite of the existence of many individual eco-driving studies, it is still not clear how different penetration rates of eco-drivers could affect the traffic flow and consequently the total emissions. Therefore, it remains unknown if eco-driving is favorable in all the situations.

1.2. Thesis structure

The thesis is structured in 5 parts and 10 chapters, which can be identified with consecutive steps of the research methodology, later detailed in Section 2.2.2. The following figure represents the thesis structure and the workflow:

Figure 1. Structure of the thesis

PART I – RESEARCH FRAMEWORK AND METHODOLOGY

PART I presents the problem in Chapter 1, while the literature review is presented in Chapter 2. This review covers the general framework of road transportation emissions and their effects in climate change and air quality in our congested cities. It follows with a description of ICT-measures which can reduce the emissions of both GHG and pollutants and some examples of application in roads

and cities around the world. Focusing afterwards in the eco-driving, we will review its definitions and variability of results found in different case studies. The literature review will conclude with the state of the art of traffic and emissions simulation tools, which will be used later to simulate the eco-driving scenarios. Chapter 2 concludes with the research objectives and the methodology.

PART II – ICT MEASURES. DATA COLLECTION

Part II corresponds to Chapter 3, which presents the case study definition in the city of Madrid. It includes a description of the *ICT-Emissions* project, framework in which this research is developed. In this chapter we present all the details of the preliminary studies and the main data collection campaign.

PART III – DATA ANALYSIS. ICT MEASURES, CONGESTION AND DRIVING DYNAMICS

Part III refers to the analysis of the data collected in the data collection campaign previously mentioned.

It starts with Chapter 4, which presents a first analysis of the data reflecting the fuel consumption effects of different ICT measures tested in Madrid. It also analyzes how the ICT measures affect the dynamics of the floating vehicles (acceleration, braking, etc.).

Once the data have been processed and structured in a database, Chapter 5 presents a second analysis to observe the relation between congestion and fuel consumption (and therefore CO₂ emissions), differentiating between urban roads and motorways.

Chapter 6 presents a statistical analysis of the collected data, including a factorial analysis and a multiple regression model, looking for the explanatory variables of fuel consumption and the amount of fuel consumption variation that can be explained by the speed profiles definition.

PART IV – NETWORK WIDE SIMULATION OF ECO-DRIVING

PART IV deals with the traffic simulation of eco-driving and its impact in several scenarios. It is composed of Chapter 7 and Chapter 8.

Chapter 7 describes the simulation process, including the selection of areas to be modeled, calibration of the base case scenario, calibration and validation of the eco-driving behavior and simulation of all the different scenarios.

Once simulated the scenarios, Chapter 8 presents all the results and analyzes them in detail.

PART V- CONCLUSIONS, FURTHER RESEARCH AND REFERENCES

Last Part V corresponds to the conclusions, further research and the list of references.

Chapter 9, Conclusions and Future Research, summarizes the main findings of the research, pointing out its limitations and, finally, giving hints and suggestion for future research work on the topic.

The thesis also includes a bibliography, Chapter 10, where are listed all references, scientific articles, working papers, project reports, etc. reviewed for this work.

ANNEX I

This document includes one annex which presents the related papers published in international journal or conferences.

2. LITERATURE REVIEW. RESEARCH OBJECTIVES AND METHODOLOGY

“In omnibus requiem quaesivi, et nusquam inveni nisi in angulo cum libro”

Thomas à Kempis

The second chapter includes a comprehensive literature review on ICT measures to reduce road transportation emissions, focusing on eco-driving. The chapter starts with the general topic of climate change and emissions caused by road transportation and then leads the reader through the specific research questions about a particular driving behavior: eco-driving. The chapter concludes with the presentation of the research methodology.

2.1. Measures to reduce emissions in road transportation. Eco-driving

2.1.1. Road transportation – Energy consumption, emission of Greenhouse Gases and pollutants

Despite the advances in the field of engine technology and in new fuels, the road transportation sector is one of the largest emitters of greenhouse gases. Emissions and overconsumption of energy resources pose a global problem, which concerns both their causes and consequences (Ramanathan and Feng, 2009).

Changes in the atmosphere by the presence of greenhouse gases and aerosols alter the energy balance of the climate system. The Intergovernmental Panel on Climate Change (2007) states that *“Warming of the climate system is unequivocal, as is now evident from observations of increases in global average air and ocean temperatures, widespread melting of snow and ice, and rising global average sea level”*.

Adaptation to the effects of climate change will require great effort from all the stakeholders related to transportation. Limiting temperature increase by less than 2°C relative to pre-industrial levels will require immediate action. The longer the community waits to take action, the greater will be the effort and the costs.

“Adaptation and mitigation are complementary strategies for reducing and managing the risks of climate change. Substantial emissions reductions over the next few decades can reduce climate risks in the 21st century and beyond, increase prospects for effective adaptation, reduce the costs and challenges of mitigation in the longer term and contribute to climate-resilient pathways for sustainable development” (Pachauri et al., 2014).

As climate change increases, the risks and impacts on transportation will increase (Burbank, Wenger and Sperling, 2012).

GHG emissions from the road transportation sector have started to decline, but still account for about 93% of the emissions attributable to the transportation sector, and approximately 20.4% of total emissions (European Environment Agency 2013). This value is slightly higher than reported for other developed countries

such as Japan (Greenhouse Gas Inventory Office of Japan, 2012). In the United States, the contribution of road transportation to total GHG emissions is even higher, reaching almost 22% (United States Environmental Protection Agency, 2013). Worldwide, the transportation sector accounted for 26% of global energy consumption in 2010, and transportation energy use is expected to increase by 1.1% every year from 2010 to 2040 according to the International Energy Outlook 2013 Reference Case (Energy Information Administration, 2013).

In addition to the global problem of GHG emissions, another major public concern is air quality in urban areas. According to the European Environment Agency (2010), during the period 1997–2008 up to 62% of the European population living in cities (70% of the total population) may have been exposed to concentrations of particulate matter, ozone or nitrogen dioxide above European Union established air quality limits. This constitutes an alarming health problem as recent studies have boosted the importance of traffic-related air pollution in respiratory diseases (Laumbach and Kipen, 2012).

Transport is widely recognized to be a significant source of air pollution, especially in metropolitan areas where urban transportation accounts for 70% of pollutants (European Environment Agency, 2010). In this context, traffic congestion is one of the main causes of the deterioration of air quality in cities all over the world.

Road congestion can be defined as the deterioration of the quality and smoothness of road traffic flows. It is associated, among other things, with high traffic volume, longer trip times, slower speeds and high deviation from free-flow speeds (Smit, Brown, and Chan, 2008).

According to the report by Cambridge Systematics (2004), congestion has several root causes that can be broken down into two main categories:

- Overcapacity in physical bottlenecks: Physical bottlenecks are locations where the physical capacity is restricted, with flows from upstream sections (with higher capacities) being funneled into smaller downstream sections.

- Traffic-influencing events: In addition to the physical capacity, external events such as accidents, bad weather or special events can have a major effect on traffic flow.

In addition to a categorization according to causes, another important classification of road congestion difference between recurring and non-recurring congestion (O'Flaherty, 1997). Recurrent congestion is generally predictable and occurs regularly. It is typically caused by an excess of demand compared with the effective capacity of a road network. On the other hand, non-recurring congestion relates to unreliable travel times resulting from unexpected, unplanned or external events that cannot be easily predicted.

Road congestion produces unwanted impacts in urban areas. More specifically, congestion causes accidents, excessive fuel consumption, noise and air pollution and emissions of greenhouse gases. All these effects are very important when monetization (or economic quantification) of these aspects are taken into account as they generate negative impact on the economy (opportunity costs, lost productivity, etc.), on the environment, health and human welfare.

The most important congestion impact is an increase in travel times due to a decrease in average speeds, which normally leads to an increase of average emissions. (Barth and Boriboonsomsin, 2010). However, moderate travel speed reductions in freeways can reduce emissions rates as most conventional vehicles have minimum fuel consumption at average speeds between 60-80 km/h (Dijkema, van der Zee, Saskia, Brunekreef, and van Strien, 2008)(See also Chapter 5).

In this context, much of the effort spent at reducing energy consumption and emissions focused on the road transportation sector. The European Commission (2009) proposed an integrated policy to tackle the problem from different approaches; these include particularly demand management, a shift towards cleaner modes, improving vehicle technologies, traffic management, and the use of information and communication technologies (ICT).

Figure 2. Integrated approach to reduce road transportation emissions. Source: Samaras et al. (2012)

ICT applied to transportation (Intelligent Transportation Systems, or ITS) is a broad field that has the potential of producing positive effects on efficiency, safety, comfort and the environment (European Commission, 2008).

2.1.2. Speed management

The main tool used by the authorities to manage speed is the setting of speed limits, which tend to be fixed. However, the optimal speed cannot remain constant at all times, since the road conditions are affected by numerous factors, mainly traffic intensity and weather conditions (Giles, 2004).

Speed can be regarded as a key factor that directly affects certain aspects of the road such as traffic performance, road safety and environmental externalities.

1) Traffic performance

Together with intensity and density, speed is one of the key factors determining road capacity. At a critical speed and the corresponding critical intensity or

density, the state of flow will change from stable to unstable and, speed differences and braking process can therefore lead to congestion and reduced road capacity (van Nes, Brandenburg and Twisk, 2008).

2) Road safety

It is generally accepted that high speeds involve a high risk to road safety. This idea is supported by a large number of studies which highlight the relationship between speed and road safety. For instance, Elvik (2005) shows an extensive review of 98 studies containing 460 estimates of the relationship between changes in speed and changes in the number of accidents or accident victims, concluding that “the relationship between speed and road safety is causal, not just statistical”.

3) Environmental externalities

Apart from vehicle technologies, speed is a very important factor determining negative environmental effects such as CO₂ emissions, pollutants (Ntziachristos and Samaras, 2000) and noise (Makarewicz and Gałuszka, 2011).

The concern of traffic authorities to adapt traffic speed to changing road conditions has led in recent years the development of variable speed limits (VSL).

Variable Speed Limits. Research review

VSL are being implemented worldwide; however their effects are not yet clearly defined, and in some cases their benefit are not fully proven.

Based on international experiments and research studies, we summarize the way in which VSL affect the parameters of traffic performance, road safety and environmental levels, and the variables that are used to assess their effectiveness.

Traffic Performance

Regarding traffic performance and traffic flow behavior, there are several parameters which may be affected by the implementation of VSL, including specifically speed and capacity.

The reduction in average speed and speed variations depends largely on the type of speed limits imposed (mandatory or recommended) and their enforcement. Most VSL operate as mandatory limits, such as the M25 controlled motorway around London (Highways Agency, 2004), although there are also some systems with recommended speed limits, such as the Motorway Control System (MCS) on the E4 in Stockholm (Nissan and Bang, 2006).

These systems are based on the capacity increase that occurs when speed and speed variations are reduced by high flow levels. Moreover, speed homogenization reduces the number of acceleration and deceleration maneuvers and, therefore, the oscillations in traffic flow (García, 2009). Heydecker and Addison (2011) shows that under certain congestion conditions, speed determines density; based on this observation, the relationship between density and speed can be estimated depending on speed limits.

The reduction of speed limits has a considerable effect on the speed differential between lanes. In van Nes et al. (2008), the conclusions show that variable speed limit systems do increase the homogeneity of the driving speed.

Based on computer simulations, some authors have evaluated positively the effects of VSL on traffic performance. Zhicai, Xiaoxiong and Hongwei (2004) show the simulation of a number of types of VSL scenarios, and the results indicate that the benefits of VSL are obvious when the traffic volume is equal to or greater than 2,800 veh/h in a double-lane freeway. Hegyi, De Schutter, and Hellendoorn (2005) simulate the effects of VSL on the prevention of congestion caused by shockwaves, obtaining a reduction in total travel time of 21.7%.

Germany has a long tradition of implementing VSL. The first experiment was implemented in 1965 on the A8 motorway between Munich and Salzburg, with good results in terms of harmonization and reduction of speed differences between lanes. These results and many others from German motorways can be found in Schick (2003). Among these cases, we can highlight the report on the A5 motorway in Frankfurt. Based on data from video recording and induction loops, the authors found a significant increase in the empirical maximum traffic intensity in the southbound direction from 5,200 veh/h to 5,900 veh/h (about a 10%

increase). However other studies in the Netherlands (Hoogendoorn and Bovy, 1999) estimate the capacity increase at around 2%.

The M25 in the U.K. can also be highlighted as a successful implementation of VSL. During the first year of operation, a section of this controlled motorway absorbed a 1.5% increase in throughput over 5-hour peak periods, without any detectable increase in congestion levels. Traffic conditions have improved as a result of the reduction in frequency and severity of shockwaves. The study (Highways Agency, 2004) revealed a reduction of over 25% in the typical number of shockwaves during the morning peak period. It has also been observed that the traffic is more evenly spread across all four lanes.

Nissan and Bang (2006) studied the application of VSL on the E4 motorway through Stockholm, showing that lane changes were reduced by over 50%, and that lane distribution became more balanced after the implementation. However, this phenomenon can have negative effects in sections with a high density of on-ramps, as this will lead to smaller gaps in the traffic on the outside lane, making the merging process more difficult and therefore creating congestion on the on-ramp (Knoop, Duret, Buisson and van Arem, 2010).

Experiments were conducted on the ASF (Autoroute du Sud de France) in France in the summer of 2004, with the implementation of an innovative traffic control system on the A7 motorway, which includes VSL. In the southbound corridor, the use of progressively slower speed limits depending on traffic volume has reduced congestion by between 16% and 40%, depending on the section (European Conference of Ministers of Transport [ECMT], 2007).

Road Safety

The effects mentioned in the previous section can also have a positive impact on road safety, since a decrease in the speed limits can lead to a reduction in the speed differences between successive vehicles, resulting in a decline in rear-end collisions.

C. Lee, Hellinga and Saccomanno (2004) present a simulation-based study showing the potential safety benefits of VSL using a real-time crash prediction model integrated with a microscopic traffic simulation model. The study found that variable speed limits can reduce average total crash potential by approximately 25%, by temporarily reducing speed limits during hazardous traffic conditions. Positive effects of VSL have also been found in other simulation-based studies, such as (Piao and McDonald, 2008).

Regarding the study of the implemented VSL, an analysis of crash data in Germany has shown that the use of dynamic speed limit and speed warning signs reduced the crash rate by 20 to 30% (Robinson, 2000). Other German studies cited by Schick (2003) estimate a reduction in the number of accidents of over 30% (A5 motorway, near Frankfurt), and a similar decline in fatalities by more than 60%. In Stuttgart, the reduction in accidents caused by fog conditions is as high as 86%.

In the UK (Highways Agency, 2004) data were analyzed from the M25 in order to compare them with trends. The impact of the controlled motorway driving environment (mainly VSL and managed lanes) had an estimated reduction of injuries of 10% during the period of operation, and a decrease in the ratio of damage of 20%.

The aforementioned program in the South of France also had very positive road safety results, with crashes reduced by 10-20% (ECMT, 2007).

Environmental effects

It is well-known that improved traffic flows can have a significant impact on emission levels (Benedek and Rilett, 1998). There are very few approaches based on simulating emissions in VSL. Of particular note is the simulation of a case study in The Netherlands based on model predictive control, where the total emissions are reduced by over 35% (Zegeye, De Schutter, Hellendoorn and Breunese, 2010).

Returning to the case of the M25 motorway in the U.K., it was found by the Highways Agency (2004) that vehicle emissions have dropped as a result of reducing start-stop driving. Depending on the particular emissions measured, the decrease was between 2% and 8%. Fuel consumption also decreased. In parallel,

there has been a favorable impact on noise as a result of the introduction of VSL systems between two consecutive junctions. The reduction in stop-start driving and the improved compliance with the speed limits reduced the weekday traffic noise adjacent to the motorway by around 0.7 decibels, with reductions at some points of up to 2.3 dB.

Another example can be found in Inn Valley in Austria. The effects of the implementation of VSL were analyzed on this motorway after one year of operation (November 2007 to November 2008). In a before/after evaluation the results showed that NO₂ emissions were reduced by 3.6%. Also, the NO₂ limit value for short-term exposure (half-hour limit: 200 g/m³) was exceeded only twice during the first year of operation, while without the VSL in operation, it was estimated that it would have been exceeded nine times (Land Tirol, 2012).

Table 1. Summary of evaluation variables used in different research studies

Ref.	Case study	Variable	Effects
<i>Traffic Performance</i>			
(Makarewicz and Gałuszka, 2011)	Simulation of 12 rural roads	Standard deviation of the average speed	Depending on scenarios
(Zhicai et al., 2004)	Simulation	Traffic volume, travel time, queue length, number of stops	Variable
(Hegyi et al., 2005)	Simulation	Total travel time	21% reduction
(Hoffmann-Leichter, 1997)	A5 Motorway, Germany	Intensity	10% increase
(Hoogendoorn and Bovy, 1999)	Simulation	Capacity	2% increase
(Highways Agency, 2004)	M25, U.K.	Throughput	1.5% increase
(Nissan and Bang, 2006)	E4 Stockholm	Lane changes	50% reduction
(ECMT, 2007)	A7 France	Congestion	16-40% reduction
<i>Road Safety</i>			
(Lee et al., 2004)	Simulation	Total crash potential	25% reduction
(Piao and McDonald, 2008)	Simulation M6, U.K.	Time-to-collision Headway	Depending on scenarios
(Robinson, 2000)	German motorways	Crash rate	20% reduction
(Highways Agency,	M25, U.K.	Damage ratio	20% reduction

2004)			
(ECMT, 2007)	A7 France	Crash number	10-20% reduction
Emissions			
(Zegeye et al., 2010)	Simulation	Total emissions	35% reduction
(Highways Agency, 2004)	M25, U.K.	Emissions levels	Between 2-8% reduction
(Highways Agency, 2004)	M25, U.K.	Noise levels	0.7-2.3 dB reduction
(Land Tirol, 2012)	A12, Austria	NO ₂ levels	3.6% reduction

2.1.3. ICT measures to reduce emissions

The European Research and Development project *ECOSTAND* has divided Intelligent Transport Systems applications into five categories: driver behavior change, navigation and travel information, traffic management and control, demand and access management and logistics and fleet management (Canaud and Faouzi, 2015).

Based on *ECOSTAND*, the project *ICT-Emissions* (see Section 3.1 for details about the project) also provides a list of ITS with 5 categories, but excluding logistics and fleet management as they are outside of the scope of the project. These are the categories included in the *ICT-Emissions* project:

- Driver behavior change
- Navigation and travel information
- Traffic management and control
- Demand and access management
- Advanced driver assistance system (ADAS) and other measures

Driver behavior change

Eco-driving is a driving style aimed at lowering fuel consumption and producing a proportional decrease in CO₂ emissions. According to Barkenbus (2010), eco-driving characteristics are generally well defined and easily typified. This behavior involves shifting up between 1500 and 2500 rpm (depending on engine technology), maintaining uniform speed as much as possible, anticipating traffic

flow and traffic lights, reducing acceleration and deceleration, and avoiding engine idling.

Driver learning and use of these techniques can be enhanced with on-board information systems such as FIAT (2010) eco:Drive which indicate the ideal time to shift gear, or offer recommendations (feedback) after analyzing the speed profiles. Eco-driving techniques are most useful in urban areas with high traffic densities or traffic signals, where fuel savings can be achieved without considerable reduction of average speeds.

A number of studies place individual fuel savings at between 5% and 10%, and in some cases as much as 20% (FIAT, 2010; Wilbers, 1999; Onoda, 2009). The variability of these data depends largely on the characteristics of the traffic and roads in each case study. The driver's ability to learn these techniques and the vehicle's sensitivity to minor changes in driving style may also have a significant influence (See Section 2.1.3. for further information).

Eco-driving behavior could be improved by some vehicle functions like a *Start & Stop system*, that turns off the engine when the vehicle is stopped for some seconds. Another function is tire pressure monitoring, which avoids the extra fuel consumption caused by underinflated tires.

Navigation and travel information

In the automotive industry, a navigation system is an on-board system which uses Global Positioning System (GPS) data to locate the user on a road map database. The navigation system has impacts on fuel consumption and emissions since it influence the route.

Apart from the basic on board-navigation system, there are enhanced systems such as Dynamic On-trip Routing or Green Navigation System. The first one uses real time data (congestion and delays) to guide the driver through the fastest route. On the other hand, the green navigation system does not calculate the fastest route, but the least fuel consumption route.

According to Pandazis and Winder (2015), fuel consumption savings range from 2% to 30% depending on the system and its application, i.e. different areas, traffic levels and penetration rates.

Traffic Management and Control

In this group of measures we can find all the infrastructure based systems that are able to monitor the traffic situation (intensity, occupation, speed, etc.) and influence in the traffic performance by modifying the speed, capacity, traffic signals etc. Under this term it is possible to find Adaptive Urban Traffic Control, Ramp Metering, Dynamic Lanes, Variable Speed Limits or Section Speed Control (Toffolo et al., 2014).

Focusing on the measures that have been tested in the case study of Madrid (see Chapter 3 for more details), the following paragraphs define Section Speed Control and Variable Speed Limits:

- Section Speed Control

Section Speed Control (point-to-point speed control or average speed control) is a measure designed primarily to improve road safety, although it may also have effects on traffic performance and emission levels. The number plates of each vehicle entering a section (usually one without intersections) are read and stored at the beginning and end of the section. By measuring the time elapsed, average speed is calculated for each vehicle, and drivers exceeding the legal speed limit are sanctioned in accordance with applicable regulations.

Apart from road safety, these systems also have an impact on emissions as they prevent speeding, and make traffic flow more uniformly. Soole, Watson and Fleiter (2013) analyzed studies showing that CO₂ emissions are reduced by 11% to 29% on certain motorway sections in the United Kingdom, with a considerable but variable reduction in vehicles travelling over the speed limit; while more modest fuel savings of about 5% are estimated in the Naples area, Italy (Cascetta, Punzo and Montanino, 2011).

- Variable Speed Limits

Variable speed limits (sometimes called dynamic speed limits) use real-time data (intensity, speed, environmental conditions and so on) to change dynamically the speed limit, adapting it to the circumstances of the road and its environment. Through a control center and variable message signs, drivers are informed of both recommended and mandatory speed limits. This system is often used on highways with high traffic levels and/or highly variable weather conditions.

Under various scenarios based on simulation, Zegeye et al. (2010) showed that potential fuel savings and CO₂ emissions range between 3% and 20%, while savings in travel time and increases in throughput are summarized in Table 1 (Section 2.1.2).

Demand Management

In its broadest sense, transport demand management is an action or a set of actions with the objective of reducing congestion by influencing travelers' behavior (Meyer, 1999). These measures have impacts on emissions since they produce changes in private traffic and modal split.

Inside this group of measures we can name the following (Toffolo et al., 2014):

- Restricted traffic zones: They avoid the private traffic in a particular area, boosting pedestrian and free emission zones. However, in general terms this measure might increase the total emissions in the city, since vehicles could be forced to drive longer routes.
- Infrastructure-use pricing: Vehicles using this infrastructure or accessing a designated area must pay a fee. London and Stockholm congestion charging areas are two well-known examples of application (Eliasson, 2009).
- Carbon-credit schemes: An incentive-based economic measure to address traffic congestion, where drivers have a certain credit to use the infrastructure. After consuming the credit, drivers start to pay per use (Grant-Muller and Xu, 2014).

- Pay-as-you-drive: This strategy may reduce the travelled kilometers but also change the driving behavior, since excessive speeds or accelerations can be also charged.

Advanced Driver Assistance Systems (ADAS)

ADAS are systems that support the driver in the longitudinal control of the vehicle and in the acceleration and braking processes. Therefore, they may have a significant impact on fuel consumption and emissions. Among these solutions we can find the following:

- Cruise Control is a driver-activated control system that maintains a constant vehicle speed, avoiding unnecessary speed changes which cause additional fuel consumption. This measure is applicable only on high-capacity (uninterrupted) roads when the traffic intensity is relatively low.
- Adaptive Cruise Control (ACC): Traffic in front of the vehicle is detected by radar and consequently the speed of the vehicle can be adapted to the traffic. When the vehicle communicates directly with the infrastructure it is called V2I (vehicle to infrastructure communications).
- Cooperative Cruise Control: Vehicles are able to exchange information between them. Through a Vehicle-to-Vehicle (V2V) communication link, the cruise control could adopt the speed profile of a preceding vehicle.
- Platooning: This is the synchronized movement of two or more vehicles driving one after the other at the same speed with relatively small gaps between them. This way, the aerodynamic drag is substantially reduced.

All these systems have direct (on the control vehicle) and indirect (on the surrounding traffic) impact on GHG emissions. According to the review of Klunder et al. (2009), the potential reduction in CO₂ emissions varies between 5% and 10%.

2.1.4. Eco-driving. Previous research

Eco-driving evolution and definition

Eco-driving evolved, especially in the United States, from the term “hypermiling”. Between 1930s to 1960s ran a coast-to-coast fuel efficiency competition which consisted in crossing North America with the least fuel possible (Killian, 2012). It was considered an important topic during World War II and again during the oil crisis in the 1970s, then remaining relatively unnoticed until the 1990s.

Recent concerns about climate change and again the oil prices have triggered a series of measures and strategies to reduce fuel consumption and emissions. Eco-driving is one of these measures, which aims at reducing fuel consumption by modifying driver behavior. From this simple definition, many concepts may be included, depending on which level of decision-making is considered (Sivak and Schoettle, 2012):

- Strategic decisions: Vehicle selection and maintenance.
- Tactical decisions: Route selection and vehicle load.
- Operational decisions: Driving behavior.

Similarly, Dietz, Gardner, Gilligan, Stern and Vandenberg (2009) named different decisions which can reduce energy use, such as fuel efficient vehicles, maintenance, carpooling, trip chaining and smooth driving behavior, characterized by slow acceleration, slower speeds on highways and reducing idling time.

However, empirical research studies focus only on operational decisions, i.e. driving behavior. In a highly influential paper, Barkenbus (2010) defined eco-driving characteristics, which involve *“accelerating moderately (with shift ups between 2000 and 2500 revolutions for those with manual transmissions), anticipating traffic flow and signals, thereby avoiding sudden starts and stops; maintaining an even driving pace (using cruise control on the highway where appropriate), driving at or safely below the speed limit; and eliminating excessive idling”*. He named other tactical decisions such as vehicle maintenance although they are not included in the research.

Therefore, in a wide sense, eco-driving can be defined as “driver’s decision aiming to reduce fuel consumption”, although eco-driving offers more benefits, including reduction of GHG and pollutants emissions, as well as greater safety and passenger comfort.

The present research is focused on the operational decisions of eco-driving, which are summarized by the project ECOWILL (2011) in the *Golden Rules of eco-driving*:

- When accelerating, shifting to a higher gear between 2,000 and 2,500 rpm for gasoline vehicles and between 1,500 and 2,000 for diesel. Shifting up the gears at these relatively low revolutions reduces fuel consumption because the engine’s internal friction increases with engine speed.
- Maintain a steady speed using the highest gear possible and driving with low engine speed.
- Anticipate the road and traffic flow as far ahead as possible to avoid unnecessary acceleration and braking processes.
- When decelerating, driving downhill or stopping, remain in gear but step off the accelerator as early as possible, for example when approaching a red light or a roundabout.
- Avoid high speeds since speeds above 80 or 90 km/h fuel consumption increases greatly.
- Check tire pressures regularly as underinflated tires increases fuel consumption.
- Use air conditioning sparingly as long as this does not imply opening a window at high speed.
- Switch the engine off when stationary for more than a minute.
- Remove roof racks, bike racks etc. when not in use.
- Avoid carrying unnecessary weight.

How to change driver behavior?

As shown in Figure 3, strategies to change the style of driving to an eco-driving behavior can be classified in four groups.

Figure 3. Changing to eco-driving behavior strategies

- **Mass media**

Depending on the type of media, different strategies are used to deliver the eco-driving message. Websites with tips (ECOWILL, 2013), commercials on television (IDAE, 2015) or even virtual games involving driving skills are becoming more common and can have an impact on driver behavior.

- **Driving license schools**

In addition to public campaigns and eco-driving courses, a successful program must include the integration of eco-driving techniques in the driving-school curricula.

For instance, the Netherlands began to restructure their driving school system already in 1998. In 2002 and 2003, more than 90% of Dutch instructors and examiners were trained in eco-driving principles and techniques, consequently taught in driving courses and reflected in examinations (Wilbers and Wardenaar, 2007).

- **Eco-driving course or recommendations**

One usual way of learning how to drive efficiently is attending specifically prepared eco-driving courses. The most common course consists of a test drive prior to the theoretical or practice course. After these two steps, the same drive is repeated following the eco-driving rules and recommendations, measuring at the same time fuel consumption and other variables such as travel time, average speed or shift gear rate.

These courses are normally performed in realistic environments rather than in closed circuits. This way, the drivers face situations of every-day traffic. After the course, the trainees may act as teachers for their relatives and acquaintances by spreading “the word”.

- Eco-Driving with Intelligent Assistant System

Adopting appropriate measures according to the real time change of traffic situation is not a simple process. Besides, the absence of positive feedback or reinforcement from energy savings actions makes it seem unlikely for individuals to maintain the behavior over time (Barkenbus, 2010). However, recent advances in ITS technologies such as the navigation system, wireless communication between vehicles or infrastructure and vehicles make this possible. With the help from ITS and other developed vehicle equipment, drivers can adopt the most appropriate eco-driving strategy at a certain time and maximize its benefits.

The project *ecoDriver - Supporting the driver in conserving energy and reducing emissions* – addresses the need to consider the human element when encouraging eco-driving, since driver behavior is a critical element in energy efficiency (Hof et al., 2012). The focus of the project is to develop an eco-driving technology working with the driver and to deliver the most effective feedback to drivers on eco-driving by optimizing the driver-power train-environment feedback loop.

Assessing the impacts of eco-driving

Though eco-driving is known for an emission reducing and fuel saving driving style, the quantification of the impacts of eco-driving is still important for designing an effective program in terms of both costs and impacts.

Many current studies adopted eco-driving under specified testing environment and many other constraints, for example, vehicle type, time of day, testing route, etc. The limited conditions of these studies can hardly prove its effectiveness in general terms and for a wide range of promotions and implementation.

Generally, there are two approaches to assess the impact of driving behaviors: field tests and traffic simulations.

- Field Tests

For evaluation purposes, especially for emissions and fuel consumption, driving behavior is usually measured and quantified through a speed-time profile. The most reliable way to assess eco-driving behavior is to record speed/gear-shift data as well as emissions with on-board equipment in the field. Doing field experiment can take into account many factors which are not considered in laboratories. The results are more realistic than driving simulators.

A field test was conducted in three different places in Sweden with the same petrol car (Johansson, Färnlund and Engström, 1999). The car was driven throughout the trial equipped with measurement equipment for driving style, position and a large number of engine parameters which could be used for calculating fuel consumption and emissions. Results show that the average speed and average acceleration remain virtually unchanged before and after instructions, while the fuel consumption is reduced by 10.9%. The same author (Johansson, Gustafsson, Henke and Rosengren, 2003) performed a second study with two vehicles and 86 drivers. The results show no significant differences in emissions between trained and untrained drivers except for CO₂. Regarding fuel consumption, in this study higher savings (8% versus 1.2%) are reported when the driver can check the instant fuel consumption on board.

In 2004, Hornung (2004) selected a group of novice drivers to attend a full-day eco-driving course with simulators and their post-course performance was recorded and compared to the other group of novices who had undergone the “standard” training. Overall, the simulator-trained eco-drivers performed better: they used 17% less fuel and used a third fewer gear changes than the other-trained eco-drivers.

Henning (2008) presented a study with 300 participants in which short term evaluation reflects average fuel consumption savings of 25%, which are in line

with other results presented in the study, saving between 20% and 26%. However, the same participants following long periods of time (> 3 years) only achieved 10% average fuel savings.

Onoda (2009) published the summary of *Eco-Drive* Program in Europe, reporting savings from 5% to 15%, depending on the existence of feedback.

Larsson and Ericsson (2009) studied the effects of an acceleration advisory tool. The acceleration advisor provides advice to drivers through resistance in the accelerator pedal when they try to accelerate rapidly. The driving pattern parameters recorded in a field test show that strong acceleration was significantly reduced, which indicated that drivers had complied with the indications. A reduction in emissions was achieved in two from the three analyzed routes. However, no significant fuel consumption reduction was achieved. This shows that the rate of acceleration is not the only factor to affect fuel consumption, but also the proportion of idle time, cruising time, etc. All these may have an influence on the efficiency of the acceleration advisory tool.

In Australia, Smit, Rose and Symmons (2010) explored and discussed the different options of quantifying the impacts of eco-driving on vehicle emissions under local conditions. They conducted a field test including 24 drivers and 6 types of vehicles both under urban and rural traffic conditions and before and after eco-driving instructions. The aim was to obtain driving cycles which comply with Australian conditions. Then, the speed profile data was used as input in the emissions predictions model to simulate emissions. It can be seen from the results that both fuel consumption and emissions vary from a reduction up to around 10% to a small increase around 0.5%. The benefits of eco-driving under the rural conditions are apparently greater than urban conditions. Besides, the emission reduction percentages of heavy vehicles are also much greater than light cars.

More recently Barkenbus (2010) concluded that “*evidence to date indicates that eco-driving can reduce fuel consumption by 10%, on average and over time, thereby reducing CO₂ emissions from driving by an equivalent percentage*”. Similarly, Alam and McNabola (2014) published a critical review of eco-driving studies where they

noted that results of field studies were consistently lower (4.8% to 6.8%) compared to modeling and review works.

A limited case study was conducted in Southern California to evaluate the effects of an on-board eco-driving device that provides instantaneous fuel economy feedback (Boriboonsomsin, Barth and Vu, 2011). The qualified participants were briefed about eco-driving advices and then drove the cars equipped with eco-driving devices for two weeks. At the same time, their driving data were collected. At the end of the study, the fuel economy was calculated separately for city and highway driving and the comparison was made between without and with eco-driving device. Results showed that the change in fuel economy for individual drivers varies. For city driving, the fuel economy of vehicles with an eco-driving device reduced by average of 6% compared with unequipped vehicles; for highway driving, the average reduction was 1%. The low improvement on highways may partly be due to congested freeways in the study area, which already had driving constraints.

H. Lee, W. Lee and Lim (2010) reported another experiment in South Korea to analyze the effects of an eco-driving system achieving different results from Boriboonsomsin et al. (2011). An eco-driving device was installed to inform the driver whether their drive was efficient and environment-friendly. The results showed that there was no significant improvement in fuel consumption after the eco-driving indicator was activated. Besides, drivers felt insecure and stressed while driving with the system activated because of the pressure to keep the green indicator light on. The research suggested that it is necessary to develop an eco-driving system where the users can unconsciously interact and also benefit all type of users.

- Simulation

Even though field tests have a clear advantage in terms of real-world accuracy, it is generally a labor-intense and time-consuming work, especially when testing different scenarios. Simulation, on the other hand, has the advantages of lower

costs and greater freedom to modify different environments, vehicle types and traffic conditions to assess their relative impacts. However, in order to obtain more accurate and valid simulation results, the model needs to be calibrated and validated with the real-world data.

Most assessments of eco-driving focus on the emissions. In this case, there are two main components in the simulation: a microscopic traffic simulation model and a microscopic emission model. The current research estimate emissions and fuel consumption either using environment assessment functions which are provided in the simulation software package or building emission models with relative parameters (see section 2.5 for further information).

Regarding the road sections controlled by traffic lights, traffic flow was affected by increased delays and stops at the lights. This fact increased fuel consumption and emissions due to inherent accelerations and braking processes required at the lights. Many studies have shown that reducing delays and stops at traffic signals can reduce emissions and fuel consumption effectively (Li, Boriboonsomsin, Wu, Zhang, and Barth, 2009; Li, Wu and Zou, 2011) . Taking this into account, we found in the literature several studies which describe dynamic eco-driving systems to optimize speed according to traffic light plans. This way, vehicles pass the signalized intersections with minimal stops and delays as well as minimal fuel consumption and emissions.

A dynamic eco-driving system collected live traffic and infrastructure data and communicate it to drivers (Rakha and Kamalanathsharma, 2011; Xia, Boriboonsomsin and Barth, 2013; Sun, Niu, Chen and Li, 2013). With such information, drivers were able to adjust speed, acceleration and braking to go through intersections with the least stops and avoiding sharp accelerations. The simulation results showed that there was indeed fuel consumption and emission reduction both for individual vehicles and the whole traffic network. Most of these studies were based on micro-simulation and it is difficult to find a validation experiment, as shown by Muñoz-Organero and Magana (2013). In this particular research, an expert system was implemented on Android mobile devices and validated in different vehicles and drivers.

Network effects

Most studies involving eco-driving focus on before-and-after comparison with respect to individual vehicles. These individual fuel consumption savings through eco-driving have been reported in many studies (Sivak and Schoettle, 2012).

In addition, eco-driving is considered as a low-cost policy option that helps to achieve the Kyoto protocol and other climate change targets and improvements in air quality in our cities. However, a research reported by Alam and Mcnabola (2014) has shown potentially negative issues that lower the credibility of the eco-driving initiatives.

Although adopting eco-driving strategies clearly benefit individual drivers, the impact remains unclear when considering eco-driving within a traffic flow with a combination of normal and eco-drivers as expected on real roads. Because of the more moderate driving style, eco-driving may slow down the average speed and reduce the acceleration at traffic lights, thereby reducing the discharge flow rate of queuing vehicles and increasing emissions and fuel consumptions. Therefore, it is of vital importance to analyze the fleet wide impacts of eco-driving within the context of a real traffic scenario. Given that the traffic flow is a complex system, *“the movement of a single vehicle can impact significantly the performance of a traffic stream”* (Elefteriadou, 2014).

Kobayashi, Tsubota and Kawashima (2007) presented a study comparing the simulated normal driving scenario and eco-driving scenario. For this study, they used a traffic micro-simulation tool (Vissim) fed with experimental speed and acceleration pattern data under different traffic volumes. The result shows that eco-driving scenarios can reduce CO₂ emissions under low traffic flow, but emissions rise under congestion. They point out that this is probably because eco-drivers accelerate so smoothly that they affect following cars. To maximize eco-driving benefits, the authors also proposed an algorithm of an eco-driving control system which makes eco-driving still beneficial under heavy traffic volume.

Similarly, Qian and Chung (2011) focused on a single intersection analyzing the effects of one particular eco-driving style which involves moderate and smooth

acceleration based on Aimsun microscopic traffic simulator. First, the speed profile during acceleration operations derived from the real data was imported into the vehicle characteristics in the simulation model to obtain more realistic simulation results. Simulation scenarios in this research include different traffic demand, increasing penetration rate of eco-drivers and different acceleration rates. The results show that traffic condition has a significant impact on the eco-driving effects. When the traffic is congested, eco-driving tends to bring increasing emissions and travel time.

The same authors (Qian and Chung, 2013) performed another study to evaluate the effects of different eco-driving penetration rates. They concluded that the understanding of “how eco-driving would perform in a traffic flow”, “how eco-drivers interact with normal drivers”, “how different penetration rates of eco-drivers would affect the traffic system” are some of the key questions for eco-driving evaluation studies. To simulate the eco-driving in Aimsun, they adjusted the acceleration operations and the response time after a stop. They prepared 20 scenarios with eco-driving penetration rates of 0% to 100%. The results show a maximum saving of 10% in fuel consumption. In this study the traffic demand is fixed, rounding 550 veh/h per lane.

The most complete study about network effects of eco-driving was presented by Orfila (2011). The author estimated the effects of eco-driving on traffic congestion and fuel consumption according to the percentage of eco-drivers among the total number of drivers. This was achieved using a class of eco-driven vehicles with a car-following model (Intelligent Driver Model) and within a particular transportation simulation software (Aimsun). Apart from the acceleration rates, headway is also adapted to simulate the eco-driving behavior. However, the study has some limitations as the networks (urban and inter-urban) are not real and it is not clear how the eco-driving behavior parameters are calibrated. Results show that the effect of eco-driving on the traffic congestion and pollution is not linearly linked to the proportion of eco-drivers and this effect varies according to the driving conditions. Indeed, fuel consumption increments were reported for scenarios with a high eco-driving penetration rate and congested traffic situation.

Summary of eco-driving research

The following table sorted by date shows a summary of the previously mentioned eco-driving studies, both field tests or simulation exercises. It also includes a brief account of other results found in the literature reviews of eco-driving studies done by Barkenbus (2010), Sivak and Schoettle (2012), Toffolo et al., (2013) and Alam and McNabola (2014):

Table 2. Summary of eco-driving research studies

Research	Study type	Variables	Effects
Johansson et al. (1999)	After eco-driving instructions. On-road test	Fuel consumption and emissions	10.9% reduction in fuel consumption
Johansson et al. (2003)	After eco-driving instructions. On-road test	Fuel consumption, emissions, speed and acceleration indicators. Engine speed	8% fuel consumption reduction with fuel consumption monitoring. 1.2% without monitoring
Hornung (2004)	On-road test after eco-driving training course.	Fuel consumption	15% in short term and 12% reduction in long term
Vermeulen (2006)	After eco-driving instructions. On road test	Fuel consumption and emissions	7% reduction for gasoline cars and 8-10% for diesel
Taniguchi (2007)	After eco-driving training. On-road test.	Fuel consumption	20% fuel consumption reduction
Kobayashi et al.(2007)	Moderate and smooth acceleration. Network Simulation	Emissions and travel time	Network effects. 3% reduction in CO ₂ for low ad medium traffic and 12% increment in congestion
Henning (2008)	After eco-driving instructions. On road test.	Fuel consumption	Average 25% reduction of fuel consumption in short term and 10% long term
Onoda (2009)	Summary of Eco Drive program in Europe. On-road test	Fuel consumption	5% after training and 10% with feedback
Symmons et al. (2009)	After eco-driving training course. On-road test	Fuel consumption, gear changes, brake applications, etc.	27% reduction in fuel consumption
Saboochi and Farzaneh (2009)	Gear change optimization. Simulation	Fuel consumption	Savings of 1.5 l/100km
Barth and Boriboonsomsin (2009)	On-road test. Dynamic eco-driving system	Fuel consumption and CO ₂	Reduction of fuel consumption of 13%. CO ₂ reduced 12%
Larsson and Ericsson (2009)	With acceleration advisory tool. On-road test	Fuel consumption, 20 driving pattern parameters	No significate changes in fuel consumption
H. Lee et al. (2010)	With eco-driving assistance system. On-road test	Fuel consumption	No difference

Research	Study Type	Variables	Effects
FIAT (2010)	After eco-driving instructions. On road with feedback test.	Fuel consumption	6% average and 16% maximum
Smit et al. (2010)	After eco-driving instructions. On-road test	Fuel consumption and emissions	Vary from a reduction up to around 10% to a small increase around 0.5%, depending on the driver and road.
Qian and Chung (2011)	Moderate and smooth acceleration. Network Simulation	Fuel consumption, CO ₂ emissions & travel time	Network effects. Fuel consumption reduced 4% for free flow and incremented 25% in congestion
Orfila (2011)	Change in car-following model. Network simulation	Fuel consumption	Increments for high eco-driving penetration rate and congested interurban. Savings up to 19.6% in urban congested
Azzi, Reymond, Mérienne and Kemeny (2011)	After eco-driving instructions. With and without feedback. On Lab	Polluting emissions	5% reduction with verbal instructions, 10% to 12% with feedback
Rakha and Kamalanathsharma (2011)	Dynamic V2I system. Modeling	Fuel consumption	Up to 23.8% fuel consumption reduction
Boriboonsomsin Barth and Vu (2011)	With eco-driving feedback device. On-road test	Vehicle fuel economy	An average of 6% reduction for city drive and an average 1% for highway drive
Andrieu and Saint Pierre (2012)	After eco-driving instructions and training course. On-road test	Fuel consumption, average speed, average acceleration, etc.	12.5% of fuel consumption reduction after instructions and 11.6% using an assistance system
Qian and Chung (2013)	Moderate acceleration. Network simulation	Fuel consumption and CO ₂ emissions	Maximal savings of 10% in fuel consumption
Sun et al. (2013)	Dynamic eco-driving system. Modeling signalized corridors	Fuel consumption and CO ₂ emissions	25% reduction of fuel consumption and CO ₂
Xia et al. (2013)	With dynamic eco-driving system. Network simulation	Fuel consumption and CO ₂ emissions	10-15% savings for individual vehicles. 1%-4% for total fleet, depending on traffic situation

2.1.5. Traffic and emissions simulation

Traffic models

Traffic simulation models are mathematical tools which help plan, manage and operate road networks. Depending on the approach, the models are able to simulate the traffic at different times and space scales (Toffolo et al, 2014).

- Macroscopic models

These models describe traffic in terms of variables, namely flow, speed and density. Traffic modeling uses numerical information on the amount of traffic on each link of a network using parameters such as traffic flow, traffic density and average speed. Macro-level modeling is used to calculate traffic density (veh/km), mean speed (km/h) and traffic flows (veh/h) in network links. Macro simulation traffic models have been in principle developed at network level for modeling the effect of strategic policy measures such as park-and-ride, congestion charging, road construction projects etc. They use different kinds of algorithms for the assignment, such as equilibrium, all or nothing and stochastic assignment. These are used to establish the origin and destination (O/D) matrices used by micro simulation models. Commercially available macro-models include the CUBE, Emme, VISUM, and the MT.Model.

- Mesoscopic models

They represent road flow at the level of detail of the single vehicle (or group of vehicles generally called packet). In this case, although representation of the traffic is discrete, the movement of each individual vehicle depends on laws that describe relations between aggregate flow variables (for example, mean speed as a function of density), or on probabilistic functions, like models based on the analogy with gas kinetics.

- **Microscopic models**

Microscopic models describe the movements of individual vehicles as the result of individual disaggregates choices and interactions with other vehicles and with the road environment (Samaras et al., 2012). These use submodules to incorporate lane changing, car-following algorithms, etc. Such models give the possibility to take into account traffic composition, priority rules, driving behaviors, traffic lights position, junction delays and queue lengths. Moreover, each flow entity (vehicle) has its own characteristics that may include: type or access to trip information, vehicle performance, such as maximum acceleration or maximum speed, and driver behavior characteristics. Examples of these models, in commercial tools, are Aimsun, Vissim and Paramics.

Micro traffic models are traditionally calibrated with aggregated traffic data such as average speed and traffic flow (Dowling, Skabardonis, Halkias, McHale and Zammit, 2004), which may not reflect changes in individual driving behavior, and thus in fuel consumption and emissions. Calibration processes including real vehicle trajectories have become more common in recent years, although few methodologies are available in the scientific literature.

In this respect it is worth noting the work by Treiber and Kesting (2013), who present a systematic approach to the whole calibration process, which includes the use of Floating Car Data (FCD) and Extended Floating Car Data (xFCD). A number of other authors investigate the validity of car-following models using FCD; Punzo and Simoneli (2005) compared different car-following models with real data obtained from floating cars driving in platoons, similar to the methodology used by Brockfeld, Kühne and Wagner (2004). Along the same lines, Kesting and Treiber (2008) focused their research on the calibration of car-following models by means of floating vehicles equipped with front radar.

Emission models

Whether during the planning phase or by assessing the effects of an already implemented measure, emission models are frequently used as one of the main inputs of environmental inventories and reports.

Emission and energy consumption models range from very detailed models based on the speed profiles of every single vehicle to the aggregated ones. The first group of models (micro models) produces accurate results but needs very detailed inputs and a comprehensive process of model construction and calibration. The main input for these family of models are the individual driving profiles and that is why traffic micro simulation software packages such as Vissim, Aimsun or Paramics already includes fuel consumption and emissions modules. Other more detailed examples found in the literature are Measure (Fomunung, Washington and Guensler, 1998), VERSIT+ (Smit, Smokers and Rabé, 2007) or Cruise (Hasewend, 2001).

Macro models or speed-flow models (also called average speed models) are used for regional large networks and their results are based on aggregated data, namely average speed, traffic flows and fleet composition. Examples of these type are MOBILE (Parrish, 2006), MOVES (Liu and Barth, 2011) and COPERT (Ntziachristos and Samaras, 2000). In these models, emission factors (g/km) are set as a function of the average speed, taking also into account the different fleet compositions and the traffic activity, i.e. distances travelled.

Average speed has been proved and accepted to be a key factor of fuel consumption and thus on CO₂ emissions (Ntziachristos and Samaras, 2000). However, from a traffic engineering point of view, average speed itself does not explain enough the variability of traffic conditions and the different congestion levels.

Between these two families of consumption and emission models, a wide range of different approaches can be found. Some of them specifically take into account a number of traffic situations for different types of roads, which include free flow, normal flow, congestion and stop-and-go traffic conditions for motorways,

highways, arterial and local roads. Examples of these models in Europe are HBEFA (Hausberger, Rexeis, Zallinger, and Luz, 2009), which use selected driving profiles for each situation and ARTEMIS (André, 2004), which generate driving cycles based on real trips.

With the aim of taking into account the different traffic conditions, the TEE model (Agostini, Lelli, Negrenti, and Parenti, 2005) produces artificial driving cycles depending on traffic parameters, such as flow, number of lanes or intersections per kilometers, which are later used to correct the estimation of average speed emission and consumption models, in this specific case COPERT.

This review on emission and energy consumption models shows a wide range of approaches, whose use depend mostly on the data availability and the spatial and temporal resolution needs.

2.2. Research objectives and methodology

2.2.1. Research objectives

According to the previous sections, different ICT measures applied to road transportation may produce benefits in energy consumption and emissions. With this background, the first objective of this research is:

- 1- *Understand how different ICT measures affect fuel consumption, emissions and driving and traffic dynamics.*

To achieve this objective, there are several steps to meet:

- A literature review of all the different measures to save energy and emissions in road transport, with special focus on eco-driving.
- The development of a data collection campaign, as there is the need of real data to calibrate the models and validate the results.
- Analysis of the collected data to establish relationships between fuel consumption and different traffic and vehicle dynamic variables.

With the focus on one of these measures, namely **eco-driving**, it is possible to find many studies presenting individual savings produced by changing the driving behavior and following the eco-driving rules. However, there are only a few studies that address this issue from a corridor or network perspective. In addition to this, these studies are based on simulation results of artificial road scenarios. Many questions still to be answered or to confirm previous research works:

- Does eco-driving behavior influence the neighboring drivers?
- What if 10% of drivers were eco-drivers? What about 25%? And more?
- Would these scenarios produce the same effect in a motorway or in a local street?
- To what extent the effects depend on the traffic demand?
- Would it produce more congestion?
- And consequently more emissions?

- Are the tendencies the same for the different pollutants and greenhouse gases?

Therefore, the second objective of this thesis is:

2- Evaluate the effects of eco-driving on traffic and emissions under different conditions of eco-driving penetration rates, traffic and roads.

The specific steps related with this second objective are:

- The construction of different traffic models which cover the different types of metropolitan roads and based on real data.
- The definition and calibration in the model of an eco-driving behavior.
- Estimation of eco-driving impacts in traffic and emissions.

2.2.2. Research methodology

Facing the two main objectives and the specific goals detailed in the previous section, the thesis is structured in 10 chapters (see Section 1.2), following the consecutive steps of the research methodology (Garcia, 2015):

- Research question.
- Literature review.
- Objectives.
- Experiment design and data collection.
- Data analysis.
- Conclusion.

The aims of this thesis emerge from the problem posed in Chapter 1, the excessive energy consumption and the emissions of greenhouse gases and pollutants produced by road transport.

From the literature review we have identified the need to understand how different ICT related measures may impact emissions and specifically the change in driving behavior under different scenarios.

Pursuing the mentioned objectives, we designed an experiment based on Floating Car Data. Three different vehicles driven by nine drivers performed some selected itineraries in the Madrid metropolitan area to record data before and after the implementation of four ICT related measures: section speed control, variable speed limits, cruise control and eco-driving. The vehicles were equipped to record instantaneous speed and fuel consumption data, which was used for analysis.

Once the data were processed and structured in a database, we started with an analysis of the data which reflects the fuel consumption effects of different ICT measures tested in Madrid. We also analyzed how the ICT measures affect the dynamics of the floating vehicles (acceleration, braking, etc.).

Consequently, the next analysis was performed to observe the relation between congestion and fuel consumption (and therefore CO₂ emissions), differentiating between urban roads and motorways.

The next step was a statistical analysis of the collected data, including a factorial analysis and a multiple regression model, looking for the explanatory variables of fuel consumption and the amount of fuel consumption variation that can be explained by the speed profiles definition.

The data collected and the mentioned analyses are the starting point of the simulation process. First of all, it is necessary to select suitable simulation tools, both for traffic and emissions. The simulation process includes the selection of areas to be modeled, calibration of the base case scenario, and calibration of the eco-driving behavior and simulation of all the different scenarios. For the calibration of the eco-driving behavior, we used real driving profiles obtained from the study area. The model parameters were adjusted following a trial and error process until they reproduced close enough the real behavior.

A total of 72 scenarios are simulated. This number comes from 3 traffic situations (night, off-peak and peak hours), 4 types of urban roads (urban motorway, urban arterial, urban collector and local streets) and 6 different eco-driving penetration rates (0%, 10%, 25%, 50% and 100%).

Figure 4. Scheme of scenarios and impacts of different eco-driving penetration rates

Once the scenarios were simulated, all the results were analyzed in detail. Last step was to identify conclusions according to our research objectives and specific goals and propose further research lines in the area.

The following figure shows the methodology steps followed in the development of this research:

Figure 5. Research methodology steps and relationships

PART II – ICT MEASURES. DATA COLLECTION

3. CASE STUDY DEFINITION – DATA COLLECTION

“Not everything that can be counted counts and not everything that counts can be counted.”

Albert Einstein

This third chapter provides an insight on the case study developed under the framework of the *ICT-Emissions* research project. In a preliminary study, variable speed limits in the urban ring motorway of Madrid were tested using Floating Car Data techniques. In the main collection campaign, four different ICT measures were tested in the roads of Madrid, namely variable speed limits, section speed control, cruise control and eco-driving behavior.

3.1. The ICT-Emissions project

The aim of the *ICT-Emissions* project (European 7th R&D Framework Programme) is to find a methodology to simulate in detail the effects on CO₂ emissions of a number of ICT measures applied to transportation, commonly known as Intelligent Transportation Systems (ITS). Each of the considered ICT measures affects CO₂ emissions differently. From a macroscopic point of view it can be considered that demand, fleet composition and average speed determine the level of emissions (Ntziachristos and Samaras, 2000). However, taking a detailed look at each vehicle, the processes of acceleration and deceleration and the engine performance are also proved to be critical. Moreover, the areas of application are highly variable and the effects in certain environments may produce undesirable results, causing the need of using models to simulate these effects before investing the large amounts of capitals that in some cases require these measures.

All this complexity which determines the measures effectiveness also causes that the simulation is not a straightforward process. The methodology proposed in the "ICT-Emissions" project is mainly based on the interaction of various simulation models on micro and macro levels. Therefore, the idea is not to create a new simulation software tool, but to join the already existing by developing the necessary links and interfaces. These models include a vehicle control model, traffic model and emissions model (micro and macro levels). The project focuses on the field of passenger cars, also analyzing the effects of the ICT measures under different fleet compositions.

Particular emphasis is given to new vehicle technologies, including start-stop systems, hybrids, plug-in hybrids and electric.

The main focus will be on the following groups of ICT measures:

1. Driver behavior change and eco driving.
2. Navigation and travel information.
3. Traffic management and control.

4. Demand & access management.
5. Advanced driver assistance system (ADAS).

As an added value of this project, it is also intended to validate the methodology with case studies in the partner cities of Rome, Turin and Madrid. In each of these cases, data collection campaigns (induction loops, cameras, floating cars, etc.) were conducted with the aim of evaluating the evolution of traffic and other vehicle parameters before and after the implementation of the ICT measures. These results are used to calibrate the vehicle and traffic models and afterwards to validate the results obtained by applying the simulation methodology to these case studies.

In collaboration with the Department of Traffic Technologies in Madrid, the consortium decided to select four different measures for testing in the Madrid case study. Two measures affect only individual vehicles: eco-driving affects driving behavior, while cruise control is related to vehicle technology. The other two measures involve traffic control and management and depend on the available ITS installations in the road network. We selected Section Speed Control and Variable Speed Limits on account of their availability for experimentation.

Further information about the ICT-Emissions project and its results can be found in ICT-Emissions Consortium (2015).

3.2. Madrid metropolitan area

The city of Madrid is the capital of Spain and of the region with the same name, officially “Comunidad Autonoma de Madrid”. The region is located in the center of the Iberian Peninsula, covers an area of 8,021 km² with a population of 6,377,364 inhabitants on January 1st 2015, while the city of Madrid has 3,165,236 inhabitants (Instituto Nacional de Estadística, 2015).

Figure 6. Location of Madrid, Spain

The road network has a radio centric structure with eight main motorways providing access to the city center. Other four ring motorways encircle the city of Madrid, connecting the peripheral districts and suburbs. The following figure shows the main motorways and local roads of Madrid metropolitan area.

Figure 7. Madrid motorway network. Source: Valdes, 2012

With regard to the public transport network, the region has four main transport systems: Madrid metro and local bus systems, the regional commuter train and the metropolitan bus.

Madrid Mobility patterns

According to the Household Mobility Survey of the Region of Madrid carried out in 2004 (CRTM, 2006), approximately 14.5 million of trips were made in the region on average in a working day.

Near one third of these trips are done on soft modes (mostly walking), another third by public transport and the rest by car, which makes approximately 5 million car trips per day (Valdes, 2012).

3.3. Preliminary study. Variable Speed Limits

This preliminary and limited study was performed with the objective of getting used to the variable speed limits system and the Floating Car Data procedure. Therefore, the conclusion extracted from this analysis must be understood in this limited framework.

3.3.1. Methodology to evaluate VSL systems using an aggregate effectiveness indicator

Effectiveness indicator. Definition

Table 1 (Section 2.1.2.) shows the large number of variables which are used in the scientific literature and other public reports to evaluate the effects of VSL. This fact highlights the need to find a single variable which makes possible to evaluate the system's effectiveness easily and concisely by aggregating the potential effects on traffic performance, road safety and emissions.

With regard to traffic performance, several of the aforementioned studies point out that the homogenization of speed (i.e., lower acceleration rates) contributes to a smooth traffic flow (García, 2009), an increase in capacity (Heydecker and Addison, 2011) and the attenuation of shockwaves (Hegyi et al., 2005).

Likewise, road safety has been proven to be related with traffic and speed homogeneity (Van Nes et al., 2008; Piao and McDonald, 2008; Fildes and Lee, 1993; Wegman, Aarts and Bax, 2008). It can therefore be concluded that there is a clear relation between speed variations and number of accidents.

Figure 8. Regression fit for CO emissions as a function of speed and acceleration rates. Source: Rakha et al. (2000)

Many research studies (Rakha, Van Aerde, Ahn and Trani., 2000; El-Shawarby, Ahn and Rakha, 2005; Joumard, Jost, Hickman and Hassel, 1995; Ding and Rakha, 2002) also state that, apart from mean or average speed, positive acceleration rates also have a major impact on emissions, as shown on Figure 8 from (Rakha et al., 2000).

It has thus been possible to pinpoint instant acceleration as a key factor by evaluating the effectiveness of implementing VSL, and then proposing an aggregate indicator as follows:

Positive Accumulated Acceleration (PAA) is defined as the sum of the speed variations on a particular road section.

Mathematically, it is the cumulative integral of the positive acceleration law (1).

$$PAA = \int_0^t a^+(t)dt \cong \sum_0^t a_t^+ \cdot \Delta t = \sum_0^t \frac{\alpha \cdot (V_t - V_{t-1})}{\Delta t} \cdot \Delta t = \sum_0^t \alpha \cdot (V_t - V_{t-1})$$

$$\text{If } (V_t - V_{t-1}) > 0 \quad \text{then } \alpha = 1 \quad (1)$$

$$\text{Otherwise} \quad \alpha = 0$$

Graphically, PAA is the positive area of the region bounded by the acceleration law, as shown on Figure 9. The units used in this analysis are m/s², as it the accumulation of positive instant acceleration.

Figure 9. Graphic representation of PAA indicator from an acceleration function

The PAA indicator makes it possible to compare the same section before and after the implementation of VSL, thus evaluating its effectiveness.

Data collection and evaluation

As already mentioned, the PAA indicator is simply based on speed variations, and the data required to calculate it is relatively easy to obtain.

Speed data are often collected by induction loops located at certain points on the road, but this method makes it impossible to establish the speed evolution between two loops, and leads to the possibility of distorted results.

It is thus essential to obtain speed data at short time intervals, and the methodology proposed is therefore based on GPS technologies. With a small portable device it is very simple to collect and download speed data and position every second, which allows a very accurate speed profile to be obtained along the road section analyzed.

The methodology is based on a before and after evaluation, by observing the evolution of the PAA indicator. Ideally, the number of trip repetitions should be fairly high in order to limit variations caused by other factors such as meteorology, extraordinary events, incidents, etc. In any case, the trips must be made in the same time slot and on days with similar behavior in terms of traffic. In the event of a limited sample, particular care must be taken to ensure that the conditions are

almost the same. The traffic intensity upstream must be guaranteed to be substantially the same when performing the before and after trips.

Once the valid data has been processed and selected, the implementation of VSL can be valued positively if the indicator PAA_a (activated) is lower than PAA_d (deactivated).

3.3.2. Preliminary analysis: West section of Madrid M30 motorway

In the afternoon peak hours on a normal working day, the M30 motorway (the inner ring motorway) has high traffic levels southbound on its east and west sections. In an attempt to avoid this habitual congestion and its externalities, the Madrid Traffic Department implemented a Variable Speed Limits (VSL) system based on recommended speed limits.

The tested section is a three-lane motorway (southbound) with traffic intensity in the afternoon peak hours of around 3,300 veh/h (upstream), and a length of 5.8 km. Most of the section is limited to 90 km/h, except the last 100 m, where the limit is 70 km/h (tunnel entrance). The congestion is usually caused by the bottleneck situated at the M500 junction, as around 2,800 veh/h merge into the M30 in afternoon and evening peak hours (Figure 10).

Figure 10. Daily Traffic profile in the west section of the M30 motorway. Southbound

The VSL system consists of three Variable Message Signs (VMS) situated before the M500 junction. These VMS display a recommended speed limit of 40, 60 or 80 km/h, depending on the control algorithm. This is based on instant speed data recorded by induction loops situated along the section.

Figure 11. West Madrid motorway ring-road and the 5.8 km. test section (from A to B) with the location of the Variable Message Signs (VMS). The bottleneck junction where the congestion usually starts (M-500) is highlighted.

A microscopic car study was undertaken in the afternoon peak traffic period between 18:00-20:00. A total of nine trips were made on 6 and 7 June 2012 (Tuesday and Wednesday) with the VSL system activated. One week later (12 and 13 June) another nine trips were performed at exactly the same times, this time with the VSL system deactivated.

Table 3 Madrid's first campaign: dates and time periods

Measure situation	Date	Time period
VSL ON	Tuesday 06/06/12 Wednesday 06/07/12	18:00 – 20:00 (Congested)
VSL OFF	Tuesday 13/06/12 Wednesday 14/06/12	

The intensity levels upstream for the test days were very similar, with a maximum deviation of 2.63% from the mean value (Table 3). The weather was sunny and there were no particular incidents or accidents during the test trips, except for unusual congestion on 6 June, which caused the system not to be automatically activated.

Table 4 Traffic flow intensities upstream (Measuring point PM 22421)

Time	Date				Mean	Max. mean deviation
	05-June	06-June	12-June	13-June		
18:00	3159	3196	3114	3324	3198	-2.63%
19:00	3501	3544	3506	3440	3498	-1.65%

The mobile study was carried out using an instrumented vehicle (Skoda Fabia TDI , year 2003) equipped with a GPS data recorder (747+ GPS Trip Recorder, 1Hz), which was subsequently downloaded as an Excel Sheet (.csv) and georeferenced (.kml) documents.

The data collected included travel distance (m), position and speed (m/s), recorded every second, enabling the PAA to be obtained as defined in previous section (Section 3.3.1)

Likewise, seven trips (Figure 12) in free flow (southbound mornings) were performed in order to study the variability of the PAA in similar conditions and to isolate the effects of VSL from any other which may influence the results (small disturbances and changes in driving style).

Figure 12. PAA indicator values in free flow. Obtained in the morning hours of 5 and 6 June.

From this analysis, it can be concluded that in free flow and in similar conditions, 99% (confidence level= 0.99, $\alpha=0.01$) of the PAA results present a deviation from the median of less than 2.19 (confidence limits). Therefore any deviations greater than this value will be assigned to the effects of VSL.

3.3.3. Analysis of results

Effects on speed homogenization

Table 5 shows the resulting values of the PAA_a (activated) and PAA_d (deactivated) from the trips performed on 5 and 12 June. The results on Wednesday 6 are considered invalid, as the system was automatically disconnected due to the unusual and extreme congestion (recorded speed under the operation thresholds).

Table 5. Values obtained for PAA effectiveness indicator. Congested trips

Activated		Deactivated	
<i>Tuesday 5 and 12. Afternoon peak</i>			
<u>Time</u>	<u>PAA values</u>	<u>Time</u>	<u>PAA values</u>
18:30	91.68	18:29	92.04
18:52	88.20	18:52	88.89
19:11	72.23	19:10	90.99
19:32	59.62	19:32	105.88
19:51	63.54	19:55	69.36

Average	75.05	Average	89.43
Wednesday 6 and 13. Afternoon peak			
18:28	125.84	18:27	99.20
18:50	124.06	18:49	86.62
19:14	130.74	19:13	90.68
19:38	73.21	19:38	76.82
Average	113.46	Average	88.33

When the effects of VSL are isolated from any other effects, as described in the paragraphs above, the result shows that the PAA_a falls by an average of 13.1%, compared to the PAA_d .

Figure 13. Comparison of the effectiveness indicator (PAA) on Tuesday 5 and 12 June

Figure 13 shows that PAA_a and PAA_d values are fairly similar, except for the trips that are highly affected by congestion. An analysis of the speed profiles in Figure 14 and the indicator values shows that in the 19:11 trip, the speed distribution is more homogeneous, although the congestion levels are similar. This fact causes the congestion on the following trip (19:32) to remain at similar levels (or even to decrease) while VSL is activated, and the queue length to increase while deactivated.

Figure 14. Comparison of speed profiles for trips with VSL activated and deactivated

Effects on traffic performance

As we have seen in the literature review (see Section 2.1.2), the effects of variable speed limits on traffic performance are site dependent, achieving most of the case studies positive results in terms of traffic throughput and travel times.

Table 6 shows the relation (in percentage) between traffic throughput downstream and upstream during the peak hours in the test days.

Table 6. Traffic throughput relation downstream/upstream the test section

Date	05-June	06-June	07-June	12-June	13-June	14-June	Mean
Activated	183%	181%	178%	-	-	-	181%
Deactivated	-	-	-	181%	177%	178%	179%

The results show a slight improvement of 2% in the relation between the traffic flow downstream and upstream during the test days.

Table 7 shows the travel times during peak hour trips on 5 and 12 June. The results on Wednesday 6 are considered invalid, as the system was automatically disconnected due to the unusual and extreme congestion (recorded speed under the operation thresholds).

Table 7. Trip travel time per day (activated/deactivated)

Activated		Deactivated	
Tuesday 5 and 12. Afternoon peak			
Time	Travel time (min:sec)	Time	Travel time (min:sec)
18:30	7:59	18:29	6:59
18:52	7:28	18:52	6:15
19:11	6:35	19:10	6:10
19:32	5:36	19:32	7:24
19:51	4:45	19:55	4:46
Average	6:28	Average	6:18
Wednesday 6 and 13. Afternoon peak			
18:28	9:34	18:27	7:21
18:50	10:13	18:49	6:32
19:14	10:29	19:13	6:56
19:38	7:02	19:38	6:04
Average	9:19	Average	6:43

Rejecting the results of 6th June and comparing similar trips of activated and deactivated days, the result shows a 3% increase in travel time with the system activated.

From the traffic performance point of view, the results are contradictory. Firstly, the application of variable speed limits produces in this case a slight improvement in the throughput relation between traffic flow downstream and upstream the controlled section. On the other hand, travel time suffers a small penalty, which is related with the more restrictive speed limits.

However, it is important to mention that although this travel time increase, PAA values decrease when the system is activated. This means that the system achieves more homogeneous speed profiles for the same travel times. (Figure 15)

Figure 15. PAA values and travel times

Environmental effects

Together with road safety considerations, positive environmental effects are one of the main reasons for implementing variable speed limits systems in motorways. Most of the studies reviewed in Chapter 2 show positive results in case of emissions and fuel consumptions.

In the presented case study, reductions of PAA values, which mean more homogeneity in speed profiles, imply reductions in emissions and fuel consumption. This reduction can be quantified by introducing the speed profiles in micro emissions models, such as VERSIT+ (Smit et al., 2007). See Sections 7.3.2 and 7.4 for further information on the emissions model.

The output of the VERSIT+ model for the presented case study is summarized in Table 8.

Table 8. Emissions per trip (activated/deactivated)

Activated			Deactivated		
Tuesday 5 and 12. Afternoon peak					
Time	CO ₂	NO _x	Time	CO ₂	NO _x
18:30	1021	1.880	18:30	1040	1.994
18:52	1037	1.985	18:52	1058	2.103
19:11	973.1	1.845	19:11	1074	2.379
19:32	961.6	1.845	19:32	1102	2.226
19:51	1014	2.209	19:51	1034	2.303
Average	1001.3	1.952	Average	1061.6	2.201

<i>Wednesday 6 and 13. Afternoon peak</i>					
Time	CO₂	NO_x	Time	CO₂	NO_x
18:28	1148	2.197	18:27	1079	2.028
18:50	1171	2.333	18:49	1047	2.206
19:14	1165	2.133	19:13	1051	2.037
19:38	1002	1.802	19:38	1023	1.958
Average	<i>1121.5</i>	<i>2.116</i>	Average	<i>1050</i>	<i>2.057</i>

As in previous analysis, rejecting the extreme results of 6th June, the emissions savings are shown on Table 9.

Table 9 Emissions savings comparing the scenarios activated vs. deactivated

Emissions	CO₂	NO_x
Savings	2.58%	4.14%

Analyzing the relation between Positive Accumulated Acceleration indicator and the emissions, both CO₂ and the pollutants show the same tendency. Despite this tendency is clear, NO_x is not highly correlated with the indicator, obtaining a low value of R². Figure 16 and 17 the relation between PAA and CO₂ and NO_x respectively.

Figure 16. PAA values and CO₂ emissions

Figure 17. PAA values and NO_x emissions

Despite this tendency is clear, NO_x is not highly correlated with the indicator, obtaining a low value of R^2 .

3.4. Main data collection campaign

In March and April 2013, the main data collection campaign took place in coordination with the Department of Traffic Technologies of Madrid. This data collection campaign consisted of conducting a representative number of trips through the selected itineraries using floating cars (FCD). With this procedure, it is possible to obtain the fuel consumption and speed profiles.

The number of drivers involved was 9. Due to contract limitations, drivers were alumni of Universidad Politécnica de Madrid (UPM) 25 to 30 years old. The sample were not gender balanced, being 8 males and 1 female.

Three FIAT passenger cars were involved in this study, a Punto 1.2L gasoline and two diesel variants, Punto and Bravo, with 1.3L and 1.6L engines, respectively. The characteristics of the vehicle were determined inside the ICT-Emissions project, taking into account the compatibility of the selected models with the application to record vehicle parameters developed by FIAT.

According to a report of the Madrid Local Government (Dirección General de Sostenibilidad y Planificación de la Movilidad, 2013), 68% of passenger cars are diesel and 31% gasoline. In this sense, the sample is representative of the Madrid fleet composition.

Regarding the vehicle segmentation, these vehicles can be classified in segments small (Fiat Punto) and medium (Fiat Bravo), which corresponds approximately to 75% of the fleet in Madrid. The three vehicles are registered under Euro 5 standards, while the average fleet age in Madrid is 9.3 years (Dirección General de Sostenibilidad y Planificación de la Movilidad, 2013).

The total number of recorded trips was initially 2,250, with results approximately 12,600 km driven. At a first filtering process, 159 trips were eliminated because of recording application failures.

The data collection campaign was focused on the M30 motorway and therefore, some of the trips include both motorway and adjacent urban sections. To isolate

the different sections, trips were split into urban and motorway trips, summing up a total of 3,072 trips.

Table 10 shows the different trips with their characteristics.

Table 10. Data collection campaign. Trips description

Trip code	Trip Name	Urban/ Motorway	Average length (km)	Vehicle	Trips per Vehicle	Variable Speed Limits		Section Speed Control		Cruise Control		Eco- driving	
						ON	OFF	ON	OFF	ON	OFF	ON	OFF
1	Mendez Alvaro/ Costa Rica	Motorway	7.8	Bravo 1.6D	11	-	-	-	11	-	-	6	5
				Punto 1.2G	12	-	-	-	12	-	-	-	-
				Punto 1.3D	14	-	-	-	14	-	-	-	-
2	Costa Rica/ O'Donnell	Motorway	5.3	Bravo 1.6D	111	-	-	-	-	-	-	47	64
				Punto 1.2G	166	-	-	-	-	-	-	-	-
				Punto 1.3D	213	-	-	-	-	-	-	-	-
3	O'Donnell/ Costa Rica	Motorway	5.8	Bravo 1.6D	107	-	-	51	56	-	-	45	62
				Punto 1.2G	180	-	-	77	103	-	-	-	-
				Punto 1.3D	202	-	-	98	104	-	-	-	-
4	J.Mª Soler/ Príncipe Pío	Motorway	12.6	Bravo 1.6D	2	-	-	-	-	-	-	1	1
				Punto 1.2G	4	-	-	-	-	-	-	-	-
				Punto 1.3D	5	-	-	-	-	-	-	-	-
5	Arroyofresno /Costa Rica	Motorway	21.4	Bravo 1.6D	14	-	-	-	-	7	7	-	-
				Punto 1.2G	-	-	-	-	-	-	-	-	-
				Punto 1.3D	-	-	-	-	-	-	-	-	-
6	ETSI Caminos / Arroyofresno	Motorway	2.9	Bravo 1.6D	14	-	-	-	-	-	-	7	7
				Punto 1.2G	5	-	-	-	-	-	-	-	-
				Punto 1.3D	11	-	-	-	-	-	-	-	-
7	San Pol / Arroyofresno	Motorway	5.4	Bravo 1.6D	84	-	-	-	-	-	-	39	45
				Punto 1.2G	132	-	-	-	-	-	-	-	-
				Punto 1.3D	143	-	-	-	-	-	-	-	-
8	Arroyofresno / San Pol	Motorway	6.7	Bravo 1.6D	78	38	40	-	-	-	-	37	41
				Punto 1.2G	119	56	63	-	-	-	-	-	-
				Punto 1.3D	139	65	74	-	-	-	-	-	-
9	Costa Rica/ Arroyofresno	Motorway	20.3	Bravo 1.6D	13	-	-	-	-	7	6	-	-
				Punto 1.2G	-	-	-	-	-	-	-	-	-
				Punto 1.3D	-	-	-	-	-	-	-	-	-
12	Calle 30 / Calle Corregidor	Urban	1.2	Bravo 1.6D	111	-	-	-	-	-	-	47	64
				Punto 1.2G	185	-	-	-	-	-	-	-	-
				Punto 1.3D	211	-	-	-	-	-	-	-	-
13	Avda. Ilustracion	Urban	1.5	Bravo 1.6D	9	-	-	-	-	-	-	4	5
				Punto 1.2G	-	-	-	-	-	-	-	-	-
				Punto 1.3D	-	-	-	-	-	-	-	-	-
14	Alfonso XIII / ETSI Caminos	Urban	7.4	Bravo 1.6D	30	-	-	-	-	-	-	16	14
				Punto 1.2G	-	-	-	-	-	-	-	-	-
				Punto 1.3D	-	-	-	-	-	-	-	-	-
15	ETSI Caminos / Alfonso XIII	Urban	6.7	Bravo 1.6D	28	-	-	-	-	-	-	15	13
				Punto 1.2G	-	-	-	-	-	-	-	-	-
				Punto 1.3D	-	-	-	-	-	-	-	-	-
17	Príncipe Pío / San Pol	Urban	1.3	Bravo 1.6D	83	-	-	-	-	-	-	39	44
				Punto 1.2G	134	-	-	-	-	-	-	-	-
				Punto 1.3D	145	-	-	-	-	-	-	-	-
18	Calle 30 / Príncipe Pío	Urban	1.6	Bravo 1.6D	79	-	-	-	-	-	-	38	41
				Punto 1.2G	133	-	-	-	-	-	-	-	-
				Punto 1.3D	132	-	-	-	-	-	-	-	-
19	Ilustración and Príncipe Pío	Urban	3.1	Bravo 1.6D	5	-	-	-	-	-	-	2	3
				Punto 1.2G	4	-	-	-	-	-	-	-	-
				Punto 1.3D	4	-	-	-	-	-	-	-	-

Figure 18 presents the calendar and schedule of the data collection campaign

Figure 18. Data collection calendar and schedule

Figure 19 provides a glance of the main monitored itineraries in Madrid following the codification of Table 10.

Figure 19. Monitored itineraries in the data collection campaign in Madrid

As in the case of Madrid, many motorways and urban roads are equipped with cameras and induction loops which record traffic flow parameters such as intensity and average speed at certain points. This data may be enough to gain a picture of the general traffic conditions at a macro level, but it lacks the necessary level of detail to determine patterns at a micro level.

The Floating Car Data method is used to determine traffic and vehicle parameters based on information collected from on-board devices. Floating cars work as moving sensors and do not require significant investment in instrumentation installed on the roadway. This method provides information about individual travel and driving behavior, simultaneously complementing the information from other fixed on-road sensors.

For many applications, the speed and GPS information recorded by smartphones may be enough. However, the vehicles participating in this campaign also provided information extracted from the on-board diagnostics (OBD) system.

The methodology included the installation of an OBD key to extract data from each vehicle's OBD system. This was used to record instantaneous position, speed, acceleration, fuel consumption (l/h down to a precision level of five significant digits) and revolutions per minute (rpm). This device is easily installed by the user in the vehicle diagnostic port, and sends the data to a mobile phone via Bluetooth with a frequency of 1 Hz (Figure 20).

Figure 20. Data collection process

Once the selected itineraries were filtered, the remaining records were processed in order to obtain the values for 75 variables for each trip, calculated according to traffic and emissions literature (Ericsson, 2001; Smit et al., 2007; Greenwood, Dunn and Raine, 2007; Beusen et al., 2009).

Based on the instant speed values recorded, variables can be calculated for each trip, including maximum speed, mean speed, maximum acceleration, maximum deceleration, number of stops and so on, and other statistically derived values such as standard deviation, 95th percentile, among others. Idling time, average rpm, coasting time and other engine variables were also calculated as they are useful for further research into fuel consumption and emissions.

The variables finally calculated and introduced into the databases can be found in the following table:

Table 11. Variables calculated in the data collection campaign

Variable code	Description	Format
Trip_ID	Trip ID	NUM
Section_type	Trip type according road type and if the trip is mixed (Urban-Motorway)	NUM
Section_ID	Section ID	NUM
Section	Name of section	TXT

Date	Recording Date	DATE
Day of the week	Day of the week	NUM
Vehicle_ID	Vehicle_ID	NUM
Driver_ID	Driver_ID	NUM
Beginning hour	Beginning time of the trip	HOUR
Temperature (°C)	Temperature	NUM
ICT Day	If motorway measures are activated	LOG
ICT	If ICT measure is applied	LOG
Panel 1	Recommended speed limit in panel1	NUM
Panel 2	Recommended speed limit in panel2	NUM
Panel 3	Recommended speed limit in panel3	NUM
Rainy day	If it is a rainy day	LOG
Rain	Raining during the trip	LOG
Cruise Speed	Cruise speed control activated	LOG
Ecodriving	Eco- driving behavior	LOG
Congestion	Congestion	LOG
Comments	Comments	TXT
consumption	consumption l/100km	NUM
trip_time	Trip time in MM:SS	HOUR
trip_time_seconds	Trip time in seconds	NUM
Trip time free flow	Trip time in seconds of the fastest recorded trip	NUM
Length (maps)	Comments in case of failure of application	TXT
Slave	Average slope	NUM
Slave+	Average positive slope	NUM
Slave-	Average negative slope	NUM
Nstops/km_<3km/h	Number of stops per km being stop speed under 3 km/h	NUM
Nstops/km_<5km/h	Number of stops per km being stop speed under 5 km/h	NUM
Nstops/km_<14.4 km/h_3	Number of stops per km being stop speed under 3 km/h and starting to count when speed >14.5	NUM
Nstops/km_<14.4 km/h_5	Number of stops per km being stop speed under 5 km/h and starting to count when speed >14.6	NUM
St t/km_<3km/h	Stop time per km being stop speed under 3km/h	NUM
St t/km_<5km/h	Stop time per km being stop speed under 5km/h	NUM
St t/km_<14.4 km/h_3	Stop time per km being stop speed under 3km/h and starting to count when speed >14.5	NUM
St t/km_<14.4 km/h_5	Stop time per km being stop speed under 5km/h and starting to count when speed >14.6	NUM
%st t_<3km/h	%Stop time being stop speed under 3 km/h	NUM
%st t_<5km/h	%Stop time being stop speed under 5 km/h	NUM
%St t_<14.4 km/h_3	%Stop time being stop speed under 3 km/h and starting to count when speed >14.4	NUM
%St t_<14.4 km/h_5	%Stop time being stop speed under 5 km/h and starting to count when speed >14.5	NUM
Vmax	Maximum recorded speed	NUM

Vave(t)	Average speed as length/time	NUM
Vave(t)_free_flow	Average speed as length/time of the fastest recorded trip	NUM
Vave w/o 3km/h	Average speed without considering speeds under 3 km/h	NUM
Vave w/o 5km/h	Average speed without considering speeds under 5 km/h	NUM
VP95	95 Percentile of instantaneous recorded speed	NUM
Vmedian	Speed median	NUM
Vsd	Standard deviation of recorded speed values	NUM
COV	Speed variation coefficient (Ratio of standard deviation to the mean %)	NUM
Aave+	Average of positive recorded acceleration	NUM
Amax+	Maximum positive acceleration	NUM
A+P95	95 percentile of positive accelerations	NUM
A-P95	95 percentile of negative accelerations	NUM
Aave-	Average of negative accelerations	NUM
Amax-	Maximum negative acceleration	NUM
Asd	Standard deviation of recorded acceleration (positive and negative)	NUM
A+sd	Standard deviation of recorded positive acceleration	NUM
A-sd	Standard deviation of recorded negative acceleration	NUM
Pacc_0.1m/s2	Time % acceleration is greater than 0.1 m/s ²	NUM
Pacc_3km/h	Time % acceleration is greater than 0.83 m/s ²	NUM
Pacc_5km/h	Time % acceleration is greater than 1.389 m/s ²	NUM
Pdec_0.1m/s2	Time % acceleration is less than -0.1 m/s ²	NUM
Pdec_3km/h	Time % acceleration is less than -0.83 m/s ²	NUM
Pdec_5km/h	Time % acceleration is less than -1.389 m/s ²	NUM
Pcru_0.1m/s2	Time % acceleration is between 0.1 and -0.1 m/s ²	NUM
Pcru_3km/h	Time % acceleration is between 0.83 and -0.83 m/s ²	NUM
Pcru_5km/h	Time % acceleration is between 1.389 and -1.389 m/s ²	NUM
PAA/km	Positive accumulated acceleration per km: Summation of $V(i+1)-v(i)$ if $V(i+1)>V(i)$	NUM
PKE/km	Positive kinetic energy per km: Summation of $V^2(i+1)-v^2(i)$ if $V(i+1)>V(i)$ per km	NUM
Power/km	Power per km: $V(i)*a(i)$ / km	NUM
DR	Delay rate: delay/length	NUM
CI	Congestion index: Free flow speed/average speed (v_{ff}/v)	NUM
CI_TomTom	Congestion index as defined by TomTom: (Trip time - free flow trip time)/Free flow trip time: $(t-t_{ff})/t_{ff}$	NUM
SRCI	Speed reduction congestion index: $v_{ff}-v/v_{ff}$	NUM
Windows	If windows were open	LOG
Air-conditioner	If air conditioner was on	LOG

PART III – DATA ANALYSIS. ICT MEASURES, CONGESTION AND DRIVING DYNAMICS

4. IMPACTS OF ICT MEASURES AND ECO-DRIVING ON FUEL CONSUMPTION AND DRIVING DYNAMICS

“The goal is to turn data into information, and information into insight”

Carly Fiorina

This fourth chapter provides an insight on the case study described previously. It explains in detail the data collection campaign, including the data processing and the impacts produced by the application of the cited measures in the speed and consumption profiles of the floating cars.

4.1. Evaluation variables

As mentioned in the Section 3.1, the data collection campaign was carried out within the framework of the *ICT-Emissions* project. In collaboration with the Department of Traffic Technologies in Madrid, the consortium decided to select four different measures for testing in the Madrid case study. Two measures affect only individual vehicles: eco-driving affects driving behavior, while cruise control is related to vehicle technology. The other two measures involve traffic control and management and depend on the available ITS installations in the road network. We selected Section Speed Control and Variable Speed Limits on account of their availability for experimentation. Therefore, the data collection campaign was focused on the M30 Motorway sections equipped with these systems and some urban roads as detailed in previous Section 3.4.

As the aim of the project is to simulate ICT measures using traffic simulation software, we carried out a review of all the dynamics and behavior-related parameters that can be adjusted by Vissim and Aimsun, two of the most commonly used tools. We identified desired speed, acceleration and deceleration with their corresponding variables, extracted from a speed profile. In the case of driving behavior, the model user is able to adjust parameters such as reaction time, safety distance and aggressiveness which are not directly measurable from a speed profile, although they have a major influence on driving patterns. As the final aim is to accurately estimate emissions and fuel consumption, another variable that correlates well with emissions (see Section 3.3) was selected as a reference to calibrate car-following and lane-changing models inside Vissim and Aimsun. The following paragraphs describe the variables selected and their correspondence with the parameters in these two models.

- 95th Percentile of Instantaneous Recorded Speed

The maximum desired speed is the speed the driver intends to maintain if traffic and road conditions allow. It is related to the speed limit, but it cannot be directly inferred from these values.

In our case, the maximum desired speed might be taken as the maximum speed recorded in each free-flow trip. However, the selected value corresponds to the 95th percentile of instantaneous recorded speed (VP95), so any minor distractions the driver might have are isolated.

Desired speed is an essential direct input in the traffic micro simulator. Vissim presents a desired speed distribution for each vehicle class that can be changed manually by the user, while Aimsum shows the normal distribution of desired speed in which the user can adjust the mean, deviation, and maximum and minimum values. Following this distribution approach, the mean, standard deviation, and maximum and minimum values have been calculated for each measure and all recorded trips.

- Maximum Recorded Acceleration

As with the maximum desired speed, the maximum desired acceleration is below the physical maximum acceleration the vehicle is able to achieve if the driver steps on the pedal. It is therefore directly related with the aggressiveness of the driver. It is calculated as the maximum value of the positive recorded acceleration.

In many of the micro simulation tools reviewed, maximum acceleration is taken as the maximum physical capacity of each vehicle type. In this case, only Vissim is able to distinguish between maximum acceleration and desired acceleration. Aimsum only allows the physical maximum acceleration of the vehicle to be changed directly, but not the acceleration desired by the driver.

- Maximum Recorded Deceleration

Maximum recorded deceleration is calculated as the maximum braking acceleration recorded for each trip. Both Vissim and Aimsum allow the desired or normal deceleration distribution to be adjusted in the same way as the desired speed distribution.

- Positive Accumulated Acceleration per Kilometer

Following the definition found in Section 3.3.3, this variable reflects the driver's tendency to maintain a constant speed, and shows good correlation with fuel

consumption and emissions. The lower the value of this variable, the more constant the speed will be. This is not a variable that can be used as direct input in any of the models, as it also depends on traffic conditions. However, its variation can be useful to indicate whether the vehicle is travelling more homogeneously as a result of the application of a particular measure. It can be indirectly used as a value for the calibration of different car-following model parameters such as headway or gap acceptance. Table 12 shows a summary of the variables analyzed in the following section.

Table 12. Variables extracted from the recorded driving profiles and their correspondence with VISSIM and AIMSUM parameters

Variable	Abbreviation	Units	Corresponding calibration parameter in Vissim	Corresponding calibration parameter in Aimsun
95th percentile of instantaneous recorded speed (Mean)	VP95_mean	km/h	Desired speed distribution (manual adjust)	Mean desired speed
95th percentile of instantaneous recorded speed (Deviation)	VP95_Sd	km/h	Desired speed distribution (manual adjust)	Standard deviation Desired Speed
95th percentile of instantaneous recorded speed (Maximum)	VP95_max	km/h	Desired speed distribution (manual adjust)	Maximum desired speed
95th percentile of instantaneous recorded speed (Minimum)	VP95_min	km/h	Desired speed distribution (manual adjust)	Minimum desired speed
Maximum recorded acceleration (Mean)	Amax_mean	m/s ²	Desired acceleration distribution (manual adjust)	Mean desired acceleration
Maximum recorded acceleration (Deviation)	Amax_Sd	m/s ²	Desired acceleration distribution (manual adjust)	Standard deviation desired acceleration
Maximum recorded acceleration (Maximum)	Amax_max	m/s ²	Desired acceleration distribution (manual adjust)	Maximum desired acceleration

Maximum recorded acceleration (Minimum)	Amax_min	m/s ²	Desired acceleration distribution (manual adjust)	Minimum desired acceleration
Maximum recorded deceleration (Mean)	Bmax_mean	m/s ²	Desired deceleration distribution (manual adjust)	Mean desired deceleration
Maximum recorded deceleration (Deviation)	Bmax_Sd	m/s ²	Desired deceleration distribution (manual adjust)	Standard deviation desired deceleration
Maximum recorded deceleration (Maximum)	Bmax_max	m/s ²	Desired deceleration distribution (manual adjust)	Maximum desired deceleration
Maximum recorded deceleration (Minimum)	Bmax_min	m/s ²	Desired deceleration distribution (manual adjust)	Minimum desired deceleration
Positive accumulated acceleration per kilometer	PAA_km	m/s ² km	Calibration of car following model (headway)	Calibration of car following model (headway)

For each of the measures tested, the values of the selected variables (Table 12) were calculated before (base-case) and after the implementation of the measure. These results and the variation percentage are shown in Tables 13–17, which also includes the results of fuel consumption (l/100 km) and the average travel time in seconds. Significance values are also reported based on the results of one-way ANOVA tests for each variable (VP95, Amax, Bmax, PAA-km and Fuel Consumption).

4.2. Section Speed Control

The section speed control (point to point speed control or average speed control) is a measure designed primarily to improve road safety. The license plates of each vehicle entering on a section (usually a section without intersections) are read and stored at the beginning and the end of the section. By measuring the time elapsed, average speed is calculated for each vehicle, proceeding to punish those that exceed the legal speed limit.

In the case study of Madrid, the system was implemented for testing in the East section of the Ring Motorway M30, northbound. Figure 21 shows a picture of the Variable Message Sign informing about the operation of the section speed control system.

Figure 21. Section Speed Control system in operation

The East section corresponds to two separate carriageways per traffic direction: 3 lanes in the central road and 3 or 4 lateral service lanes. The section is limited to 90 km/h and equipped with section speed control system. In the morning peak hour the intensity reaches 11,500 veh/h northbound (Figure 22), producing severe congestion.

Figure 22. Madrid case study. Traffic intensities on a weekday at M30 East section northbound

The speed limit is 90 km/h and the total length is 5.8 km. A total of 489 trips were recorded in this itinerary, 262 of which corresponded to the base case and 226 to the section speed control activated scenario. The results are shown in Table 13.

Table 13. Changes in vehicle trajectory variables produced by the activation of a section speed control system

Parameters	Base Scenario	Section Speed Control Activated	Variation %
VP95_mean ***	90.2	88.8	-1.6%
VP95_Sd	3.9	3.0	-23.1%
VP95_max	101.2	98.4	-2.8%
VP95_min	78.9	79.9	1.3%
Amax_mean †	0.8	0.8	0.0%
Amax_Sd	0.2	0.3	50.0%
Amax_max	1.6	2.3	43.8%
Amax_min	0.3	0.4	33.3%
Bmax_mean ***	0.9	1.0	11.1%
Bmax_Sd	0.4	0.3	-25.0%
Bmax_max	2.4	2.1	-12.5%
Bmax_min	0.4	0.4	0.0%
PAA_km †	3.4	3.3	-2.9%
Fuel consump. ***	4.67	4.49	-3.8%
Travel time**	256	258	0.8%

* Significant at $p < 0.1$; **Significant at $p < 0.05$; *** Significant at $p < 0.01$; † No statistically significant differences between group means.

It is worth noting that enforcement produces a 23% reduction in the standard deviation values of the 95th percentile of instantaneous speed, representing a more homogeneous distribution of speed. The higher maximum braking values when the enforcement is activated can be explained by drivers' tendency to brake when the enforcement section begins.

4.3. Variable Speed Limits

The West section is a 3 lane motorway (southbound) with traffic intensity in the afternoon peak hours of about 3,300 veh/h (before M500 junction) and with a length of 6.7 km.

Figure 23. Madrid case study. Traffic intensities on a weekday at M30 West section southbound

Most of the section has a speed limit of 90 km/h, except the last 100 m, which are limited to 70 km/h (tunnel entrance). The congestion is usually caused by the bottleneck situated in the M500 junction, as around 2,800 vehicles merge into the M30, with peaks of 6,000 veh/h (Figure 23).

Figure 24 shows the West section (southbound from A to B) with the Variable Message Signs (VMS) as well as the bottleneck junction where the congestion usually starts (M-500).

Figure 24. Madrid case study. M30 West section southbound with detail of the bottleneck junction

As a function of the speed recorded downstream, the variable message sign displays recommended speed limits of 80, 70, 60, 50 or 40 km/h.

Figure 25. Recommended Variable Speed Limit in operation at the M30 West Section

It is important to note that in the Madrid case study, the speed limits displayed in the variable message signs along the motorway are only a recommendation.

Drivers react lowering their speed although the results do not show relevant differences among the recommended speed displayed; only between not activated (base-case) and activated. The length of the section under analysis is 6.7 km. of a total of 336 trips, 177 were recorded with the Variable Speed Limits deactivated, while the system was operative in the other 159 trips. The results obtained are shown in Table 14.

Table 14. Changes in vehicle trajectory variables produced by the activation of a Variable Speed Limit system

Parameters	Base Scenario	Variable Speed Limits Activated	Variation %
VP95_mean †	90.9	90.9	0.0%
VP95_Sd	4.2	3.2	-23.8%
VP95_max	101.3	96.9	-4.3%
VP95_min	76.2	85.8	12.6%
Amax_mean **	0.9	1.2	33.3%
Amax_Sd	0.6	0.6	0.0%
Amax_max	3.0	3.1	3.3%
Amax_min	0.3	0.5	66.7%
Bmax_mean *	1.3	1.5	15.4%
Bmax_Sd	0.9	0.7	-22.2%
Bmax_max	3.4	3.0	-11.8%
Bmax_min	0.3	0.4	33.3%
PAA_km †	5.1	6.2	21.6%
Fuel consump. †	4.13	4.05	-1.94%
Travel time †	356	343	-3.65%

* Significant at $p < 0.1$; ** Significant at $p < 0.05$; *** Significant at $p < 0.01$; † No statistically significant differences between group means.

In the case of variable speed limits, no influence is observed on mean desired speed, while the extreme values tend to be closer to the mean, reducing the standard deviation by 23.8%. However, acceleration and braking values are higher, probably as a result of driver reactions to variable message signs.

4.4. Cruise Control

Cruise Control is measure that is applicable only to individual vehicles on certain roads and under specific traffic conditions, and particularly only on high-capacity roads when traffic intensity is relatively low. The section under study corresponds to a multilane ring motorway, with 3 or 4 lanes and a normal speed limit of 90 km/h and with a tunnel section with a strictly enforced limit of 70 km/h.

Figure 26. Entrance to the M30 tunnel section limited to 70 km/h

The length of the section analyzed is 21.3 km. Almost 277 km were driven with the system deactivated, and 298 km when the system was activated by the driver. The results obtained are shown in Table 15.

Table 15. Changes in vehicle trajectory variables produced by the use of a Cruise Control system

Parameters	Base Scenario	Cruise Control Activated	Variation %
VP95_mean **	92.5	91.0	-1.6%
VP95_Sd	1.4	1.6	14.3%
VP95_max	95.1	94.8	-0.3%
VP95_min	90.3	88.4	-2.1%
Amax_mean *	0.9	1.0	11.1%
Amax_Sd	0.3	0.2	-33.3%
Amax_max	1.4	1.3	-7.1%
Amax_min	0.6	0.8	33.3%
Bmax_mean †	0.9	0.8	-11.1%
Bmax_Sd	0.4	0.2	-50.0%
Bmax_max	1.9	1.4	-26.3%
Bmax_min	0.5	0.6	20.0%
PAA_km ***	3.4	1.8	-47.1%
Fuel consump. †	3.61	3.44	-4.70%
Travel time†	960	945	-1.6%

* Significant at $p < 0.1$; ** Significant at $p < 0.05$; *** Significant at $p < 0.01$; † No statistically significant differences between group means.

Cruise control enables the driver to control speeding more effectively, and reduces the maximum speed by around 1.5 km/h. Maximum braking and acceleration values are reduced, although the largest variation in this case is in accumulated acceleration, as the system avoids the minor oscillations that occur under normal driving behavior conditions.

4.5. Eco-Driving

Eco-driving behavior was tested on different urban and motorway sections, so the results are aggregated by urban or motorway itineraries. Table 16 below presents aggregate values for motorway itineraries in which 212 trips correspond to normal behavior and 168 were driven following eco-driving recommendations.

Table 16. Changes in vehicle trajectory variables produced by eco-driving behavior in motorway itineraries

Parameters	Base Scenario	Eco-Driving Motorway	Variation %
VP95_mean [†]	91.9	91.6	-0.3%
VP95_Sd	4.0	2.8	-30.0%
VP95_max	98.9	97.9	-1.0%
VP95_min	71.7	83.7	16.7%
Amax_mean ***	0.9	0.8	-11.1%
Amax_Sd	0.3	0.3	0.0%
Amax_max	2.0	1.8	-10.0%
Amax_min	0.4	0.3	-25.0%
Bmax_mean ***	1.0	0.7	-30.0%
Bmax_Sd	0.4	0.5	25.0%
Bmax_max	2.4	2.9	20.8%
Bmax_min	0.4	0.3	-25.0%
PAA_km ***	4.6	3.8	-17.4%
Fuel consump. **	4.18	3.82	-8.61%
Travel time [†]	270	268	-0.7%

* Significant at $p < 0.1$; ** Significant at $p < 0.05$; *** Significant at $p < 0.01$; [†] No statistically significant differences between group means.

The results show that eco-driving in metropolitan motorways has almost no influence on average maximum speed, although the standard deviation is reduced considerably. Average maximum acceleration and deceleration values are considerably reduced, while at the same time the speed profile is much more homogeneous, as shown by the reduction in accumulated acceleration.

Figure 27. Urban itinerary for eco-driving testing

For urban itineraries, almost the same kilometers are recorded with normal driving behavior and eco-driving behavior from a total of 776 km. The results are shown in Table 17. In the case of urban itineraries, the mean of the 95th percentile of instantaneous speed shows a clear reduction of 6.4%, as do the mean values of acceleration and braking. Speed profiles are also considerably more homogeneous according to the Positive Accumulated Acceleration indicator.

Table 17. Changes in vehicle trajectory variables produced by eco-driving behavior in urban itineraries

Parameters	Base Scenario	Eco-Driving Urban	Variation %
VP95_mean ***	53.5	50.1	-6.4%
VP95_Sd	6.1	6.0	-1.6%
VP95_max	79.0	65.8	-16.7%
VP95_min	34.1	37.5	10.0%
Amax_mean ***	2.0	1.8	-10.0%
Amax_Sd	0.3	0.3	0.0%
Amax_max	2.7	2.6	-3.7%
Amax_min	1.1	0.7	-36.4%
Bmax_mean ***	2.3	2.1	-8.7%
Bmax_Sd	0.6	0.6	0.0%
Bmax_max	5.3	5.5	3.8%
Bmax_min	1.2	1.1	-8.3%

PAA_km ***	36.9	32.6	-11.7%
Fuel consump. ***	4.34	4.03	-7.14%
Travel time***	366	419	12.6%

* Significant at $p < 0.1$; ** Significant at $p < 0.05$; *** Significant at $p < 0.01$; † No statistically significant differences between group means.

5. CONGESTION EFFECTS ON FUEL CONSUMPTION

“What gets measured, gets managed”

Peter Ferdinand Drucker

The aim of this chapter is to investigate in detail, how traffic congestion affects fuel consumption and to evaluate the importance of including traffic congestion in modeling and driver information systems. This analysis is based on empirical data from the data collection campaign described in Section 3.4. The results show considerable increase in fuel consumption under congested traffic conditions compared with free flow conditions, but also points to the differences depending on the type of itinerary.

5.1. Traffic congestion in energy and emission models

The energy and emission models are normally developed from a large number of measurements made both in laboratories and field trips. These models usually emphasize the importance of the fleet composition and, depending on the level of detail, these vehicles are aggregated into categories with similar values of consumption and emission per kilometer.

The fuel consumption and emission models can be classified according to their level of disaggregation. They range from the very detailed ones based on the speed profiles of each vehicle to the aggregate ones used for national emissions inventories.

After examining some emission models, Smit et al. (2008) concluded that most of them do explicitly consider the traffic situation in the modeling process. However, the main problem lies in the use at a local scale of models designed for emission inventories at regional or national level, as their improper use can lead to serious over- or underestimations.

Macro-level models are applied for the analysis of large networks. In this family of models, the average speed models consider the traffic demand, average speed, and fleet composition of each itinerary to estimate emissions and fuel consumption. Examples of this type of models are MOBILE (Parrish, 2006) and COPERT (Ntziachristos and Samaras, 2000).

Average speed is considered as a key factor in fuel consumption and CO₂ emissions. However, from a traffic engineering point of view, the average speed itself does not sufficiently explain the variability of traffic conditions and its implications (Ahn and Rakha, 2007). For example, an average speed of 40 km/h in an arterial road with traffic light coordination could reflect free-flow conditions, achieving an almost constant speed. The same average speed on a motorway section can represent high congestion levels, which has clear implications on fuel consumption and emissions. Figure 28 shows the speed profiles of two recorded trips made with the same vehicle and with a similar average speed in two different

itineraries. However, the differences in traffic conditions lead to an increase in fuel consumption of about 40% for the congested section.

Figure 28. Urban and ring motorway itineraries with the same average speed but with different fuel consumption

5.2. Congestion indicators and data processing

Due to the availability of data and the nature of demand models, the most commonly used indicator has been the volume-to-capacity ratio, although this indicator has a number of shortcomings when analyzing traffic congestion in detail (Boarnet, Kim and Parkany, 1998). The main issue is that drivers, in general, ignore this kind of information, but rather give importance to travel times.

Based on the literature review (Smit, 2006; Taylor, 2000; Cohn, Kools and Mieth, 2012; Schrank, Eisele and Lomax, 2012) and trends in software and application developers, the following congestion indicators are highlighted:

- Delay: Difference between current travel time and free flow travel time.
- Delay rate: Difference between current travel time and free flow travel time per kilometer.
- Congestion Index (CI): Ratio between travel time and free flow travel time
- Speed reduction congestion index (SRCI): Mean speed reduction from free-flow to current conditions over free flow mean speed. Index normalized to a 0 to 10 scale.
- Tom Tom congestion index: Difference between current travel time and free flow travel time over free-flow travel time.
- Level of Service (LOS) is a qualitative measure of the quality of driving conditions. On a scale of A to F, it describes a range of flow conditions where A represents free-flow conditions; and F severe congestion.

In this chapter we will analyze the traffic congestion using the delay rate. On one hand, from the point of view of drivers, delay is the most understandable and interesting indicator, as it reflects the time lost in congestion. The use of a length ratio makes possible the comparison between sections with similar characteristics but different length.

Data Processing

As mentioned before, the data collection campaign was performed in the

framework of the “*ICT-Emissions*” research project, which includes testing some traffic management measures, such as variable speed limits and section speed control. For the purpose of this study, the trips on which these measures were in operation were not considered, as they could distort the fuel consumption and travel time results.

Once filtered, the remaining trips were grouped by vehicle and itinerary. The total number for this analysis is 2,412, distributed as specified in Table 18 and following the itinerary ID number set in Table 10 (Chapter 3).

Table 18. Number of Analyzed Trips According to Itinerary ID Number and Vehicle

Itinerary number and vehicle	<i>M30 ring Motorway itineraries</i>				<i>Urban itineraries</i>			Total per vehicle
	3	2	7	8	12	17	18	
Length (km)	5.3	5.8	5.4	6.7	1.2	1.3	1.6	na
Fiat Bravo 1.6D	124	72	46	44	124	86	82	578
Fiat Punto 1.3D	215	104	72	74	214	146	133	958
Fiat Punto 1.2G	172	103	70	63	191	140	137	876
Total trips per itinerary	511	279	188	181	529	372	352	2,412

The delay rate is calculated using the following formula for each trip:

$$DR = \frac{\frac{(t - t_0)}{60}}{l} \quad (2)$$

where,

t = current travel time (s)

t_0 = free flow travel time (s)

l = length of itinerary (km)

The fastest trip of each itinerary was set as the free flow travel time of that itinerary. For these reason, specific off-peak measurements were performed with low traffic intensities, although overnight hours were not considered. The selected reference trips where investigated in detail to confirm the absence of any reception failure or anomalous driving behavior.

Measurements of ring motorway trips have been grouped, according to the levels

of service (LOS) defined by the AAHSTO (2001), in particular taking into account the average speed. Since most of the registered trips are close to the area of flow instabilities (when congestion is about to start) and to achieve more accuracy, service levels A and B have been divided equally into three sublevels, C and D into two, while E and F are kept as a unique level of service.

5.3. Results. Fuel consumption as a function of delay

After calculating the delay and consumption values following the methodology proposed in the previous section, the trips have been filtered by itinerary and vehicle, obtaining the relation between the delay rate and fuel consumption, both graphically and analyzing best fitting curve. The following paragraphs discuss some of these relations.

Fuel Consumption and Delay Rate of Urban Motorway Itineraries

In the case of itineraries of M30 Ring Motorway, the graphs show a growing trend of fuel consumption due to the increase in the level of congestion. As an example, Figure 29 shows graphically the relation between fuel consumption and delay rate for the same vehicle on two different itineraries; values grouped by level of service.

Figure 29. Relation between fuel consumption and delay rate - Example of two itineraries in M30 Ring Motorway

Thus, for every vehicle and itinerary, the regression can be obtained that best fit the consumption values as a function of the delay rates. Table 19 shows the slopes of the regression lines.

Table 19. Slope and Goodness-of-Fit of the Regression Line for each Motorway Itinerary and Vehicle

Itinerary number and vehicle		<i>M30 ring Motorway itineraries</i>			
		2	3	7	8
Fiat Bravo 1.6D	Slope	0.9405	0.8388	1.2212	1.3697
	R ²	0.91	0.71	0.17	0.90
Fiat Punto 1.3D	Slope	0.1888	0.5549	-0.8125	0.8100
	R ²	0.19	0.74	0.41	0.90
Fiat Punto 1.2G	Slope	0.9035	0.7761	-3.0272	0.6454
	R ²	0.70	0.63	0.51	0.56

We would expect all the slopes to be positive but, surprisingly, itinerary 7 presents declining fuel consumptions as the delay rate increases. This can be explained by the fact that high levels of congestion were not experienced in this itinerary, so that increase in delay does not involve braking and acceleration phenomena. The delay in this case, is due to mere slight reduction in the current average speed compared to free flow conditions. When only the service levels close to the free flow (LOS A and LOS B) were analyzed, the regression lines present mostly negative slopes, as reflected in Table 20.

Table 20. Slope and Goodness-of-Fit of the Regression Line in Service Levels and Sublevels A and B, for each Itinerary and Vehicle

Itinerary number and vehicle		<i>M30 ring Motorway itineraries</i>			
		2	3	7	8
Fiat Bravo 1.6D	Slope	1.4155	-1.3797	1.2212	0.207
	R ²	0.22	0.40	0.17	0.01
Fiat Punto 1.3D	Slope	-3.8528	-2.0475	-0.8125	-0.7977
	R ²	0.88	0.93	0.41	0.29
Fiat Punto 1.2G	Slope	-3.8255	-6.076	-3.0272	-4.1423
	R ²	0.95	0.95	0.51	0.67

Consequently, Figure 30 shows the graphs of the same itineraries presented in Figure 29, but considering only LOS A and LOS B. We can observe high values of R² when the slope is negative, but very low in case of positive or nearly horizontal regression lines.

Adjusting to a second degree polynomial, we obtain the following values of goodness-of fit (R²):

Table 21. Goodness-of-Fit of the second degree polynomial in Service Levels and Sublevels A and B, for each Itinerary and Vehicle

Itinerary number and vehicle		<i>M30 ring Motorway itineraries</i>			
		2	3	7	8
Fiat Bravo 1.6D	R ²	0.92	0.94	0.90	0.52
Fiat Punto 1.3D	R ²	0.95	0.93	0.92	0.65
Fiat Punto 1.2G	R ²	0.98	0.99	0.99	0.96

As expected, second degree polynomial achieves a better goodness-of-fit, obtaining this way a curve with a minimum for delay rate values between 0.05 and 0.10. Examples are shown in Figure 30.

Figure 30. Fitting curve of fuel consumption for delay rates close to free flow conditions (LOS A and LOS B)

Analysis of fuel consumption with reference to the homogeneity of the speed profile

In order to investigate the reason for the occurrence of minimum in consumption, it is necessary to analyze an indicator that reflects the speed homogeneity along an itinerary. Thus, in Section 3.3.1 is defined Positive Accumulated Acceleration (PAA) as an indicator obtained from the analysis of the speed profile in an itinerary which graphically represents the area under the positive accelerations curve. Thus, a trip in which the speed varies considerably tends to have a comparatively much greater PAA value than those of other trips on the same itinerary but with uniform speed.

Figure 31. Example of Positive Accumulated Acceleration and fuel consumption as a function of delay, for an itinerary of M30 urban motorway

Analyzing where the minimum of fuel consumption and PAA curves are situated in the plot, it is possible to set 3 different areas as a function of the delay rate (Figure 31).

For delay rates close to zero, fuel consumption decreases because the average speed also drops while maintaining a homogenous speed along the itinerary.

In the second zone, increase in traffic intensities lead to instabilities producing increasing braking and acceleration, consequently decreasing the average speed. When the minimum is reached, the average speed reduction is not enough to counter the effect of acceleration-braking process on fuel consumption.

Finally, in the third stage, fuel consumption increases since both the negative effects of increasing accumulated acceleration and the fact that at those high speeds the vehicle no longer lies in the area of maximum efficiency.

Fuel consumption and delay rate in urban itineraries

For urban itineraries, it was not necessary to group the values based on LOS, as the slopes of the regression lines show consistent and linear tendencies, and the trips

recorded are well distributed among the whole range of traffic conditions. Table 22 shows the slope of regression lines for every urban itinerary and vehicle. It is remarkable that the vehicle with a higher engine displacement presents consistently a larger slope for each of the urban itineraries studied. Graphically, this fact can be also observed in the examples shown in Figure 32.

Table 22. Slope and Goodness-of-Fit of the Regression Line for each Urban Itinerary and Vehicle

Itinerary number and vehicle		<i>Urban itineraries</i>		
		<i>12</i>	<i>17</i>	<i>18</i>
Fiat Bravo 1.6D	Slope	1,514	1,0353	1,3394
	R ²	0.34	0.40	0.63
Fiat Punto 1.3D	Slope	1,3506	0,6922	1,0964
	R ²	0.38	0.12	0.37
Fiat Punto 1.2G	Slope	1,4401	0,9041	1,1746
	R ²	0.50	0.44	0.62

Figure 32. Fuel consumption as a function of the delay rate in urban itinerary 12

In contrast to the motorway itineraries analyzed in the last section, it is not possible to observe a decrease in consumption with increasing delay rates. This is in line with the fact that for the range of speeds in urban itineraries, a drop of the average speed on an itinerary always involves an increase in fuel consumption

following the performance curves of vehicles' engines (Barth and Boriboonsomsin, 2010). In urban areas, both consumption and cumulative positive acceleration (PAA) behave linearly, as opposed to what was observed in the case of urban motorways (Figure 33).

Figure 33. Regression lines of fuel consumption and positive accumulated acceleration as a function of the delay rate in urban itinerary 17

5.4. Conclusions on fuel consumption and congestion

It has been observed that the congestion effects on fuel consumption are not taken into consideration in some route planners and transport demand models. However, the results of the case study presented in this paper show a clear relationship between congestion and fuel consumption. In the case of urban motorways as the case of M30 in Madrid, the data collected show that small increases in traffic starting from free flow conditions are positive in terms of fuel economy, but the general trend is that congestion increases fuel consumption.

Thus, for each itinerary of motorway it is possible to achieve optimum fuel consumption as a function of the delay rate. Once this optimum is exceeded, increasing traffic intensities cause speed profiles to become less homogeneous, and hence increases consumption.

On the other hand, the data analysis in urban areas presents a different behavior. For the speed range analyzed in these areas, fuel consumption increases linearly as a function of congestion.

The analysis of the speed profile homogeneity reveals that the fuel consumption largely depends on the point at which increasing traffic intensities cause flow instabilities. Hence, the optimum is reached at a different point depending on the type of road.

Therefore, the need to include a congestion parameter in fuel consumption models is obvious, since the consumption increase due to the level of traffic can exceed 100%. Moreover, the use of a single indicator (usually average speed) involves some risk, since the optimal fuel consumption depends also on the accumulated acceleration in the section, i.e., speed homogeneity. Similar average speeds do not mean similar fuel consumptions for different types of roads.

For greater accuracy in the calculation of fuel consumption without resorting to microscopic models which require very detailed data, it would therefore be advisable to adjust the average speed models by adding a factor of congestion or traffic homogeneity based on the type of road. Heavy duty vehicles should also be

object of further research, as they are major contributions to CO₂ emissions, especially in interurban itineraries.

6. FUEL CONSUMPTION EXPLANATORY VARIABLES

“Analyzing data really is a skill, not a recipe book!”

Andy Field

This chapter gets into detail of the statistical analysis of the collected data from the Madrid campaign. The objective is to get how much of the fuel consumption variance can be explained by the collected speed profiles. The first step will be an exploratory factor analysis which will classify the variables in factors. Using one variable of each factor, the aim is to propose a multiple regression model with the fuel consumption as dependent variable.

6.1. Reducing the number of variables. Factor Analysis

6.1.1. Definitions and theoretical background

According to Child (2006), a factorial analysis is a statistical technique for identifying groups or clusters of variables. Among other uses, this technique can be used to explore and understand the structure of a set of variables and to reduce a data set to a more manageable size while retaining as much of the original information as possible.

Factor analysis achieves simplicity by explaining the maximum amount of common variance using the smallest number of explanatory variables.

Following the methodology proposed by Comendador, Lopez-Lambas, and Monzon (2014), and Hernandez and Monzon (2015), the following steps must be carried out to perform a proper factor analysis.

Step 1. Data suitability: Before starting the factorial analysis is necessary to ensure that the data is consistent:

- Sample size: There are many opinions and “*rules of thumb*” in the literature. According to Field (2013), the common rule is to suggest a sample size of 10 or 15 times the number of variables.
- Reliability. The Cronbach alpha test measures the reliability of the internal consistency. Values above from 0.7 are generally accepted (Wittwer, 2014).
- Sample adequacy: Another alternative is to use the Kaiser–Meyer–Olkin measure of sampling adequacy (KMO). It represents the ratio of the squared correlation between variables to the squared partial correlation between variables. The KMO index ranges from 0 to 1, with 0.50 is considered suitable for Factor Analysis. Furthermore, values between 0.5 and 0.7 are mediocre, values between 0.7 and 0.8 are good, values between 0.8 and 0.9 are great and values above 0.9 are superb (Hutcheson and Sofroniou, 1999).

- Significance. The Bartlett test of sphericity is applied as quality criterion. The Bartlett measure tests the null hypothesis that the original correlation matrix is an identity matrix. Therefore, this test has to be significant, which implies a significance value less than 0.05.

Step 2. Factor extraction method. The aim of the extraction is to simplify the factor structure of a group of items, which means that high item loadings on one factor and smaller item loadings on the remaining factor. There are numerous ways to extract factors, but the Principal Component Analysis and Principal Axis Factoring are the most common in the published literature (Comendador et al., 2014).

Step 3. Rotational Method. The objective of this step is to discriminate among factors to load the variables properly. There are two types of rotation: orthogonal rotation and oblique rotation. If there are theoretical grounds to think that the factors are independent, then orthogonal rotations must be chosen. However, in theory factors might correlate, oblique rotation is the suitable solution (Field, 2013).

Step 4. Number of factors. The aim of data extraction is to reduce a large number of items into factors. According to Hernandez and Monzon (2015), there are two different criteria to extract the latent factors:

- Scree plot (Y-axis represents each eigenvalue against its factor associated X-axis) and the cut-off point for selecting factors should be at the point of inflexion of the curve.
- The Kaiser criterion. This method retains all factors with eigenvalues greater than 1.

6.1.2. Application to the case study of Madrid

In our study, following the previous steps, the Principal Component Analysis is applied to the case study of Madrid described in Chapter 3. The analysis was performed using the software SPSS v.20 from IBM.

The database contains 76 variables, as specified in table 11 of Chapter 3. From these 76 variables, 40 variables were initially selected. These 40 variables include the ones which were comparable between different trips. For instance, number of stops cannot be compared between trips with different longitude; therefore we will use the variable which represents number of stops per kilometer. It is also important to highlight that fuel consumption will not enter as variable. This will be the dependent variable in the regression model described later on Section 6.2.

Step 1. Data suitability

- Sample size: The initial sample consisted of 3,076 recorded trips. After graphically identifying 6 outliers for an excessive fuel consumption (Figure 34), the final amount was 3,070 trips, well above the number of 600 (15 times 40 variables, see 6.1.1)

Figure 34. Box-and-whisker plot for the variable fuel consumption, differentiating among vehicles

- Reliability: The first analysis of reliability performed with the 40 mentioned variables reflects unaccepted values, as the output from the Cronbach alpha shows (Figure 35).

Reliability Statistics	
Cronbach's Alpha ^a	N of Items
-1.130	40

a. The value is negative due to a negative average covariance among items. This violates reliability model assumptions.

Figure 35. Results of reliability analysis for the first set of considered variables

For this reason, is necessary to perform some changes in the variables:

- o Change sign of the negative accelerations, substituting the negative acceleration variable for brake accelerations with positive sign.

- Eliminate variables which reflect maximum values, such as maximum speed or acceleration
- Calculate all the variables transformed as squared root, square, inverse and logarithm in base 10. For all these new variables the values of skewness and kurtosis are calculated.
- Based on the skewness and kurtosis results, one variable of each group (original variable and transformed) is selected.

After this process, 30 variables are finally selected, and the results of the reliability tests are as follows:

Reliability Statistics	
Cronbach's Alpha	N of Items
.779	30

Figure 36. Reliability test of the final 30 variables

The result of the Cronbach alpha is greater than 0.7, therefore acceptable.

- Sample adequacy: the Kaiser–Meyer–Olkin measure of sampling adequacy presents a “superb” result ($KMO > 0.9$) according to Hutcheson and Sofroniou (1999).

Table 23. Results of Kaiser-Meyer-Olkin and Bartlett's test

KMO and Bartlett's Test	
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.	.904
Bartlett's Test of Sphericity	Approx. Chi-Square
	371551.244
	df
	435
	Sig.
	.000

- Significance. The Bartlett test of sphericity is applied as quality criterion. The test is significant, since the significance values is 0.000.

Step 2. The factor extraction method selected is Principal Component Analysis (PCA), as it is “conceptually less complex than factor analysis” (Field, 2013).

Step 3. Rotational Method. The objective of this step is to discriminate among factors to load the variables properly. Since there are theoretical grounds in our study to think that the factors might correlate, therefore oblique rotation is the suitable option, specifically “direct oblimin”.

Step 4. Number of factors. Both the scree plot and the Kaiser criterion are used to determine the number of factors, resulting both in 3.

Table 24. Total variance explained by factors with eigenvalue > 1. Extraction Method: Principal Component Analysis.

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
1	24.139	80.463	80.463	24.139	80.463	80.463	22.530
2	2.425	8.084	88.548	2.425	8.084	88.548	18.964
3	1.238	4.126	92.673	1.238	4.126	92.673	4.691
4	.616	2.053	94.726				
5	.404	1.348	96.074				
6	.300	1.000	97.074				
7	.254	.846	97.920				
8	.135	.450	98.370				
9	.103	.342	98.712				
10	.082	.273	98.985				
11	.064	.212	99.197				
12	.052	.172	99.369				
13	.041	.136	99.505				
14	.033	.110	99.614				
15	.030	.099	99.714				
16	.026	.086	99.800				
17	.021	.070	99.870				
18	.011	.035	99.905				
19	.009	.028	99.934				
20	.006	.020	99.954				
21	.004	.014	99.968				
22	.003	.010	99.978				
23	.002	.008	99.986				
24	.002	.006	99.992				
25	.001	.004	99.995				
26	.001	.003	99.998				
27	.001	.002	100.000				
28	7.096E-005	.000	100.000				
29	3.624E-005	.000	100.000				
30	4.511E-006	1.504E-005	100.000

Figure 37. Scree plot with the tendency lanes crossing in 3 factors

With all these conditions, a principal component analysis (PCA) was conducted on the 30 items with oblique rotation (direct Oblimin). The Kaiser–Meyer–Olkin measure verified the sampling adequacy for the analysis, $KMO = 0.904$ ('superb'). The Bartlett test of sphericity $\chi^2 (435) = 371551.244$, $p < .001$, indicated that correlations between items were sufficiently large for PCA. An initial analysis was run to obtain eigenvalues for each component in the data. Three components had eigenvalues over the Kaiser criterion of 1 and in combination explained 92.673% of the variance. The scree plot was also quite clear, showing the adequacy of 3 factors. Table 25 shows the factor loadings in the structure and pattern matrix.

Table 25. Pattern Matrix and variable loadings to each component

Variable code	Component		
	1	2	3
Sttkm_lt14.4kmh_5	.997		
Sttkm_lt14.4kmh_3	.993		
Nstopskm_lt5kmh	.990		
Nstopskm_lt3kmh	.983		
Nstopskm_lt14.4kmh_5	.953		
Nstopskm_lt14.4kmh_3	.948		
Sttkm_lt5kmh_SQRT	.920		
Sttkm_lt3kmh_SQRT	.920		
Vavet_inv	.918		
Sttkm_lt14.4kmh_3	.917		
Sttkm_lt14.4kmh_5	.915		
stt_lt5kmh	.855		
stt_lt3kmh	.846		
PAAkm	.768		.356
Vavewo3kmh_inv	.727		.355
Vavewo5kmh_inv	.714		.360
Powerkm	.621		.402
Pdec_5kmh_SQRT	.561		
Asd_A	.545	.443	
PKEkm	.474		.379
Pacc_5kmh_inv		.991	
Pcru_5kmh_inv		.890	
BrakeAve		.875	
Pcru_3kmh_inv		.873	
Asd_B		.851	
Asd		.782	
Vsd		.622	
Aave	.494	.506	
Pacc_3kmh	.438	.461	
Pacc_0.1ms			.864

Extraction Method: Principal Component Analysis.

Rotation Method: Oblimin with Kaiser Normalization.

a. Rotation converged in 12 iterations.

**Variable description can be found on Table 11, Section 4.3*

The first component explains the time that the traffic is stopped in each itinerary. Component number 2 deals with high accelerations while the third component reflects the amount of time driving at homogeneous speed.

Three variables have been selected, one per each factor. The variables must have a high load in its factor and low in the two others. Likewise, these variables must be easy to calculate subsequently in the traffic simulation tool. Taking these conditions into account, the three variables selected are:

- Nstopskm_lt3kmh: Number of stops per km being stop speed under 3km/h.
- Pacc_0.1ms: Time % acceleration is greater than 0.1 m/s².
- Pacc_5kmh_inv: Inverse of time % acceleration is greater than 1.39 m/s².

6.2. Explaining the fuel consumption variation. Multiple regression model

Related with the research objectives of this thesis, the aim of constructing a regression model was to know how much of the fuel consumption variance can be explained with variables selected in the previous section, i.e. variables which can be extracted from a speed profile.

Multiple Regression analysis is a way of predicting an outcome variable from several predictor variables.

From the rest of the chapter, we will consider only the data from the vehicle FIAT Bravo 1.6 Diesel, as this was the only one used to test the eco-driving techniques.

When a regression model needs to be generalized, there are several assumptions that must be true: Non-zero variance, no perfect multicollinearity, independence, etc. (Berry, 1993). However, for the thesis, the intention is not to generalize the conclusion, but to analyze the goodness of fit of our regression model by means of R^2 . Therefore it is not necessary to check the assumptions (Field, 2013). By making no assumptions about the importance of the predictors, the method of regression chosen is the forced entry method. With this method, taking decision about the order in which variables are entered is, therefore, not necessary.

The results of the analysis are presented in the table 26 that shows the descriptive statistics of both the dependent and independent variables, while Table 27 shows the correlation matrix. We can observe that none of the variables correlate too highly ($R > 0.9$)

Table 26. Descriptive statistics of the dependent and independent variables

	Mean	Standard Deviation	N
consumption	4.650765	1.7133073	776
Pacc_0.1ms	30.581942	6.0869526	776
Nstopskm_lt3kmh	.861223	1.1430605	776
Pacc_5kmh_inv	.6959	.34454	776

Table 27. Variable correlation matrix

		consumption	Pacc_0.1 ms	Nstopskm _lt3kmh	Pacc_5kmh _inv
Pearson Correlation	consumption	1.000	.278	.820	-.782
	Pacc_0.1ms	.278	1.000	.085	-.164
	Nstopskm_lt3kmh	.820	.085	1.000	-.861
	Pacc_5kmh_inv	-.782	-.164	-.861	1.000
Sig. (1- tailed)	consumption	.	.000	.000	.000
	Pacc_0.1ms	.000	.	.009	.000
	Nstopskm_lt3kmh	.000	.009	.	.000
	Pacc_5kmh_inv	.000	.000	.000	.
N	consumption	776	776	776	776
	Pacc_0.1ms	776	776	776	776
	Nstopskm_lt3kmh	776	776	776	776
	Pacc_5kmh_inv	776	776	776	776

Table 28 shows the summary of the proposed multiple regression model, with the fuel consumption as dependent variable:

Table 28. Summary values of the regression model

R	R Square	Std. Error of the Estimate	Change Statistics				
			R Square Change	F Change	df1	df2	Sig. F Change
.854	.729	.8940394	.729	691.386	3	772	.000

The value of R^2 is 0.729, which implies that with only the speed profile as information, we can explain the 72.9% of the variation of the fuel consumption of a trip.

The coefficients of the multiple regression model are shown in the following table:

Table 29. Multiple regression model coefficients

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	3.092	.286		10.824	.000
Number of stops per km being stop speed under 3km/h	.959	.061	.615	15.718	.000
Time % acceleration is greater than 0.1 m/s ²	.049	.006	.168	8.307	.000
Pacc_5kmh_inv	-1.081	.205	-.208	-5.274	.000

a. Dependent Variable: consumption l/100km

6.3. Consideration on the slope of the itineraries

Average slopes were calculated for each of the trips based on the altitude data collected from Google Earth Pro, as altitude data from the GPS was not accurate enough.

Longitudinal slope in the previous analyses were not been considered. The main reason is that the slope is not a variable to compare different trips in the same itinerary, and therefore it is useless for the eco-driving simulation process described in Part IV of this thesis. In addition to this, average slopes are not remarkable, with all of them between -1.5% to 1.5% and only 4 of them higher than 1% in absolute value. The following table shows the length and average slope of each trip:

Table 30. Trips average slope

Trip code	Trip Name	Urban/ Motorway	Length (km)	Average slope %
1	Mendez Alvaro/ Costa Rica	Motorway	7.8	1.3
2	Costa Rica/ O'Donell	Motorway	5.3	-1.4
3	O'Donell/ Costa Rica	Motorway	5.8	1.4
4	J.M ^a Soler/ Príncipe Pío	Motorway	12.6	-0.9
5	Arroyofresno /J.M ^a Soler	Motorway	21.4	0.4
6	ETSI Caminos / Arroyofresno	Motorway	2.9	-0.9
7	San Pol / Arroyofresno	Motorway	5.4	0.4
8	Arroyofresno / San Pol	Motorway	6.7	0.4
9	J.M ^a Soler/ Arroyofresno	Motorway	20.3	-0.4
12	Calle 30 / Calle Corregidor	Urban	1.2	0.3
13	Avda. Ilustracion	Urban	1.5	-1.2
14	Alfonso XIII / ETSI Caminos	Urban	7.4	-0.5
15	ETSI Caminos / Alfonso XIII	Urban	6.7	0.5
17	Príncipe Pío / San Pol	Urban	1.3	-0.4
18	Calle 30 / Príncipe Pío	Urban	1.6	0.7
19	Ilustración and Príncipe Pío	Urban	3.1	-0.3

Although it is not necessary to simulate eco-driving, it is interesting to know how much of the fuel consumption variance can be explained by adding the slope as independent variable in the multiple regression model.

Therefore, Table 31 shows the summary of the proposed multiple regression model, with the fuel consumption as dependent variable:

Table 31. Summary of the regression model including slope as predictor

Model	R	R Square	Adjusted R Square
1	.896 ^a	.803	.802

The result shows that when adding the slope as predictor, it is possible to explain 80.3% of the variance of the fuel consumption. It is a 7.4% more than the regression model described in Section 6.2.

Finally, the following table describes the coefficients of the multiple regression model:

Table 32. Multiple regression model coefficients

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	2.968	.231		12.868	.000
Number of stops per km being stop speed under 3km/h	.952	.049	.610	19.330	.000
Time % acceleration is greater than 0.1 m/s ²	.051	.005	.175	10.732	.000
Pacc_5kmh_inv	-1.036	.165	-.200	-6.263	.000
slope	.674	.033	.326	20.377	.000

a. Dependent Variable: consumption l/100km

PART IV – NETWORK WIDE SIMULATION OF ECO-DRIVING

7. ECO-DRIVING SIMULATION IN DIFFERENT TYPES OF ROADS

“If you can’t explain it simply, you don’t understand it well enough”

Albert Einstein

Chapter 7 is a presentation of the methodology employed for simulating eco-driving using a traffic micro simulator. The chapter starts with the selection of itineraries to model followed by the process of model construction, the calibration of the base-case and the calibration of the eco-driving behavior. At the end of the chapter a definition is given of the scenarios depending on the congestion level and the eco-drivers penetration rate.

7.1. Selection of itineraries to model

According to the traditional classification of urban roads (AAHSTO, 2001), these can be classified in four categories:

- Principal arterial
- Minor arterial
- Collector street
- Local street

Similarly, the European Commission (2015) proposed that, at the urban level, road function can be divided into three groups - arterial or through traffic flow routes, distributor roads, and access roads.

Following this classification for the case of Spain, urban roads are defined as follows (Kraemer et al., 2009):

- **Motorways and speedways:** these roads are needed in large metropolitan areas (cities with over one million inhabitants) where the length of trips makes high speed roads necessary. These roads are used exclusively by through traffic, and are characterized by:
 - o They are designed for through traffic only, and the access to adjacent properties is not allowed.
 - o Trip longitude in such roads may exceed 5 kilometers.
 - o The junctions are built at different levels, sometimes regulated by traffic lights, but preferably with multi-level interchanges in order to enable high speeds.
 - o Urban motorways are designed for lower speeds and with closer junctions than the interurban motorway.
- **Arterials:** They are necessary to communicate the different parts of the city. They capture traffic that comes mostly from local streets and collector-distributor, and are characterized by:
 - o These rarely provide direct access to adjacent properties.
 - o The trips in such streets are normally longer than 2 km.

- The intersections are built at the same level (regulated by traffic lights) or at different levels with over- or underpasses.
- **Collectors:** These roads lead directly traffic from its origin to its destination or connecting local stress. They are distinguished by:
 - Access to surrounding buildings is allowed.
 - Trips are around 1 km. long and at lower speeds than arterial.
 - Intersections with local streets or other collectors are at the same level, regulated by traffic signals or just priority rules.
- **Local streets:** lead traffic from its origin to its destination or to collectors. They are distinguished by:
 - Access to adjacent buildings and properties is allowed.
 - Trips are normally shorter than 1 km. and with low speeds.
 - Intersections with local streets or collectors are at the same level and rarely regulated by traffic signals.

Following this classification and considering the FCD itineraries described in Section 3.4, the next sections details the characteristics of the selected ones to be modeled.

7.1.1. Urban motorway

The section selected for our study corresponds to the itinerary 8 of the data collection campaign (See section 3.4), Arroyofresno/San Pol. It is a 3 lane motorway (southbound) with traffic intensity in the afternoon peak hours of about 3,300 veh/h (before M500 junction) and with a length of 6.7 km.

Figure 38. Madrid case study. Traffic intensities on a weekday at M30 West section southbound

Most of the section has a speed limit of 90 km/h, except the last 100 m, which are limited to 70 km/h (tunnel entrance). The congestion is usually caused by the bottleneck situated in the M500 junction, as around 2,800 vehicles merge into the M30.

Figure 39. Urban Motorway Itinerary. M30 west section

Figure 40. Aerial view of the west section of the M30 ring motorway and the M500 junction

7.1.2. Urban arterial

The urban arterial corresponds to a section of the itinerary 14 of the data collection campaign (See section 3.4), Alfonso XIII/E.T.S.I. Caminos. More specifically, it covers the segment from Lopez de Hoyos to Cuatro Caminos, with a length of 2.2 km. It is a multilane street with intersections regulated with traffic signals and an overpass and underpass in the crossing with other urban arterials. Left turns are allowed and regulated in one of the intersections. The annual average daily traffic (AADT) rounds 30,000 vehicles in most of the segments, with peaks of 2,900 vehicles per hour.

1.3 km. It is a two-lanes street with some intersections regulated with traffic signals and access to nearby houses and garages. Left turns are only allowed in the last segment of the itinerary. The annual average daily traffic (AADT) is around 10,000 vehicles in the busiest segment, with peaks of 800 vehicles per hour.

Figure 43. Urban Collector from Principe Pio to San Pol

Figure 44. Aerial view of Paseo de la Florida to San Pol

7.1.4. Local street

Figure 46. Aerial view of crossing of Padre Claret with Luis de Salazar

7.2. Model construction and calibration of the basecase

The modeling process was performed with PTV Vissim v7, which is one of the most used micro simulation tool worldwide, both in transport planning and research. Its selection is based on requirements in the ICT-Emissions project and its availability.

Vissim is a microscopic, behavior-based multi-purpose traffic simulation program. It offers a variety of urban and highway applications, integrating public and private transportation with pedestrians. The editing of networks in Vissim is based on background maps such as intersection layout sketches and aerial photography.

The simulation program includes stochastic elements such as distributions of desired speed, acceleration rates, and car-following behavior. VISSIM has a car-following model with time steps as low as 1/10 second and a calibrated lane changing model for urban and freeway traffic. Different driving behaviors are also supported in the model by setting up the behavioral parameters.

The traffic flow model is a discrete, stochastic, time step based microscopic model, with driver-vehicle-units as single entities. The model contains a psycho-physical car following model (Wiedemann) for longitudinal vehicle movement and a rule-based algorithm for lateral movements (lane changing).

On multi-lane links moved up vehicles check whether they improve by changing lanes. If so, they check the possibility of finding acceptable gaps on neighboring lanes. Car following and lane changing together form the traffic flow model, being the kernel of Vissim.

Figure 47 shows a scheme of the car-following model. When a faster vehicle is approaching a leading vehicle, it enters first in the perception threshold and it starts decelerating. The braking action point depends on the speed difference, distance and driver depended behavior. Once the two vehicles are separated by the follower safety distance, an oscillating process, in which the speed difference and the distance oscillate around given values.

Driver specific perception abilities and individual risk behavior is modelled by adding random values to each of the parameters as shown for ΔX . For a complete listing of the random values see Wiedemann and Reiter (1992).

Figure 47. Scheme of Wiedemann car-following model (PTV, 2014)

Number of replications

Given the inherent variability existing between microsimulation runs (due to the random seed number), it is necessary to ensure the representativeness of the model and to guarantee that it is not skewed towards a statistical outlier.

The Washington State Department of Transportation [WSDOT] (2014) recommends at least 11 replications, while Toffolo et al. (2015) recommend 15, being 10 as the minimum number of replications. To be on the conservative side, 15 runs for every simulated scenario were performed for this thesis.

Model inputs

Vissim requires several inputs to complete the necessary data to develop the model and simulate the base-case. Some other parameters not mentioned in the following list, have been set as default in the first model version and changed when necessary during the calibration process.

- Section trace based on background.
- Vehicle inputs.
- Routes.
- Desired speed decisions and reduced speed areas.
- Data collection points.
- Vehicle types and vehicle classes.
- Vehicle composition.
- Functions:
 - Maximum acceleration.
 - Desired acceleration.
 - Maximum deceleration.
 - Desired deceleration.
- Distributions
 - Desired speed.
 - Weight.
 - Power.

Calibration Criteria

“Calibration is the process used to achieve adequate reliability or validity of the model by establishing suitable parameter values so that the model replicates local traffic conditions as closely as possible” (WSDOT, 2014).

This manual set two different measures of effectiveness (MOEs):

- Traffic Volumes.
- Average speed or travel times.

Regarding traffic volumes, the GEH formula was employed, which is commonly used in traffic engineering. For hourly throughput volumes, the GEH formula is:

$$GEH = \sqrt{\frac{2(m-c)^2}{m+c}} \quad (3)$$

m = output traffic throughput volumes from the simulation model (veh/h/lane).

c = traffic throughput volumes based on field data (veh/h/lane).

Considering $GEH \leq 5$ as acceptable.

With regards to travel times, different allowable differences for free flowing facilities (motorway) and interrupted facilities (urban streets) are provided:

Free flowing facility,

$$\Delta = \frac{1}{\frac{1}{t} - \frac{4.4}{L}} - t \quad (4)$$

And interrupted facility,

$$\Delta = \frac{1}{\frac{1}{t} - \frac{0.1 * 5280 S}{3600L}} - t \quad (5)$$

Δ = Allowable Travel Time Variation (+/- seconds).

t = Real World Travel Time (seconds).

L = Length (feet).

S = Free Flow Speed (mph); Posted Speed may be used for FFS if unknown

The next paragraphs describe the details for each of the four models designed in Vissim and the calibration parameters following the *Protocol for VISSIM simulation* of the Washington State Department of Transportation (WSDOT, 2014).

7.2.1. Urban Motorway

Section trace based on M30 background

In order to trace the section of the M30 ring motorway under study, Calle 30 (M30 road authority) has provided documentation with M30 detailed cartography. Based on this cartography, the section is drawn considering every ramp along the way. Afterwards, with Google Earth tool, another background from satellite view was obtained to get better visual results.

Figure 48. Model construction based on Calle30 cartography

Vehicle inputs

Vehicle inputs are needed at the beginning of the section and in every ramp included in the model network. On the M30 ring road there are several measuring points (induction loops) placed along the section, including some entrance and exits ramps.

Existing measurement points on Calle30 provided the data for the modeling section. The data included information on date and time, traffic intensity, speed and occupancy every 5 minutes. However, measuring points do not always work properly so that there were some missing data. To solve this problem, an Excel spreadsheet was developed, filling missing data with average values of similar workdays within the month (excluding holiday periods).

Moreover, there is no specific information about traffic intensities at some entrances of the network model. In these cases, downstream measuring points and Visum model of Madrid region (Valdes, 2012) were used to complete the missing information.

The data is added every 15 minutes for each measurement point. Subsequently, this 15 minutes data is introduced for every entrance in Vissim model.

Routes

In this model, static routing decision every 15 minutes. This way, for each entrance, exit percentages at every exit of the network must be set. The available data was converted to percentages and introduced in Vissim, adjusting the values during the calibration process.

Desired speed decisions and reduced speed areas

Basically, desired speed decisions and reduced speed areas are the instruments to limit desired speed in Vissim models. A desired speed decision is to be placed at a location where a permanent speed change should become effective, simulating the effects of speed signs in reality. In this model, desired speed decisions were placed before the tunnel entrance and in the exits ramps. On the other hand, reduced speed areas were used when modeling short sections of different speed characteristics, therefore perfectly suitable for entrance ramps and curves within the model.

Data collection points

Cartography provided by Calle 30 was used to determine the position of the measurement points in the network. Speed and intensity data provided by this virtual data collection points were used in the calibration model to compare with real induction loops data.

Vehicle types and vehicle classes

Vissim user manual defines vehicle type as a group of vehicles with similar technical characteristics and physical driving behavior. In the case of vehicle class, one or more vehicle types can be combined in one vehicle class. Speeds, evaluations, route choice behavior and certain other network elements refer to vehicle classes.

Four vehicle types were considered in the model:

- Passenger Cars (PC).

- Light Duty Vehicles (LDV).
- Medium and High Duty Vehicles (MDV+HDV).
- Bus.

Each vehicle type is related with a vehicle class with the same name. However, other vehicle classes were created to group all type of vehicles, passenger cars, vehicles of a specific segment or trucks, to make the assignment of the desired speed distributions easier.

Vehicle composition

Fleet composition data were customized for the M30 motorway following a report by the Madrid Local Government (Dirección General de Sostenibilidad y Planificación de la Movilidad, 2013).

Percentages assigned to each vehicle type are shown in Table 33.

Table 33. Vissim input. Relative flow per vehicle type in M30 Motorway

Vehicle type	Relative flow (%)
Passenger Car	88.6
LDV	8.5
MDV+HDV	2.0
Bus	0.9

Functions: maximum acceleration, desired acceleration, maximum deceleration, desired deceleration

For the base-case, the acceleration and deceleration functions were set as the default in Vissim.

Figure 49. Maximum acceleration as a function of instantaneous speed

Distributions: desired speed, weight, power

Three general desired speed distributions (passenger cars, LDV and MDV+HDV) were set for the whole network, and will be applicable except in the areas affected by local desired speed or reduced speed zones. The values were calibrated according to average speed values obtained from induction loops in free flow conditions. On average, the desired speed rounds off to 90 km/h, according to the posted speed limit.

The distribution of desired speeds varies in the area just before the tunnel entrance, and merges in and out of the network modelled. Distributions of weight and power remain unchanged, thus maintaining Vissim default values.

Calibration

The calibration process was based on average speed and traffic intensity data recorded by induction loops and travel times data from the floating cars.

The first step consisted in adjusting routing decisions to ensure similar traffic intensities in most of the measuring points. Some of the induction loops had to be rejected due to its failure to fit the flow continuity equations. Table 34 shows the comparison of the average values of traffic flows and the GEH (WSDOT, 2014) statistic formula for the valid measuring points in an interval of 30 minutes with a congested traffic situation.

Table 34. Comparison of real and simulated intensities in 5 different measuring points of the M30 West section

Measuring point	21941	22121	22241	22471	42052
Average 15 runs	5,671	3,756	3,372	5,095	1,363
Real	5,570	3,754	3,580	5,106	1,420
GEH	1.3	0.0	3.5	0.2	1.5
WSDOT Calibration criterion	TRUE				

Once acceptable values in the reference measuring points ($GEH \leq 5.0$) were achieved, average speeds were also checked and adjusted. The most relevant changes in this sense include reduced speed areas in entrance ramps and the reduction of safety distance factor regarding the driver behavior. Reflecting the model of an urban motorway, with these changes, drivers behave more aggressively than in the general default motorway behavior recommended in Vissim.

The final calibration was done with the travel time measurements from floating vehicles. Some routing decisions and speed decision were adjusted to best fit travel times while maintaining the same level of accuracy in traffic flows. Figure 50 shows the comparison between real and simulation travel times and Table 35 presents the WSDOT calibration criterion.

Figure 50. Travel time calibration for 4 hours of simulation

Table 35. Travel time calibration for 15 replications

	Travel distance (m)	Travel time (s)
Average 15 runs	7020.8	405.4
Real	7021	436.6

Travel Time calibration criterion of WSDOT VISSIM Protocol.

Allowable travel time difference: 39.7 s.

Calibration criterion: **TRUE.**

7.2.2. Urban arterial

Model trace based on Bing background

The model has been drawn based on the Bing Maps (Aerial View), as shown in Figure 51.

Figure 51. Arterial model designed based on Bing Maps

Vehicle inputs

Vehicle inputs are added at both ends of the corridor and in every street that feeds the corridor. For this reason, manual counts were performed based on video recordings in every intersection of the corridor.

Pedestrian inputs

Pedestrian counts were done in all intersections, where there were interaction with road traffic. The counts were based on the video recording in each intersection.

Public transport

Public transport routes, stops and frequencies were adopted from the official sources, published by the EMT (2015). Bus dedicated lanes were considered in the main corridor.

Figure 52. Frame of one the videos recorded to count vehicles, pedestrians and adjust the traffic signal programs

Traffic signal programs

Traffic signals programs were designed according to times recorded in the video.

Figure 53. Traffic signal program of the urban arterial

Routes

Routes were modeled following the turning movements in every intersections recorded by video, keeping the route distribution constant during the simulation and for every scenario. This way, Origin/Destination routes were calculated to comply with the turning movements observed.

Desired speed decisions and reduced speed areas

A desired speed decision has to be placed at a location where a permanent speed change should become effective, simulating the effects of speed limit signs in reality. In this model, the desired speed decisions were placed in streets entering or leaving the main corridor. On the other hand, reduced speed areas are used for modeling short sections with different speed characteristics, therefore perfectly suitable for intersections and curves within the model.

For this purpose we analyzed the vehicles trajectories, observing the real speed in every segment of the floating cars itinerary.

Figure 54. Instant speed and position. Urban arterial

Data collection points

Five data collection measurements were strategically placed in the model to cover main movements and according to video counts. Intensity data provided by this virtual data collection points were used in the calibration model to compare with real counts.

Vehicle types and vehicle classes

Four vehicle types were considered in the model:

- Passenger Cars (PC).
- Motorbikes.
- Light Duty Vehicles (LDV).
- Medium and High Duty Vehicles (MDV+HDV).
- Bus.

Each vehicle type is related with a vehicle class with the same name. However, other vehicle classes were created to group all type of vehicles, passenger cars, vehicles of a specific segment or trucks, to make the assignment of desired speed distributions easier.

Vehicle composition

Fleet composition data were customized for inner M30 urban area following a report by the Madrid Local Government (Dirección General de Sostenibilidad y Planificación de la Movilidad, 2013).

Percentages assigned to each vehicle type are shown in Table 36.

Table 36. Vissim input. Relative flow per vehicle type in M30 Motorway

Vehicle type	Relative flow (%)
Passenger Car	85.0
Motorbikes	9.0
LDV	4.8
MDV+HDV	1.0
Bus	0.2

Functions: maximum acceleration, desired acceleration, maximum deceleration, desired deceleration

For the base-case, the acceleration and deceleration functions were set as the default in Vissim.

Calibration

The calibration process was based on traffic intensity data recorded by video counts and travel times data from the floating cars.

The first step consisted in adjusting routing decisions to ensure similar traffic intensities in most of the measuring points. Table 37 shows the comparison of the average values of traffic flows and the GEH (WSDOT, 2014) statistic formula for the valid measuring points for an interval of 30 minutes in peak hour traffic conditions.

Table 37. Comparison of real and simulated intensities in 5 different measuring points of the selected urban arterial

Measuring point	1	2	3	4	5
Average 15 runs	2,984	1,938	2,404	1,708	536
Real	2,832	2,136	2,424	1,608	540
GEH	1.4	3.1	0.2	1.7	0.1
WSDOT Calibration criterion	TRUE				

Once acceptable values in the reference measuring points ($GEH \leq 5.0$) were reached, average speeds were also checked and adjusted. The most relevant changes in this context included some reduction in maximum acceleration rates at slow speeds.

The final calibration were done with the travel time measurements from floating vehicles. Some routing decisions and speed decision were adjusted in order to best fit travel times while maintaining the same level of accuracy in traffic flows. Table 38 presents the WSDOT calibration criterion.

Table 38. Travel time calibration for 15 replications. Urban arterial

	Travel distance (m)	Travel time (s)
Average 15 runs	2,193.3	261.1
Real	2192	256.9

Travel Time calibration criterion of WSDOT VISSIM Protocol.

Allowable travel time difference: 49.9 s.

Calibration criterion: **TRUE.**

7.2.3. Urban collector

Model trace based on Bing background

The model was drawn based on the Bing Maps (Aerial View), as shown in Figure 55.

Figure 55. Collector model based on Bing Maps

Vehicle inputs

Vehicle inputs were added at both ends of the corridor and in every street that feeds the corridor. For this reason, manual counts were performed based on video recordings in every intersection of the corridor.

Pedestrian inputs

Pedestrian counts were done in all intersections, where there was an interaction with road traffic. The counts were based on the video recording at each intersection.

Public transport

Public transport routes, stops and frequencies were adopted from official sources published by the EMT (2015). There are two dedicated ramps only for busses entering or leaving the bus station.

Figure 56. Frame of one the videos recorded to count vehicle, pedestrian and adjust the traffic signal programs

Traffic signal programs

Traffic signal programs were designed according to times recorded in the video.

Routes

Routes were modeled following the turning movements in every intersections recorded by video, keeping the routes constant during the simulation and for every scenario. This way, Origin/Destination routes were calculated to comply with the observed turn movements.

Desired speed decisions and reduced speed areas

A desired speed decision is to be placed at a location where a permanent speed change should become effective, simulating the effects of speed signs in reality. In this model, the desired speed decisions were placed in when entering or leaving the main corridor. On the other hand, reduced speed areas were used when modeling short sections of different speed characteristics, therefore perfectly suitable for intersection and curves within the model.

For this purpose we analyzed the vehicle trajectories, observing the real speed in every segment of the floating cars itinerary.

Figure 57. Instant speed and position. Urban collector

Data collection points

Five data collection measurements were strategically placed in the model to cover the main movements according to video counts. Intensity data provided by this virtual data collection points were used in the calibration model to compare with real counts.

Vehicle types and vehicle classes

Four vehicle types have been considered in the model:

- Passenger Cars (PC).
- Motorbikes.
- Light Duty Vehicles (LDV).

- Medium and High Duty Vehicles (MDV+HDV).
- Bus.

Each vehicle type was classified to a vehicle class with the same name. However, other vehicle classes were created to group all types of vehicles, passenger cars, vehicles of a specific segment or trucks, to make the assignment of desired speed distributions easier.

Vehicle composition

Fleet composition data were customized for inner M30 urban area following a report of the Madrid Local Government (Dirección General de Sostenibilidad y Planificación de la Movilidad, 2013)

Percentages assigned to each vehicle type are shown in Table 35.

Table 39. VISSIM input. Relative flow per vehicle type in the area within the M30 motorway

Vehicle type	Relative flow (%)
Passenger Car	85.0
Motorbikes	9.0
LDV	4.8
MDV+HDV	1.0
Bus	0.2

Functions: maximum acceleration, desired acceleration, maximum deceleration, desired deceleration

For the basecase, the acceleration and deceleration functions have been set as the default in Vissim.

Calibration

The calibration process was based on traffic intensity data recorded by video counts and travel times data from the floating cars.

The first step consisted in adjusting routing decisions to assure similar traffic intensities in most of the measuring points. Table 36 shows the comparison of the average values of traffic flows and the GEH (WSDOT, 2014) statistical formula for the valid measuring points for an interval of 30 minutes in peak hour traffic conditions.

Table 40. Comparison of real and simulated intensities in 5 different measuring points of the selected urban collector

Measuring point	1	2	3	4	5
Average 15 runs	739	631	405	370	363
Real	756	552	360	396	348
GEH	0.4	2.3	2.3	0.9	0.8
WSDOT Calibration criterion	TRUE				

Once reaching acceptable values in the reference measuring points ($GEH \leq 5.0$), average speeds were also checked and adjusted. The most relevant changes in this context include some reductions in maximum acceleration rates at slow speeds.

The final calibration was done with the travel time measurements from floating vehicles. Some routing decisions and speed decision were adjusted in order to best fit travel times while maintaining the same level of accuracy in traffic flows. Table 37 presents the WSDOT calibration criterion.

Table 41. Travel time calibration for 15 replications. Urban arterial

	Travel distance (m)	Travel time (s)
Average 15 runs	1246.5	253.7
Real	1.3430	234.3

Travel Time calibration criterion of WSDOT VISSIM Protocol.

Allowable travel time difference: 82.8 s.

Calibration criterion: **TRUE.**

7.2.4. Local street

Model trace based on Bing background

The model was drawn based on the Bing Maps (Aerial View), as shown in Figure 58.

Figure 58. Local street model based on Bing Maps

Vehicle inputs

Vehicle inputs were added at both ends of the corridor and in every street that feeds the modeled area. For this reason, manual counts were performed based on video recordings at every intersection.

Pedestrian inputs

Pedestrian counts were done in all intersections, where there was an interaction with vehicles. The counts were based on the video recordings at each intersection.

Public transport

Public transport routes, stops and frequencies were adopted from official sources, published by the EMT (2015). There are no dedicated lanes for public transport.

Figure 59. Frame of one the videos recorded to count vehicle, pedestrian and adjust the traffic signal programs

Traffic signal programs

Traffic signal programs were been designed according to the time recorded on the video.

Routes

Routes were modeled following the turns movement in every intersections recorded by video, keeping the routes constant during the simulation and for every scenario. This way, Origin/Destination routes were calculated to comply with the turn movements observed.

Desired speed decisions and reduced speed areas

A desired speed decision is to be placed at a location where a permanent speed change should become effective, simulating the effects of speed signs in reality. In this model, desired speed decisions were placed in when entering or leaving the main corridor. On the other hand, reduced speed areas were used when modeling short sections of different speed characteristics, therefore perfectly suitable for intersection and curves within the model.

For this purpose we have analyzed the vehicles trajectories, observing the real speed at every segment of the floating cars itinerary.

Figure 60. Instant speed and position. Local street

Data collection points

Five data collection measurements were placed strategically in the model to cover main movements according to video counts. Intensity data provided by this virtual data collection points were used in the calibration model to compare with real counts.

Vehicle types and vehicle classes

Four vehicle types were considered in the model:

- Passenger Cars (PC).
- Motorbikes.
- Light Duty Vehicles (LDV).
- Medium and High Duty Vehicles (MDV+HDV).
- Bus.

Each vehicle type is related with a vehicle class with the same name. However, other vehicle classes were created to group all type of vehicles, passenger cars,

vehicles of a specific segment or trucks, to make the assignment of desired speed distributions easier.

Vehicle composition

Fleet composition data were customized for inner M30 urban area following a report by the Madrid Local Government (Dirección General de Sostenibilidad y Planificación de la Movilidad, 2013)

Percentages assigned to each vehicle type are shown in Table 42.

Table 42. VISSIM input. Relative flow per vehicle type in the area within the M30 motorway

Vehicle type	Relative flow (%)
Passenger Car	85.0
Motorbikes	9.0
LDV	4.8
MDV+HDV	1.0
Bus	0.2

Functions: maximum acceleration, desired acceleration, maximum deceleration, desired deceleration

For the base-case, the acceleration and deceleration functions were set as the default in Vissim.

Calibration

The calibration process was been based on traffic intensity data recorded by video counts and travel times data from the floating cars.

The first step consisted in adjusting routing decisions to ensure similar traffic intensities in most of the measuring points. Table 43 shows the comparison of the average values of traffic flows and the GEH (WSDOT, 2014) statistic formula for the valid measuring points for an interval of 30 minutes in peak hour traffic conditions.

Table 43. Comparison of real and simulated intensities in 5 different measuring points of the selected local streets

Measuring point	1	2	3	4	5
Average 15 runs	470	566	695	420	164
Real	552	588	720	384	180
GEH	2.6	0.9	0.5	1.3	1.2
WSDOT Calibration criterion	TRUE				

Once acceptable values in the reference measuring points ($GEH \leq 5.0$) were reached, average speeds were also checked and adjusted. The most relevant changes in this context include some reductions in maximum acceleration rates at slow speeds.

The final calibration has been done with the travel time measurements from floating vehicles. Some routing decisions and speed decision have been adjusted in order to best fit travel times while maintaining the same level of accuracy in traffic flows. Table 44 presents the WSDOT calibration criterion.

Table 44. Travel time calibration for 15 replications. Urban arterial

	Travel distance (m)	Travel time (s)
Average 15 runs	725.8	166.1
Real	725.8	196.1

Travel Time calibration criterion of WSDOT VISSIM Protocol.

Allowable travel time difference: 117.7 s.

Calibration criterion: **TRUE.**

7.3. Adjustment of micro simulation tool parameters to reproduce eco-driving behavior

7.3.1. Eco-driving effects on speed profiles

As explained in Chapter 6, a factor analysis reduced the speed profiles components to three. Representing each component, we selected three variables which together can explain 72.9% of the variation in fuel consumption as reflected in the multiple regression model. The three variables are:

- Nstopskm_lt3kmh: Number of stops per km being stop speed under 3km/h.
- Pacc_0.1ms: Time % acceleration is greater than 0.1 m/s².
- Pacc_5kmh: Time % acceleration is greater than 1.39 m/s².

The aim of this section was to analyze how the selected variables change in each itinerary when an eco-driving behavior is applied. The analysis is based on the real data extracted from the main data collection campaign detailed in Chapter 3, taking trips with similar traffic condition for both normal and eco-driving behavior.

The following table 41 reflects the percentage of variation of the three selected variable and the fuel consumption for each of the itineraries already described in Section 6.1.

Table 45. Percentage of variation when applying eco-driving

	Nstopskm_lt3kmh	Pacc_0.1ms	Pacc_5kmh	Fuel consump.
Urban Motorway	-20.0%	-2.9%	-21.3%	-4.8%
Urban arterial	-25.2%	1.5%	-24.6%	-7.5%
Urban Collector	-33.3%	-5.2%	-62.0%	-12.5%
Local street	-7.1%	5.1%	-32.6%	-7.7%

We can observe that both the number of stops and the high acceleration values are clearly reduced in all the cases, while smooth accelerations values experiment less change and with no clear tendency.

7.3.2. Eco-driving simulation in VISSIM

Car-following parameters

The calibration of eco-driving behavior was done by replicating a floating car trip in the model. Following the changes in the three key variables, the Vissim parameters were edited to obtain similar change tendencies in the simulated speed profiles of each of the urban road types. Likewise, CO₂ emissions variation between eco-driving and base-case floating car simulated trips was compared with the fuel consumption variation between normal and eco-driving real world test.

As shown in Section 5.1, average speed models may not reflect properly the variation on speed profiles caused by different driving behaviors. Therefore, it has been selected an emission model at micro level was selected. In particular, the emissions were calculated with the software EnViVer (Eijk, Ligterink and Inanc, 2013), based on VERSIT+ emission model (Smit et al., 2007). The selection is based in its availability, as it is an add-on module included in Vissim for scientific purposes.

VERSIT+ uses advanced statistical modeling techniques to find the best fitting emission factor equation for any given driving pattern.

Speed profiles of the simulated floating car were exported from Vissim to VERSIT+. In this case vehicle composition in the emission model were set to reproduce the floating vehicle, i.e. passenger diesel car under Euro 5 standards.

The Wiedemann car following model controls the movement of vehicles inside Vissim simulation software. As shown in Figure 61, there are some parameters that can be set to adjust the driving behavior.

Driving Behavior Parameter Set

No.: 3 Name: Freeway (free lane selection)

Following Lane Change Lateral Signal Control

Look ahead distance
min.: 0.00 m
max.: 250.00 m
2 Observed vehicles

Look back distance
min.: 0.00 m
max.: 150.00 m

Temporary lack of attention
Duration: 0.00 s
Probability: 0.00 %

☐ Smooth closeup behavior
☐ Standstill distance for static obstacles: 0.50 m

Car following model
Wiedemann 99

Model parameters

CC0 (Standstill Distance):	1.50	m
CC1 (Headway Time):	0.90	s
CC2 ('Following' Variation):	4.00	m
CC3 (Threshold for Entering 'Following'):	-8.00	
CC4 (Negative 'Following' Threshold):	-0.35	
CC5 (Positive 'Following' Threshold):	0.35	
CC6 (Speed dependency of Oscillation):	11.44	
CC7 (Oscillation Acceleration):	0.25	m/s ²
CC8 (Standstill Acceleration):	3.50	m/s ²
CC9 (Acceleration with 80 km/h):	1.50	m/s ²

OK Cancel

Figure 61. Driving behavior parameters in Wiedemann 99

Apart from the acceleration and deceleration functions, the next parameters can be edited to simulate eco driving behavior in a trial and error process (PTV, 2014):

Table 46. Meaning of the driving behavior parameters of the Wiedemann 99 car following model.
Source: PTV (2014)

Parameters	Description
CC0 (Standstill Distance)	The average desired standstill distance between two vehicles. It has no variation.
CC1 (Headway Time)	It is the distance in seconds which a driver wants to maintain at a certain speed. The higher the value, the more cautious the driver is. Thus, at a given speed v [m/s], the average safety distance is computed as: $dx_{safe} = CC0 + CC1 \cdot v$ The safety distance is defined in the car following model as the minimum distance a driver will maintain while following another vehicle. In case of high volumes this distance becomes the value which has a determining influence on capacity.
CC2	It restricts the distance difference (longitudinal oscillation) or how much more distance than the desired safety distance a driver allows before he intentionally moves closer to the car in front. If this value is set to e.g. 10

	m, the following behavior results in distances between dx_{safe} and $dx_{safe} + 10m$. The default value is 4.0m which results in a quite stable following behavior.
CC3	It controls the start of the deceleration process, i.e. the number of seconds before reaching the safety distance. At this stage the driver recognizes a preceding slower vehicle.
CC4	Defines negative speed difference during the following process. Low values result in a more sensitive driver reaction to the acceleration or deceleration of the preceding vehicle.
CC5	Defines positive speed difference during the following process. Enter a positive value for CC5 which corresponds to the negative value of CC4 . Low values result in a more sensitive driver reaction to the acceleration or deceleration of the preceding vehicle.
CC6	Influence of distance on speed oscillation while in following process. - Value 0: If set to 0 the speed oscillation is independent of the distance - Larger values: Larger values lead to a greater speed oscillation with increasing distance.
CC7	Oscillation during acceleration.
CC8	Desired acceleration when starting from standstill (limited by maximum acceleration defined within the acceleration curves).
CC9	Desired acceleration at 80 km/h (limited by maximum acceleration defined within the acceleration curves).
Observed vehicles	The number of observed vehicles affects how well vehicles in the link can predict other vehicles' movements and react accordingly. Vehicles take into account the look-ahead distance in addition to the entered number of preceding vehicles.

Eco-driving calibration process

First of all, acceleration levels were changed according to the values found in the analysis of real life trips, as shown in section 3.5.4. Four functions were change:

- Maximum acceleration.
- Desired acceleration.
- Maximum deceleration.
- Desired deceleration.

The following table reflects the changes done in the maximum value of each of the acceleration functions:

Table 47. Maximum values of the acceleration functions in VISSIM for motorway and urban trips

Function	Motorway		Urban	
	Normal	Eco	Normal	Eco
Maximum acceleration	3.5	3	3.5	3.1
Desired acceleration	3.5	2.8	3.5	2.3
Maximum deceleration	-6.0	-5.5	-6.0	-4.0
Desired deceleration	-4.1	-3.8	-2.8	-1.9

After the change in the acceleration functions, the next step was the adjustment of the car following model parameters. This was a trial and error process until getting CO₂ variation percentages were close to the real fuel consumption variation.

Table 48 shows the variation in the car following model for each of the itineraries:

Table 48. Final calibration values of car following parameters

Parameters	Normal	Motorway	Arterial	Collector	Local
CC0 (Standstill Distance)	1.50	1.50	1.50	1.50	1.50
CC1 (Headway Time)	0.90	1.00	1.50	1.50	1.50
CC2	4.00	4.00	4.00	4.00	4.00
CC3	-8.00	-8.00	-10.00	-10.00	-10.00
CC4	-0.35	-0.35	-0.50	-0.50	-0.50
CC5	0.35	0.35	0.50	0.50	0.50
CC6	11.44	11.44	11.44	11.44	11.44
CC7	0.25	0.25	0.05	0.05	0.05
CC8	3.50	3.50	2.90	2.90	2.90
CC9	1.50	1.50	1.50	1.50	1.50
Observed vehicles	2	4	10	10	8

Table 48 shows that the three interrupted itineraries have almost the same values of the parameters. The main objectives with these changes were to increase the ability of the driver to anticipate traffic (CC1, CC3 and number of observed vehicles), reduce the sensitivity to changes in the preceding vehicles (CC4 and CC5) and reduce the speed oscillation (CC7). However, for the urban motorway, every attempt to change these parameters had led to higher values of CO₂ emissions.

Speed profiles of the simulated floating car were exported from Vissim to VERSIT+. Vehicle composition in the emission model was set to reproduce the floating vehicle, i.e. passenger diesel car under Euro 5 standards.

The variation of real fuel consumption and simulated CO₂ emissions are reflected in the following table:

Table 49. Real fuel consumption and simulated CO₂ emissions variation after applying eco-driving

	Motorway	Arterial	Collector	Local
Real fuel consumption variation	-4.8%	-7.5%	-12.5%	-7.7%
Simulated CO₂ emission variation	-1.6%	-6.2%	-9.6%	-5.6%

We can observe that except of the urban motorway, the other urban itineraries present similar values of savings. In fact, in these cases the simulated results are within the 72.9% of variation that can be explained by the simulation (see section 5.2).

7.4. Scenarios to simulate

Every scenario was run for one hour. The first half hour was taken as warm-up time and therefore not considered for evaluation. In the last 30 minutes the evaluation parameters were activated, recording speed profiles and aggregated values of intensity and travel times.

Three different traffic situations were considered:

- Peak hour (ph): From 8:00 to 9:00. Mostly congested traffic.
- Day off-peak hour (oh): From 11:00 to 12:00. Medium average traffic.
- Night off-peak hour (nh): From 3:00 to 4:00. Free flow conditions.

For the calculation of the traffic demand in each traffic situation we considered the traffic profile of the M30 as pattern, assuming the profile was the same in all the models i.e., in urban motorway, urban arterial, urban collector and local street. From Figure 61, we extracted that night time traffic was 4.1% of the peak hour traffic and off-peak traffic was 72.4%. Starting for the vehicle counting performed in each type of road, it was a straightforward process to calculate the traffic demand in the other two traffic situations.

Figure 62. Daily traffic distribution in M30 East. The peak, off-peak and night hour selected are highlighted

Starting with the vehicles counting performed in each type of road, it is a straightforward process to calculate the traffic demand in the other two traffic situations. The following table shows the volume to capacity ratio for each type of road and traffic conditions:

Table 50. Volume to capacity ratio for each scenario

Traffic situation\ Type of road	Urban Motorway	Urban Arterial	Urban Collector	Local Street
Capacity (veh/h)	3,540	2,758	956	354
Peak hour (V/C)	1.00	0.89	0.78	0.76
Off-peak hour (V/C)	0.70	0.46	0.61	0.57
Night hour (V/C)	0.04	0.02	0.07	0.07

Regarding the eco-driving penetration, six different situations were considered: 0% (base-case), 10%, 25%, 50%, 75% and 100%. It was assumed that only passenger car drivers change their driving, following the behavior described in the previous section (7.3). However, the emission calculation was performed for all vehicles in the network, as we want to measure the global impact of eco-driving and not only the vehicles affected. Fleet composition was replicated in Vissim according to the Dirección General de Sostenibilidad y Planificación de la Movilidad (2013).

Emissions by Heavy Duty Vehicles and Buses are calculated using the VERSIT+ default settings for 2013. Passenger Cars settings correspond to the age and fuel distribution values reported by the Dirección General de Sostenibilidad y Planificación de la Movilidad (2013). Figure 63 shows the customized settings for passenger cars in the software tool.

Custom vehicle parc

Bravo
Passenger_Cars_Madrid_City

Vehicle parc

Road type:
☒ Urban ☐ Highway

Vehicle type:
☒ Light-duty ☐ Bus ☐ Heavy-duty

Name: Passenger_Cars_Madrid_City

Era: 2013

Reset to road & vehicle type defaults

Fuel type

	Percentage	Lock
Petrol:	31.6	☐
Diesel:	68.2	☐
LPG:	0.1	☐
CNG:	0.1	☐
Electric:	0.1	☐

Vehicle age distribution

Newer than 1 year: 5.5 %

Average vehicle age: 9.3 year

Average exit age: 18.7 year

Maximum age: 40 year

Emission legislation

Euro norm	Regular date	Introduction date
Euro 1:	01/07/1992	1992 Year
Euro 2:	01/01/1996	1996 Year
Euro 3:	01/01/2000	2000 Year
Euro 4:	01/01/2005	2005 Year
Euro 5:	01/09/2009	2009 Year
Euro 6:	01/09/2014	2014 Year

Average regional CO2 emission

Petrol: 166 g/km

Diesel: 158 g/km

OK Cancel

Figure 63. Passenger Car settings in the VERSIT+ emissions model

The number of scenarios was 72: 4 road types, 3 traffic situations and 6 penetration rates. The total number of simulated kilometers was 271,754. If we consider 15 replications for each scenario, the final number is more than 4 million vehicle-kilometers.

The following table shows the code, road type, traffic situation and eco-driving penetration rate for each of the scenarios:

Table 51. Summary of simulated scenarios

Scenario code	Road type	Traffic situation	Eco-driving %
um_nh_0	Urban Motorway	Night off-peak	0%
um_nh_10	Urban Motorway	Night off-peak	10%
um_nh_25	Urban Motorway	Night off-peak	25%
um_nh_50	Urban Motorway	Night off-peak	50%
um_nh_75	Urban Motorway	Night off-peak	75%
um_nh_100	Urban Motorway	Night off-peak	100%
um_oh_0	Urban Motorway	Day off-peak	0%
um_oh_10	Urban Motorway	Day off-peak	10%
um_oh_25	Urban Motorway	Day off-peak	25%
um_oh_50	Urban Motorway	Day off-peak	50%
um_oh_75	Urban Motorway	Day off-peak	75%
um_oh_100	Urban Motorway	Day off-peak	100%
um_ph_0	Urban Motorway	Peak hour	0%
um_ph_10	Urban Motorway	Peak hour	10%
um_ph_25	Urban Motorway	Peak hour	25%
um_ph_50	Urban Motorway	Peak hour	50%
um_ph_75	Urban Motorway	Peak hour	75%
um_ph_100	Urban Motorway	Peak hour	100%
ua_nh_0	Urban arterial	Night off-peak	0%
ua_nh_10	Urban arterial	Night off-peak	10%
ua_nh_25	Urban arterial	Night off-peak	25%
ua_nh_50	Urban arterial	Night off-peak	50%
ua_nh_75	Urban arterial	Night off-peak	75%
ua_nh_100	Urban arterial	Night off-peak	100%
ua_oh_0	Urban arterial	Day off-peak	0%
ua_oh_10	Urban arterial	Day off-peak	10%
ua_oh_25	Urban arterial	Day off-peak	25%
ua_oh_50	Urban arterial	Day off-peak	50%
ua_oh_75	Urban arterial	Day off-peak	75%
ua_oh_100	Urban arterial	Day off-peak	100%
ua_ph_0	Urban arterial	Peak hour	0%
ua_ph_10	Urban arterial	Peak hour	10%
ua_ph_25	Urban arterial	Peak hour	25%
ua_ph_50	Urban arterial	Peak hour	50%
ua_ph_75	Urban arterial	Peak hour	75%
ua_ph_100	Urban arterial	Peak hour	100%
uc_nh_0	Urban collector	Night off-peak	0%
uc_nh_10	Urban collector	Night off-peak	10%
uc_nh_25	Urban collector	Night off-peak	25%
uc_nh_50	Urban collector	Night off-peak	50%
uc_nh_75	Urban collector	Night off-peak	75%
uc_nh_100	Urban collector	Night off-peak	100%
uc_oh_0	Urban collector	Day off-peak	0%
uc_oh_10	Urban collector	Day off-peak	10%
uc_oh_25	Urban collector	Day off-peak	25%
uc_oh_50	Urban collector	Day off-peak	50%
uc_oh_75	Urban collector	Day off-peak	75%

uc_oh_100	Urban collector	Day off-peak	100%
uc_ph_0	Urban collector	Peak hour	0%
uc_ph_10	Urban collector	Peak hour	10%
uc_ph_25	Urban collector	Peak hour	25%
uc_ph_50	Urban collector	Peak hour	50%
uc_ph_75	Urban collector	Peak hour	75%
uc_ph_100	Urban collector	Peak hour	100%
ls_nh_0	Local street	Night off-peak	0%
ls_nh_10	Local street	Night off-peak	10%
ls_nh_25	Local street	Night off-peak	25%
ls_nh_50	Local street	Night off-peak	50%
ls_nh_75	Local street	Night off-peak	75%
ls_nh_100	Local street	Night off-peak	100%
ls_oh_0	Local street	Day off-peak	0%
ls_oh_10	Local street	Day off-peak	10%
ls_oh_25	Local street	Day off-peak	25%
ls_oh_50	Local street	Day off-peak	50%
ls_oh_75	Local street	Day off-peak	75%
ls_oh_100	Local street	Day off-peak	100%
ls_ph_0	Local street	Peak hour	0%
ls_ph_10	Local street	Peak hour	10%
ls_ph_25	Local street	Peak hour	25%
ls_ph_50	Local street	Peak hour	50%
ls_ph_75	Local street	Peak hour	75%
ls_ph_100	Local street	Peak hour	100%

8. IMPACTS OF DIFFERENT ECO-DRIVING PENETRATION RATES ON TRAFFIC AND EMISSIONS

“Where we go is not determined by where we want to go”

Marty Rubin

In this chapter are presented the results of the traffic and emission models at the micro scale. They show the CO₂ and NO_x emissions according to the percentage of eco-drivers and the traffic volumes for the four urban road types. It also includes the values of the traffic parameters for every scenario. Finally the summary and discussion of the results are presented in the last sections.

8.1. Simulation results for the base-case scenarios

The average speed was selected as one of the indicators for the analysis of eco-driving impacts on traffic. The average speed values include all the vehicles in the network, so it reflects not only the vehicles in the main corridor but also the ones in adjacent streets.

Figure 64 shows the average speed for 0% of eco-drivers (base-case) of each type of road.

Figure 64. Average speed for the base-case scenarios

As expected, the greater differences in average speed were found between the uninterrupted (motorway) and the urban interrupted traffic. In all the types of roads the average speed was substantially reduced in peak hour traffic, highlighting the arterial with a 44% reduction of speed compared with the night hours traffic conditions. During peak hours, the average speed was very similar in the arterial, collector and local streets. This means that the congestion affects more those roads with higher capacity.

Figure 65 shows the emissions of CO₂ per kilometer for 0% of eco-drivers (base-case) of each scenario.

Figure 65. CO₂ emissions per kilometer for the base-case scenarios

Emission results show clearly how emissions increase when the level of service drops. Regarding CO₂ emissions, the values are higher for local streets and also during peak hours, this is in line with the average speed results. On the other hand, in collector roads and local roads NO_x emissions are slightly higher during the off-peak traffic than the peak traffic situation.

Figure 66. NO_x emissions per kilometer for the base-case scenarios

As expected, NO_x emissions are lower in the motorway segments than in urban interrupted itineraries.

8.2. Eco-driving impacts. Results

This section is a glance at the results of the simulations. Emissions of CO₂ and NO_x in grams per kilometer were selected as emission indicators. This way, the concerns about climate change and air quality in urban areas are represented.

Regarding traffic performance, three indicators are considered in the following tables. Traffic activity is reflected through the total distance travelled in vehicle kilometers. With this indicator we can evaluate whether the different eco-driving penetration rates produce a capacity reduction in each type of road. Both the delay rate and the average speed reveal whether the eco-driving slows down the traffic flow and increases congestion. The following tables present the average emission and traffic indicators values. The results represent the average of 15 replications per scenario. The total simulated vehicle-kilometers rounds 4 million.

Table 52. Emission and traffic simulation results per traffic situation and eco-driving penetration rate. Urban motorway

Traffic demand	Indicators	Emissions indicators		Traffic indicators		
	Scenario code	CO ₂ g/km	NO _x g/km	Veh*km	Delay rate(s/km)	Average speed (km/h)
Night	um_nh_0	160.1153	0.4453	735	0.0	84.7
	um_nh_10	158.3483	0.4383	735	0.0	84.7
	um_nh_25	157.4048	0.4330	735	0.0	84.8
	um_nh_50	155.4197	0.4157	735	0.0	84.8
	um_nh_75	157.5596	0.4312	735	0.0	84.8
	um_nh_100	160.8017	0.4541	735	0.0	84.8
Off-peak	um_oh_0	164.4539	0.4936	13,439	0.9	83.0
	um_oh_10	162.8943	0.4832	13,438	0.9	82.9
	um_oh_25	163.4849	0.4875	13,438	0.9	83.0
	um_oh_50	164.1421	0.4910	13,438	0.9	82.9
	um_oh_75	164.2067	0.4897	13,438	0.9	82.9
	um_oh_100	164.8899	0.4953	13,414	1.3	82.2
Peak	um_ph_0	186.6770	0.6066	18,196	7.7	72.1
	um_ph_10	191.3996	0.6203	17,932	10.5	68.1
	um_ph_25	191.2088	0.6199	17,688	12.3	65.8
	um_ph_50	192.7208	0.6272	17,673	13.6	64.3
	um_ph_75	192.5770	0.6289	17,260	13.7	64.3
	um_ph_100	198.9291	0.6590	17,043	17.7	60.1

Table 52 shows the results for the urban motorway. It is interesting to highlight that eco-drivers have almost no influence on the traffic flow for low traffic demand, i.e. at night and off-peak hours. On the other hand, the critical capacity drops in peak hour scenarios when the percentage of eco-driver increases. The vehicle-kilometers and the average speed fell, thus producing higher emission rates.

Table 53 shows the results for the urban arterial. In the case of this interrupted traffic facilities it is possible to observe how the average speed drops slightly in night traffic conditions. Regarding traffic activity it is important to highlight again the reduction of the road capacity in peak hour for high eco-driving penetration rates. Longer distances between vehicles and slower acceleration rates at traffic lights produce this clear increase of congestion.

Table 53. Emission and traffic simulation results per traffic situation and eco-driving penetration rate. Urban arterial

Traffic demand	Indicators	Emissions indicators		Traffic indicators		
	Scenario code	CO ₂ g/km	NO _x g/km	Veh*km	Delay rate(s/km)	Average speed (km/h)
Night	ua_nh_0	239.8480	0.7461	322	39.9	34.8
	ua_nh_10	240.2120	0.7479	322	40.2	34.8
	ua_nh_25	238.9648	0.7456	322	40.3	34.7
	ua_nh_50	239.5636	0.7560	322	40.8	34.6
	ua_nh_75	236.3316	0.7292	322	41.2	34.4
	ua_nh_100	234.5122	0.7231	322	41.8	34.2
Off-peak	ua_oh_0	285.8588	0.9716	3,929	50.4	31.3
	ua_oh_10	284.6208	0.9682	3,927	50.8	31.2
	ua_oh_25	282.6633	0.9591	3,927	51.5	31.0
	ua_oh_50	279.8301	0.9464	3,926	52.6	30.7
	ua_oh_75	277.6238	0.9346	3,927	53.6	30.4
	ua_oh_100	276.1538	0.9231	3,926	55.1	30.0
Peak	ua_ph_0	360.3351	1.2357	7,215	120.2	19.5
	ua_ph_10	355.8605	1.2119	7,116	124.8	19.0
	ua_ph_25	352.1193	1.1960	6,992	130.9	18.4
	ua_ph_50	351.4162	1.1755	6,786	149.0	16.9
	ua_ph_75	355.8857	1.1869	6,577	170.8	15.3
	ua_ph_100	360.7943	1.2002	6,340	193.6	14.0

Regarding the urban collector, the following table shows trends similar to the urban arterial. Although the capacity drops less intensively than in urban arterial congestion increases more in the urban collector. Its characteristics produce higher increments in the delay for the peak hour traffic situations.

Table 54. Emission and traffic simulation results per traffic situation and eco-driving penetration rate. Urban collector

Traffic demand	Indicators	Emissions indicators		Traffic indicators		
	Scenario code*	CO ₂ g/km	NO _x g/km	Veh*km	Delay rate(s/km)	Average speed (km/h)
Night	uc_nh_0	315.1531	1.0081	34	52.9	28.1
	uc_nh_10	314.3752	1.0119	34	53.5	27.9
	uc_nh_25	311.2069	0.9799	34	54.1	27.8
	uc_nh_50	307.8656	0.9590	34	55.6	27.4
	uc_nh_75	306.4025	0.9650	34	57.2	27.1
	uc_nh_100	303.7901	0.9603	34	57.7	27.0
Off-peak	uc_oh_0	447.4918	1.6775	583	77.4	27.0
	uc_oh_10	445.0170	1.6576	583	79.9	22.0
	uc_oh_25	443.9128	1.6640	583	83.5	21.5
	uc_oh_50	443.1101	1.6511	583	90.9	20.6
	uc_oh_75	441.9659	1.6465	584	100.3	19.6
	uc_oh_100	440.3003	1.6366	582	109.6	18.8
Peak	uc_ph_0	456.7567	1.6628	794	97.1	18.0
	uc_ph_10	454.9581	1.6492	794	103.3	19.7
	uc_ph_25	462.5167	1.6837	791	124.6	17.7
	uc_ph_50	466.8037	1.7050	760	153.5	15.4
	uc_ph_75	463.0630	1.6808	740	174.2	14.1
	uc_ph_100	462.7120	1.6772	717	193.8	13.1

Regarding local street scenarios, Table 55 shows how in these cases the total distance traveled (veh*km) is not affected by the percentage of eco-drivers. Even in peak hours, local streets and their intersections do not reach their critical capacity. Slower acceleration cause increments in the delay, but this does not produce higher congestion.

Table 55. Emission and traffic simulation results per traffic situation and eco-driving penetration rate. Local Street

Traffic demand	Indicators	Emissions indicators		Traffic indicators		
	Scenario code	CO ₂ g/km	NO _x g/km	Veh*km	Delay rate(s/km)	Average speed (km/h)
Night	ls_nh_0	375.0313	1.2556	62	75.5	24.2
	ls_nh_10	373.6214	1.2348	62	75.5	24.2
	ls_nh_25	372.7340	1.2344	62	76.4	24.1
	ls_nh_50	368.6483	1.2077	62	77.1	24.0
	ls_nh_75	364.4695	1.1706	62	77.9	23.8
	ls_nh_100	364.8413	1.1853	62	78.8	23.7
Off-peak	ls_oh_0	520.7640	1.9868	405	104.2	19.1
	ls_oh_10	519.0063	1.9717	405	105.2	19.0
	ls_oh_25	518.3109	1.9722	405	107.7	18.8
	ls_oh_50	514.2478	1.9587	405	109.2	18.6
	ls_oh_75	511.2031	1.9428	405	112.9	18.3
	ls_oh_100	509.5736	1.9296	405	115.6	18.0
Peak	ls_ph_0	523.0964	1.9505	548	122.1	17.7
	ls_ph_10	520.2160	1.9248	548	125.9	17.4
	ls_ph_25	521.3064	1.9433	549	129.9	17.1
	ls_ph_50	516.1196	1.9098	547	138.0	16.4
	ls_ph_75	514.9325	1.9060	548	147.4	15.8
	ls_ph_100	512.0108	1.8803	547	154.9	15.3

8.3. Analysis of eco-driving impacts in each type of road

The following paragraphs analyze in detail the impact on traffic performance and emissions for each of the considered urban road types with variable penetration rates of eco-drivers and traffic conditions.

8.3.1. Urban motorway

Figure 67 shows the average speed for the three considered traffic conditions (night, off-peak and peak hour) and the different eco-driving penetration rates in the urban motorway segment.

Figure 67. Average speed values for each scenario in the urban motorway model

The figure reflects how the speed keeps constant in night scenarios, as there is almost no interaction between neighboring cars. On the other hand, average speed is reduced almost by 17% in peak hours when all the passenger car drivers follow

the eco behavior. In off-peak traffic conditions, the average speed remains constant, with a slight reduction in the 100% penetration rate scenario.

Therefore, it seems clear that an increasing rate of eco-drivers has an influence on traffic in congested situations. Smoother accelerations and longer gaps between vehicles reduce road capacity, thus increasing the congestion upstream of the bottleneck. Hence, this fact will have an important effect on the road transport emissions, as we can see in the following figures.

According to the values presented in Table 52, the following figure shows the variation of CO₂ for the different traffic conditions and penetration rates with reference to the base-case scenario (0% eco-driving):

Figure 68. CO₂ variation with reference to base-case per traffic situation and eco-driving penetration rates. Urban motorway

In the case of an urban motorway, there are no clear tendencies with regards to the penetration rate. For congested traffic situations, CO₂ emissions increase for higher penetration rates. In the off peak traffic situation, we find slight CO₂ savings except for the 100% eco-driving penetration rate.

On the other hand, for night traffic situations, savings reach a peak when half of the passenger cars drivers follow the eco-driving behavior, while we can hardly find an increase for the 100% penetration rate.

Figure 69 shows the NO_x emissions for the scenarios simulated in the urban motorway model.

Figure 69. NO_x variation with reference to base-case per traffic situation and eco-driving penetration rates. Urban motorway

The graph shows a similar pattern to the previous CO₂ figure, although in this case, extreme values are higher. Savings in night hours reach 6.7% percent with a 50% of eco-driving penetration rate while in peak hours NO_x emissions increase almost 9%.

For low traffic levels and penetration rates, eco-driving is beneficial in urban motorways. However, for peak hour traffic conditions any eco-driving percentage leads to worse emission results.

8.3.2. Urban arterial

Figure 68 shows the average speed for the three traffic situations (night, off-peak and peak hour) and the different eco-driving rates in the urban arterial model.

Figure 70. Average speed values for each scenario in the urban motorway model

The figure shows decreasing average speeds with increasing penetration rates although they are small in the case of night and off-peak traffic situations. These are most probably produced by the smoother accelerations at traffic lights. Apart from influencing the speed of each vehicle, this fact reduces the discharge rate at traffic lights, reducing the capacity of the arterial.

Therefore, increasing penetration rates will have an influence on emissions. The following figure shows the variation of CO₂ for the different traffic situations and penetration rates with reference to the base-case scenario (0% eco-driving).

Figure 71. CO₂ variation with reference to base-case per traffic situation and eco-driving penetration rates. Urban arterial

Although not very sharply, eco-driving produces CO₂ savings in almost all of the scenarios simulated in the urban arterial model. It reaches 3.4% savings for a 100% eco-drivers in the off-peak traffic situation while during the peak traffic situation the maximum saving is about 50% eco-driving penetration rate. In this situation, a 100% penetration rate produces a CO₂ emissions increment which voids the individual eco-driving savings.

The results are similar in the case of NO_x emissions although in this case, even for a 100% penetration rate during peak hours we obtain NO_x savings. The case of 50% eco-drivers in a night traffic situation is worth mentioning, where NO_x emissions are 1.3% higher than in the base-case, thus breaking the decreasing tendency.

Figure 72. NO_x variation with reference to base-case per traffic situation and eco-driving penetration rates. Urban arterial

8.3.3. Urban collector

Figure 73 shows the average speed for the three traffic situations (night, off-peak and peak hour) and the different eco-driving rates in the urban collector model.

Figure 73. Average speed values for each scenario in the urban collector model

The figure shows decreasing average speeds with increasing eco-driving penetration rates. The drop is particularly pronounced in the off-peak traffic situation, where the average speed is reduced by 5 km/h and only increasing the penetration rate to 10%.

Regarding the effects of eco-driving on emissions, the next figure shows the CO₂ variation for the different traffic conditions and penetration rates in the urban collector.

Figure 74. CO₂ variation with reference to base-case per traffic situation and eco-driving penetration rates. Urban collector

It is important to highlight that for eco-driving penetration rates higher than 10% t peak hour traffic situations, there was an increasing amount of CO₂ emissions, reaching a 2.2% increment when 50% of the passenger cars change their driving to eco behavior.

On the other hand, we can find increasing savings at night and off-peak traffic situations when the percentage of eco-drivers grows.

The following figure shows NO_x emissions savings and increment peaks for a 50% eco-drivers rate. During the night traffic situation, savings reached 4.9% with reference to the base-case, while during peak hours NO_x emissions increases significantly by 2.5%.

Figure 75. NO_x variation with reference to base-case per traffic situation and eco-driving penetration rates. Urban collector

In the off-peak traffic situation the maximum savings were reached for 100% of eco-drivers as individual savings were added.

8.3.4. Local streets

Figure 76 shows the average speed for the three traffic situations (night, off-peak and peak hour) and the different eco-driving rates in the local street traffic model.

Figure 76. Average speed values for each scenario in the local street model

The CO₂ emissions in local streets show the following variation when compared with the base-case scenario, i.e. 0% of eco-drivers.

Figure 77. CO₂ variation with reference to base-case per traffic situation and eco-driving penetration rates. Local street

It can be observed in figure 77 how CO₂ emission reductions increase almost in every situation for higher penetration rates. It is also interesting to note that for scenarios with low eco-driving penetration rates (10%), savings are higher for the peak hour traffic situations. On the other hand, with increasing penetration rates the tendency changes resulting in higher reductions for the night traffic situations.

During off peak and night traffic situations, the tendency and values are quite similar to the urban collector.

The NO_x emissions follow similar tendencies as shown in the following figure 78:

Figure 78. NO_x variation with reference to base-case per traffic situation and eco-driving penetration rates. Local street

Maximal NO_x emissions savings can be found for eco-driving penetration rates of 75% and 100%, especially during night traffic conditions.

8.4. Aggregation of eco-driving impacts in an urban area

The aim of this analysis is to apply the results of each type of road to an urban area. Based on the macro traffic model of the Madrid region built by Valdes (2012), it is possible to distribute the vehicles kilometer in the 4 types of urban roads presented in this document. Likewise, it is possible to differentiate the 3 traffic demand conditions: peak, off-peak and night hours. The area selected includes all the roads and streets inside the second ring motorway M40 (M40 excluded), which represents the central and peripheral area (Figure 79).

Figure 79. Madrid highways and urban consolidated areas

The following table reflects the amount of vehicles kilometers on each type of road and per traffic situation:

Table 56. Traffic distribution per type of road inside Madrid second ring road (M40)

	Night		Off-peak		Peak	
	Veh*km	%	Veh*km	%	Veh*km	%
Urban Motorway	250,165	41.9	504,283	42.6	610,951	38.4
Urban Arterial	95,387	16.0	189,039	16.0	248,483	15.6
Urban Collector	157,235	26.3	312,822	26.4	449,551	28.2
Local street	94,337	15.8	177,252	15.0	283,917	17.8
Total	597,124	100	1,183,396	100.0	1,592,902	100

Using these percentages, the following figures show the weighted values of average speed and CO₂ and NO_x emissions variation.

Figure 79 shows the average speed values for an average trip in Madrid.

Figure 80. Aggregated average speeds for Madrid area under different scenarios

It is possible to observe that on the aggregated values there is almost no variation for the night scenarios while for peak hours, the average speed declines by more than 7 km/h for eco-driving penetration rates of 100%.

The following figure shows the CO₂ variation for different eco-driving penetration rates and traffic situations with reference to the base-case (0% eco-drivers):

Figure 81. CO₂ variation with reference to base-case per traffic situation and eco-driving penetration rates. Aggregated values for Madrid area

These aggregated values show maximal CO₂ savings for penetration rates of 75% and 100%. On the other hand, in peak hour the emissions increase up to 1.3% for 100% eco-drivers.

In the case of NO_x emissions, the following figure shows the variation with respect to the base-case scenario.

Figure 82. NO_x variation with reference to base-case per traffic situation and eco-driving penetration rates. Aggregated values for Madrid area

Emissions of NO_x are in line with CO₂ emissions reaching maximal savings of around 4% in night and night traffic conditions. Conversely, at peak hours the NO_x emissions increase slightly up to a value of 0.5% for all the drivers following the eco-behavior.

The results clearly indicate that the general recommendation at peak times should be not to eco-drive because it produces higher emissions of GHG and pollutants. On the other hand, for scenarios without congestion or low congestion levels eco-driving is globally beneficial despite changes according to the type of road (see Section 8.3). Therefore the policy recommendation is that the authorities should not recommend eco-driving on congested roads.

8.5. Eco-driving impacts. Time aggregation

The objective of this section is to calculate the daily average speed and variation of CO₂ and NO_x when introducing different percentages of eco-drivers. A typical daily traffic profile was selected, with the assumption that the profile is the same on every type of road such as the East side of the M30 urban motorway in Madrid. According to this traffic profile (Figure 82), the following periods were considered:

Figure 83. Daily traffic distribution. Peak, off-peak and night periods in Madrid

- From 0:00 to 7:00, night.
- From 7:00 to 8:00, off-peak.
- From 8:00 to 10:00, peak.
- From 10:00 to 14:00, off-peak.
- From 14:00 to 16:00, peak.
- From 16:00 to 18:00, off-peak.
- From 18:00 to 20:00, peak.
- From 20:00 to 23:00, off-peak.
- From 23:00 to 0:00, night.

Thus, the 24 hours were split into 6 peak hours, 10 off-peak hours and 8 night hours. The following figures reflect the daily weighted average taking into account the number of hours and the traffic demand in each period.

Figure 84. Average speed per type of road and eco-driving penetration rate

Figure 83 shows the average speed reduction on every type of roads when the eco-driving penetration rate increases. The highest drop happens in the urban collector, where the average speed is reduced by almost 30%.

The following figure gives the CO₂ emission variation per type of road and eco-driving penetration rate for a daily average:

Figure 85. CO₂ variation with reference to base-case per traffic situation and eco-driving penetration rates. Daily aggregation

The urban motorway shows a clear increasing tendency when more eco-drivers are added in the traffic flow. On the other hand, higher reductions of CO₂ emissions on local streets and urban collector roads occur for 100% of eco-drivers. In between, the maximum savings were found for half of the drivers following the eco-behaviour. For higher eco-driving penetration rates, traffic flow conditions are worsened and this fact begins to erode the positive effects of eco-driving.

Figure 86. NO_x variation with reference to base-case per traffic situation and eco-driving penetration rates. Daily aggregation

In the case of NO_x emissions, the tendencies were the same as for CO₂ emissions except for the urban arterial. For this type of urban road, the maximal saving in NO_x takes place for a 100% eco-driving penetration rate.

8.6. Summary of results

The following tables provide the summary of eco-driving impacts on traffic (average speed) and emissions (CO₂ and NO_x) at a glance. In both tables, the sign “+” implies positive impacts, i.e. less emissions and higher average speeds.

Table 57. Summary of eco-driving effects per type of road

Eco-driving penetration rate	Indicator	Motorway	Arterial	Collector	Local
Low %	Ave. speed	—	≈	—	≈
	CO ₂	—	+	≈	+
	NO _x	—	+	≈	+
Medium %	Ave. speed	— —	—	— —	—
	CO ₂	— —	++	—	++
	NO _x	— —	++	≈	++
High %	Ave. speed	— — —	— —	— — —	— —
	CO ₂	— — —	+	+	+++
	NO _x	— — —	+++	+	+++

High eco-driving penetration rates have positive effects on emissions in roads with interrupted traffic flow. On the other hand in the urban motorway the effects are negative, both for traffic performance and emissions. Regarding the traffic performance, it seems clear that the average speed is progressively reduced when the eco-driving penetration rate increases.

Table 58. Summary of eco-driving effects per traffic situation

Eco-driving penetration rate	Indicator	Night	Off-peak	Peak
Low %	Ave. speed	≈	—	—
	CO ₂	+	+	≈
	NO _x	+	+	+
Medium %	Ave. speed	≈	—	— —
	CO ₂	++	+	—
	NO _x	+++	+++	≈
High %	Ave. speed	≈	— —	— — —
	CO ₂	+++	++	— —
	NO _x	+++	++	—

As expected eco-driving has almost no effect on the average speeds of the night traffic situation. Comparatively, the largest percentage of CO₂ and NO_x emissions occur at night. On the other side, speed is clearly reduced in peak hours when the eco-driving penetration rates are close to 100%.

The results clearly indicate that the general recommendation at peak times should be not to eco-drive since it produces higher emissions of GHG and pollutants. On the other hand, for scenarios without congestion or low congestion levels eco-driving is globally beneficial despite changes according to the type of road (see Section 8.3).

8.7. Answers to research questions

This section includes the answers to the questions raised in the research objectives.

- Does eco-driving behavior influence the neighboring drivers?

Looking at the tables in Section 8.1 can be demonstrated that eco-driving behavior does affect the neighboring drivers in most of the scenarios, since the average speed of all vehicles in the network change with the percentage of eco-drivers. The only scenario in which the average speed remains constant is the urban motorway under night traffic conditions. In this situation, the traffic intensity is so low that vehicles do not interact with each other. On the other hand, in urban arterial, collector and local streets, vehicles influence each other even during night hours, since they have to stop at traffic lights and yield to other vehicles or pedestrians.

- What if 10% of drivers were eco-drivers? What about 25%? And 100%?

As the percentage of eco-drivers increases, so does the interaction between vehicles. Looking at the tables in Section 8.2, it is clear that an increasing number of eco-drivers means lower speeds and in most of the cases increase in emissions. For low penetration rates emissions normally decrease, as there are individual savings due to lower acceleration and deceleration values. However, for higher penetration rates emissions increase as there are more interactions between vehicles. This fact seems to produce more stop and go movement in the traffic flow.

- **Would these scenarios produce the same effect in a motorway as in a local street?**

The graphs in Section 8.3 clearly show that the emissions impacts of eco-driving are different for each type of road. The variation of CO₂ and NO_x are different on every type of road, finding some similar tendencies in the case of urban traffic.

On the other hand, impacts on traffic performance have similar effects, since average speed is reduced with higher penetration rates in every of the tested types of roads.

- **To what extent the effects depend on the traffic demand?**

As a general rule of thumb, it is possible to conclude that for low traffic flows the effect is positive for high penetration rates of eco-drivers. Individual savings accumulate producing the largest savings for 100% penetration rates. However, for peak hour traffic conditions, larger penetration rates mean more emissions due to deterioration of traffic flow.

- **Would eco-driving produce more congestion?**

Yes, during peak hour traffic conditions the answer to this question is clear according to the results achieved from the traffic and emissions simulations. The delay rate increases with the penetration rates and so decrease the total number of kilometers travelled. Apparently, the capacity of the road is affected, as vehicles keep longer safety distances. In the same way, lower acceleration rates produce lower discharge rates at intersections and traffic lights.

- **And consequently more emissions?**

As shown in Chapter 5, generally speaking an increment in the congestion levels (more delay) produces more emissions. There are some situations on urban motorways where the increase in traffic levels can decrease the average speed

while keeping the traffic fluid. However, that was found in real data analysis cannot be strongly affirmed in the simulation results, where the eco-driving individual savings may also have an influence.

- **Are the tendencies the same for the different pollutants and greenhouse gases?**

The figures in Section 8.3 show similar tendencies for CO₂ and NO_x emissions, with higher reductions for Nitrogen Oxides.

8.8. Results compared to previous research

This doctoral thesis includes a complete insight on eco-driving impacts, by analysing the developed methodology for 72 scenarios. Compared to previous research, this work contributes the state of knowledge by applying different penetration rates to real base-case conditions.

The following paragraphs include a comparison of the present results with previous research works:

- Kobayashi et al. (2007).

In a fictitious network that is comparable to an urban collector, the authors simulate eco-driving only for scenarios with 0% and 100% penetration rates. The results show CO₂ savings of 3.5% for low traffic situations and increments of up to 12% in congested traffic. Tendencies are in line with the results presented in Chapter 8, although CO₂ increments are too high in the case of congestion, since it reaches an increment of 1.3% in the results presented in this thesis.

- Qian and Chung (2011).

These authors simulate only one intersection with real data, finding moderate CO₂ savings for low traffic demand and increments up to 25% in congested traffic and a 100% eco-driving penetration rate, which are much higher than the 1.3% found in this thesis.

- Orfila (2011).

Again for a “theoretical interurban road”, Orfila obtained high savings in fuel consumption, while in our case CO₂ emissions increased sharply by 6.6% for a penetration rate of 100%. Regarding urban roads, Orfila found savings two or three times higher than those presented in this thesis.

- Qian and Chung (2013).

In this study the authors changed the penetration rate, keeping a medium traffic flow level. The savings reported are in line with those presented in this thesis for off-peak hours in an urban arterial road.

PART V – CONCLUSIONS, FURTHER RESEARCH AND REFERENCES

9. CONCLUSIONS AND FURTHER RESEARCH

“The most complicated skill is to be simple.”

Dejan Stojanovic

Chapter 9 includes the conclusions of this research. It starts with a review of the objectives presented in Chapter 2 and their accomplishment. This is followed by a discussion of the results and the main findings. Finally, a short discussion on the limitations of the research is presented with an outline of further lines which would be interesting to follow in future research.

9.1. Objectives compliance review

As previously explained in Chapter 2, the objectives of this doctoral thesis were twofold:

Objective 1: *Understand how different measures affect fuel consumption, emissions and driving and traffic dynamics.*

Regarding this first objective, the following conclusions can help us understand how different measures affect traffic and emissions.

- The literature review shows the potential of ICT measures to reduce fuel consumption and emissions. It also shows differences in the results, that make it necessary to analyze new case studies.
- From Section 3.3 it is possible to extract conclusions regarding speed homogeneity. Emissions of CO₂ (and therefore fuel consumption) are highly correlated with the speed profile homogeneity. Although this is a pilot study with a limited number of trips, emissions of NO_x behave in the same way, the more homogenous the speed profile, the fewer emissions.
- In Chapter 4 is reported a similar correlation between fuel consumption and the speed profile homogeneity. The results presented in this chapter provide a basis for the simulation of the selected measures in other similar areas where specific Floating Car Data is not available. However, it is important to observe that due to the local nature of the microscopic model, the input values depend, to a large extent, on the characteristics of each case study. For instance, fleet composition and driver behavior vary from one area to another, while the desired speed depends largely on the characteristics of the infrastructure and speed limit compliance. Thus, the main aim of this chapter was not to provide direct input values, but to offer a percentage of change as an order of magnitude when a similar road or network is affected by any of the ICT measures analyzed.

- Although in this work are tested a limited number of measures, a methodology is described that can be used to collect and analyze FCD to obtain reference values for traffic models, and be applied to any other ITS measure in any application area. The advances in smartphone technologies and their increasingly generalized use have made it easier to track vehicle journeys, thus offering more opportunities for applications relating to the accuracy of traffic and emission models.
- The results presented in Chapter 5 show a clear relationship between congestion and fuel consumption. In urban motorways as in the case of M30 in Madrid, the data collected show that small increases in traffic starting from free flow conditions are positive in terms of fuel economy, but the general trend is that congestion increases fuel consumption. However, there are some differences in each type of roads, making further analysis advisable to distinguish, at least, between free and interrupted roads.
- Chapter 6 is a statistical analysis of the factors which explain the fuel consumption variation. It is worth noting that the multiple regression model show that factors taken from speed profiles can explain 72.9% of the variation of the fuel consumption of a trip. This has implications in the modeling process, since normally the emission simulation tools only take into account the speed profiles. This way, there is a 27.1% of the fuel consumption variation that is affected by other and uncontrolled variables, such as gear shifting, engine speed, etc.

Objective 2: *Evaluate the effects of eco-driving on traffic and emissions under different conditions of eco-driving penetration rates, traffic and roads.*

Chapter 7 includes the methodology to simulate eco-driving, adjusting the driven behavior according to real trips, complying with the specific goals:

- Four different traffic models were constructed following the four different types of road defined. The sections were selected to meet the characteristics specified in the literature and the real data available.
- The car-following parameters were reviewed in selected micro-simulation tool (PTV Vissim), and making the necessary settings adjustments for eco-driving behavior for those recorded under real conditions and in the same trips.
- Seventy two scenarios were systematically recreated to cover all the possible scenarios combining different type of road, eco-driving penetration rates and three representative congestion levels.
- The simulation results show that eco-driving produce negative results under congested conditions. In fact, slower acceleration rates and higher safety distances reduce the road critical capacity and increment delays which produce higher CO₂ and NO_x emissions. From the results it is possible to observe that there are differences in the impacts of eco-driving according to the type of roads. In medium and low traffic levels, high penetration rates of eco-driving are beneficial for traffic while the impact on traffic performance is low.

9.2. Main findings

This doctoral thesis has a complete review of measures related with Information and Communication Technologies that can help reduce the emissions of greenhouse gases and pollutants attributable to road transportation in urban areas.

Based on a consistent data collection campaign of floating car data, this study presents the impacts of four ICT measures applied to real conditions. It has been proven in this thesis that section speed control, variable speed limits, cruise control and eco-driving have positive effects on fuel consumption and therefore on CO₂ emissions. The savings range from 1.5% up to more than 10% in the case of eco-driving in selected itineraries.

Also based on the same field data, the effects of traffic congestion in fuel consumption are also established. It is interesting to observe that there are some differences between continuous and interrupted flow. For continuous traffic (urban motorway) small delays can reduce fuel consumption and emissions as the average speed is reduced without increasing brake and acceleration processes.

The collected field data was also analyzed to calculate the amount of fuel consumption variance that can be explained with speed related variables. After reducing the number of factors to three, it was determined that 72.6% can be explained with only the speed profile. And by adding the average slope as a new variable, this percentage increases to the 80%.

The main achievement of this thesis is the methodology to simulate the effects of eco-driving under different scenarios. The methodology is based on the adjustment of driving behavior parameters in a traffic simulation model at a micro scale. It is able to simulate 72 different traffic scenarios, including four types of road in three different traffic situations and six eco-driving penetration rates.

The results show interesting conclusions:

- Eco-drivers not only influence their own vehicle but also the surrounding vehicles and therefore traffic flow.

- The effects of eco-driving are not the same on a local road than in an urban motorway which also depends on traffic demand. Under night traffic conditions the maximal savings occur for 75% or 100% while in peak hours, these percentages have an increment of CO₂ and NO_x emissions.
- Eco-driving behavior produces more congestion, especially in interrupted traffic. Lower acceleration and brake rates lead to longer gaps between vehicles, which reduce capacity and causes more congestion. Likewise, the discharge flow rate at traffic lights is clearly affected, by reducing capacity and causing more congestion and therefore, more emissions.

9.3. Limitations and future research lines

The development of this thesis leave open some interesting possibilities to continue researching in this field.

Future research lines could be to explore the simulation of eco-driving with other traffic simulation tools, such as Aimsum or Paramics. Engine speed, although very important in real eco-driving, is not taken into account in the emission model. It would be advisable to continue research by adapting the existing emission model to be able to simulate changes in engine speed and gear shifting.

The selection of modeled itineraries was based on objective traffic characteristics found in the literature. However, every street has specific conditions and affects the results accordingly.

For this thesis we used indirect variables such as number of stops or percentage of time accelerating but we did not have values of direct variables such as headways, which would be very useful to adapt behavior more precisely. It would be necessary to collect specific data with equipped floating cars.

The simulation was limited to 30 minutes and, especially during peak hour traffic conditions, there is some latent demand that cannot be considered due to inherent model aspects. It is unknown whether this demand would use another mode because of the congestion (more travel time and fuel consumption) or simply we would have a longer peak hour than in the base-case scenario, i.e. 0% eco-drivers. Following the methodology proposed by the *ICT-Emissions* project, it would be very interesting to upscale the result to a macro level and run the model for the entire metropolitan network to observe the impacts on the whole transportation system.

Once the modeling effort is done, these models can be used to study the effect on traffic and emissions of different aspects. For instance:

- The impact of real or simulated slopes.
- Different fleet compositions, particularly the percentage of heavy duty vehicles.

- Future scenarios with more presence of hybrids and electric vehicles

The results presented here may be useful to calibrate average speed emission models such as COPERT for different traffic situations: peak, off-peak and night traffic conditions.

The same methodology could be applied to other cities to compare whether the effects of different eco-driving penetration rates follow the same trends. Similarly, the impact on interurban roads could be measured by building the respective models.

We are heading towards an era of cars being connected with the infrastructure and other vehicles. Taking advantage of these developments, it would be interesting for a future research line to simulate in the same way we did in this thesis and calculate the impacts of vehicles equipped with ADAS (Advanced Driver Assistance System) and ISA (Intelligent Speed Adaptation) or any other kind of connection to the infrastructure (traffic lights or ramp metering).

10. REFERENCES

- AASHTO. (2001). *Policy on geometric design of highways and streets*. Washington, DC: American Association of State Highway and Transportation Officials.
- Agostini, A., Lelli, M., Negrenti, E., & Parenti, A. (2005, March). TEE2003: Transport Energy & Environment: an advanced software tool for the estimation of direct impacts from transport. In *Urban Transport XI: Urban Transport and the Environment in the 21st Century*. Southampton, England: Wit Press.
- Ahn, K., & Rakha, H. A. (2007). Energy and environmental impacts of route choice decisions. *Transportation Research Board 86th Annual Meeting*, (07-1190).
- Alam, M. S., & McNabola, A. (2014). A critical review and assessment of eco-driving policy & technology: Benefits & limitations. *Transport Policy*, 35, 42-49.
- André, M. (2004). The ARTEMIS European driving cycles for measuring car pollutant emissions. *Science of the Total Environment*, 334, 73-84.
- Andrieu, C., & Saint Pierre, G. (2012). Comparing effects of eco-driving training and simple advices on driving behavior. *Procedia-Social and Behavioral Sciences*, 54, 211-220.
- Azzi, S., Reymond, G., Mérienne, F., & Kemeny, A. (2011). Eco-driving performance assessment with in-car visual and haptic feedback assistance. *Journal of Computing and Information Science in Engineering*, 11(4), 041005.
- Barkenbus, J. N. (2010). Eco-driving: An overlooked climate change initiative. *Energy Policy*, 38(2), 762-769.
- Barth, M., & Boriboonsomsin, K. (2009). Energy and emissions impacts of a freeway-based dynamic eco-driving system. *Transportation Research Part D: Transport and Environment*, 14(6), 400-410.
- Barth, M., & Boriboonsomsin, K. (2010). Traffic congestion and greenhouse gases. *TR News*, (268).
- Benedek, C., & Rilett, L. (1998). Equitable traffic assignment with environmental cost functions. *Journal of Transportation Engineering*, 124(1), 16-22. doi:10.1061/(ASCE)0733-947X(1998)124:1(16).
- Berry, W. D. (1993). *Understanding regression assumptions*. Sage Publications. Newbury Park, CA: Sage.
- Beusen, B., Broekx, S., Denys, T., Beckx, C., Degraeuwe, B., Gijssbers, M., ... & Panis, L. I. (2009). Using on-board logging devices to study the longer-term impact of an

eco-driving course. *Transportation Research Part D: Transport and Environment*, 14(7), 514-520. doi: <http://dx.doi.org/10.1016/j.trd.2009.05.009>

Boarnet, M. G., Kim, E. J., & Parkany, E. (1998). Measuring traffic congestion. *Transportation Research Record: Journal of the Transportation Research Board*, 1634(1), 93-99.

Boriboonsomsin, K., Barth, M. J., & Vu, A. (2011). Evaluation of driving behavior and attitude toward eco-driving: Southern California limited case study. *Transportation Research Board 90th Annual Meeting*, (11-0151).

Brockfeld, E., Kühne, R. D., & Wagner, P. (2004). Calibration and validation of microscopic traffic flow models. *Transportation Research Record: Journal of the Transportation Research Board*, 1876(1), 62-70.

Burbank, C. J., Wenger, J. A., & Sperling, D. (2012). Climate change and transportation: Summary of key information. *Transportation Research e-Circular*, (E-C164).

Canaud, M., & Faouzi, N. E. (2015). ECOSTAND: Towards a standard methodology for environmental evaluation of ITS. *Transportation Research Procedia*, 6, 377-390. doi: <http://dx.doi.org/10.1016/j.trpro.2015.03.028>

Cascetta, E., Punzo, V., & Montanino, M. (2011). Empirical analysis of effects of automated section speed enforcement system on traffic flow at freeway bottlenecks. *Transportation Research Record*, (2260), 83-93. doi:10.3141/2260-10.

Child, D. (2006). *The essentials of factor analysis*. A&C Black.

Cohn, N., Kools, E., & Mieth, P. (2012). The TomTom congestion index. *19th ITS World Congress*, Vienna, Austria, 22 to 26 October 2012.

Comendador, J., López-Lambas, M. E., & Monzón, A. (2014). Urban built environment analysis: Evidence from a mobility survey in Madrid. *Procedia - Social and Behavioral Sciences*, 160, 362-371. doi: <http://dx.doi.org/10.1016/j.sbspro.2014.12.148>

CRTM. (2006). *Encuesta domiciliaria de movilidad 2004*. Madrid: Consorcio Regional de Transportes de Madrid.

Dietz, T., Gardner, G. T., Gilligan, J., Stern, P. C., & Vandenberg, M. P. (2009). Household actions can provide a behavioral wedge to rapidly reduce US carbon emissions. *Proceedings of the National Academy of Sciences of the United States of America*, 106(44), 18452-18456. doi:10.1073/pnas.0908738106.

Dijkema, M. B., van der Zee, Saskia C., Brunekreef, B., & van Strien, R. T. (2008). Air quality effects of an urban highway speed limit reduction. *Atmospheric Environment*, 42(40), 9098-9105.

Ding, Y., & Rakha, H. (2002). Trip-based explanatory variables for estimating vehicle fuel consumption and emission rates. *Water, Air, & Soil Pollution: Focus*, 2(5), 61-77.

Dirección General de Sostenibilidad y Planificación de la Movilidad. (2013). *Estudio del parque circulante de la ciudad de Madrid. Año 2013*. Madrid. Spain: Dirección General de Sostenibilidad y Planificación de la Movilidad.

Dowling, R., Skabardonis, A., Halkias, J., McHale, G., & Zammit, G. (2004). Guidelines for calibration of microsimulation models: Framework and applications. *Transportation Research Record: Journal of the Transportation Research Board*, 1876(1), 1-9.

European Conference of Ministers of Transport. (2007). Congestion management measures that release or provide new capacity. In OECD/ECMT (Ed.), *Managing urban traffic congestion* (pp. 229). France: OECD Publishing.

ECOWILL. (2011). *Ecodriving standards for ECOWILL seminars*. (Public Deliverable No. D 3.2) Intelligent Energy Europe.

ECOWILL. (2013). The golden rules of eco-driving. Retrieved from http://www.ecodrive.org/en/what_is_ecodriving/the_golden_rules_of_ecodriving/

Eijk A., Ligterink N., & Inanc S. (2013). *EnViVer 4.0 pro and enterprise manual*. (Manual). Delft, The Netherlands: TNO.

Elefteriadou, L. (2014). *An introduction to traffic flow theory*. Springer.

Eliasson, J. (2009). A cost-benefit analysis of the Stockholm congestion charging system. *Transportation Research Part A: Policy and Practice*, 43(4), 468-480. doi:<http://dx.doi.org/10.1016/j.tra.2008.11.014>

El-Shawarby, I., Ahn, K., & Rakha, H. (2005). Comparative field evaluation of vehicle cruise speed and acceleration level impacts on hot stabilized emissions. *Transportation Research Part D: Transport and Environment*, 10(1), 13-30.

Elvik, R. (2005). Speed and road safety - synthesis of evidence from evaluation studies. *Statistical Methods; Highway Safety Data, Analysis, and Evaluation; Occupant Protection; Systematic Reviews and Meta-Analysis*, (1908), 59-69.

EMT. (2015). Navega por Madrid. Retrieved from <http://www.emtmadrid.es/mapaweb/emt.html>

Energy Information Administration. (2013). *International Energy Outlook*. (No. DOE/EIA-0484(2013)). Washington D.C: U.S. Department of Energy.

Ericsson, E. (2001). Independent driving pattern factors and their influence on fuel-use and exhaust emission factors. *Transportation Research Part D: Transport and Environment*, 6(5), 325-345. doi: [http://dx.doi.org/10.1016/S1361-9209\(01\)00003-7](http://dx.doi.org/10.1016/S1361-9209(01)00003-7)

European Commission. (2008). *Action plan for the deployment of intelligent transport systems in Europe*. (No. Tech. Report. COM (2008) 886). Brussels, Belgium: European Commission

European Commission. (2009). *Mobilising information and communication technologies to facilitate the transition to an energy efficient*. (No. COM (2009) 111). Brussels, Belgium: European Commission

European Commission. (2015). Road classification. Retrieved from http://ec.europa.eu/transport/road_safety/specialist/knowledge/road/designing_for_road_function/road_classification_en.htm

European Environment Agency. (2010). *The European Environment. State and Outlook 2010. Urban Environment*. Copenhagen, Denmark: Publications Office of the European Union. ISBN 978-92-9213-151-7.

European Environment Agency. (2013). *Annual European Union greenhouse gas inventory 1990-2011 and inventory report 2013*. Copenhagen, Denmark: Publications Office of the European Union.

FIAT. (2010). Eco-driving uncovered- the benefit and challenges of eco-driving, based on the first study using real journey data. Retrieved from <http://www.ecodriver-project.eu/library/other-documents/ecodriving-uncovered/>

Field, A. (2013). *Discovering statistics using IBM SPSS statistics*. Sage Publications.

Fildes, B., & Lee, S. (1993). The speed review: Road environment, behaviour, speed limits, enforcement and crashes. Monash University Accident Research Centre, prepared for Road Safety Bureau. New South Wales, and Federal Office of Road Safety, Canberra, Australia.

Fomunung, I., Washington, S., & Guensler, R. (1999). A statistical model for estimating oxides of nitrogen emissions from light duty motor vehicles. *Transportation Research Part D: Transport and Environment*, 4(5), 333-352.

García, A. (2009). *Estudio sobre la gestión variable de la velocidad en las vías de acceso a las áreas urbanas*. Barcelona, Spain: Cambra Oficial de Comerç, Indústria i Navegació de Barcelona.

García, A. (2015). El método de investigación. *Curso De Formación De Evaluadores De La Dirección General De Tráfico*, Cercedilla, Madrid, Spain.

- Giles, M. J. (2004). Driver speed compliance in Western Australia: A multivariate analysis. *Transport Policy*, 11(3), 227-235. doi:10.1016/j.tranpol.2003.11.002
- Grant-Muller, S., & Xu, M. (2014). The role of tradable credit schemes in road traffic congestion management. *Transport Reviews*, 34(2), 128-149. doi:10.1080/01441647.2014.880754
- Greenhouse Gas Inventory Office of Japan. (2012). *National greenhouse gas inventory report of Japan (2012)*. Japan: Greenhouse Gas Inventory Office of Japan.
- Greenwood, I., Dunn, R., & Raine, R. (2007). Estimating the effects of traffic congestion on fuel consumption and vehicle emissions based on acceleration noise. *Journal of Transportation Engineering*, 133(2), 96-104.
- Hasewend, W. (2001). AVL Cruise—Driving performance and fuel consumption simulation. *ATZ Worldwide*, 103(5), 10-13.
- Hausberger, S., Rexeis, M., Zallinger, M., & Luz, R. (2009). *Emission factors from the model PHEM for the HBEFA version 3*. (No. I-20/2009). Graz, Austria: TU Graz.
- Hegyi, A., De Schutter, B., & Hellendoorn, J. (2005). Optimal coordination of variable speed limits to suppress shock waves. *IEEE Transactions on Intelligent Transportation Systems*, 6(1), 102-112. doi:10.1109/TITS.2004.842408
- Henning, W. (2008). Ford eco-driving: Best practice training and evaluation. *ECODRIVEN Final Conference*, Prague, Czech Republic.
- Hernandez, S., & Monzon, A. (2015). Key factors for defining an efficient urban transport interchange: Users' perceptions. *Cities*, 50, 158-167. doi: <http://dx.doi.org/10.1016/j.cities.2015.09.009>
- Heydecker, B. G., & Addison, J. D. (2011). Analysis and modelling of traffic flow under variable speed limits. *Transportation Research Part C: Emerging Technologies*, 19(2), 206-217. doi:10.1016/j.trc.2010.05.008.
- Highways Agency. (2004). *M25 controlled motorways. Summary report*. (No. Issue 1). Bristol (UK): Highways Agency Publications Group.
- Hof, T., Conde, L., Garcia, E., Iviglia, A., Jamson, S., Jopson, A., et al. (2012). *A state of the art review and users' expectations*. (Deliverable No. D11.1). Brussels, Belgium.
- Hoffmann-Leichter. (1997). *Untersuchung der Auswirkung der Verkehrsbeeinflussungsanlage auf der A5 Freidberg – Frankfurt auf Verkehrsablauf, Verkehrssicherheit und Reisezeit*. (Schlussbericht). Germany.
- Hoogendoorn, S. P., & Bovy, P. H. L. (2000). Continuum modeling of multiclass traffic flow. *Transportation Research Part B: Methodological*, 34(2), 123-146.

Hornung, W. (2004). *Summary: Evaluations of eco-drive training courses*. Bern, Switzerland: Quality Alliance Eco-Drive and Swiss Energy.

Hutcheson, G. D., & Sofroniou, N. (1999). *The multivariate social scientist: Introductory statistics using generalized linear models* Sage.

ICT-Emissions Consortium (2015). *The ICT-Emissions Project Handbook*. (Deliverable No. 6.4). Brussels, Belgium.

IDAE. (2015). Conducción eficiente. Controlas tu energía. Retrieved from <http://www.controlastuenergia.gob.es/multimedia/Paginas/contenidos-multimedia.aspx>

Instituto Nacional de Estadística. (2015). Population figures and demographic censuses. Retrieved from http://www.ine.es/en/inebmenu/mnu_cifraspob_en.htm

Intergovernmental Panel on Climate Change. (2007). Climate change 2007: The physical science basis. *Agenda*, 6(07), 333.

Johansson, H., Färnlund, J., & Engström, C. (1999). *Impact of EcoDriving on emissions and fuel consumption, a prestudy*. (No. 1999:165E). Stockholm, Sweden: Swedish National Road Administration.

Johansson, H., Gustafsson, P., Henke, M., & Rosengren, M. (2003). Impact of EcoDriving on emissions. *Transport and Air Pollution. Proceedings from the 12th Symposium*, Avignon, France.

Joumard, R., Jost, P., Hickman, J., & Hassel, D. (1995). Hot passenger car emissions modelling as a function of instantaneous speed and acceleration. *Science of the Total Environment*, 169(1-3), 167-174.

Kesting, A., & Treiber, M. (2008). Calibrating car-following models by using trajectory data: Methodological study. *Transportation Research Record: Journal of the Transportation Research Board*, 2088(1), 148-156.

Killian, R. (2012). Ecodriving: The science and art of smarter driving. *TR News*, (281).

Klunder, G. A., Malone, K., Mak, J., Iwilmink, I. R., Schirokoff, A., Sihvola, N., . . . Kosmatopoulos, E. (2009). *Impact of information and communication technologies on energy efficiency in road transport*. (Final Report).

Knoop, V. L., Duret, A., Buisson, C., & van Arem, B. (2010). Lane distribution of traffic near merging zones influence of variable speed limits. *Intelligent Transportation Systems (ITSC), 2010 13th International IEEE Conference on*, 485-490.

- Kobayashi, I., Tsubota, Y., & Kawashima, H. (2007). Eco-driving simulation: Evaluation of eco-driving within a network using traffic simulation. *Urban Transport XIII. Urban Transport and the Environment in the 21st Century*.
- Kraemer, C., Pardillo, J. M., Rocci, S., Romana, M., Sanchez Blanco, V., & del Val, M. A. (2009). Las redes viarias. *Ingeniería de carreteras. Volumen I* (2nd ed., pp. 8-9). Madrid, Spain: McGraw Hill.
- Land Tirol. (2012). Tempo 100 auf der Autobahn - Warum? Retrieved from <http://www.tirol.gv.at/themen/verkehr/verkehrsplanung/verkehrsprojekte/tempo100>
- Larsson, H., & Ericsson, E. (2009). The effects of an acceleration advisory tool in vehicles for reduced fuel consumption and emissions. *Transportation Research Part D: Transport and Environment*, 14(2), 141-146. doi: <http://dx.doi.org/10.1016/j.trd.2008.11.004>
- Laumbach, R. J., & Kipen, H. M. (2012). Respiratory health effects of air pollution: Update on biomass smoke and traffic pollution. *Journal of Allergy and Clinical Immunology*, 129(1), 3-11. doi: <http://dx.doi.org/10.1016/j.jaci.2011.11.021>
- Lee, C., Hellinga, B., & Saccomanno, F. (2004). Assessing safety benefits of variable speed limits. *Transportation Research Record: Journal of the Transportation Research Board*, 1897(-1), 183-190.
- Lee, H., Lee, W., & Lim, Y. (2010). The effect of eco-driving system towards sustainable driving behavior. *CHI'10 Extended Abstracts on Human Factors in Computing Systems*, 4255-4260.
- Li, M., Boriboonsomsin, K., Wu, G., Zhang, W., & Barth, M. (2009). Traffic energy and emission reductions at signalized intersections: A study of the benefits of advanced driver information. *International Journal of Intelligent Transportation Systems Research*, 7(1), 49-58.
- Li, J., Wu, G., & Zou, N. (2011). Investigation of the impacts of signal timing on vehicle emissions at an isolated intersection. *Transportation Research Part D: Transport and Environment*, 16(5), 409-414. doi: <http://dx.doi.org/10.1016/j.trd.2011.03.004>
- Liu, H., & Barth, M. (2011). Analysis of US EPA's MOVES Model's operating modes and handling of history effects. In *90th Annual Meeting of the Transportation Research Board, Washington, D.C.*
- Makarewicz, R., & Gałuszka, M. (2011). Road traffic noise prediction based on speed-flow diagram. *Applied Acoustics*, 72(4), 190-195. doi: <http://dx.doi.org/10.1016/j.apacoust.2010.11.010>

- Meyer, M. D. (1999). Demand management as an element of transportation policy: Using carrots and sticks to influence travel behavior. *Transportation Research Part A: Policy and Practice*, 33(7-8), 575-599. doi: [http://dx.doi.org/10.1016/S0965-8564\(99\)00008-7](http://dx.doi.org/10.1016/S0965-8564(99)00008-7)
- Muñoz-Organero, M., & Magana, V. C. (2013). Validating the impact on reducing fuel consumption by using an EcoDriving assistant based on traffic sign detection and optimal deceleration patterns. *IEEE Transactions on Intelligent Transportation Systems*, 14(2), 1023-1028. doi:10.1109/TITS.2013.2247400.
- Nissan, A., & Bang, X. (2006). Evaluation of impacts of the motorway control system (MCS) in Stockholm. In *European Transport Conference 2006 Proceedings*.
- Ntziachristos, L., & Samaras, Z. (2000). Speed-dependent representative emission factors for catalyst passenger cars and influencing parameters. *Atmospheric Environment*, 34(27), 4611-4619.
- O'Flaherty, C. (1997). *Transport Planning and Traffic Engineering*. Elsevier.
- Onoda, T. (2009). IEA policies—G8 recommendations and an afterwards. *Energy Policy*, 37(10), 3823-3831. doi: <http://dx.doi.org/10.1016/j.enpol.2009.07.021>
- Orfila, O. (2011). Impact of the penetration rate of ecodriving on fuel consumption and traffic congestion. Paper presented at the YRS11: Young Researchers Seminar 2011, 15p.
- Pachauri, R. K., Allen, M., Barros, V., Broome, J., Cramer, W., Christ, R., . . . Dasgupta, P. (2014). *Climate change 2014: Synthesis report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. Geneva, Switzerland: IPCC.
- Pandazis, J., & Winder, A. (2015). *Study of intelligent transport systems for reducing CO2 emissions for passenger cars*. ACEA.
- Parrish, D. D. (2006). Critical evaluation of US on-road vehicle emission inventories. *Atmospheric Environment*, 40(13), 2288-2300. doi: <http://dx.doi.org/10.1016/j.atmosenv.2005.11.033>
- Piao, J., & McDonald, M. (2008). Safety impacts of variable speed limits - A simulation study. *Intelligent Transportation Systems, 2008. ITSC 2008. 11th International IEEE Conference on*, 833-837.
- PTV. (2014). *PTV VISSIM 7 user manual*. PTV AG.
- Punzo, V., & Simonelli, F. (2005). Analysis and comparison of microscopic traffic flow models with real traffic microscopic data. *Transportation Research Record: Journal of the Transportation Research Board*, 1934(1), 53-63.

- Qian, G., & Chung, E. (2011). Evaluating effects of eco-driving at traffic intersections based on traffic micro-simulation. *Australasian Transport Research Forum (ATRF), 34th, 2011, Adelaide, South Australia, Australia*, 34(0092).
- Qian, G., & Chung, E. (2013). Microscopic simulation study of eco-driving performance at urban intersections. In *13th World Conference on Transport Research*, Rio de Janeiro, Brasil.
- Rakha, H., Van Aerde, M., Ahn, K., & Trani, A. A. (2000). Requirements for evaluating traffic signal control impacts on energy and emissions based on instantaneous speed and acceleration measurements. *Transportation Research Record: Journal of the Transportation Research Board*, 1738(-1), 56-67.
- Rakha, H., & Kamalanathsharma, R. K. (2011). Eco-driving at signalized intersections using V2I communication. *14th International IEEE Conference on Intelligent Transportation Systems (ITSC), 2011*, 341-346. doi:10.1109/ITSC.2011.6083084.
- Ramanathan, V., & Feng, Y. (2009). Air pollution, greenhouse gases and climate change: Global and regional perspectives. *Atmospheric Environment*, 43(1), 37-50. doi:<http://dx.doi.org/10.1016/j.atmosenv.2008.09.063>
- Robinson, M. (2000). Examples of variable speed limit applications. *79th Annual Meeting of Transportation Research Board*, Washington DC, United States.
- Saboochi, Y., & Farzaneh, H. (2009). Model for developing an eco-driving strategy of a passenger vehicle based on the least fuel consumption. *Applied Energy*, 86(10), 1925-1932. doi: <http://dx.doi.org/10.1016/j.apenergy.2008.12.017>
- Samaras, Z., Ntziachristos, L., Burzio, G., Toffolo, S., Tatschl, R., Mertz, J., & Monzon, A. (2012). Development of a methodology and tool to evaluate the impact of ICT measures on road transport emissions. *Procedia - Social and Behavioral Sciences*, 48, 3418-3427. doi: <http://dx.doi.org/10.1016/j.sbspro.2012.06.1306>
- Schick, P. (2003). *Einfluss von Streckenbeeinflussungsanlagen auf die Kapazität von Autobahnabschnitten sowie die Stabilität des Verkehrsflusses*. doi:ISSN 0932 - 402X
- Schrank, D., Eisele, B., & Lomax, T. (2012). TTI's 2012 Urban Mobility Report. *Texas A&M Transportation Institute*.
- Sivak, M., & Schoettle, B. (2012). Eco-driving: Strategic, tactical, and operational decisions of the driver that influence vehicle fuel economy. *Transport Policy*, 22, 96-99. doi:10.1016/j.tranpol.2012.05.010
- Smit, R. (2006). *An examination of congestion in road traffic emission models and their application to urban road networks*. (Doctoral dissertation, Griffith University).

Smit, R., Smokers, R., & Rabé, E. (2007). A new modelling approach for road traffic emissions: VERSIT+. *Transportation Research Part D: Transport and Environment*, 12(6), 414-422. doi:<http://dx.doi.org/10.1016/j.trd.2007.05.001>

Smit, R., Brown, A. L., & Chan, Y. C. (2008). Do air pollution emissions and fuel consumption models for roadways include the effects of congestion in the roadway traffic flow? *Environmental Modelling & Software*, 23(10-11), 1262-1270. doi:<http://dx.doi.org/10.1016/j.envsoft.2008.03.001>

Smit, R., Rose, G., & Symmons, M. (2010). Assessing the impacts of ecodriving on fuel consumption and emissions for the Australian situation. In *Proceedings of the 33rd Australasian Transport Research Forum (ATRF), 2010, Canberra, ACT, Australia (Vol. 33)*.

Soole, D. W., Watson, B. C., & Fleiter, J. J. (2013). Effects of average speed enforcement on speed compliance and crashes: A review of the literature. *Accident Analysis & Prevention*, 54(0), 46-56. doi:10.1016/j.aap.2013.01.018

Sun, J., Niu, D., Chen, S., & Li, K. (2013). Development and investigation of a dynamic eco-driving speed guidance strategy for signalized highway traffic. *Transportation Research Board 92nd Annual Meeting*, (13-2272).

Symmons, M., Rose, G., & Van Doorn, G. (2009). Ecodrive as a road safety tool for Australian conditions. *Road Safety Grant Report (2009-004)*.

Cambridge Systematics (2004). *Traffic congestion and reliability: Linking solutions to problems. Executive summary*. Washington D.C.: Federal Highway Administration.

Taniguchi, M. (2007). A study on the effect of eco-driving training to fuel consumption. *Proceedings of JSAE Annual Congress*, (137-07) 9-12.

Taylor, M. A. (2000). Network modelling of the traffic, environmental and energy effects of lower urban speed limits. *Road and Transport Research*, 9(4), 49-56.

Toffolo, S., Morello, E., Di Rocco, D., Maier, W., Valdes, C., & Garcia-Castro, A. (2013). *Deliverable 2.1: Methodology*. (Deliverable No. D5.1). Brussels, Belgium.

Toffolo, S., Morello, E., Samaras, Z., Ntziachristos, L., Christian, V., Maier, W., & Garcia-Castro, A. (2014). ICT-emissions methodology for assessing ITS and ICT solutions. *Proceedings of the Transport Research Arena, Paris, France, 14-17 June*.

Toffolo, S., Vock, C., Ntziachristos, L., Samaras, Z., Maier, W., Valdes, C., & Garcia-Castro, A. (2015). *Manual of procedures for use of the methodology*. (Deliverable No. D5.2). Brussels, Belgium: ICT-Emissions Consortium.

- Treiber, M., & Kesting, A. (2013). Microscopic calibration and validation of car-following models – A systematic approach. *Procedia - Social and Behavioral Sciences*, 80(0), 922-939. doi:<http://dx.doi.org/10.1016/j.sbspro.2013.05.050>
- United States Environmental Protection Agency. (2013). *Inventory of U.S. greenhouse gas emissions and sinks: 1990 - 2011*. (No. EPA 430-R-13-001). Washington, DC: U.S. Environmental Protection Agency.
- Valdes, C. (2012). *Optimization of urban mobility measures to achieve WIN-WIN strategies*. (Doctoral Dissertation, Universidad Politécnica de Madrid).
- van Nes, N., Brandenburg, S., & Twisk, D. (2008). Dynamic speed limits; effects on homogeneity of driving speed. *Intelligent Vehicles Symposium, 2008 IEEE*, 269-274.
- Vermeulen, R. (2006). The effects of a range of measures to reduce the tail pipe emissions and/or the fuel consumption of modern passenger cars on petrol and diesel. *TNO Report.Dec.*
- Wegman, F., Aarts, L., & Bax, C. (2008). Advancing sustainable safety: National road safety outlook for The Netherlands for 2005–2020. *Safety Science*, 46(2), 323-343. doi:10.1016/j.ssci.2007.06.013.
- Wiedemann, R., & Reiter, U. (1992). Microscopic traffic simulation: The simulation system MISSION, background and actual state. *Project ICARUS (V1052) Final Report, 2*, 1-53.
- Wilbers, P. (1999). The new driving force: A new approach to promote energy-efficient purchasing and driving behaviour. *EcoDrive Conference Proceedings, Graz, Austria*. 44-47.
- Wilbers, P., & Wardenaar, H. (2007). The Dutch national ecodriving programme Het Nieuwe Rijden: A success story. In *European Council for an Energy-Efficient Economy* (pp. 1673-1678).
- Wittwer, R. (2014). Cluster-analytical-creation of a typology of young Adults' Travel behavior in Germany. *Procedia - Social and Behavioral Sciences*, 160, 64-73. doi: <http://dx.doi.org/10.1016/j.sbspro.2014.12.117>
- Washington State Department of Transportation. (2014). *Protocol for Vissim Simulation*.
- Xia, H., Boriboonsomsin, K., & Barth, M. (2013). Dynamic eco-driving for signalized arterial corridors and its indirect network-wide Energy/Emissions benefits. *Journal of Intelligent Transportation Systems*, 17(1), 31-41. doi: 10.1080/15472450.2012.712494.

Zegeye, S. K., De Schutter, B., Hellendoorn, J., & Breunese, E. A. (2010). Variable speed limits for area-wide reduction of emissions. *Intelligent Transportation Systems (ITSC), 2010 13th International IEEE Conference on*, 507-512.

Zhikai, J., Xiaoxiong, Z., & Hongwei, Y. (2004). Simulation research and implemented effect analysis of variable speed limits on freeway. *Intelligent Transportation Systems, 2004. Proceedings of the 7th International IEEE Conference on*, 894-898.

ANNEX I- SCIENTIFIC PUBLICATIONS

List of original publications

Garcia-Castro, A., & Monzon, A. (2014). Using floating car data to analyse the effects of ITS measures and eco-driving. *Sensors*, 14(11), 21358-21374.

* *Journal Citation Report (JCR), Impact Factor 2014: 2.245, Q1*

Garcia-Castro, A., & Monzon, A. (2014). Homogenization effects of variable speed limits. *Transport and Telecommunication Journal*, 15(2), 130-143.

**SCImago Journal Rank (SJR) 2014: 0.247, Q2*

Garcia-Castro, A., & Monzon, A. (2015). Measuring the effects of traffic congestion on fuel consumption. *Transportation Research Board 94th Annual Meeting*, Washington, January 11-15. (15-2087)

Garcia-Castro, A., Monzon, A., & Valdes, C. (2014). ICT measures to reduce CO2 emissions in metropolitan areas. The case study of Madrid. *Transport Research Arena (TRA) 5th Conference: Transport Solutions from Research to Deployment*, Paris, June 14-17.

Samaras, C., Tsokolis, D., Toffolo, S., Garcia-Castro, A., Vock, C., Ntziachristos, L., & Samaras Z. (2014). Limits of applicability of COPERT model to short links and congested conditions. *20th International Transport and Air Pollution Conference*, Graz, Austria. 18-19 September.

Toffolo, S., Morello, E., Samaras, Z., Ntziachristos, L., Christian, V., Maier, W., & Garcia-Castro, A. (2014). ICT-emissions methodology for assessing ITS and ICT solutions. *Transport Research Arena (TRA) 5th Conference: Transport Solutions from Research to Deployment*, Paris, June 14-17.