Modeling different penetration rates of eco-driving in urban areas: Impacts on traffic flow and emissions

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ABSTRACT

Climate change and air quality are two main environmental challenges in metropolitan areas. As road transportation is one of the main contributors, public administrations are facing these problems with a number of complementary policy measures: shift to cleaner modes, new fuels and vehicle technologies, demand management, and the use of information and communication technologies (ICT) applied to transportation. Eco-driving is one of the measures that present large fuel savings at individual level. Although these savings are well documented in the literature, few studies focus on how eco-drivers driving patterns affect the surrounding vehicles and the traffic in general, and more particularly what would be the impact when the number of eco-drivers grows. Using a traffic microsimulation tool, four models in urban context have been built, corresponding to the different types of urban roads. Both the base-case and the parameters setting to simulate eco-driving have been calibrated with real data collected through floating vehicles performing the trips with normal and eco behaviors. 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 a microscopic emission model. The results show that in scenarios with low or medium demand levels and increasing number of eco-drivers, the effects are positive in terms of emissions. On the other side, 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.

KEYWORDS

Eco-driving; emissions; traffic

1. Introduction: The role of driver behavior in road transportation emissions

1.1 The problem of road transportation emissions

Greenhouse gases (GHG) emissions and overconsumption of energy resources represent a global problem, which concerns both their causes and consequences (Ramanathan & Feng, 2009). Changes in the atmospheric presence of GHG and aerosols alter the energy balance of the climate system (Intergovernmental Panel on Climate Change, 2007). The transportation sector is one of the largest emitters (Emberger, 2015) despite the advances in the field of engine technology. This sector accounted for 26% of global energy consumption in 2010, and transportation energy use is expected to increase by 1.1% every year to 2040 according to the International Energy Outlook 2013 Reference case (Energy Information Administration, 2013).

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 & Kipen, 2012). Transportation 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). Transportation based on private passenger cars is unsustainable for reasons of congestion, energy consumption, safety, and environmental and human health (Shay & Khattakb, 2010).

In this context, much of the effort dedicated to reducing energy consumption and emissions has been focused on the road transportation sector. The European Commission (2009) proposed an integrated policy to tackle the problem from different approaches; these included particularly demand management, a shift to cleaner modes, improving vehicle technologies, traffic management, the use of information and communication technologies (ICT), and driver behavior change. The latter corresponds mainly to eco-driving, which incorporates a number of techniques oriented to reduce the fuel consumption.

1.2 Eco-driving: definition and previous research

Concerns about climate change and oil prices have triggered a number of measures and strategies to reduce fuel consumption

and emissions. Dietz, Gardner, Gilligan, Stern, & Vandenbergh (2009) named different decisions that 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 less idling time.

Eco-driving is one of these measures, which aims to reduce fuel consumption by modifying the driver behavior. From this simple definition, many concepts may be included, depending on which level of decision-making is considered (Sivak & Schoettle, 2012):

- Strategic decisions: Vehicle selection and maintenance.
- Tactical decisions: Route selection and vehicle load.
- Operational decisions: Driving style oriented to keep speed constant, accelerate smoothly, etc.

In a highly widespread 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. Apart from recommendations, eco-driving can also be applied using driver assistance systems, which adapt the speed to minimize the fuel consumption (Barth & Boriboonsomsin, 2009; Rakha, Ahn, & Park, 2012).

Most studies involving eco-driving focus on before-and-after comparison with respect to routes of individual vehicles. These individual fuel consumption savings through eco-driving have been reported in many studies (Sivak & Schoettle, 2012). They show a great variability, from 2% savings in fuel consumption to reach above 30% in some cases. However, very few studies have considered different percentages of eco-drivers penetration among all drivers. In these studies, the first evidence suggests that a high percentage of eco-drivers might not be positive in scenarios with high traffic volumes.

Kobayashi, Tsubota, & Kawashima (2007) presented a study comparing the simulated normal driving scenario and eco-driving scenario. For this study, they used a traffic microsimulation 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.

Similarly, Qian & 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 demands,

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 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 interurban) 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.

The aim of this study is to analyze the impacts of different eco-driving percentages (penetration rates) on traffic and emissions under different scenarios of traffic demand and type of road using floating car data for the model calibration. Compared with the previous studies, this research adds a complete case study with four itineraries in different types of roads in a metropolitan area. The methodology is also innovative as it includes a statistical analysis of the fuel consumption explanatory variables to calibrate the eco-driving behavior in the microsimulation model. It also includes aggregated results for the whole metropolitan area.

This paper is organized as follows: The methodology based on floating car data is presented in in Section 2. Data analysis is detailed in Section 3. Section 4 presents the eco-driving simulation, while the results are described in Section 5. Finally, some conclusions are included in Section 6.

2. Floating car data collection: the case study of Madrid

2.1 Micro-macro modeling of Intelligent Transportation System (ITS) measures in European cities

The research presented in this paper has been developed in the frame of the *ICT-Emissions* project (EU 7th R&D Framework Programme). Its aim was to find a methodology to simulate in detail the effects on CO₂ emissions of a number of ITS measures applied to transport. The project methodology is mainly based on the interaction of various simulation models at micro and macro levels. Therefore, the idea was not to create a new simulation software tool, but to link the already existing ones by developing the necessary interfaces. These models included a vehicle control model, traffic model, and emissions model (micro and macro levels). The project focused on the field of passenger cars, also analyzing the effects of the ITS measures under different fleet compositions.

The ICT-Emissions methodology was validated 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 selected ICT measures. These results were used to calibrate the vehicle and traffic models and afterward to validate the results obtained by applying the simulation methodology to these case studies (ICT-Emissions Consortium, 2015).

2.2 The case study of Madrid, Spain

Four different measures were selected for testing in the Madrid case study in collaboration with the Department of Traffic Technologies (Garcia-Castro & Monzon, 2014). One of these measures was eco-driving.

The 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.

Nine drivers and three vehicles 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 decided within ICT-Emissions project, taking into account the compatibility of the selected models with the application to record vehicle parameters developed by FIAT.

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 drivers were asked to perform specific trips covering different urban areas and sections of the M30 urban motorway where the measures under study were applied. Data were recorded in 21 week days, including peak and off-peak hours (Garcia-Castro & Monzon, 2014).

The data collection campaign was focused on the M30 ring 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.

Motorways and urban roads in Madrid are equipped with cameras and induction loops, which record traffic flow parameters such as intensity and average speed at certain points. These data may be enough to gain a picture of the general traffic conditions at a macro level, but they lack the necessary level of detail to determine patterns at a micro level. The floating car data method was used to determine traffic and vehicle parameters based on information collected from on-board devices. 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 how to use data from each vehicle's OBD system to record instantaneous position, speed, acceleration, fuel consumption (l/h), and revolutions per minute (rpm). This device is easy to be installed by the user in the vehicle diagnostic port, and data are sent to a mobile phone via Bluetooth with a frequency of 1 Hz (Figure 1).

Once the selected itineraries were filtered, the remaining records were processed in order to obtain the values for 76 variables for each trip, calculated according to traffic and emissions literature (Ericsson, 2001; Smit, Smokers, & Rabé, 2007; Greenwood, Dunn, & 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.

3. Fuel consumption explanatory factors

Once the driving performance and traffic flow variables have been recorded, it is necessary to proceed to their statistical analysis. The objective was to know how much of the fuel consumption variance can be explained by the collected speed profiles. The first step was an exploratory component analysis to associate all the variables to a number of significant key factors or components. Selecting the most relevant variable of each factor, we could formulate a multiple regression model with fuel consumption as dependent variable.

3.1 Selecting key explanatory variables

The database contained 76 variables calculated for every trip recorded of the three vehicles, making 3,072 trips in total. Among these 76 variables, we selected only 40 with the criteria of comparability between different trips; for instance, number of stops cannot be compared between trips with different length; therefore, we use the variable that represents number of stops per kilometer. It is also important to highlight that fuel consumption does not enter as variable. This will be the dependent variable in the regression model described in Section 3.2.

Figure 1. Floating car data collection process through OBD-key device.

Table 1. Pattern matrix and variable loadings to each factor.

Variable	Variable code	Factors		
		1	2	3
Stop time per km (thresholds 14.4 and 5 km/h)	Sttkm_lt14.4kmh_5	0.997		
Stop time per km (thresholds 14.4 and 5 km/h)	Sttkm_lt14.4kmh_3	0.993		
Number of stops per km (threshold 5 km/h)	Nstopskm_lt5kmh	0.990		
	Nstopskm_lt3kmh *	0.983		
Number of stops per km (thresholds 14.4 and 5 km/h)	Nstopskm_lt14.4kmh_5	0.953		
Number of stops per km (thresholds 14.4 and 3 km/h)	Nstopskm_lt14.4kmh_3	0.948		
Stop time per km (threshold 5 km/h)	Sttkm_lt5kmh_SQRT	0.920		
Stop time per km (thresholds 3 km/h)	Sttkm_lt3kmh_SQRT	0.920		
Average speed	Vavet_inv	0.918		
Stop time percentage (thresholds 14.4 and 3 km/h)	Stt_lt14.4kmh_3	0.917		
Stop time percentage (thresholds and 14.4 and 5 km/h)	Stt_lt14.4kmh_5	0.915		
Stop time percentage (threshold 5 km/h)	stt_lt5kmh	0.855		
Stop time percentage (threshold 3 km/h)	stt_lt3kmh	0.846		
Positive accumulated acceleration per km	PAAckm	0.768		0.356
Average speed (thresholds 3 km/h)	Vavewo3kmh_inv	0.727		0.355
Average speed (thresholds 3 km/h)	Vavewo5kmh_inv	0.714		0.360
Power per km	Powerkm	0.621		0.402
Time percentage deceleration is greater than 5 km/h s	Pdec_5kmh_SQRT	0.561		
Standard deviation of positive acceleration	Asd_A	0.545	0.443	
Positive kinetic energy per km	PKEkm	0.474		0.379
			0.991	
Time percentage acceleration is between 5 and -5 km/h s	Pcru_5kmh_inv		0.890	
Average deceleration	BrakeAve		0.875	
Time percentage acceleration is between 3 and -3 km/h s	Pcru_3kmh_inv		0.873	
Standard deviation of deceleration	Asd_B		0.851	
Standard deviation of acceleration	Asd		0.782	
Standard deviation of speed	Vsd		0.622	
Average acceleration	Aave	0.494	0.506	
Time % acceleration is greater than 3 km/h s	Pacc_3kmh	0.438	0.461	
Time % acceleration is greater than 0.1 m/s ²				0.864

*The selected representative variables are highlighted.

With the aim of reducing the number of variables, a principal component analysis (PCA) was conducted with oblique rotation (direct Oblimin), using SPSS v.20 software from IBM. The Kaiser–Meyer–Olkin measure verified the sampling adequacy for the analysis, KMO = 0.904 (“superb”). The Bartlett test of sphericity χ^2 (435) = 371551.244, $p < 0.001$, indicated that correlations between items were sufficiently large for PCA. An initial analysis was run to obtain eigenvalues for each factor in the data. Three factors had eigenvalues over the Kaiser criterion of 1 and in combination explained 92.673% of the variance. Table 1 shows the three factor loadings in pattern matrix.

Factor 1 explains the time that the traffic is stopped in each itinerary. Factor number 2 deals with high accelerations, while the factor 3 reflects the amount of time driving at homogeneous speed. Three variables have been selected, one per each factor. The selected variables must have a high load factor for one of the factors and low for the two

others. Likewise, these variables must be easy to calculate subsequently with the output of the traffic simulation tool. Taking these conditions into account, the three variables selected are:

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

3.2 Explaining fuel consumption variation: Multiple regression model

After the factor analysis, a regression model was built to explain how much of the fuel consumption variance can be explained by variables selected in the previous section, which characterize a speed profile.

For the multiple regression model, only the data from the vehicle FIAT Bravo 1.6 Diesel is considered, as this was

Table 2. Multiple regression model explanatory of fuel consumption.

Multiple regression model	Unstandardized coefficients		Standardized coefficients		
	B	Std. Error	Beta	t	Sig.
(Constant)	3.092	0.286		10.824	0.000
Number of stops per km being stop speed under 3 km/h	0.959	0.061	0.615	15.718	0.000
Time % acceleration is greater than 0.1 m/s ²	0.049	0.006	0.168	8.307	0.000
Inverse of time % acceleration is greater than 5 km/h s	-1.081	0.205	-0.208	-5.274	0.000
R ²	.729				

Table 3. Characteristics of the four types of modeled streets.

Traffic situation/type of road	Urban motorway	Urban arterial	Urban collector	Local street
Length (km)	6.7	2.2	1.3	0.7
Signalized intersections	No	Yes	Yes	Yes
Lanes	3	4	2	1
Reserved public T. Lane	No	Yes	No	No
Capacity (veh/h)	3,540	2,758	956	354

the only one used to test the eco-driving techniques, with a total of 776 trips recorded. By making no assumptions about the importance of the predictors, the method of regression chosen is the forced entry method (Field, 2013). With this method, taking decision about the order in which variables are entered is, therefore, not necessary. Table 2 shows the summary of the resulting multiple regression model, with the fuel consumption as dependent variable. As expected, we can observe how the coefficient of the number of stops is positive i.e., the fuel consumption is directly proportional to the number of stops. Time percentage with low acceleration rates has small influence in the consumption, while the last factor show that the higher acceleration rates we got, the higher the fuel consumption will be. Table 2 also includes the goodness of the model with R^2 of 0.729, which implies that with only the speed profile, characterized by three variables, 72.9% of the variation of the fuel consumption is explained for each trip.

4. Eco-driving simulation

The aim of this section is to build a model to reproduce the real eco-driving behavior. This process is based on the floating car and field data recorded in the case study of Madrid from the vehicle FIAT Bravo 1.6 Diesel. The driver performed the trips during 2 weeks and after that was instructed to follow the eco-driving rules by a professional driving instructor. Then, the driver performed the same trips during another 2 weeks.

4.1 Selection of itineraries to model

The AASHTO (2001) proposed a traditional classification of urban roads into four categories: Principal arterial, Minor arterial, Collector Street, and 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 of the

case study of Madrid are classified as follows (Kraemer et al., 2009): Motorways and speedways, Arterials, Collectors, and Local streets. Taking into account these definitions, the itineraries analyzed with floating car data have been classified into four types of sections to be modeled. Table 3 shows the main characteristics of the selected itineraries to model.

Calibration of base cases has been performed following the *Protocol for Vissim Simulation* of the Washington State Department of Transportation (2014). More details about the calibration results can be found in Garcia-Castro (2016).

4.2 Real effects of eco-driving on the speed and consumption profiles

The objective of this section is to analyze how the three variables that explain fuel consumption—see Section 3.2—change in each type of road when an eco-driving behavior is applied. The analysis is based on the real data extracted from the data collection campaign detailed in Section 2, taking trips with similar traffic conditions for both normal and eco-driving behavior.

Table 4 reflects the percentage of variation of the three selected variables and the fuel consumption for each of the roads.

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.

4.3 Modeling eco-driving behavior in traffic and emissions micro-simulators

The calibration of eco-driving behavior was done by replicating a floating car trip in the simulation model VisSim v7 (PTV, 2014). Following the changes in the three key variables, the VisSim parameters were set up to obtain similar change tendencies in the simulated speed profiles of each of the 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.

Average speed models may not reflect properly the variation on speed profiles caused by different driving behaviors. Therefore, it was selected a micro level emission model called EnViVer, which is based on VERSIT+ emission model (Smit et al., 2007). This interface uses second-by-second speed profiles produced in VisSim to simulate the emissions of CO₂ and NO_x. Different vehicle types can be

Table 4. Percentage of variation of the explanatory variables and fuel consumption when applying eco-driving.

	Number of stops per km (threshold 3 km/h) (%)	Time % acceleration is greater than 5 km/h s (%)	Time % acceleration is greater than 0.1 m/s ² (%)	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

Data recorded from FIAT Bravo 1.6D.

Table 5. Maximum values of the acceleration functions in VISSIM for motorway and urban trips.

Function	Motorway		Urban	
	Normal	Eco	Normal	Eco
Maximum acceleration (m/s^2)	3.5	3	3.5	3.1
Desired acceleration (m/s^2)	3.5	2.8	3.5	2.3
Maximum deceleration (m/s^2)	-6.0	-5.5	-6.0	-4.0
Desired deceleration (m/s^2)	-4.1	-3.8	-2.8	-1.9

defined in the interface to faithfully reproduce the real fleet composition, including some parameters related to the age of vehicles, engine technologies (Gasoline, diesel, LPG, and electric), and emission standards (EURO).

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 was set to reproduce the floating vehicle, i.e., passenger diesel car under Euro 5 standards.

4.4 Eco-driving calibration process

The Wiedemann car-following model controls the movement of vehicles inside VisSim simulation software. Apart from the acceleration and deceleration functions, there are some parameters that can be edited to simulate eco-driving behavior (PTV, 2014). The first step was to adjust acceleration levels according to the values found in the analysis of real trips. Four functions in VisSim were changed: maximum acceleration, desired acceleration, maximum deceleration, and desired deceleration.

Table 5 reflects the changes done in the maximum value (acceleration from standstill or deceleration to stop) of each of the acceleration functions:

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 the CO_2 variation percentages that were close to the real fuel consumption variation.

The three interrupted sections (arterial, collector, and local) have almost the same values of the parameters as shown in Table 6. 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

Table 7. Real fuel consumption and simulated CO_2 emissions variation after applying eco-driving.

	Motorway	Arterial	Collector	Local
Real fuel consumption variation (%)	-4.8	-7.5	-12.5	-7.7
Simulated CO_2 emission variation (%)	-1.6	-6.2	-9.6	-5.6

changes in the preceding vehicles (CC4 and CC5), and reduce the speed oscillation (CC7). 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 calibration of the eco-driving behavior has been performed in off-peak traffic conditions, as this was the traffic condition with the majority of real recorded trips. The simulated emission values are based on the results of a simulated vehicle run in 15 replications with different random seeds. The variation of real fuel consumption and simulated CO_2 emissions are reflected in Table 7.

We can observe that except 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, and we could therefore consider the model validated.

5. Results on traffic performance and emissions

5.1 Simulation of scenarios

The eco-driving simulation model has been tested in a number of scenarios, combining the four different road types, three traffic situations and six eco-driving penetration rates. The combination of these three different elements produces a total of 72 different scenarios. The total number of simulated kilometers was 271,754. We considered 15 replications for each scenario, with account for more than 4 million vehicle-kilometers.

Three different traffic situations considered were:

- Peak hour: from 8:00 to 9:00. Mostly congested traffic.
- Day off-peak hour: from 11:00 to 12:00. Medium average traffic.
- Night off-peak hour: from 3:00 to 4:00. Free flow conditions.

The temporal profile of the traffic in Madrid was taken from counts in the M30 ring motorway. It was assumed that the profile was the same in all the models, i.e., in urban motorway,

Table 6. Final calibration values of car following parameters.

Parameters	Default values	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 (distance difference)	4.00	4.00	4.00	4.00	4.00
CC3 (start of deceleration process)	-8.00	-8.00	-10.00	-10.00	-10.00
CC4 (negative speed difference during following process)	-0.35	-0.35	-0.50	-0.50	-0.50
CC5 (positive speed difference during following process)	0.35	0.35	0.50	0.50	0.50
CC6 (influence of distance on speed oscillation)	11.44	11.44	11.44	11.44	11.44
CC7 (oscillation during acceleration)	0.25	0.25	0.05	0.05	0.05
CC8 (desired acceleration from standstill)	3.50	3.50	2.90	2.90	2.90
CC9 (desired acceleration at 80 km/h)	1.50	1.50	1.50	1.50	1.50
Observed vehicles	2	4	10	10	8

Figure 2. Daily traffic distribution in M30 East. The peak, off-peak, and night hour selected are highlighted.

urban arterial, urban collector, and local street. From the profile shown in Figure 2, we extracted that hourly night time traffic was 4.1% of the peak hour traffic, and off-peak traffic was 72.4%.

The capacity was calculated in representative sections of each type of road testing traffic demands higher than the congested conditions until the saturation is reached. Table 8 shows the volume to capacity ratio for each type of road and traffic conditions:

Regarding the eco-driving penetration, six different rates were modeled: 0% (base-case), 10%, 25%, 50%, 75%, and 100% (all traffic do eco-driving). It was assumed that only passenger car drivers change their driving style, following the behavior described in the previous section. 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 Madrid fleet composition (Dirección General de Sostenibilidad y Planificación de la Movilidad, 2013). Every scenario was run for 1 h. The first half hour was taken as warm-up time and therefore not considered for evaluation. In the last 30 min, the evaluation parameters were activated, recording speed profiles and aggregated values of traffic intensity and travel times.

Emissions by heavy duty vehicles and buses were calculated using the VERSIT+ default settings for year 2013. Passenger cars settings correspond to the age and fuel distribution values reported by Madrid Mobility Planning Department (Dirección General de Sostenibilidad y Planificación de la Movilidad, 2013).

Table 8. 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

5.2 Eco-driving impacts: Simulation results

This section presents at a glance in four tables the results of the simulations. Emissions indicators of CO₂ and NO_x have been added to measure the impact on climate change and air quality.

Regarding traffic performance, three indicators are considered in the Tables 9–12. Traffic activity is considered through the total distance traveled in vehicle-kilometers. This indicator evaluates if the different eco-driving penetration rates produce a capacity reduction in each type of road. Both the delay rate and the average speed reveal if the eco-driving slow down traffic flows and increase the congestion. The following tables present the average emissions and traffic indicators values of 15 replications per scenario. It includes the standard deviation and an analysis of the significance of the results. In particular, a one-way analysis of variance (ANOVA) was performed, focusing the significance of the F-ratio to evaluate whether the group means are the same. If the significance level between groups is less than or equal to 0.05, we reject the hypothesis of equal means, in the case it is greater than 0.05, we accept equality of means, i.e., significant differences do not exist between groups (Field, 2013).

Table 9 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 fall, thus producing higher emission rates. 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.

Table 10 presents the results for the urban arterial. In the case of this interrupted traffic facility, it is possible to observe how the average speed drops slightly in night traffic conditions. Regarding the traffic flow, it is worth mentioning again the reduction of the road capacity in peak hour for high eco-driving penetration rates. Longer gaps between vehicles and slower acceleration rates at traffic lights produce this clear increase of congestion.

Table 9. Urban motorway—Emissions and traffic simulation per traffic situation and eco-driving penetration rate.

Traffic demand (time)	Eco-driving penetration rate %	Emissions indicators		Traffic indicators		
		CO ₂ g/km	NO _x g/km	Veh*km	Delay rate (s/km)	Average speed (km/h)
Night	0 (none)	160.11 (5.91)	0.44 (0.04)	735 (26)	0.0 (0.0)	84.7 (0.2)
	10	158.34 (3.81)	0.44 (0.03)	735 (26)	0.0 (0.0)	84.7 (0.2)
	25	157.40 (5.14)	0.43 (0.04)	735 (26)	0.0 (0.0)	84.8 (0.2)
	50	155.42 (2.52)	0.42 (0.02)	735 (26)	0.0 (0.0)	84.8 (0.1)
	75	157.56 (4.38)	0.43 (0.04)	735 (26)	0.0 (0.0)	84.8 (0.2)
	100 (all cars)	160.80 (5.62)	0.45 (0.05)	735 (26)	0.0 (0.0)	84.8 (0.1)
	F Significance	0.03	0.13	1.00	1.00	0.77
Off-peak	0 (none)	164.45 (1.19)	0.49 (0.01)	13,439 (117)	0.9 (0.0)	83.0 (0.1)
	10	162.89 (0.84)	0.48 (0.01)	13,438 (117)	0.9 (0.0)	82.9 (0.1)
	25	163.48 (1.10)	0.49 (0.01)	13,438 (117)	0.9 (0.0)	83.0 (0.1)
	50	164.14 (1.19)	0.49 (0.01)	13,438 (118)	0.9 (0.0)	82.9 (0.1)
	75	164.21 (1.16)	0.49 (0.01)	13,438 (117)	0.9 (0.0)	82.9 (0.1)
	100 (all cars)	164.89 (1.05)	0.50 (0.01)	13,414 (116)	1.3 (0.1)	82.2 (0.2)
	F Significance	0.00	0.00	0.99	0.00	0.00
Peak	0 (none)	186.68 (10.32)	0.61 (0.04)	18,196 (212)	7.7 (3.7)	72.1 (5.7)
	10	191.40 (4.90)	0.62 (0.02)	17,932 (99)	10.5 (2.1)	68.1 (3.1)
	25	191.21 (5.34)	0.62 (0.02)	17,688 (88)	12.3 (0.9)	65.8 (1.1)
	50	192.72 (0.85)	0.62 (0.01)	17,673 (109)	13.6 (1.5)	64.3 (1.7)
	75	192.57 (1.46)	0.62 (0.01)	17,260 (97)	13.7 (0.5)	64.3 (0.6)
	100 (all cars)	198.92 (3.63)	0.65 (0.02)	17,043 (99)	17.7 (2.1)	60.1 (2.2)
	F Significance	0.00	0.00	0.00	0.00	0.00

Average values with standard deviation in parentheses.

Although not very sharply, eco-driving produces CO₂ savings in almost all 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, maximum savings are observed at 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.

Concerning the urban collector, Table 11 shows trends similar to the urban arterial. Although the capacity drops less intensively than in the urban arterial, the congestion affects more in the urban collector. Its characteristics produce higher increments in the delay for the peak hour traffic situations. It is important to highlight that for eco-driving penetration rates higher than 10% in 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.

Table 10. Urban arterial—Emission and traffic simulation per traffic situation and eco-driving penetration rate.

Traffic demand	Eco-driving penetration rate (%)	Emissions indicators		Traffic indicators		
		CO ₂ (g/km)	NO _x (g/km)	Veh*km	Delay rate (s/km)	Average speed (km/h)
Night	0 (none)	239.85 (4.84)	0.75 (0.04)	322 (27)	39.9 (2.8)	34.8 (1.0)
	10	240.22 (4.06)	0.75 (0.03)	322 (27)	40.2 (2.8)	34.8 (1.0)
	25	238.97 (4.55)	0.75 (0.04)	322 (27)	40.3 (2.7)	34.7 (0.9)
	50	239.57 (5.40)	0.76 (0.05)	322 (27)	40.8 (2.7)	34.6 (0.9)
	75	236.34 (3.35)	0.73 (0.03)	322 (27)	41.2 (2.7)	34.4 (0.9)
	100 (all cars)	234.52 (2.96)	0.72 (0.03)	322 (27)	41.8 (2.7)	34.2 (0.9)
	F Significance	0.00	0.16	1.00	0.40	0.40
Off-peak	0 (none)	285.86 (1.63)	0.97 (0.01)	3,929 (69)	50.4 (0.6)	31.3 (0.2)
	10	284.62 (1.78)	0.97 (0.01)	3,927 (68)	50.8 (0.7)	31.2 (0.2)
	25	282.66 (2.81)	0.96 (0.02)	3,927 (68)	51.5 (0.8)	31.0 (0.2)
	50	279.83 (1.81)	0.95 (0.01)	3,926 (67)	52.6 (0.7)	30.7 (0.2)
	75	277.62 (2.19)	0.93 (0.01)	3,927 (67)	53.6 (0.7)	30.4 (0.2)
	100 (all cars)	276.15 (1.74)	0.92 (0.01)	3,926 (67)	55.1 (0.9)	30.0 (0.2)
	F Significance	0.00	0.00	1.00	0.00	0.00
Peak	0 (none)	360.34 (5.31)	1.23 (0.02)	7,215 (111)	120.2 (6.4)	19.5 (0.7)
	10	355.86 (4.25)	1.21 (0.02)	7,116 (116)	124.8 (5.3)	19.0 (0.5)
	25	352.12 (4.52)	1.20 (0.02)	6,992 (103)	130.9 (5.6)	18.4 (0.5)
	50	351.42 (7.47)	1.18 (0.03)	6,786 (82)	149.0 (8.9)	16.9 (0.7)
	75	355.88 (11.60)	1.19 (0.04)	6,577 (107)	170.8 (12.4)	15.3 (0.8)
	100 (all cars)	360.79 (9.69)	1.20 (0.03)	6,340 (83)	193.6 (14.6)	14.0 (0.8)
	F Significance	0.00	0.00	0.00	0.00	0.00

Average values with standard deviation in parentheses.

Table 11. Urban collector—Emission and traffic simulation per traffic situation and eco-driving penetration rate.

Traffic demand	Eco-driving penetration rate (%)	Emissions indicators		Traffic indicators		
		CO ₂ (g/km)	NO _x (g/km)	Veh*km	Delay rate (s/km)	Average speed (km/h)
Night	0 (none)	315.15 (21.05)	1.01 (0.13)	34 (5)	52.9 (8.3)	28.1 (1.9)
	10	314.38 (16.18)	1.01 (0.10)	34 (5)	53.5 (8.0)	27.9 (1.8)
	25	311.21 (15.59)	0.98 (0.10)	34 (5)	54.1 (8.0)	27.8 (1.8)
	50	307.87 (15.35)	0.96 (0.09)	34 (5)	55.6 (8.0)	27.4 (1.8)
	75	306.40 (15.75)	0.96 (0.08)	34 (5)	57.2 (7.5)	27.1 (1.6)
	100 (all cars)	303.80 (16.70)	0.96 (0.10)	34 (5)	57.7 (7.6)	27.0 (1.6)
	F Significance	0.38	0.51	1.00	0.44	0.41
Off-peak	0 (none)	447.50 (6.46)	1.68 (0.04)	583 (14)	77.4 (2.9)	22.3 (0.4)
	10	445.01 (6.33)	1.66 (0.04)	583 (15)	79.9 (3.4)	22.0 (0.5)
	25	443.91 (7.19)	1.66 (0.05)	583 (14)	83.5 (3.9)	21.5 (0.5)
	50	443.11 (9.95)	1.65 (0.06)	583 (14)	90.9 (9.0)	20.6 (1.0)
	75	441.97 (11.51)	1.65 (0.07)	584 (14)	100.3 (16.0)	19.6 (1.4)
	100 (all cars)	440.30 (11.47)	1.64 (0.05)	582 (17)	109.6 (25.9)	18.8 (1.8)
	F Significance	0.35	0.33	1.00	0.00	0.00
Peak	0 (none)	456.76 (15.06)	1.66 (0.06)	794 (21)	97.1 (19.3)	20.4 (1.9)
	10	454.96 (13.19)	1.65 (0.05)	794 (19)	103.3 (17.7)	19.7 (1.7)
	25	462.52 (11.86)	1.68 (0.06)	791 (30)	124.6 (24.0)	17.7 (2.0)
	50	466.80 (10.48)	1.70 (0.06)	760 (30)	153.5 (24.3)	15.4 (1.8)
	75	463.06 (9.94)	1.68 (0.06)	740 (28)	174.2 (16.6)	14.1 (1.1)
	100 (all cars)	462.71 (6.47)	1.68 (0.04)	717 (19)	193.8 (12.9)	13.1 (0.6)
	F Significance	0.06	0.14	0.00	0.00	0.00

Average values with standard deviation in parentheses.

Similarly, 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%.

Regarding the local street, Table 12 shows how in this case the total distance traveled (veh*km) is not affected by the percentage of eco-drivers. Even in peak hour, the local street and its intersection do not reach their critical capacity. Slower acceleration cause increments in the delay, but this does not produce higher congestion.

Emissions of CO₂ savings 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.

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

5.3 Aggregated impact of eco-driving 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

Table 12. Local street emission and traffic simulation per traffic situation and eco-driving penetration rate.

Traffic demand	Eco-driving penetration rate (%)	Emissions indicators		Traffic indicators		
		CO ₂ (g/km)	NO _x (g/km)	Veh*km	Delay rate (s/km)	Average speed (km/h)
Night	0 (none)	375.03 (18.62)	1.26 (0.10)	62 (6.6)	75.5 (6.8)	24.2 (1.1)
	10	373.62 (17.03)	1.23 (0.09)	62 (6.6)	75.5 (6.7)	24.2 (1.1)
	25	372.73 (15.73)	1.23 (0.07)	62 (6.6)	76.4 (7.1)	24.1 (1.1)
	50	368.65 (16.19)	1.20 (0.09)	62 (6.6)	77.1 (7.3)	24.0 (1.1)
	75	364.47 (15.12)	1.17 (0.07)	62 (6.6)	77.9 (7.5)	23.8 (1.1)
	100 (all cars)	364.84 (15.59)	1.18 (0.09)	62 (6.6)	78.8 (7.4)	23.7 (1.1)
	F Significance	0.33	0.06	1.00	0.76	0.74
Off-peak	0 (none)	520.76 (5.64)	1.99 (0.03)	405 (11)	104.2 (5.7)	19.1 (0.5)
	10	519.01 (6.63)	1.97 (0.04)	405 (11)	105.2 (5.0)	19.0 (0.5)
	25	518.31 (5.58)	1.97 (0.03)	405 (11)	107.7 (5.0)	18.8 (0.5)
	50	514.25 (5.78)	1.96 (0.04)	405 (11)	109.2 (5.5)	18.6 (0.5)
	75	511.20 (6.33)	1.94 (0.04)	405 (11)	112.9 (7.0)	18.3 (0.6)
	100 (all cars)	509.57 (6.26)	1.93 (0.04)	405 (11)	115.6 (6.5)	18.0 (0.5)
	F Significance	0.00	0.00	1.00	0.00	0.00
Peak	0 (none)	523.10 (8.44)	1.95 (0.04)	548 (18)	122.1 (8.1)	17.7 (0.7)
	10	520.22 (9.24)	1.92 (0.05)	548 (17)	125.9 (12.5)	17.4 (1.0)
	25	521.31 (9.01)	1.94 (0.04)	549 (17)	129.9 (10.3)	17.1 (0.8)
	50	516.12 (7.81)	1.91 (0.04)	547 (16)	138.0 (12.3)	16.4 (0.9)
	75	514.93 (8.71)	1.91 (0.05)	548 (16)	147.4 (14.1)	15.8 (0.9)
	100 (all cars)	512.01 (8.62)	1.88 (0.05)	547 (16)	154.9 (12.3)	15.3 (0.8)
	F Significance	0.00	0.00	1.00	0.00	0.00

Average values with standard deviation in parentheses.

Figure 3. Madrid highways and urban consolidated areas. Highlighted the M40 ring motorway.

Table 13. 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

Madrid region built by Valdes (2012), it is possible to distribute the total vehicles-kilometer in the four types of urban roads presented in this paper. Likewise, it is possible to differentiate the three traffic demand conditions: peak, off-peak, and night

Figure 4. Aggregated average speeds for Madrid area under different scenarios.

hours. The area selected includes all the roads and streets encircled by the second ring motorway M40 (M40 excluded), which represent the central and peripheral areas of the city of Madrid (Figure 3).

Table 13 reflects the amount of vehicle-kilometers by type of road and traffic situation according to the model of Valdes (2012):

Using these percentages, Figures 4–6 show the weighted values of average speed and CO₂ and NO_x emissions variation.

Figure 4 shows the average speed values for an average trip in Madrid. It is possible to observe that on the aggregated values, there is almost no variation for the night scenarios, while in peak hours, the average speed declines more than 7 km/h for eco-driving penetration rates of 100%.

Figure 5 shows the CO₂ variation for different eco-driving penetration rates and traffic situations with reference to the base-case (0% eco-drivers). This 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, Figure 6 shows the variation with respect to the base-case scenario. Emissions of NO_x are in line with CO₂ emissions reaching maximal savings of around 4% in night and night traffic conditions. Conversely, in peak hour, the NO_x emissions increase slightly up to a value of 0.5% for all the drivers following the eco-behavior.

The results indicate clearly that the general recommendation at peak times should be to avoid eco-driving 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 5.2).

Figure 5. CO₂ variation with reference to base-case per traffic situation and eco-driving penetration rates. Aggregated values for Madrid area.

Figure 6. NO_x variation with reference to base-case per traffic situation and eco-driving penetration rates. Aggregated values for Madrid area.

6. Conclusions

This paper presents a 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. The collected field data are 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 is determined that a 72.6% of the fuel consumption variance can be explained with the speed profile.

The methodology is successfully applied to simulate 72 different traffic scenarios, combining four types of road

with three different traffic situations and six eco-driving percentages (penetration rates). Compared to previous research, this work contributes to the state of knowledge by applying different penetration rates to real base-case conditions. Although emissions variations are lower in this study, results are in line with the research of Kobayashi et al. (2007), Qian & Chung (2011) and Orfila (2011). Variations might be lower as the emissions are calculated for the whole fleet, while only passenger cars are performing eco-driving, not heavy duty vehicles, trucks, or buses.

Regarding the limitations, it should be considered that the calibration of the eco-driving is based in the data from one vehicle, thus assuming that all eco-drivers behave exactly in the same way. In the traffic models, adjacent streets have been considered; however, it is assumed that every road behaves exactly like the corresponding model.

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 results show interesting conclusions:

- Eco-drivers have influenced not only their own vehicle but also the surrounding vehicles and therefore the traffic flow.
- The effects of eco-driving are not the same in a local road as in an urban motorway, and they also depend on the level of traffic demand. In night traffic conditions, the maximal savings occur when more than half of the drivers follow eco-driving behavior. In peak hours, any percentage of eco-drivers entails increments of CO₂ and NO_x emissions.
- The eco-driving behavior produces more congestion, especially in interrupted traffic roads (intersections at the same level). Lower acceleration and brake rates lead to higher gap between vehicles, which reduces the capacity and causes more congestion. Likewise, the discharge flow rate at traffic lights is clearly affected, thus reducing the capacity and causing more congestion and therefore, more emissions.

Therefore, the policy recommendation is that the public authorities should promote eco-driving, indicating that it is not advisable in congested periods. Although eco-driving can be individually positive, the promotion of eco-driving may bring global undesired increments of emissions of pollutants and CO₂ in urban areas.

With regard to further research lines, 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 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 inter-urban roads could be measured by building the respective models.

Acknowledgments

The authors acknowledge the collaboration of the City of Madrid and Madrid Calle-30 in the process of data collection.

Funding

This work was supported in part by the European Commission under the ICT-Emissions project 2011–2015, “Development of a methodology and tools for assessing the impact of ICT measures in road transport emissions,” Grant Agreement No. 288568.

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