Available online at www.sciencedirect.com

ScienceDirect

Transportation Research Procedia 00 (2018) 000–000

Transportation Research Procedia

www.elsevier.com/locate/procedia

World Conference on Transport Research - WCTR 2019 Mumbai 26-31 May 2019

Tools for Customized Consumer Information on Vehicle Energy Consumption and Costs - A European Case Study

Caterina Mogno[a], Vincenzo Arcidiacono[a], Biagio Ciuffo[a], Lorenzo Maineri[a], Michail Makridis[a], Jelica Pavlovic[a], Stefanos Tsiakmakis[a], and Georgios Fontaras[a*]

[a]*European Commission Joint Research Centre, Ispra, 21027, Italy*

Abstract

The European Commission's Joint Research Centre, in line with the European Strategy for Low-Emission Mobility, has launched in 2016 the Green Driving Tool, an interactive web-based tool aiming at estimating fuel costs and CO_2 emissions of individual car journeys. In parallel, it has developed U-SAVE, a routing system for fuel-efficient trip planning aiming at fuel consumption minimization and vehicle specific calibration. This paper provides a first assessment of the performance of the two tools in predicting fuel consumption and CO_2 emissions over real-world trips. The analysis focused on the accuracy and uncertainty of the two tools when varying the detail of vehicle input data and of the velocity profile used in the calculation. These elements are particularly important in case of future integration of the tools with traffic simulation models where the level of detail regarding the vehicle input or the speed profile may vary. Results show that U-SAVE prediction is positively affected by the detail of vehicle specifications, while is not significantly sensitive to the detail of the velocity profile. Contrary, Green Driving didn't show any remarkable change when varying both parameters. Overall, U-SAVE demonstrates a good performance in predicting CO_2 emissions over on-road tests reaching an average prediction accuracy over an entire test trip of -4.6% and a standard deviation of 5.2%, while Green Driving exhibit higher uncertainty (on average 12%) but lower bias which ranged in the order of 0 to +3% depending on the vehicle and the test trip considered.

© 2018 The Authors. Published by Elsevier B.V.
Peer-review under responsibility of WORLD CONFERENCE ON TRANSPORT RESEARCH SOCIETY.

Keywords: Green Driving Tool, U-SAVE, Vehicle Energy Consumption, Consumer information, Validation

* Corresponding author. Tel.:+39 0332786425;
E-mail address: georgios.fontaras@ec.europa.eu

2352-1465 © 2018 The Authors. Published by Elsevier B.V.
Peer-review under responsibility of WORLD CONFERENCE ON TRANSPORT RESEARCH SOCIETY

Nomenclature

CO_2	Carbon Dioxide
CO_2MPAS	CO_2 Model for PAssenger and commercial vehicles Simulation
EU	European Union
GDT	Green Driving Tool
JRC	European Commission's Joint Research Centre
LDV	Light Duty Vehicles
PEMS	Portable Emissions Measurement System
RWT	Real World Test
U-SAVE	fUel SAVing trip plannEr
VELA	Vehicle Emissions LAboratory

1. Introduction

Road transport consumes significant quantities of fossil fuels and accounts in Europe for more than 70% of the overall transport generated CO_2 and pollutant emissions (EC DG Clima, n.d.). In the last decades, policymakers and industrial stakeholders have focused their efforts on reducing vehicle emissions by mainly improving vehicle performance and efficiency over standardized conditions. However, driver behavior and route-choice/planning are widely recognized as factors that can significantly influence fuel consumption and pollutant emissions in real-world operating conditions (Ahn and Rakha, 2008; Walnum and Simonsen, 2015; Zheng et al., 2017). Also, the high influence of the driver style on fuel consumption and CO_2 emissions has been reported by various researchers (Fontaras et al., 2017). From a different perspective, various organizations draw attention that accurate consumer information can have in accelerating the introduction of fuel-efficient technologies in the vehicle fleet. Several studies highlighted how eco-driving and eco-routing have the potential for saving fuel consumption and for reducing emissions significantly. Indeed, case-studies about eco-routing training demonstrate that it is possible to achieve a reduction in fuel consumption up to 4,6% (Ayyildiz et al., 2017; Barla et al., 2017; Jeffreys et al., 2018), while implementing eco-routing strategies can reduce network-wide fuel consumption and emissions. (Kyoungho Ahn e Rakha 2013; Yao e Song 2013; J. M. Bandeira et al. 2018). Consumers should have access to the information and tools necessary in order to make the most sustainable selection of vehicle and trip path according to their needs.

In 2016 the European Commission's Joint Research Centre (JRC), in line with the ambition to move towards low and zero-emission vehicles according to the European Strategy for Low-Emission Mobility (European Commission, n.d.), has launched an online vehicle fuel and consumption calculation tool, the Green Driving Tool (https://green-driving.jrc.ec.europa.eu) The Green Driving Tool (GDT) was presented in the Second Mobility Package of the European Commission as "*A tool allowing consumers to compare the impact of different technologies on fuel consumption and CO_2 emissions*" (European Commission, 2017). Indeed, Green Driving is an interactive web-based tool aiming at estimating fuel costs and CO_2 emissions of individual car journeys on the basis of vehicle specifications given by the user. It will, therefore, aim to help citizens to estimate fuel costs and CO_2 emissions of their daily commute or holiday trips, as well as to raise awareness of the impact of their car journeys.

In the last decade, the use of navigation systems has increased dramatically. However few solutions offer fuel consumption based route optimization. In response to the increasing fuel costs and the rising of the environmental awareness of drivers, eco-routing, velocity suggestions, and smart navigation appear as possible options for minimizing fuel consumption and emissions. However, the intrinsic complexity of routing problems and the related computational requirements have led to simplifications in the road geometry, speed profile and fuel consumption model when developing eco-routing applications, thus influencing significantly the accuracy of the solutions provided. Moreover, the eco-friendly route may differ according to specific vehicle characteristics (mass, transmissions, gear-shifting, fuel-saving technologies etc.) and drive-style (Arcidiacono et al., 2017; Bandeira et al., 2014; Turkensteen, 2017). For example, ViaMichelin (www.viamichelin.com) provides the most fuel-efficient option, but the street slope is not accurately considered and many car and trip-related parameters, are missing. Also,

Mappy (en.mappy.com), a similar web application, has limited options selection for vehicle parameters and doesn't take the road slope into account. On the contrary E-distance (e-distance.com) ask the user to provide an average fuel consumption value as an input, which is further used as the main indicator for calculating the fuel consumption over the trip (Arcidiacono et al., 2017). Thus, accordingly to the current state-of-the-art, more detailed and comprehensive approaches providing accurate emissions and eco-routing suggestions to the driver seem necessary, in parallel with the necessity to validate these green-routing systems under realistic driving conditions.

In the perspective of enhancing the Green Driving's functionalities, in 2017 the JRC developed a second tool, U-SAVE, a routing system for minimum fuel consumption path calculation, able to give optimal velocity suggestions. U-SAVE is based on a routing machine algorithm, and it takes advantage of Green Driving and CO_2MPAS, a detailed vehicle simulation model crafted to estimate and type-approve CO_2 emissions from light-duty vehicles according to the EU legislation (Fontaras et al., 2018). An open-access version of U-SAVE is expected to become available in order to provide users with customized, fuel consumption-optimized routing (Arcidiacono et al., 2017).

Both Green Driving and U-SAVE are currently being extensively validated in order to verify that the accuracy in fuel consumption estimation and routing suggestions reaches a required level. For this purpose users can communicate the fuel consumption they experience in their daily vehicle use, thus allowing to monitor significant deviation of the tool from the reality. In addition, field test campaigns to further validate and optimize the tools have been designed and the process is currently on-going. The aim of this paper is to assess the accuracy of the two tools in predicting fuel consumption and CO_2 emissions. This is done using measurement data from real-world trips, thus providing a first comprehensive and comparative analysis of their performance and, also, setting a benchmark for future reference. Also, the present paper performs an accuracy and uncertainty study of Green Driving and U-SAVE, taking into consideration different levels of input data availability regarding vehicle characteristics and different data quality regarding the velocity profile occurring during the trip. These are two fundamental factors influencing the results of any vehicle energy consumption calculation model and are particularly important in case of future integration of the tools with traffic simulation models where the level of detail regarding the vehicle input or the speed profile may vary.

2. Methodology

2.1. Overview

For assessing the capacity of GDT and U-SAVE to predict CO_2 emissions over real-world conditions, tests over two real-world trips with Portable Emissions Measurement System (PEMS) were performed for four different passenger cars (2x4 on-road tests in total). Test results concerning the trip and the kinematic data of the vehicle, combined with vehicle specifications, have been used as input to calculate the CO_2 emissions of each vehicle-trip combination with the two tools. Subsequently, the model predictions over each test trip have been compared with the corresponding measured CO_2 emissions. In particular, the prediction performance of each model has been tested over 6 different configurations, combining the level of precision of the velocity profile (3 configurations) and the detail of vehicle specification provided (2 configurations). The three configurations for the velocity profile consist in (in order of increasing precision):

- velocity profile estimated by the Open Source Routing Machine (OSRM, http://project-osrm.org/),
- an average over every 300 m of the measured velocity profile,
- the real (measured) velocity profile.

Figure 1 shows the three velocity profiles over one test trip. It is worth stressing that for the OSRM velocity profile idling consumption phases of the on-road tests were added, in order to have the same CO_2 emissions target for the averaged and real velocity profiles. On the other hand, the two configurations for the vehicle specifications take into account a set of generic and a set of specific vehicle inputs, as indicated in Table 1. In particular, for U-SAVE the two configurations differ in the number of vehicle specifications provided, while for GDT in the level of detail of some of them. Figure 2 summarizes the assessment plan for the two models over all the 6 configurations.

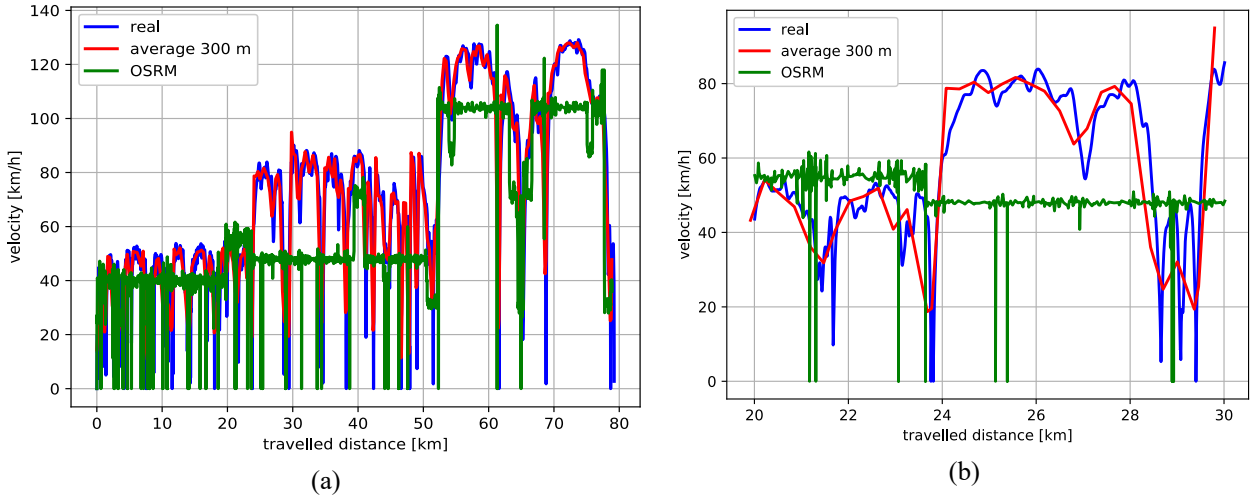


Figure 1. Comparison with the OSRM, averaged and real velocity profile, over an entire test trip (a) and on an enlargement of 10 km (b).

Table 1. Vehicle specifications detail used for U-SAVE and Green Driving.

USAVE		GREEN DRIVING	
Generic	**specific**	**Generic**	**Specific**
-mass in running order -fuel type -engine capacity -engine max power -vehicle body -gearbox type -start-stop yes/no -start-stop activation time	All generic inputs plus: -eco mode -auxiliaries power loss -road loads -engine idle fuel consumption -tyre code -wheel drive -vehicle width -vehicle height -engine speed at max power -engine max torque -engine stroke -engine turbo yes/no -velocity max -final drive ratio -gearbox ratios	-n passengers -fuel type -vehicle category -euro standard -wheel drive -tyre class -gearbox type -driving style -air condition yes/no -energy recuperation yes/no -start-stop yes/no -roof box yes/no -vehicle mass (preselected option) -cargo mass (preselected option) -engine capacity (preselected option) -engine max power (preselected option)	All generic inputs except: -vehicle mass (real) -cargo mass (real) -engine capacity (real) -engine max power (real)

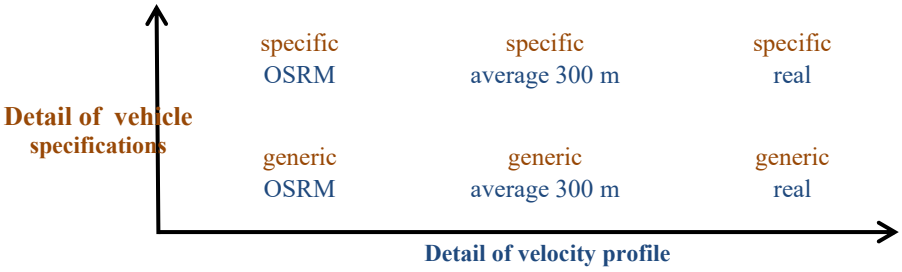


Figure 2. Summary of the configurations tested for each model.

2.2. Selected vehicles and real-world tests

Four different vehicles were selected for this exercise. The vehicle selection tried to cover the most common passenger cars segments in use in Europe in terms of mass, power, engine technology, and transmission. For each vehicle, two real-world tests were performed. The experimental condition applied for all road tests (choice of routes, driving cycle followed, driving time, vehicle operating conditions) have been chosen to be compliant with the European EU-RDE LDV regulations, as detailed described in (Valverde Morales and Bonnel, 2018). To assess emissions performance of vehicle over on-road tests, CO_2 emissions were measured following the general guidelines of the EU regulation, with standard PEMS equipment, whose characteristics are described in (AVL M.O.V.E GAS PEMS IS) and in (AVL M.O.V.E EFM Exhaust Flow Meter). All the data acquired had a frequency of 1Hz. The main characteristics of the four tested vehicles can be found in Table 2. PEMS instrumentation has shown significant potential in a variety of studies related to real-world emissions: in the direct analysis of the gaseous emissions from light-duty diesel vehicle (Luján et al., 2018; Mahesh et al., 2018), in the assessment of the impact of different driving styles and route characteristics on on-road exhaust emissions (Gallus et al., 2017), and in the development and validation of passenger car emissions factors (Kousoulidou et al., 2013).

2.3. Green Driving Tool and U-SAVE methodologies

The GDT and U-SAVE, are presented below. As already indicated, the GDT is an interactive web-based tool able to predict CO_2 emissions and fuel consumptions for vehicles according to a user defined route. The users can build up their cars by selecting different vehicle specifications, different driving styles, and different travel options. Fuel consumption and CO_2 emissions are calculated for the route selected by the user. The core of GDT CO_2MPAS, the vehicle CO_2 emissions and energy consumption model created in order support the introduction of the new WLTP-based certification system for CO_2 emissions in Europe (Fontaras et al., 2018). However, for computation time-related reasons, the integration of CO_2MPAS in the web-platform hosting GDT was not possible. For these reasons, a Kriging approximation of the CO_2MPAS model has been produced and integrated into the GDT. The Kriging based method employed in Green Driving is based on the findings in (Ciuffo et al., 2013). With respect to other meta-models, Kriging models are specifically applied when it is necessary to reproduce the behavior of a certain model or physical system both globally and locally. This is also attested by the fact that Kriging approximations are used in global optimization to find the minimum value of expensive black-box functions (the literature on this topic is increasingly wide, see e.g. Kleijnen, 2008). Providing details on Kriging meta-models is beyond the aim of the present paper. The interested reader can refer to Kleijnen (2008) for a review on this class of meta-models and for further details on this topic. In order to be sufficiently accurate to correctly reproduce the behavior of different vehicle segments and technology configurations, 18 classes of Kriging metamodels were estimated (considering 9 vehicle segments and 2 fuel types, namely gasoline and diesel).

	Vehicle 1	Vehicle 2	Vehicle 3	Vehicle 4
Body type	4/5seater hatchback	4/5seater suv/sports	4/5seater hatchback	4/5seater hatchback
Engine	3 cyl turbocharged gasoline	4 cyl turbocharged diesel with common rail	4 cyl gasoline	4 cyl turbocharged diesel with common rail
Capacity	999 cc	1956 cc	1242 cc	1968 cc
Max Power	70 kW @5000-5500 RPM	103 kW @ 4000 RPM	51 kW @ 5500 RPM	110 kW @ 3500 RPM
MRO†	1453 kg	1789 kg	1253 kg	1719 kg
Max Torque	160 Nm @ 1500-3500 RPM	350 Nm @ 1750 RPM	102 Nm @ 3000 RPM	320 Nm @ 1750-3000 RPM
Max Speed	186 km/h	190 km/h	164 km/h	214 km/h
Drive	front	All	front	Front
Gearbox	5-speed manual	9 speed automatic	5-speed manual	6-speed manual
Wheels	215/40R17	225/45R18	175/65R14	225/40R18
Euro-class	EURO-6	EURO-6	EURO-6	EURO-6
Type approval CO_2	98 g/km	144 g/km	119 g/km	117 g/km
PEMS test load	140 Kg	110 kg	140 kg	140 Kg

Table 2. Main characteristics of the selected vehicles.

Each class is composed by 18 meta-models each of which reproduces one of the outputs of CO_2MPAS used by the GDT for the simulation of CO_2 emissions, fuel consumption and electric energy consumption of the different types of powertrains simulated by the GDT. In particular, the simulation of electrified powertrains as well as of gas-fuelled vehicles adopts a simplified approach directly implemented in GDT which makes use of the power request to the vehicle and some efficiency parameters derived from CO_2MPAS. Each class of Kriging meta-model was estimated on the basis of approximately 4000 CO_2MPAS simulations in which different inputs are varied in a quasi-Montecarlo fashion over the range of variability related to the relevant vehicle segment. A total of approximately 72.000 CO_2MPAS simulations are therefore used to estimate the parameters of 324 kriging meta-models. The estimation of the parameters of the Kriging metamodels has been carried out using the DACE MATLAB toolbox (Matlab et al., 2002).

Differently, from GDT, U-SAVE is a tool for trip planning taking into consideration fuel consumption minimization, based on a routing machine algorithm. It takes advantage of CO_2MPAS (Fontaras et al., 2018) for achieving vehicle specific calibration and where this is not possible of GDT. Indeed, U-SAVE is designed to use all vehicle, driver, and road data to calibrate a fuel consumption raster which is then used to predict the most fuel-efficient path, the vehicle fuel consumption, and the optimized velocity profile. Specifically, the overall U-SAVE methodology can be split into three subsequent tasks (Arcidiacono et al., 2017) :

- Find the most fuel-efficient path. The problem is sometimes called the single-pair shortest path problem. To solve it, U-SAVE takes advantage of the Open Source Routing Machine (OSRM) server.
- Calibration of the fuel consumption raster. The raster is a discrete bilinear map extracted from a collection of data, acquired from real tests or simulations. For calibrating the raster, U-SAVE performs a series of simulations with CO_2MPAS model and with the Green Driving meta-model using the vehicle data and the

† For this exercise, Mass in Running Order MRO = Empty weight of the vehicle + 75x2 drivers weight + 85% fuel tank capacity + PEMS test load.

road data from the OSRM server. The obtained fuel consumption raster can be a function of the power-velocity variables or slope-velocity variables.

- Calculation of the fuel consumption for a specific vehicle on each route's sub-segment using the calibrated raster.

Form the above description, one can deduce that one core advantage of U-SAVE is the capacity of using multiple data sources to calibrate an advanced model and accurately predict vehicle fuel consumption.

3. Results

In this section, the results of GDT and U-SAVE simulations for the real world tests (RWT) performed are analyzed and compared to the measured CO_2 values. Table 4 and Table 3 summarize the prediction results for the six vehicle specifications-velocity profile configurations analyzed (Figure 2), for GDT and U-SAVE respectively. For U-SAVE in the real velocity profile configuration, both the slope-velocity and power-velocity raster were considered. In the other two cases (averaged and real velocity profiles), the slope-velocity raster was the only possible approach. The results of the two tables refer to the average over all the eight on-road tests performed. In particular, each table provides the average CO_2 prediction error over the entire trip, and the same error for a detailed prediction for each km traveled, expressed in relative value respect to the average CO_2 emissions per km for each vehicle considered. The following subsections focus on the detailed analysis and comparison of the two models when varying the detail of the vehicle specifications and of the velocity profile, while the last subsection gives an overall assessment of the two models.

3.1. Models assessment over the vehicle specifications detail

Table 3 presents the results for the GDT. Indeed, with generic vehicle inputs, the average prediction for the total CO_2 emissions are slightly over-estimated up to 2.9%, while when supplied with more specific inputs the performance improves on average of 1.7% for each vehicle profile. Differently, the correspondent standard deviation slightly deteriorates, shifting from a maximum uncertainty of 10.8% in the generic input configuration to a maximum of 12.8% in the specific vehicle configuration. Comparable results arise for the CO_2 predictions expressed on a per kilometer basis with comparable figures (Table 3 columns 3 and 4): in the generic input configuration, the average prediction lies between 1.8% and 2.2% and it improves to values between -0.6% and 0.1% in the specific input configurations, while the standard deviation worsens from a range of 10.3% - 11.5% to 13.5% - 16.3%. These results suggest that GDT is not significantly sensitive to vehicle input precision. On the contrary, if specific inputs and not preset inputs are given to the model, GDT seems to shift the average prediction towards zero and while the uncertainty of the prediction increases. Moreover, the small changes in these two metrics can also be implied to the few vehicle specifications inputs that can be adjusted in Green Driving when passing from a generic configuration to a specific configuration (recall Table 1).

Concerning the vehicle specifications, in the generic configuration U-SAVE on average under-estimates the total CO_2 emissions, with values ranging from -9.3% to -15.5% over the different speed profiles Table 4, Column 1). On the contrary, when specific vehicle inputs are used, U-SAVE accuracy for the prediction over the entire trip improves significantly. For each velocity profile, there is a positive shift in the average prediction of around +13%. As a result, with the specific vehicle U-SAVE on average tends to over-predict the total CO_2 emissions with a maximum of +4,7%. The only configuration that shows an under-prediction is the real velocity profile when the power-velocity raster is used (-3.9%). This happens because with the generic vehicle inputs the same velocity configuration reached the lower prediction (-15.5%). On the contrary, the standard deviation of the total CO_2 prediction (Table 4 column 2) is not influenced by the number of the vehicle inputs, remaining constant between 4.5% and 5.6%. Similar considerations done for the total CO_2 prediction can be done for the detailed prediction per each km traveled (Table 4 columns 3 and 4): with generic vehicle inputs, the average U-SAVE prediction lies between -16.6% and -10% (net under-estimation) with a fix standard deviation between 5.6% and 5.8%, while with specific inputs the average prediction per km improves reaching figures between -4.3% and 2.2% and the standard deviation remains constant between 4.9% to 5.6%, thus comparable with the standard deviation for generic inputs. From these results, it emerges how U-SAVE accuracy is clearly sensitive to the number of vehicle input data

provided, while the model precision doesn't. This behavior can be explained by the fact that CO_2MPAS physical model underlying U-SAVE is a detailed vehicle simulator of energy flow and losses at various vehicle components, thus more vehicle inputs are given to the model more accurate are the results that it can achieve. On the contrary, the precision of the model, indicated by the standard deviation, can be considered as an intrinsic characteristic of the model itself, thus not affected significantly by changing the number of inputs.

Table 3. Green Driving simulations results.

GREEN DRIVING					
Detail of Vehicle specifications	**Detail of Velocity profile**	**total CO_2 error (%)**		**CO_2 error g/km**	
		average	**std. dev.**	**average**	**std. dev.**
Generic	OSRM	2.7	10.8	1.8	11.5
	Average 300m	2.7	10.1	2.2	107
	real	2.9	10.2	1.8	10.3
Specific	OSRM	0.6	14.6	-0.6	16.2
	Average 300m	1.3	12.6	-0.3	13.9
	real	1.3	12.8	0.1	13.5
total average performance		**1.9**	**11.9**	**1.0**	**12.7**

Table 4.U-SAVE simulations results.

U-SAVE					
Detail of Vehicle specifications	**Detail of Velocity profile**	**total CO_2 error (%)**		**CO_2 error g/ km**	
		average	**std. dev.**	**average**	**std. dev.**
Generic	OSRM	-9.9	5.5	-10.6	5.8
	average 300m	-9.3	5.5	-10.0	5.7
	real-slope	-9.4	5.6	-10	5.7
	real-power	-15.5	4.6	-16.6	5.6
Specific	OSRM	2.4	5.6	2.2	5.6
	average 300m	4.5	5.0	4.6	4.9
	real-slope	4.7	4.9	7.6	4.9
	real-power	-.39	4.5	-4.3	4.9
total average performance		**-4.6**	**5.2**	**-4.7**	**5.5**

It is clear that providing specific input increases the performance of the models and the possibility to predict a more energy efficient path, and more accurate energy consumption of vehicles. This is becoming increasingly interesting

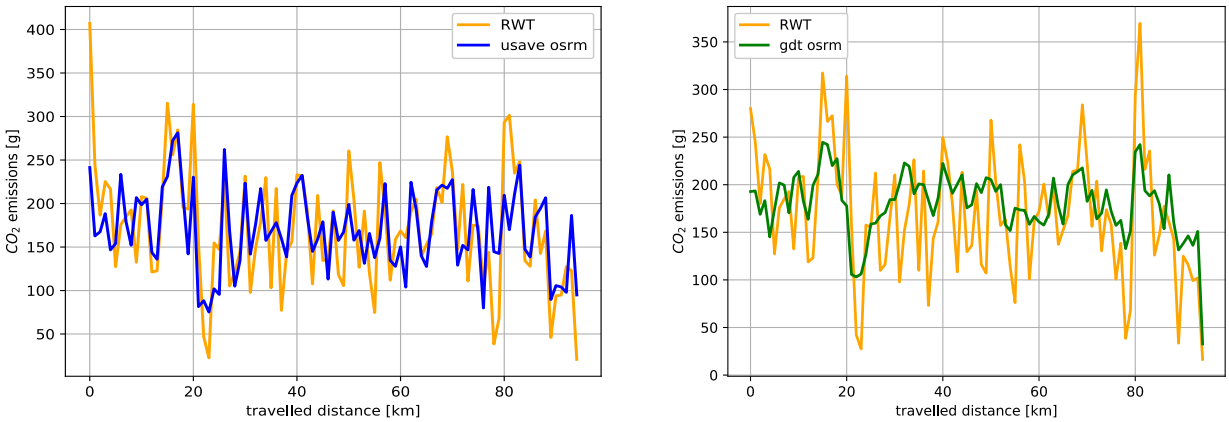
in the case of traffic simulations and particularly when it comes to questions related to traffic optimization, autonomous vehicles management and improving the energy performance of existing and future fleets. The car-following models used in microsimulation studies do not always represent realistically the vehicle dynamics and the distribution of different driving behaviors (Ciuffo et al., 2018). Therefore, they cannot be considered highly accurate in impact assessment studies regarding congestion, emissions, and energy consumption. Approaches such as the ones presented above could provide a new dimension to traffic-related studies when coupled to existing traffic simulation instruments by providing more accurate estimates of the energy and fuel consumption of vehicles. Of course, it becomes clear that additional accuracy is achieved through higher detail in the vehicle, and road characteristics, that come as additional information cost to take into consideration. However, recent advancements in data collection and availability, computing power, and of course traffic simulation tools allow for more refined approaches that balance between traditional macro-scale, fleet level, energy consumption calculations, and street-level, small scale, micro calculations.

3.2. Models assessment over velocity profile detail

The GDT doesn't show significant sensitivity to the detail of the velocity profile. For the average total CO_2 prediction (Table 3column1) in the generic vehicle inputs configuration, the OSRM error prediction (2.7%), the average profile prediction (2.7%) and the real velocity profile one (2.9%) are almost the same, and the same happens in the specific vehicle inputs configuration (prediction error of 0.6%, 1.3%, and 1.3% respectively). Also for the correspondent uncertainty of GDT predictions (Table 3 column2), the velocity profile detail doesn't affect the results: the standard deviation lies between 10.1% and 10.8% for the generic vehicle specifications, while between 12.6% and 14.6% for the specific ones. This trend can partially be attributed to the fact that when running GDT, the underlying meta-model performs a series of velocity averages independently from the input provided. As a consequence, different input velocity profiles lose their peculiarity after this averaging process, overall leading to similar results in the CO_2 predictions. Also when considering the local CO_2 prediction per km, the precision of the velocity profile doesn't influence GDT's performance. With a similar trend that arises for the total CO_2 prediction, the average error per km (Table 3 column3) varies between 1.8% and 2.2% (generic vehicle inputs) and between -0.6% and 0.1% (specific vehicle inputs). For the correspondent standard deviation (Table 3 column 4) the range is between 10.3% and 11.5% and 13.5% and 16.2% respectively. As for U-SAVE then, also Green Driving doesn't improve the accuracy and the precision of its performance accordingly the detail of the velocity profile, both for global and local CO_2 predictions.

U-SAVE exhibited a small sensitiveness to this parameter. Indeed, for the total CO_2 emission over a trip, (Table 4 column 1) the average prediction error for generic vehicle specifications varies from -9.3% to -15.5%, and between 4.7% to -3.9% for specific vehicle parameters. In both cases the prediction accuracy given by the OSRM, the averaged profile over 300 m, and the real profile using the slope-velocity raster is comparable (-9.9%, -9.3% and -9.4% respectively for generic vehicle specifications; 2.4%, 4.5%, and 4.7% respectively for specific vehicle inputs). Similar behavior can be found also in the correspondent standard deviation (Table 4 column 2), that in all the cases considered remains constant between 4.6% and 5.6%. As regards a comparison between the approach with slope-velocity raster and power-velocity raster when the real profile is used, it emerges from (Table 4 column 1) that there is a net difference in the averaged total CO_2 prediction achieved, in both vehicle specification configurations. For generic vehicle inputs, the slope approach gives an error of -9.4%, while the raster approach -15.5%, and for specific vehicle inputs an error of 4.7% and -3.9% respectively. This can be due to the fact that the slope approach uses a more dynamic velocity profile to calibrate the raster (the one used in the official type approval certification) respect to the power approach that uses directly the RWT velocity profile given as input. As a consequence, the velocity-slope raster gives a higher prediction value with respect to the velocity-power raster when dealing with RWT. Moreover, from these results, it emerges that the slope approach gives a better prediction than the raster approach in RWT when generic vehicle inputs are used, while the two approaches are comparable when using specific vehicle inputs. When dealing with the detailed CO_2 prediction per km, U-SAVE exhibits a trend similar to the total CO_2 predictions (compare Table 4 column 1 and column 2 with Table 4 column 3 and column 4 respectively). Thus, improving the precision of the velocity profile doesn't improve significantly the local CO_2 prediction. Given the above results, one can conclude that U-SAVE and GDT can individually achieve similar

accuracy using also less precise velocity profile for the vehicle. This is an interesting but counter-intuitive outcome. Contrary to what might be expected, increased detail in the velocity profile won't obviously translate in a better fuel consumption prediction. This observation need to be further investigated and analyzed. If proven consistent it could lead to reduction in data acquisition and analysis costs.



(a) (b)

Figure 3. CO_2 error prediction over an entire trip for U-SAVE (a) and Green Driving (b). Configuration: specific vehicle inputs - OSRM velocity profile. The trip refers to Vehicle 1 Test 2.

3.3. Global assessment of the two models

In the view of the results of the previous subsections, when comparing the global performance of the two models over RWT, U-SAVE (Table 4) emerges to be more precise than GDT (Table 3). U-SAVE shows an average uncertainty of around 5.5% both for the total CO_2 and the detailed CO_2 prediction per km, while for GDT this value is almost double, about 12%. To evaluate the goodness of these estimations, it is interesting to compare these values for the uncertainty of the two models with the on-road test uncertainty, with value σ=3%. This value has been calculated as the dispersion of the average measured CO_2 emission per km, for each vehicle and test considered. Thus, U-SAVE uncertainty lies between 2σ (two times on road uncertainty), that is a remarkable result, while GDT uncertainty between 4σ, two times U-SAVE performance. On the contrary, when comparing the global accuracy of the two models, GDT seems to have a better average CO_2 prediction than U-SAVE, with values between 1% and 2% and -4,5% and -5% respectively.

When comparing the two models performance for a specific test trip (Figure 3), it is clear how U-SAVE is able to capture more accurately the CO_2 emissions profile, by achieving good prediction also over steep CO_2 emission variations (Figure 3 (a)). On the other hand, Green Driving shows a lower sensitivity in matching the CO_2 emissions trend over short-segments of the trip (Figure 3 (b)). Despite this behavior, GDT can achieve a good CO_2 prediction result over the entire trip. This is caused by the canceling-out of the over and under-predictions for certain peaks of the trip, as shown for example in (Figure 3 (b)). As a consequence, even if locally the prediction is not so accurate, it can be more accurate globally (as an example, see the performance for Vehicle 2 test 2 in Figure 3: the total error achieved is 1.4%).

4. Conclusions

This paper aimed to investigate and assess the performance of the Green Driving Tool and U-SAVE in predicting CO_2 emissions over on-road tests, in particular when varying the detail of vehicle specifications and velocity profile detail as inputs, two important parameters when dealing with real fuel consumption estimations. To achieve this goal, the CO_2 prediction performance of the two models has been evaluated on a set of on-road PEMS measurements for four selected passenger cars, for different configurations of vehicle specifications (generic and specific) and velocity profile (OSRM, averaged and real). Overall, U-SAVE demonstrates good performance in predicting CO_2 emissions over on-road tests, while Green Driving shows wider uncertainty. Results show that the Green Driving Tool has shown an increased sensitivity both on the detail of the vehicle specifications and velocity profile. Contrary, U-SAVE is not significantly sensitive to the velocity profile detail, achieving a good accuracy when using also less precise velocity profile for the vehicle.

From the results of this paper emerge the potential of the two tools for improved use in policy as first conceived, and for further application in traffic simulations. In the view of policy applications of reducing CO_2 emissions, U-SAVE demonstrates to be suitable as eco-driving and eco-routing planner in an urban environment, potentially providing the citizen with a more reliable fuel consumption/CO_2 emissions prediction, especially on short distances. On the other hand, Green Driving Tool emerges to be overall reliable on long distances, thus applicable to highways/rural roads trips or more importantly for aggregated fleet-wide estimates and global emissions assessments. In a longer view, both tools could help to move towards lower network-wide fuel consumption and emissions in cities. On the other hand, the U-SAVE approach could bring advantages in traffic-related studies when coupled to existing traffic simulation instruments, by providing more accurate estimates of the energy and fuel consumption of vehicles. The low-detailed velocity profiles needed from U-SAVE to predict reliable fuel consumption reduce both the cost for data acquisition and computational demand, without significantly compromising the accuracy of the estimates. In this content, future work concerning U-SAVE could be addressed to refine vehicle specifications in order to achieve higher accuracy, while for Green Driving further effort would be put in improving the model precision, and in exploring which other parameters can improve its performance. Moreover, long-term work would be needed to fully and extensively validate the two models for real-world emissions, and then planning how to deliver these tools both to citizens and to traffic simulation developers/users.

References

Ahn, K., Rakha, H., 2008. The effects of route choice decisions on vehicle energy consumption and emissions. Transportation Research Part D: Transport and Environment 13, 151–167. https://doi.org/10.1016/j.trd.2008.01.005

Ahn, K., Rakha, H.A., 2013. Network-wide impacts of eco-routing strategies: A large-scale case study. Transportation Research Part D: Transport and Environment 25, 119–130. https://doi.org/10.1016/j.trd.2013.09.006

Arcidiacono, V., Maineri, L., Tsiakmakis, S., Fontaras, G., Thiel, C., Ciuffo, B., European Commission, Joint Research Centre, 2017. fUel-SAVing trip plannEr (U-SAVE) a product of the JRC PoC instrument: final report.

AVL M.O.V.E EFM Exhaust Flow Meter - Content - avl.com [WWW Document], n.d. URL https://www.avl.com/-/avl-m-o-v-e-exhaust-flow-meter-efm- (accessed 6.23.18).

AVL M.O.V.E GAS PEMS iS - Development [WWW Document], n.d. . AVL. URL https://www.avl.com/vehicle-development/-/asset_publisher/gYjUpY19vEA8/content/avl-m-o-v-e-gas-pems-is (accessed 6.23.18).

Ayyildiz, K., Cavallaro, F., Nocera, S., Willenbrock, R., 2017. Reducing fuel consumption and carbon emissions through eco-drive training. Transportation Research Part F: Traffic Psychology and Behaviour 46, 96–110. https://doi.org/10.1016/j.trf.2017.01.006

Bandeira, J.M., Fernandes, P., Fontes, T., Pereira, S.R., Khattak, A.J., Coelho, M.C., 2018. Exploring multiple eco-routing guidance strategies in a commuting corridor. International Journal of Sustainable Transportation 12, 53–65. https://doi.org/10.1080/15568318.2017.1328545

Bandeira, J.M., Fontes, T., Pereira, S.R., Fernandes, P., Khattak, A., Coelho, M.C., 2014. Assessing the Importance of Vehicle Type for the Implementation of Eco-routing Systems. Transportation Research Procedia, 17th Meeting of the EURO Working Group on Transportation, EWGT2014, 2-4 July 2014, Sevilla, Spain 3, 800–809. https://doi.org/10.1016/j.trpro.2014.10.063

Barla, P., Gilbert-Gonthier, M., Lopez Castro, M.A., Miranda-Moreno, L., 2017. Eco-driving training and fuel consumption: Impact, heterogeneity and sustainability. Energy Economics 62, 187–194. https://doi.org/10.1016/j.eneco.2016.12.018

Ciuffo, B., Casas, J., Montanino, M., Perarnau, J., Punzo, V., 2013. Gaussian Process Metamodels for Sensitivity Analysis of Traffic Simulation Models. Case Study of AIMSUN Mesoscopic Model. Transportation Research Record 2390, 87–98. https://doi.org/10.3141/2390-10

Ciuffo, B., Makridis, M., Toledo, T., Fontaras, G., 2018. Capability of Current Car-Following Models to Reproduce Vehicle Free-Flow Acceleration Dynamics. IEEE Transactions on Intelligent Transportation Systems 19, 3594–3603. https://doi.org/10.1109/TITS.2018.2866271

EC DG Clima, n.d. Road transport: Reducing CO2 emissions from vehicles | Climate Action [WWW Document]. URL http://ec.europa.eu/clima/policies/transport/vehicles_en (accessed 11.28.16).

European Commission, n.d. European Commission - PRESS RELEASES - Press release - A European Strategy for low-emission mobility [WWW Document]. URL http://europa.eu/rapid/press-release_MEMO-16-2497_it.htm (accessed 7.11.18).

Fontaras, G., Valverde, V., Arcidiacono, V., Tsiakmakis, S., Anagnostopoulos, K., Komnos, D., Pavlovic, J., Ciuffo, B., 2018. The development and validation of a vehicle simulator for the introduction of Worldwide Harmonized test protocol in the European light duty vehicle CO2 certification process. Applied Energy 226, 784–796. https://doi.org/10.1016/j.apenergy.2018.06.009

Fontaras, G., Zacharof, N.-G., Ciuffo, B., 2017. Fuel consumption and CO2 emissions from passenger cars in Europe – Laboratory versus real-world emissions. Progress in Energy and Combustion Science 60, 97–131. https://doi.org/10.1016/j.pecs.2016.12.004

Gallus, J., Kirchner, U., Vogt, R., Benter, T., 2017. Impact of driving style and road grade on gaseous exhaust emissions of passenger vehicles measured by a Portable Emission Measurement System (PEMS). Transportation Research Part D: Transport and Environment 52, 215–226. https://doi.org/10.1016/j.trd.2017.03.011

Jeffreys, I., Graves, G., Roth, M., 2018. Evaluation of eco-driving training for vehicle fuel use and emission reduction: A case study in Australia. Transportation Research Part D: Transport and Environment, Special Issue on Traffic Modeling for Low-Emission Transport 60, 85–91. https://doi.org/10.1016/j.trd.2015.12.017

Kousoulidou, M., Fontaras, G., Ntziachristos, L., Bonnel, P., Samaras, Z., Dilara, P., 2013. Use of portable emissions measurement system (PEMS) for the development and validation of passenger car emission factors. Atmospheric Environment 64, 329–338. https://doi.org/10.1016/j.atmosenv.2012.09.062

Luján, J.M., Bermúdez, V., Dolz, V., Monsalve-Serrano, J., 2018. An assessment of the real-world driving gaseous emissions from a Euro 6 light-duty diesel vehicle using a portable emissions measurement system (PEMS). Atmospheric Environment 174, 112–121. https://doi.org/10.1016/j.atmosenv.2017.11.056

Mahesh, S., Ramadurai, G., Shiva Nagendra, S.M., 2018. Real-world emissions of gaseous pollutants from diesel passenger cars using portable emission measurement systems. Sustainable Cities and Society 41, 104–113. https://doi.org/10.1016/j.scs.2018.05.025

Matlab, A., Toolbox, K., N. Lophaven, S., Nielsen, H., Sndergaard, J., 2002. DACE - A MATLAB Kriging Toolbox.

Turkensteen, M., 2017. The accuracy of carbon emission and fuel consumption computations in green vehicle routing. European Journal of Operational Research 262, 647–659. https://doi.org/10.1016/j.ejor.2017.04.005

Valverde Morales, V., Bonnel, P., 2018. On-road testing with Portable Emissions Measurement Systems (PEMS).

Walnum, H.J., Simonsen, M., 2015. Does driving behavior matter? An analysis of fuel consumption data from heavy-duty trucks. Transportation Research Part D: Transport and Environment 36, 107–120. https://doi.org/10.1016/j.trd.2015.02.016

Yao, E., Song, Y., 2013. Study on Eco-Route Planning Algorithm and Environmental Impact Assessment. Journal of Intelligent Transportation Systems 17, 42–53. https://doi.org/10.1080/15472450.2013.747822

Zheng, F., Li, J., van Zuylen, H., Lu, C., 2017. Influence of driver characteristics on emissions and fuel consumption. Transportation Research Procedia 27, 624–631. https://doi.org/10.1016/j.trpro.2017.12.142