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The Application of the CO_2MPAS Model for Vehicle CO_2 Emissions Estimation over Real Traffic Conditions*

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Abstract

A vehicle simulation model, CO_2MPAS supports the introduction of the new WLTP-based certification system for CO_2 emissions in Europe. This paper investigates the possibility to use the underlying simulation methodology to accurately calculate CO_2 emissions over real-world trips, thus to extend the use of the methodology beyond vehicle certification. As a reference, the analysis used measurement data obtained from four vehicles over two different routes under real-world driving conditions. The CO_2 emissions were measured using portable emissions measurement systems. The formal CO_2MPAS methodology and two modified versions of it that require a reduced number of input data were assessed about their capacity to predict the measured CO_2 emissions. The analysis focused on the accuracy and uncertainty of the three different methodology configurations. As an additional benchmark, the analysis considered the CO_2 emissions estimates obtained from the EMEP/EEA Guidebook methodology used for emissions inventorying in Europe. Results show that the basic CO_2MPAS configuration demonstrates good performance in predicting CO_2 emissions over on-road tests, reaching a prediction accuracy over an entire test trip of -0,3% and a standard deviation of 3,1%. The modified versions showed slightly higher biases up to 3% and uncertainties (5-7%), but remaining within reasonable limits considering the reduced number of inputs used in each case. Given its ability to predict CO_2 emissions accurately on a local base, CO_2MPAS could be used for the prediction of instantaneous CO_2 emissions in traffic micro-simulation exercises.

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Keywords: Light Duty Vehicles; CO_2 Emissions; CO_2MPAS; COPERT; Real-world; Fuel consumption gap

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Nomenclature

CO_2MPAS	CO_2 Model for PAssenger and commercial vehicles Simulation
CO_2	Carbon Dioxide
EEA	European Environmental Agency
EMEP	European Monitoring and Evaluation Programme
EU	European Union
JRC	Joint Research Centre
LDV	Light Duty Vehicles
NEDC	New European Driving Cycle
PEMS	Portable Emissions Measurement System
RWT	Real World Test
U-SAVE	fUel SAVing trip plannEr
VELA	Vehicle Emissions LAboratory
WLTP	Worldwide Harmonized Light-Duty Vehicle Test Procedure

1. Introduction

The officially reported fuel consumption and CO_2 emissions values for European passenger cars are known for not being representative of actual driving. Scientific studies have shown that the offset between officially reported and actual CO_2 emissions in Europe is continuously increasing with new model generations. For 2016, this divergence was estimated to be of the order of 40%(Tietge et al. 2017). The contributing factors affecting fuel consumption of light-duty vehicles (LDVs) over laboratory and real-world driving conditions have been identified and related to both, the vehicle characteristics and the environmental and traffic conditions. (Fontaras, Zacharof, e Ciuffo 2017; Li et al. 2017). There has been a growing effort in the European Union (EU) to improve the certification procedures for vehicles' fuel consumption and CO_2 emissions in order to report more realistic values to the consumers. To address this issue, the European Commission has replaced the old New European Driving Cycle (NEDC) test procedure by the Worldwide harmonised Light vehicles Test Procedure (WLTP) for the type-approval of vehicles. However, being a lab-based test-procedure, the WLTP, can only compensate the CO_2 offset partially, as it cannot tackle uncertainties linked to the real world conditions (e.g. ambient conditions, traffic, use of auxiliary consumers etc). To further address the gap, a combination of additional measures could be used such as a) onboard fuel consumption measurement systems that could keep track of fuel consumption throughout the vehicles' lifetime and b) model-based tools that would provide additional customized information to consumers (Marotta et al. 2015; Pavlovic et al. 2017). The concept of real-world measured emissions (not CO_2) is not new to the EU regulatory framework (Hooftman et al. 2018). There are reasons why the current real-world emissions testing framework would not be optimal for addressing the gap including the fact that any official real-world test is also subjected to strict boundary conditions, and potentially is executed by specific drivers possibly over predefined routes. So part of the real-world CO_2 emissions variability is still not captured. However, a fleet-wide monitoring approach throughout the lifetime of the vehicle is indeed interesting and offers significant advantages. Regarding point, b), model-based tools can be used for informative purposes for the citizens, they are available online, easily implementable and they can pass directly the correct messages to the public, raising awareness of important issues and contributing to the reduction of the CO_2 emissions by promoting better driving and vehicle use practices. Hence a combination of the two approaches seems to be necessary to address future aspects of the gap. This paper focuses on the second.

Various tools exist for calculating CO_2 emissions and simulating vehicle operation, offering different accuracy, and resolution levels. For time-based analyses, vehicle specific solutions reach a resolution up to a second and below, or a couple of meters when considering distance-based analyses. On a vehicle specific level, the EU recently introduced a vehicle simulation model, CO_2MPAS, for CO_2 certification purposes (Fontaras et al. 2018). CO_2MPAS is a detailed vehicle simulation model, and it achieves low errors in the prediction of the NEDC cycle of the order of, 2% with a standard deviation of about 5% (Fontaras et al. 2018). When it comes to large-scale simulations, like

those performed in traffic simulation models, the quality of the simulations is usually limited by processing capacity, while the accuracy in the prediction by the quality of input data (Forehead e Huynh 2018). On a fleet-wide scale different approaches exist for estimating emissions based on the 'average speed', 'traffic situation', 'traffic variable', 'cycle variable', used for generic and specific purposes (Saharidis and Konstantzos 2018; Smit, Ntziachristos, and Boulter 2010). One of the most commonly used methodologies for fleet-wide emissions assessment is the emissions inventorying methodology included in the EMEP/EEA guidebook (EMEP/EEA, 2016). The latter is the reference instrument designed to facilitate reporting of on-road emissions in European countries and is known by its software implementation (COPERT) (EMISIA SA, 2018).

In this broad context, this paper investigates the capacity of the CO_2MPAS model, and the underlying methodology to simulate CO_2 over real-world trips, thus to extend their use beyond their actual purposes and to potentially make a contribution in reducing the gap between official and real-world CO_2 emissions. Calculation of CO_2 emissions is also part of studies that focus on the environmental impact of the vehicles over a network on the short or the long term. Traffic simulation software such as AIMSUN or VISSIM integrate tools in order to quantify such impacts. In principle, emission models used in such studies can be divided in two main categories: classical models and instantaneous models. Classical models are usually considered as the reference tool to compute emissions at national or regional scale, but they do not adequately reflect the driving effects, simplifying acceleration-deceleration processes that significantly influence emissions at a finer scale (Borge et al. 2012). Instantaneous emissions models are essential in assessing environmental impacts on road traffic (Fontes et al. 2015), as they use second-by-second vehicle activity (deceleration, idling, acceleration and cruising) to calculate the instantaneous emissions and energy consumption. Consequently, CO_2MPAS, which fits in the latter category, can be used as a reference lightweight, reliable and robust tool for prediction of emissions over large, complex networks, taking into account the network' traffic dynamics.

The present paper analyzes the accuracy and uncertainty of three different CO_2MPAS configurations and compares it against actual on-road tests and the methodology of the Guidebook. To achieve this, the prediction results of CO_2MPAS are compared with real-world testing carried out by means of PEMS, and with those calculated according to the EMEP/EEA methodology.

2. Methodology

For assessing CO_2MPAS CO_2 emissions prediction performance over real-world conditions, a set of on-road measurements with PEMS has been performed for different passenger cars. Test results concerning the trip and the kinematic data of the vehicle, combined with vehicle specifications, have been used as input to simulate the CO_2 emissions of each vehicle-trip combination. Subsequently, the model predictions over each test trip have been compared with the corresponding measured CO_2 emissions. This section presents the vehicles used in the experiments and information regarding the CO_2MPAS and EMEP/EEA methodologies.

2.1. Selected vehicles and real-world tests

Four different vehicles were selected for this exercise. The vehicle selection aims to cover the most common passenger cars segments in Europe in terms of mass, power, engine technology, and transmission. All vehicles were tested over the WLTP and NEDC in the Vehicle Emissions Laboratory (VELA) of the Joint Research Centre (JRC) and according to the legislative procedures for type approval. For each vehicle, two real-world tests were performed. The two routes and the driving cycle followed in all the tests are described in (Valverde Morales and Bonnel 2018). CO_2 emissions were measured according to 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 1.

Table 1. Main characteristic of selected vehicles.

	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
Mass (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
Test load	140 Kg	110 kg	140 kg	140 Kg

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, Ramadurai, e Shiva Nagendra 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 emission factors (Kousoulidou et al. 2013).

2.2. CO_2 emissions models

The two models chosen for this exercise the CO_2MPAS and EMEP/EEA methodology are presented below. As mentioned in the introduction, CO_2MPAS is a vehicle CO_2 emissions and energy consumption simulator, created to facilitate the introduction of the WLTP test protocol in the European legislation. The core of CO_2MPAS is a backward-looking, longitudinal dynamics physical model simulating energy flow and losses at various components. Data from WLTP certification test data combined with NEDC relevant parameters of the vehicle (e.g. mass, road loads and test boundary conditions) are provided as input for the model. After calibrating and optimizing the physical model using the WLTP test data, the final model configuration for the specific vehicle is used to predict the NEDC CO_2 emissions (Fontaras et al. 2018). CO_2MPAS is open source tool, and it is available online with all is documentation at (http://co2mpas.io). Three different variations of the CO_2MPAS methodology were investigate in this study:

- the basic configuration (CO_2MPAS-basic) (Fontaras et al. 2018)
- a generic version (CO_2MPAS-generic) similar to the approach presented by (Tsiakmakis et al. 2017)
- a version were fuel consumption is simulated through a bi-dimensional matrix (raster approach**)** (Arcidiacono et al. 2017) **.**

The basic configuration operates in the same way as over the certification process. Data originating from a WLTP-test are used to calibrate the model. In this study CO_2MPAS physical model was calibrated and optimized by

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

using the WLTP test-data for each of the vehicles selected. Subsequently, instead of predicting NEDC CO_2 emissions, CO_2MPAS was used to predict the CO_2 emissions over the real world tests. CO_2MPAS-generic configuration uses to some extent the same input data as the CO_2MPAS basic but doesn't undergo the calibration process for each specific vehicle. Instead, generic empirical models are used to model the operation of vehicle components such as the engine or the gearbox (Tsiakmakis et al. 2017). The usefulness of CO_2MPAS generic becomes evident in cases of studies were only limited information is available regarding the vehicles being simulated. Finally, the raster approach is a "downsized" version of the CO_2MPAS-generic methodology, where the fuel consumption is calculated using a two-dimensional function/table (raster) of velocity and power. The raster can be either calibrated using CO_2MPAS, or receive input by the user based on experimental data or other sources. This methodology has been implemented in the JRC's U-SAVE tool, a software customized for optimal fuel consumption routing and velocity optimization (Arcidiacono et al. 2017). The raster configuration of CO_2MPAS offers improved characteristics with respect to code execution speed and adaptability, features that are necessary for routing and path optimization applications. All three CO_2MPAS configurations take as input from the real world tests, velocity time-series and the road grade. Original data resolution of 1 Hz has been kept for the calculation of CO_2 emissions.

The most known software implementation of the EMEP/EEA Guidebook methodology for the calculation of air pollutant emissions from road transport is COPERT that is used by many EU states for emissions inventorying purposes and by individual users for scientific applications and academic research (EMISIA SA, 2018; EEA, 2016; Saharidis and Konstantzos 2018). According to the EMEP/EEA approach, energy consumption is calculated based on the average speed of the vehicles and of a series of tabulated coefficients that take into account the vehicle class, fuel type, and engine technology; the main advantage of this is that its methodology can achieve detailed emissions calculations with the use of few input data (Kouridis et al. 2010). Subsequently the energy consumption is linked to vehicle type and fuel characteristics in order to calculate the resulting tailpipe CO_2 emissions. In this exercise, the latest version of the methodology was used, as described in (EMEP/EEA, 2016). In further detail, following the EMEP/EEA approach, as implemented in COPERT version 5, first the energy consumption was calculated through the velocity time-series and the travelled distance, then the corresponding CO_2 emissions are derived after the fuel consumption calculation. Only hot emissions were considered in the study, because the cold start emissions were calculated to be of marginal impact, given the length of the test trip without significant stops (less than 1% of the total CO_2 over each trip). Furthermore, an additive correction in the fuel consumption (and consequently, in the CO_2 emissions) proposed by (Ntziachristos et al. 2014) was implemented. This correction takes into account the type approval fuel consumption, engine capacity, and vehicle effective mass. Moreover, the overall procedure described above has been applied on averaged velocity time series per each kilometre travelled, in order to match the suitable spatial and temporal resolution for using this methodology.

3. Results

In this section, the results of CO_2MPAS prediction for emissions from the real world tests (RWT) performed are analyzed and compared to the measured CO_2 value and the one simulated using the EMEP/EEA methodology. First, the total CO_2 predictions over each test trip is discussed. Subsequently, a more detailed analysis of the local CO_2 predictions over the test trips is provided.

3.1. Global CO_2 emissions predictions

Table 2 summarizes the overall CO_2 predictions results for all the models, by test trip and by vehicle. Overall, CO_2MPAS basic emerges to be the most precise and accurate model for the total CO_2 prediction. For the set of vehicles and test trips simulated, CO_2MPAS basic shows a prediction accuracy within a maximum error of -4.4% from the real total CO_2 emissions for the single test trip, and it displays a significant precision with only a 3.1% standard deviation for the entire set of predictions. Moreover, considering the combined CO_2MPAS basic results in Table 2, this model doesn't exhibit any evident bias for under-prediction or for over-prediction of the total real CO_2. This is confirmed by the average prediction error of only – 0.3%.

Table 2. Prediction error for the total CO_2 for each vehicle and test considered.

Test	Vehicle	Prediction error for the total CO_2 (%)			
		CO_2MPAS basic	**CO_2MPAS generic**	**CO_2MPAS raster**	**EMEP/EEA**
Test 1	Vehicle 1	-0.3	-2.8	-1.2	-14,2
	Vehicle 2	-3.9	-12.2	-11.0	-18,0
	Vehicle 3	3.5	1.3	6.7	0,3
	Vehicle 4	-4.4	-4.5	-3.7	-13,9
Test 2	Vehicle 1	0.6	-5.3	-3.0	-13,8
	Vehicle 2	-0.8	-9.1	-8.5	-13,2
	Vehicle 3	4.1	3.9	8.7	0,7
	Vehicle 4	-1.3	2.6	3.4	-8,1
Average prediction error		**-0,3**	**-3.3**	**-1.1**	**-10.0**
Standard deviation		**3,1**	**5.7**	**7.0**	**7.0**

The CO_2MPAS generic and the CO_2MPAS raster versions give on average less accurate and precise results, with an average prediction error of -3.3% and -1.1%, and with a standard deviation of 5.7% and 7.0% respectively. From these results, one could argue that overall the global accuracy (bias) of all three CO_2MPAS configurations is comparable; however precision clearly degrades, as the inputs are reduced with CO_2MPAS generic presenting a lower uncertainty compared to the CO_2MPAS-raster. However, these two CO_2MPAS versions exhibit a similar behaviour considering the trend in the predictions for each vehicle and test trip. Finally, EMEP/EEA appears to have a bias of the order of -10%, and a standard deviation of the order of 7%, a value comparable to that of CO_2MPAS raster. EMEP/EEA shows a tendency to under-predict the total CO_2 emissions. For the three vehicles, the EMEP/EEA model always under-estimates the total CO_2 emissions, within a range of values between -8% and -18%. Only for one vehicle out of four (Vehicle 3) there are slight over-predictions, with values below the 1%. This observation could be case-specific however, global emission models are in general calibrated to provide minimum bias over an entire fleet conditions and aggregate annual operating conditions. This is the most interesting case as results for Vehicle 3 seem to contradict the overall considerations expressed above. Indeed, the best total CO_2 predictions for Vehicle 3 are given by the EMEP/EEA model followed by CO_2MPAS generic, CO_2MPAS basic and lastly CO_2MPAS raster. This occurs for both tests (compare the prediction error for the different models for both Test 1 and Test 2 in Table 2). However, to fully explain these results, it is necessary to analyze in detail the local CO_2 predictions for the four models (see the next subsection). Finally, it is worth mentioning that, for all three models tested, no significant correlation between the vehicle fuel type or the test trip number (Test 1 or Test 2) and the total CO_2 prediction emerged from the results.

3.2. Local CO_2 emissions predictions

Table 3 summarizes the average prediction error per km for the three configurations of CO2MPAS and for the EMEP/EEA calculations. The results refer to the average of the mean error per km and of the respective standard deviation over the eight trips performed. The relative error is considered with respect to the average CO_2 emissions per km, calculated from the RWT for the specific vehicle and trip under consideration. From the table it is evident that also locally CO_2MPAS basic has the best accuracy and precision among the three CO_2MPAS version, with an average error per km of -0.3% with an average dispersion of 15.2%. It is followed by CO_2MPAS generic and CO_2MPAS raster, that comes out to have a comparable local prediction, with a mean error of -3.1% and -0.9% and mean dispersion of -21.5% and 21.2% respectively. These figures confirm the tendency of the EMEP methodology to underestimate the CO_2 emissions also locally other than globally. A visual representation of these results is given in Figure 1 and in Figure 2. Histograms in Figure 1 show the distribution of the relative error per km for an average

performance of each model. The average performance for each model has been chosen as the single trip prediction whose metrics were closest to the overall average error and average standard deviation. Comparing the four histograms, it emerges clearly the relative precision of the models, also from the shape of the distributions. As a comprehensive example, Figure 2 shows the comparison of the error distributions for the trip of Vehicle 3 in Test 1. Figure 3 shows in more detail the time-series of the simulation performed. In particular, it displays the CO2 emissions per each km travelled over the specific test trip. An average performance and the best performance in the CO_2 predictions series are presented for each CO_2MPAS version and for the EMEP/EEA methodology. For each model, the average performance is depicted in Figure 1, while the best performance has been chosen as the performance with the lower relative error per km and lower standard deviation. Taking into account the average performance, it is evident CO_2MPAS basic's capacity to match accurately the real CO2 emissions profile, by achieving good prediction also over steep CO_2 emission variations (Figure 3 (a)). This could be attributed both to the level of detail of the general CO_2MPAS' physical model, and CO_2MPAS basic's calibration capability. In each case CO_2MPAS basic was self-calibrated on the respective vehicle using WLTP test-data. On the other hand, the incongruity in the CO_2 emissions prediction in some parts of the trip, especially in some central emissions peaks visible in Figure 3 (a), can be attributable to different factors:

Table 3. Average prediction error per km for the detailed CO_2 for each model.

Prediction error per km for the detailed CO_2 (%)				
	CO_2MPAS basic	**CO_2MPAS generic**	**CO_2MPAS raster**	**EMEP/EEA**
Average	-0.3	-3.1	-0.9	-12.3
standard deviation	**15.2**	**21.5**	**21.2**	**36.3**

- Uncertainties in the input data retrieved from the RWT that lead to making assumptions on variables such as ambient temperature and road loads. In the WLTP test cycle, the values of these variables are fixed, but they can differ from the values during the RWT.
- Driver behaviour and lack of information about driving conditions e.g. the real gear shifting during the RWT is different from the one used for the WLTP.
- Vehicle features such as the Start-stop system that may not function as expected during a RWT e.g. there can be stops for which the engine does not turn off (speed equal to zero but engine power non zero)
- Use of auxiliary systems that consume fuel such as air-conditioning, radio and other car equipment that impact the results, but for which information was not recorded during the tests.

If all this extra information was known, CO_2MPAS basic's results could further improve avoiding uncertainties and the use of qualified assumptions. However, as stated before, even with all these assumptions, CO_2MPAS basic is able to predict with high accuracy almost the entire trip. Figure 3 (b) shows the best performance of CO_2MPAS basic in predicting the detailed CO_2 for a test trip. It is worth noticing that even for an average local prediction performance, a very good result can be achieved on the CO_2 prediction over the entire trip. Indeed, for the average local performance for CO_2MPAS basic (Figure 3 (a)), the corresponding total CO_2 prediction has an error of -0.8%. This is caused by the cancelling-out of the over and under-predictions for certain peaks of the trip, as shown in Figure 3 (a). As a consequence, even if locally the prediction is not so accurate, it can be more accurate globally. This mechanism of compensation is much more evident in the EMEP/EEA detailed CO_2 predictions. Figure 3 (c) and (d) show how EMEP/EEA detailed prediction is far from accurate considering the CO_2 emissions profile.

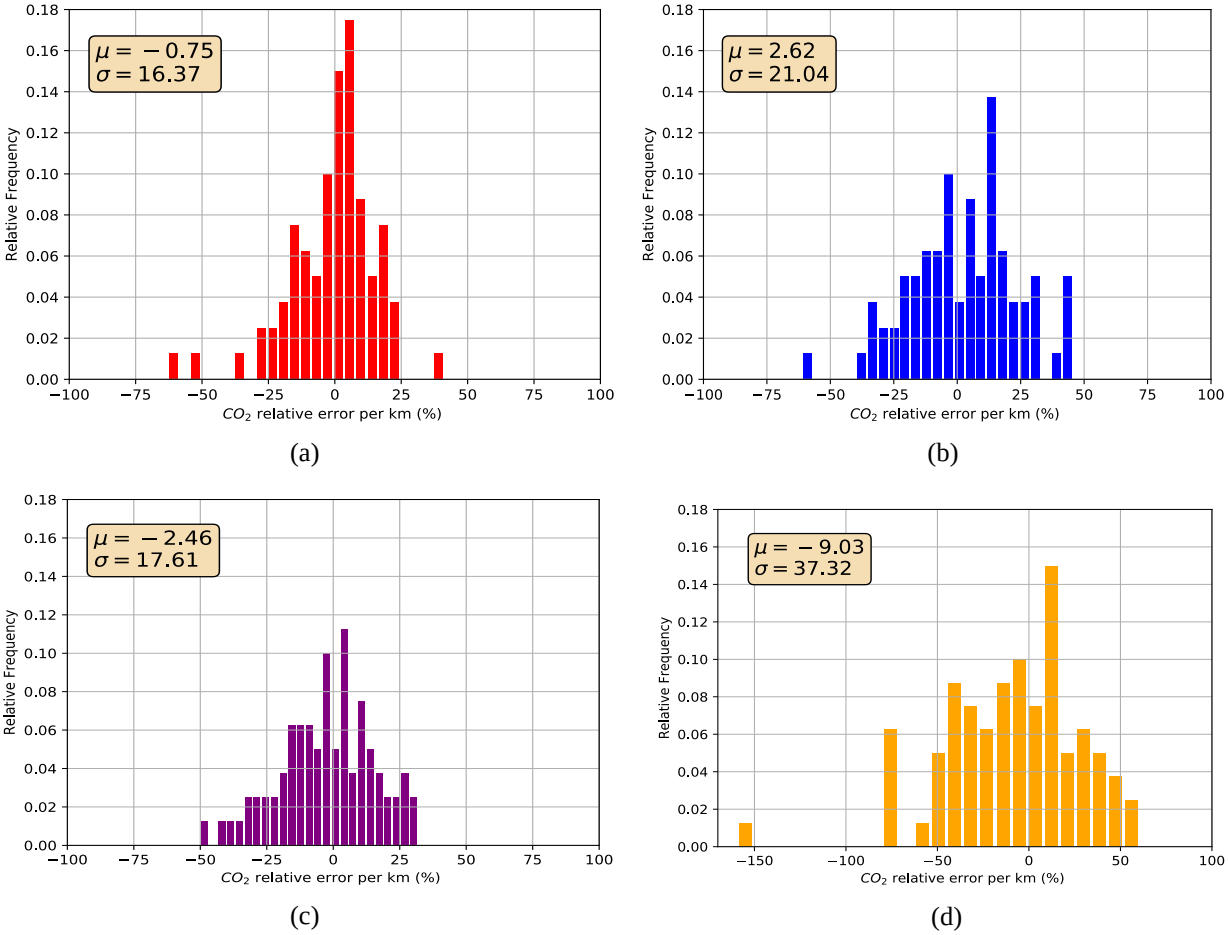

Figure 1.Relative error distributions for the detailed CO_2 prediction of CO_2MPAS and EMEP/EEA for the corresponding average performance of: (a) CO_2MPAS basic for Vehicle 2 Test 2; (b) CO_2MPAS generic for Vehicle 4 Test 2; (c) CO_2MPAS raster for Vehicle 1 Test 2; and (d) EMEP/EEA for Vehicle 4 Test 2.

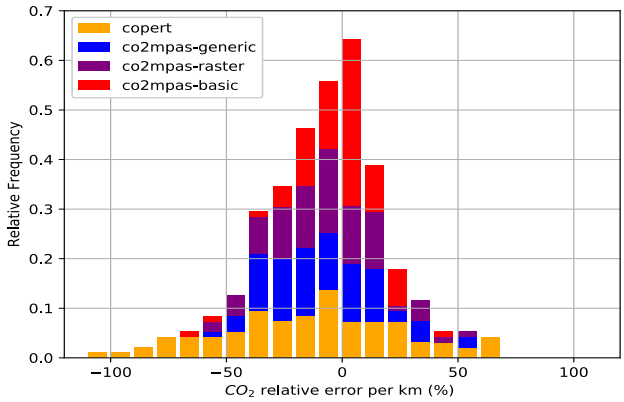

Figure 2. Comparison of the relative error distribution for Vehicle 2 Test 1.

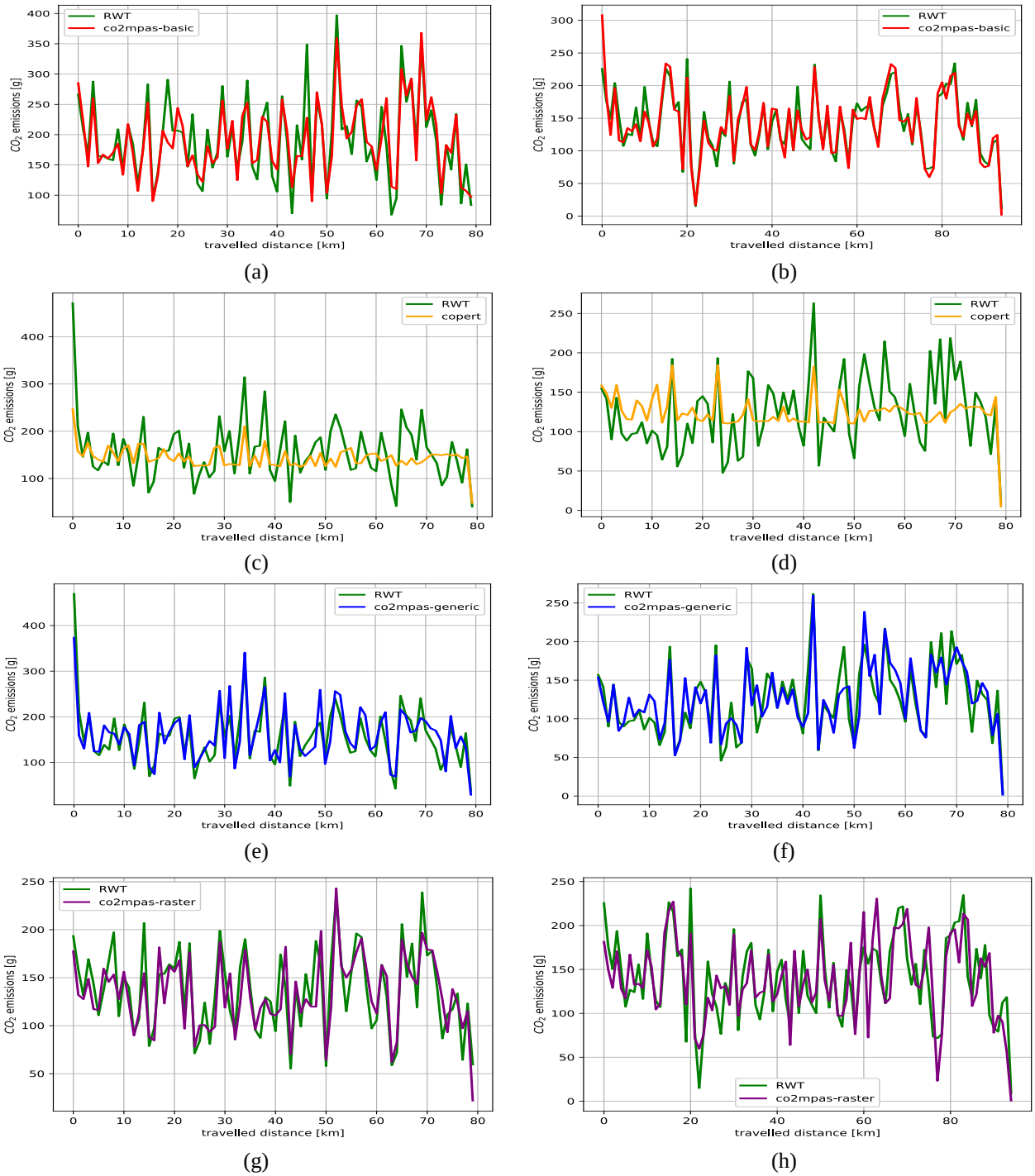

Figure 3. Average and best performance for the detailed CO_2 prediction. CO_2MPAS basic: (a) average for Vehicle 2 Test 2, (b) best for Vehicle 1 Test 1, (c) EMEP/EEA: average for Vehicle 4 Test 2 and (d) best for Vehicle 3 Test 1, (e) CO_2MPAS generic: average for Vehicle 4 Test 2, (f) best for Vehicle 3 Test 1, (g) CO_2MPAS raster: average for Vehicle 1 Test 2 and (h) best for Vehicle 1 Test 1(h).

Over the entire trip, the compensation between over-predictions and under-predictions can result in a very accurate total CO_2 prediction, as it occurs for the case of Vehicle 3. However, this circumstance is not systematic, and as a consequence overall the EMEP/EEA approach exhibits wider biases. This behaviour is due to the fact that the EMEP/EEA model operates with few input information and aims to capture rather the emissions of the entire fleet over a high-mileage and to a lesser extent those of individual vehicles over specific (short) trips. The EMEP/EEA methodology is indeed used mainly in the compilation of regional and national emissions inventories.

Finally, the performance of CO_2MPAS generic and CO_2MPAS raster ranks in between those CO_2MPAS and EMEP/EEA. This is an expected result as both models operate on less input information compared to CO_2MPAS but more compared to EMEP/EEA. Figure 3 (e) and (f) show an average performance and the best performance for CO_2MPAS generic, while Figure 3 (g) and (h) show the same for CO_2MPAS raster. Comparing qualitatively these figures with Figure 3 (a) and (b) (CO_2MPAS basic) and with Figure 3 (a) and (b) it is evident that the accuracy and the precision of CO_2MPAS generic and CO_2MPAS raster are much higher accuracy and precision, but a bit lower than CO_2MPAS basic one. For these two CO_2MPAS versions, generic and raster, the detailed CO_2 prediction match qualitatively the real CO_2 emissions profile for the vast majority of each test trip. Moreover, the qualitative behaviour in the local prediction follows the same trend, like in the case of the total prediction, as mentioned in the previous subsection.

4. Conclusions

This study investigated the performance of the CO_2MPAS model and the underlying methodology in predicting CO_2 emissions over on-road tests. To achieve this goal, the CO_2 prediction performance of three configurations of the model, (namely basic, generic, and raster), have been evaluated on a set of on-road PEMS measurements for different selected passenger cars and benchmarked against a well-established emissions methodology provided by EMEP/EEA. Results show that CO_2MPAS basic leads to the best results, both in predicting the cumulative CO_2 emissions over a trip (average prediction error of -0.30% and standard deviation of 3.1%) and the detailed CO_2 (over each kilometer of the trip) prediction (mean error of -0.3% with a dispersion of 15.2%). CO_2MPAS generic version and CO_2MPAS raster version have as well a good prediction both for the global and the local CO_2 emissions (global prediction: mean error of -3.3% and -1.1%, standard deviation of 5.7% and 7.0% , respectively; local prediction: mean error per km of -3.1% and -0.9%, standard deviation of 21.5% and 21.2% respectively). The results for the EMEP/EEA methodology based calculations show a slightly bigger bias and a precision comparable to the generic and raster CO_2MPAS which was expected given the less detailed nature of the model (global prediction: mean error -10%, dispersion -7%; local prediction: mean error per km of -12.3% and dispersion of 36.3%). CO_2MPAS demonstrates good performance in predicting CO_2 emissions over on-road tests and could be used beyond its certification purpose. Moreover, given their ability to predict CO_2 emissions accurately on a local base, the CO_2MPAS generic and CO_2MPAS raster could be used for predicting CO_2 emissions in traffic micro-simulation exercises. Additional work would be needed to fully and extensively validate CO_2MPAS and its alternative configurations.

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