Capability of Current Car-Following Models to Reproduce Vehicle Free-Flow Acceleration Dynamics

Biagio Ciuffo, Michail Makridis, Tomer Toledo, and Georgios Fontaras

Abstract—**Microscopic traffic simulation models are widely used to assess the impact of measures and technologies on the road transportation system. The assessment usually involves several measures of performance, such as overall traffic conditions, travel time, energy demand/fuel consumption, emissions, and safety. In doing so, it is usually assumed that traffic models are able to capture not only traffic dynamics but also vehicle dynamics (especially to compute energy/fuel consumption, emissions, and safety). However, this is not necessarily the case with the possibility of achieving unreliable outcomes when extrapolating from traffic to measures of performance related to the vehicle dynamics. The objective of the present paper is to assess the capability of existing car-following models to reproduce observed vehicle acceleration dynamics. A set of experiments was carried out in the Vehicle Emissions Laboratories of the European Commission Joint Research Centre in order to generate relevant data sets. These experiments are used to test the performance of three well-known car-following models. Although all models have been largely tested against their capability to correctly reproduce traffic dynamics, the findings raise concerns about their capability (and thus of the traffic models using them) to predict the effect on the microscopic vehicle dynamics and thus on emissions and energy/fuel consumption. The results of the present work can be considered valid beyond the analyzed car-following models, as simple acceleration rules are usually assumed in the vast majority of the traffic simulation frameworks. Consequently, it can be concluded that there is a number.**

Index Terms—**Car-following models, traffic simulation, vehicle acceleration, vehicle dynamics.**

I. Introduction

TRANSPORTATION systems are facing substantial changes in their operation and performance, with the introduction of advanced driving assistance systems (ADAS), automated and connected vehicles, electric vehicles, and shared mobility. These innovations will affect not only traffic flows and safety, but also external factors such as emissions and energy consumption [1]. Despite the known uncertainties, researchers in the traffic community are called to use existing tools in order to provide estimations of the effect of new vehicle technologies on traffic flow, safety, pollution and energy consumption. As some researchers have already pointed out, such estimations can be imprecise, unreliable or wrong [2], [3]. Thus, there is a need for the development of tools and methodologies that take into account some of the aforementioned uncertainties in order to consequently provide better predictions with acceptable compromises on computational complexity.

The models usually used to assess the effect of new vehicle technologies on traffic explicitly simulate the movements of individual vehicles (e.g. car-following, lane changing models). This gives the impression to users that these models are able to take into account microscopic vehicle operations and vehicle dynamics. In reality, they usually provide a very simplistic and abstract representation of the vehicle-driver system having the objective to capture and reproduce traffic dynamics (which has been demonstrated they are eventually able to do) rather than the dynamics of the individual vehicles. To do so, car-following models, which are at the core of representing driving behavior within microscopic traffic simulation frameworks, focus on the interaction between a vehicle and its leader and are tailored to describe crash avoidance behavior. Allowing vehicles to move in a dynamically unrealistic way [4] (e.g. experience strong deceleration and accelerations, make abrupt lateral shifts) helps avoid crashes and guarantee the stability of the simulated flow. Furthermore, accelerations in free flow conditions are often modeled by rather simplistic rules that do not take into account the vehicle's characteristics. In this light, their capability to effectively reproduce the effect on traffic flow, on energy/fuel consumption and emissions, and on safety of the introduction of technologies having an impact on vehicle dynamics is a subject still vastly unexplored.

In spite of these limitations, traffic simulation models are frequently used for predictions of external effects of traffic on emissions and energy consumption (e.g. [5]–[8]). In these applications the acceleration profiles are used directly as inputs to the externalities models (e.g. [2], [9]–[13]). Driving actions of gear-changing, break and accelerator pedal control and their filtering through the vehicle system dynamics are not taken into account in common simulation frameworks, although they

Manuscript received October 15, 2017; revised May 15, 2018; accepted August 7, 2018. Date of publication October 11, 2018; date of current version November 9, 2018. The work of T. Toledo was supported by a grant from the Israeli Ministry of National Infrastructures, Energy and Water Resources. The Associate Editor for this paper was V. Punzo. *(Corresponding author: Biagio Ciuffo.)*

B. Ciuffo, M. Makridis, and G. Fontaras are with the European Commission Joint Research Centre, 21027 Ispra, Italy (e-mail: biagio.ciuffo@ec.europa.eu; michail.makridis@ec.europa.eu; georgios.fontaras@ec.europa.eu).

T. Toledo is with the Faculty of Civil and Environmental Engineering, Technion–Israel Institute of Technology, Haifa 32000, Israel (e-mail: toledo@technion.ac.il).

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Digital Object Identifier 10.1109/TITS.2018.2866271

strongly impact fuel consumption and emissions. To the best of the authors' knowledge, the only attempt to provide a model able to better reproduce vehicle dynamics has been proposed by Ahn and Rakha [2], Fadhloun *et al.* [14], Rakha *et al.* [15], and Ahn *et al.* [16], thus showing the limited understanding currently existing in the field literature. Finally, in the study proposed by Song *et al.* [4], the authors clearly state that the vehicle trajectories generated by car-following models may not represent the real driving characteristics, thus leading to significant emission estimation errors. The authors use field data, which they try to reproduce with microsimulation using two well-known car following models, the Wiedemann and Fritzsche.

The objective of the present paper is to confirm, strengthen and generalize the findings reported in the aforementioned references by considering different car-following models and by applying a different experimental setup in which only free-flow acceleration dynamics are considered in order not to risk that the results of the assessment are affected by a compensation between free-flow and car-following regimes. In addition, the use of the positive energy demand as assessment metric seems a more suitable choice as it allows to isolate the pure vehicle dynamics from more complex and broader processes which are eventually involved in the vehicle fuel consumption and emissions.

In particular, this paper evaluates the ability of three indicative acceleration models to reproduce field observations of free-flow acceleration. There is a vast and increasing literature of car-following models and this number increases over time. One common thing for the vast majority of these models is that they don't attempt to replicate vehicle dynamics and gear shifting. The results demonstrate the limited ability of these models to reproduce the observed acceleration profiles and the impact of these deviations on energy demand and consequently emissions predictions. Although the microscopic simulation using a model based on vehicle dynamics would add computational complexity, the authors firmly believe that in certain scenarios involving vehicle dynamics measures of performance, the usage of a simplistic model in simulating the vehicles' acceleration can lead to unrealistic and misleading results. In order to support the above argument, a set of experiments were run in the Vehicle Emissions Laboratories (VELA) of the European Commission Joint Research Centre in order to generate relevant data sets including vehicle acceleration scenarios. The results of these experiments are used to test the performance of three indicative free-flow acceleration models. Findings raise concerns about the capability of current traffic models to predict the effect of technologies having an impact on the vehicle dynamics. After calibration on the acceleration domain, the models fail to provide accurate results in terms of positive energy demand. On the other hand, each calibration procedure provides different parameter sets for the model and therefore, it is clear that all three models have very weak generative ability. Thus, the conclusion is that in studies focusing on energy/fuel consumption and pollutant emissions, or in any study where the relationship between acceleration and speeds plays a significant role there is a clear need for a deeper integration of traffic and vehicle models, leading to new approaches where the vehicle characteristics, the driver profile, as well as their interaction, is explicitly taken into account. The rest of the paper is organized as follows: the next section describes free-flow acceleration component of different traffic simulation models. The third section presents a laboratory experiment that was conducted with real vehicles in order to collect relevant data on accelerations in free-flow conditions. The fourth section presents results demonstrating the ability of various acceleration models to reproduce the observed free-flow accelerations and to reproduce the resulting energy demand predictions. The last section provides summary and discussion of the results and sketches some possible future perspectives.

II. Free-Flow Regime in Acceleration Model

The power of a vehicle is closely related with its ability to accelerate fast and therefore the authors believe that due to this close relationship the impact of vehicle dynamics on the simulation is mainly reflected on the acceleration part of the car-following models. This is the reason why this work focuses on the acceleration models where the authors' arguments can be observed in a clear way. Many car-following models can be found in the literature and new ones are continuously being proposed. For reviews see, for example, [17]–[19]. In the absence of a leader vehicle, the various models predict accelerations that would allow the vehicle to reach its maximum or desired speed. A common thing among these models is that there is a clear connection between the vehicle speed and the vehicle's acceleration in the next simulation step. This relationship is no clear at all in a real speed profile, as it depends on various factors such as the selected gear, the gearbox ratio, the type of the vehicle, the driver etc. Often, in car-following models, all this uncertainty is aggregated into a stochasticity factor. Assuming that this or similar behavior for the acceleration models is clear, the authors preferred to use in the experimental results section three well known, widely used and simple models rather than providing an extended comparison of various car-following models of various underlying logics, which is considered outside of this paper's scope.

A. Linear Model

The simplest free-flow model has a linear form and it is used in the experimental campaign of this work. This was used, for example, by Ahmed [20] and Toledo [21]:

$$a_n^{ff}(t) = a\left[V_n^{des} - V_n(t)\right] = a_n^{\max}\left[1 - \frac{V_n(t)}{V_n^{des}}\right] \qquad (1)$$

Where, $a_n^{ff}(t)$ is the free flow acceleration of vehicle n at time t. $V_n(t-\tau)$ and V_n^{des} are the subject vehicle's speed and its desired speed, respectively. τ is a reaction time. a is a sensitivity parameter.

B. Gipps Model

Gipps' model [22] is a widely-used acceleration model. See [23] for a detailed analysis of this model. In free-flow conditions it assumes that drivers do not exceed their desired

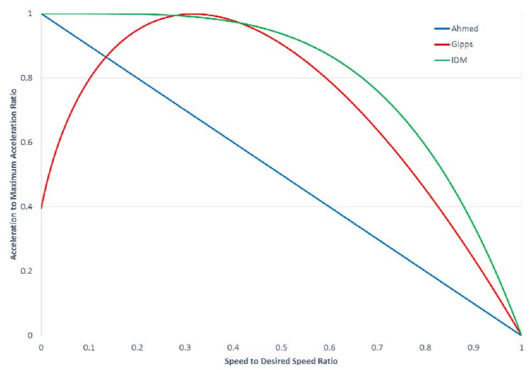

Fig. 1. Normalized Speed-Acceleration profiles for Linear, Gipps and IDM acceleration models.

speed and that their acceleration decreases with increasing speed:

$$a_n^{ff}(t) = a a_n^{\max}\left(1 - \frac{V_n(t)}{V_n^{des}}\right)\left(\beta + \frac{V_n(t)}{V_n^{des}}\right)^{\gamma} \quad (2)$$

Where, $a_n^{\max}$ is the vehicle's maximum acceleration. α, β and γ are parameters (default values 2.5, 0.025 and 0.5, respectively).

C. IDM Model

The Intelligence Driver Model, IDM, [24] is another widely-used model and the third one used here. It assumes that accelerations are determined by social forces that repel vehicles from each other and pushes them to attain a desired speed [25]. In free-flow conditions the acceleration is given by:

$$a_n^{ff}(t) = a_n^{\max}\left[1 - \left(\frac{V_n(t)}{V_n^{des}}\right)^{\gamma}\right] \quad (3)$$

Where, γ is a parameter (default value = 4).

Fig. 1 shows the speed-acceleration relationship proposed by these three models with their default parameter values proposed by the authors. The speed-acceleration diagram represents on one hand the vehicle's capability to provide the necessary power to accelerate from a given speed and on the other hand the behavior of the driver to reach the desired speed. The main difference is in the accelerations when the vehicle starts from stop. The Linear and IDM models predict that the maximum acceleration is obtained when standing and reduces in higher speeds. The decline in acceleration over approaching desired speed is faster initially with the Linear model. Gipps' model predicts accelerations of about 40% of the maximum acceleration for stopped vehicles. The maximum acceleration is reached when the vehicle is at about a third of the desired speed. These differences in modeling accelerations from a stop may affect not only the modeling of vehicle dynamics and subsequently emissions and energy demand, but also the reproduction of traffic flow phenomena of stop-and-go situations, capacity drops and traffic instabilities.

The dominance of these simple models within traffic simulations is one of the reasons for the gap between traffic and vehicle models. This gap is due to the different objectives of these models, and to the fact that the effect of vehicle technologies on traffic has been considered negligible. Although when calibrated these models can replicate quite accurately the specific behavior of the vehicle for which the model has been calibrated, the lack of structural elements affecting the vehicle dynamics leads to poor predictive performances. Furthermore, results in this work show that calibration based on one factor e.g. on acceleration, provides weak simulation in terms of another factor e.g. emissions or energy demand. Depending on the case, according to the authors, a more explicit description of the vehicle dynamics within traffic model is therefore necessary.

III. Experimental Setup

A. Specifications

Collection of free-flow speed-acceleration data in the field is difficult due to the inability to avoid interactions with other vehicles and the presence of substantial measurement errors. In order to overcome these issues, a laboratory experiment was conducted in the Vehicle Emission Labs (VELA) of the European Commission Joint Research Centre. Within the VELA lab actual vehicles are connected to a chassis dynamometer and tested in a controlled facility. The driver controls the vehicle pedals and the gearbox (in case of manual transmission vehicles). Chassis dynamometer measures vehicle speed at 10Hz frequency.

Four drivers, all with extensive experience driving at the VELA facility, were asked to drive three pre-defined scenarios. The driving scenarios were defined by the maximum speed that the drivers were asked to reach. These were 70, 100 and 130 km/h. In each case they were instructed to accelerate as they would do in real life from a standing position to the maximum speed, keep that speed for about one minute and then decelerate normally until the vehicle is stopped again. Three different vehicles were used in the experiment:

- V1 with a 2.0 litre Diesel engine providing power up to 110kW with an automatic transmission
- V2 with a 2.5 litre hybrid-gasoline engine providing power up to 114kW with an automatic transmission
- V3 with a 1.6 litre Diesel engine providing power up to 73kW with a manual transmission

In order not to be influenced by cold-start engine conditions, the vehicles were warmed-up before the acceleration tests. Each of the four drivers drove all three acceleration scenarios (with different maximum speeds) on each of the three vehicles. The experimental campaign consisted of a total of 36 acceleration experiments which are based on three different desired speeds, 70, 100 and 130km/h.

An example of the time-speed profiles that were collected for vehicle 1 is shown in Fig. 2. The 12 profiles shown in the figure are for the three maximum speeds for each of the four drivers.

B. Analysis

The data collected in the experiment was used to fit the parameters of the three free-flow acceleration models mentioned above. In each case, the model parameters were estimated in

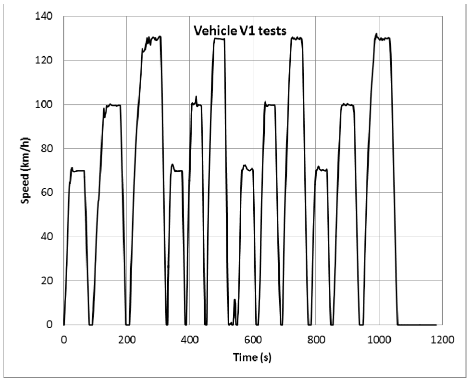

Fig. 2. Speed profiles within the acceleration experiments with vehicle.

two different ways, referred to in the paper as physical and statistical estimation.

1) Physical Estimation: In the physical estimation the model parameters are set on the basis of direct observation of the values that correspond to their physical meaning, such as desired speed and maximum acceleration. For other parameters, the default values proposed by the model developers, or those commonly adopted when the models are used, are considered. This method is attractive due to its simplicity and intuitive interpretation of the parameter values. Moreover, the model simulate the acceleration based on pre-defined specification (i.e. accelerate from 0 to 100km/h normally) and therefore physical estimation can demonstrate the generative capability of the model.

2) Statistical Estimation: In the statistical estimation, the model parameters are selected in order to minimize the distance between the model results and the experimental data. The maximum likelihood method is used to fit the model parameters to the observations. In the experiments, desired speeds were explicitly prescribed to the drivers. Estimated values for this parameter were close to these values. Therefore, the values of these parameters were set accordingly for each experiment and not estimated with the other parameters. Statistical estimation of the model's parameters demonstrates the capability of the model to fit on an acceleration profile.

The performance of the various models and the two estimation methods are evaluated with respect to their fit to the speed-acceleration data and their indirect effect on predicted positive energy demand that use the speed profiles as inputs. The results section is divided into three sub-sections:

The first part of the results section below statistically analyzes the estimations and the fit of the above-mentioned three car-following models. The fit is performed using both statistical and physical estimation of the model parameters. Log likelihood and RMSE of accelerations per model, driver, vehicle and desired speed-specific parameters provide the goodness of fit. Additionally, visual comparison between models and measurements is provided as such representations reveal the capability of each model to fit to the measurement and to simulate the vehicle dynamics. To understand the meaning of the numbers presented in the first part, in the second part, some of the resulting speed profiles are visually presented in order to provide an overview of the model capabilities to reproduce the overall trajectory.

TABLE I
STATISTICAL ESTIMATION RESULTS OF FREE FLOW MODELS

Parameter	Model			
	Linear	Gipps, $\beta = 0$	Gipps, $\beta = 0.025$	IDM
a^{max}	1.911 (0.013, p<0.001)	3.306 (0.032, p<0.001)	3.635 (0.035, p<0.001)	1.293 (0.009, p<0.001)
γ	-	0.299 (0.007, p<0.001)	0.427 (0.008, p<0.001)	5.963 (0.196, p<0.001)
σ	0.681 (0.005, p<0.001)	0.551 (0.004, p<0.001)	0.556 (0.004, p<0.001)	0.549 (0.004, p<0.001)
Log likelihood	-9391.1	-7459.0	-7540.7	-7433.7

In the third part of the results section, the authors compare the capability of each model to predict the vehicle's positive energy demand at the wheels in each experiment. Energy demand comparison is computed for the same distance travelled.

IV. RESULTS

A. Model Estimation and Fit

Results of the statistical estimation of the models are presented in Table I. The numbers in parenthesis are the standard errors of the parameter estimates and their p-values. Note that for Gipps' model, the parameters $a^{\max}$ and α cannot be distinguished. The estimated value of $a^{\max}$ that is reported in the table actually captures the product of these two parameters. Also note that in this model, when the parameter β was estimated freely, its optimal value was very small and not statistically different from zero, and so omitted from the final model. However, eliminating β from the model dictates that the mean acceleration when the vehicle is stopped will be zero. Therefore, estimation results for the Gipps model fixing the value of this parameter to its default value ($\beta = 0.025$) are also reported. The fit of this model is inferior to the one with $\beta = 0$ although accepting this value would make the simulated vehicles unable to accelerate. This apparent contradiction is explained by the fact that the max-likelihood approach for the statistical estimation of the parameters of car-following does not take into account the propagation of the error in simulating the whole vehicle trajectory with those parameters. This aspect raises significant concern about the suitability of such an approach to calibrate this type of models, although its widespread use in the field literature.

For the physical estimation, $a^{\max}$ is theoretically set to the maximum acceleration values observed in the data. However, these may be extreme and unrealistic. Lower values representing the 99th and 95th percentiles of accelerations were also used, and yielded better fit to the measured accelerations. Using even lower percentile values further improved the model fit, but these parameters then lose their physical meaning.

Table II presents the root mean squared errors (RMSE) of accelerations for the various models. For Gipps model the two values are for the models with the two different β values. The other parameters in Gipps' and IDM models were set to

TABLE II
ROOT MEAN SQUARED ERRORS (RMSE) OF ACCELERATIONS

Model	Statistical	Physical		
		100th	99th	95th
Linear	0.681	1.755	0.846	0.691
Gipps	0.551/0.556	2.420	1.058	0.682
IDM	0.549	2.885	1.298	0.815
a^{max} value	-	4.915	2.844	2.124

their default values. σ is the standard deviation of a normally distributed error term.

The differences between the Gipps and IDM models in terms of fit are minor. Both these nonlinear models fit the data substantially better compared to the linear model. The fit obtained with the statistical estimation is superior to that of the physical estimation, especially for the two nonlinear models. Furthermore, the results of the physical models vary depending on how exactly the value of maximum acceleration was set. Simply using the absolute maximum value that was measured yielded the worst results. These results seem to recommend the use of the statistical estimation and justify the additional effort it requires. However, the overall prediction power of all three models is rather low. This can be seen in the large values of σ in the various models and in the RMSE, considering the magnitudes of measured accelerations.

To further demonstrate this, Fig. 3 shows the measured and predicted accelerations for all points in the data-set. In all cases, the points show a wide scatter around the 45 degree line (which would represent the perfect fit). Furthermore, with the statistical estimations, the model results limit the maximum accelerations possible to values that are lower than the largest values observed in the data.

The models presented above assumed that a single set of parameters fit the data from all experiments. However, this does not capture systematic differences in the behavior between the different drivers, vehicles or desired speeds that may exist. In order to evaluate the extent of the error that is generated by these sources, separated estimations are carried out considering the data of each driver, vehicle, or desired speed-specific. The fit of these models in terms of likelihood values and RMSE are presented in Table III. The addition of the specific parameters does not significantly contribute to improve the estimation quality. This clearly show that all the three models have large structural deficiencies which do not allow them to reproduce the actual vehicle dynamics even when a smaller and more homogeneous data set is used in the calibration. As a result the deficiencies identified in the present paper can be considered independent from the specific vehicle considered or the experiment carried out as the car-following models used simply do not take into account many of the elements characterizing the vehicle dynamics (vehicle inertia, transmission and engine efficiency, gear-shifting lags, etc.). In this light the size of the experiment carried out can be considered sufficient to highlight the problems of such models in reproducing detailed vehicle operations.

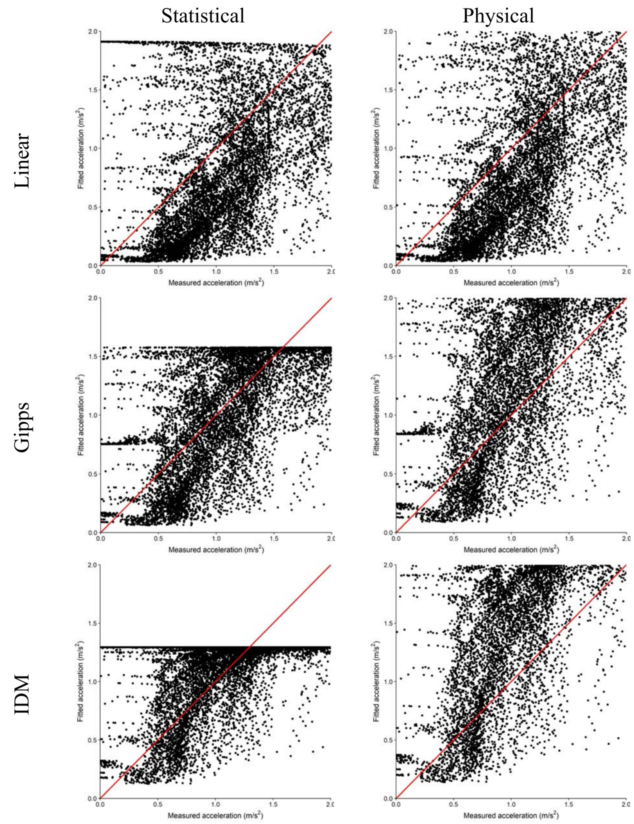

Fig. 3. Measured and predicted accelerations using (top to bottom) Linear, Gipps, IDM models with parameter from Statistical (left) and physical estimations (right).

TABLE III
LOG LIKELIHOOD AND RMSE OF ACCELERATIONS OF MODELS ESTIMATED CONSIDERING DRIVER, VEHICLE AND DESIRED SPEED-SPECIFIC PARAMETERS

Model	Generic	Driver	Vehicle	Desired speeds
	Log Likelihood, RMSE (# parameters)			
Linear	-9391.1, 0.681 (1)	-9307.2, 0.675 (4)	-9359.4, 0.679 (3)	-9370.6, 0.680 (3)
Gipps	-7459.0, 0.551 (2)	-7349.3, 0.544 (8)	-7364.4, 0.545 (6)	-7318.7, 0.542 (6)
IDM	-7433.7, 0.549 (2)	-7315.0, 0.542 (8)	-7375.3, 0.546 (6)	-7236.6, 0.537 (6)

In order to further strengthen the previous statement, the speed-acceleration plots of the various experiments were examined. Two examples are shown in Fig. 4. They are both for desired speeds of 130 km/hr. They demonstrate the large deviations between the measured data and values predicted by the three models both locally and globally. This once again shows that the models fail to capture the dynamicity of the speed-acceleration relationship. In particular, the effect of the various gears and gear-shifting behavior is clearly missing. The gear-shift points are easily visible in the sudden and deep acceleration drops. Their magnitude and duration depend on the type of vehicle, and as expected are more pronounced in the vehicle with manual transmission (Bottom figure). Gear-shifts reduce the smoothness of acceleration profiles

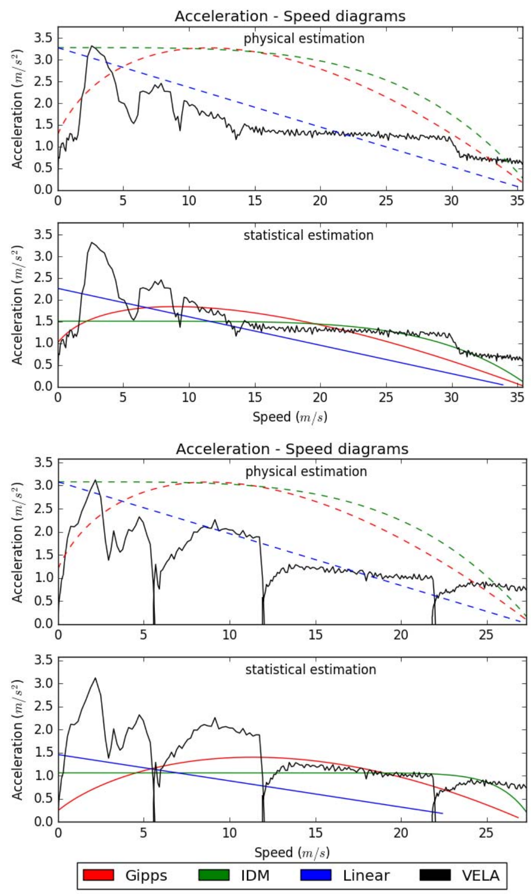

Fig. 4. Examples of speed-acceleration plots.

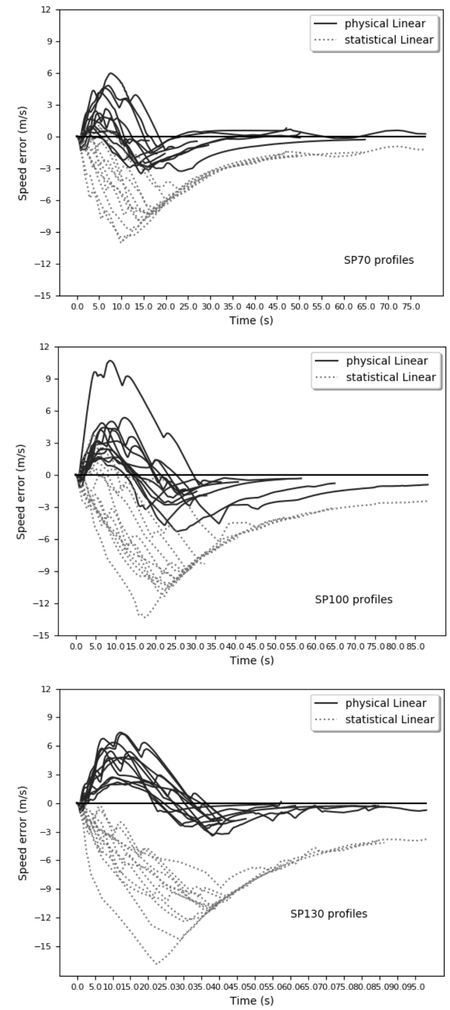

Fig. 5. Deviation between measured speeds and those simulated by the linear model.

and add substantial variability to accelerations, which is not captured by the free-flow models. Furthermore, different gears allow different maximum accelerations. An example of this is shown in the plots in Fig. 4. Different gears exhibit different maximum accelerations and profiles within the gear range. The fitted free-flow acceleration models are unable to represent this behavior. Finally, in most experiments, the maximum accelerations were not achieved when the speed was zero or very low, which is by design the case with the linear and IDM models. At the same time, the observations (of which the plots in Figure 4 represent just a small sample) show the maximum acceleration is systematically achieved sooner than the 30% of the maximum speed as assumed by the Gipps model showing that in any case also this different assumption is too simplistic to reproduce a realistic vehicle dynamics.

B. Free-Flow Trajectories

The free-flow models estimated above provide instantaneous accelerations at a given speed. They do not explicitly capture the propagation of errors in consecutive time steps. At this level, the results indicate that they are not able to fully represent vehicle movements. However, for many applications, it may be sufficient that the models can reproduce a more aggregated measure of the overall trajectory of the vehicle or a function of it, and not the second-by-second accelerations. To evaluate this, simulations of the free-flow acceleration process, from a standstill to the desired speed were conducted.

Results are reported in Figs. 5, 6 and 7 for the Linear, the Gipps and the IDM models, respectively. Each figure is composed of three graphs corresponding to the three different maximum speed tests. Within each graph, the various plots represent the speed difference between the measurements and the corresponding simulated profile using both the statistically and physically estimated model parameters.

The three figures confirm findings previously mentioned. First, all three models, when using the physically estimated parameters, overestimate speeds, especially at the early stages of the simulation. This is due to to the assumption that the largest accelerations are obtained at zero or low speeds, which is not the case in many of the experiments (the only exception is with the Gipps model for which a mild underestimation of the speed appears at the very beginning of the acceleration because in this model the maximum acceleration is achieved when the speed is approximately at 30% of the desired speed). In contrast, the simulations with the statistically estimated parameters tend to underestimate speeds at the early stages of acceleration. In both cases the deviations are significant and achieve values of 10m/s in both directions.

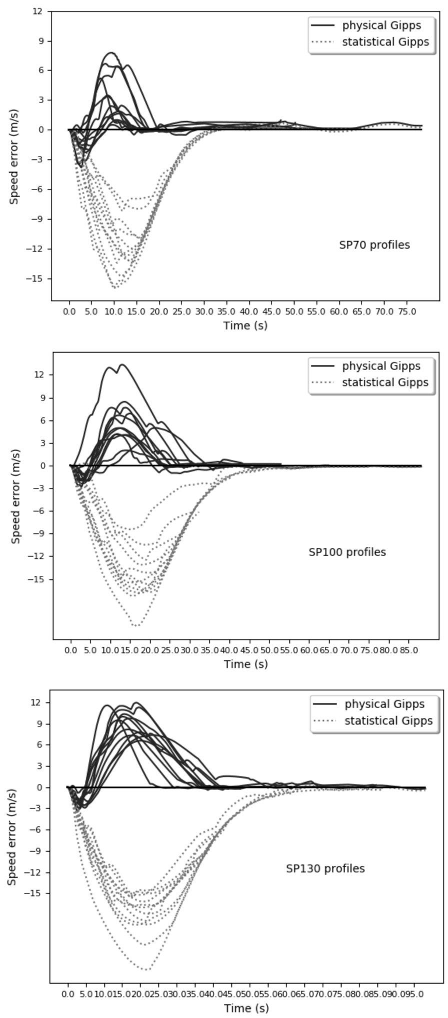

Fig. 6. Deviation between measured speeds and those simulated by Gipps model.

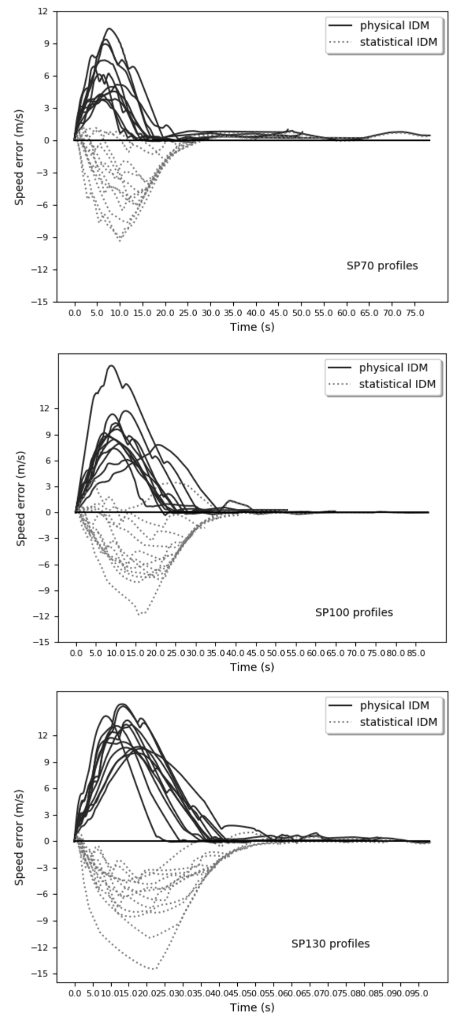

Fig. 7. Deviation between measured speeds and those simulated by IDM model.

After the initial deviation, in all cases, as the speed approaches the desired one, the error becomes negligible with both physical and statistical estimation of the model parameters. This means that the assumption that acceleration tends to zero as speed approaches the desired speed is valid.

However, considering the typical stop-and-go traffic conditions existing in urban contexts, the desired speed is never achieved and therefore it is expected that our models, even if calibrated on real data, will always experience significant deviations during the short accelerations of the vehicles. This again raises concerns about the capability of the models to reproduce traffic dynamics, fuel/energy consumption and emissions in this contexts. The main uncertainty of the model is therefore in the way the acceleration is simulated. In addition, the figures show that the deviations of Gipps and IDM models follow similar patterns, while the deviations of the linear model oscillate around the zero error. However, regardless of the functional form adopted by the model, an acceleration function that only relies on the speed and maximum acceleration seems too simplistic. Therefore, it is apparent that new approaches, which explicitly take into account vehicle dynamics (possibly including the gear-shift behavior, which I clearly observed in the observations) are necessary. This may be especially useful in cases where upcoming new technologies (in the path towards automated driving) need to be assessed and compared with existing behaviors in terms of traffic implications, energy consumption and emissions.

C. Positive Energy Demand

Speed and acceleration trajectories simulated using a traffic simulation model are usually also used as input to determine externalities of the traffic flow, such as energy consumption or emissions. This section quantifies the error in prediction of positive energy demand on the wheels over an acceleration trajectory when using the three free-flow acceleration models. The total positive energy demand by the vehicle is calculated by integrating the power required at the wheels over time. The power required at the wheels at a given point in time is composed of two components: i) the power to overcome the resistances to vehicle motion (rolling and aerodynamic resistances, which depend on the speed of the vehicle), and ii) the power need to accelerate the vehicle. The first component is obtained from the product of the resistance force and the speed

TABLE IV

COMPUTED POSITIVE ENERGY DEMAND AND AVERAGE PREDICTION ERRORS USING THE VARIOUS MODELS FOR VEHICLES V1, V2 AND V3

Parameter estimation	Vela Labs E(kJ)	Gipps	IDM	Linear
Vehicle 1 Physical	883.64	4.11%	6.03%	-18.52%
Vehicle 1 Statistical		-7.23%	-6.09%	-29.72%
Vehicle 2 Physical	1040.95	7.74%	9.02%	-13.72%
Vehicle 2 Statistical		-11.64%	-6.34%	-29.32%
Vehicle 3 Physical	783.62	12.09%	12.65%	-7.20%
Vehicle 3 Statistical		-3.60%	-1.56%	-26.23%

of the vehicle. The second component can be obtained from the product of the acceleration, the mass of the vehicle and its speed. The time integration of the power can be approximated by a summation over the discrete values at measurement (or simulation time steps) points. The formulation used in the present work to calculate the energy required by the vehicle is given by:

$$\mathrm{E} = \sum_{t=0}^{T} \mathrm{P}_t \, \Delta t = \sum_{t=0}^{T} \left(F_0 + F_1 v_t + F_2 v_t^2 + 1.03 m a_t \right) v_t \, \Delta t \tag{4}$$

Where, F_0, F_1 and F_2 are the road load coefficients that describe the relationship between overall resistances to motion and the vehicle speed (forces applied to the vehicle when it is on road), m is the vehicle mass, v_t and a_t are the speed and acceleration of the vehicle at time t. Δt is the time interval between consecutive measurement points or the simulation time step, while T is the total duration of the movement period. The road load coefficients (F_0, F_1 and F_2) values are those corresponding to the vehicles tested. It is worth mentioning that the summation in equation 4 is only extended to the simulation steps where the power is positive (to represent the energy requested to the engine which is responsible for energy/fuel consumption and emissions). More details are presented in [26].

The positive energy demand from the measurements in the experiment is calculated from the start of the movement of the vehicle from a standstill, until it reaches 95% of the desired speed. In order to provide a meaningful comparison in terms of energy consumed, the comparisons with simulated trajectories is made on the basis of the same distance travelled, regardless of the simulated speeds reached. Table IV reports the computed positive energy demand for the three vehicles, respectively, as resulting from the measured data and the speed profile simulated using physically and statistically estimated parameters in the models.

In line with the findings regarding the speed trajectories, the results show that the energy demand predicted when using the Gipps and IDM models with physically estimated parameters consistently overestimates the measured values with all three vehicles. Between the two models, the overestimation produced by the Gipps model with physically estimated parameters is smaller than that of the IDM model. This is due to the IDM models' property that the maximum acceleration is achieved at zero speed, which leads to obtaining higher speeds faster, but is not supported by the experimental data.

With the statistically estimated parameter, the results are towards the opposite, which is again in consistency with the speed trajectory results. The two models underestimate energy demand, due to the underestimation of accelerations in the initial stages, which leads to lower speeds during longer periods of time and distances. The linear model underestimated energy demand in all the experiments with larger deviations compared to the two other models. The main reason for this is that in this model the acceleration drops at a higher rate as a function of speed and so the vehicle does not reach the desired speed, which causes underestimation of energy demand. The overall absolute error is slightly lower for the models with statistically estimated parameters compared to with the physical ones for the Gipps and IDM model, and larger for the linear model.

If the results in terms of positive energy demand for Gipps and IDM may appear overall reasonable, it is necessary to distinguish different cases. For cases where the desired speed is reached and mainted over time with mild disturbances (e.g. under-saturated motorway traffic conditions), the error in the estimation of the vehicle energy demand is expected to be negligible as the main factor will be the speed, that the current car-following models are able to achieve and maintain. When on the contrary, the main factor is the vehicle acceleration/deceleration (e.g. saturated traffic and stop-and-go conditions), the resulting deviation are expected to be extremely important (in line with the speed deviations observed in Fig. 5-7). Furthermore low errors on the energy demand do not ensure low errors also on fuel consumption and pollutant emissions as in these cases more complex phenomena take place affecting the efficiency of the engine and of the after-treatment system. In general, since consumption and in particular emissions are particularly important during the initial acceleration phase, higher errors for these quantities can be expected when the results of existing car-following models are used as input in their estimation.

For all these reasons, the results show that all three models not only cannot reliably reproduce the detailed movement of the vehicle, but also produce substantial errors in predicting more aggregated measures that depend on their movement, such as the energy demand.

V. CONCLUSIONS AND FUTURE CHALLENGES

This paper aims to contribute to the evolution of car-following models to better assess the implications for traffic and related externalities of the introduction of advanced vehicle technologies. In particular the paper performs a thorough analysis of the limitations of three well known and widely used car-following models in reproducing free-flow vehicle acceleration dynamics. With this aim, vehicle acceleration experiments were carried out and used in this study. Findings

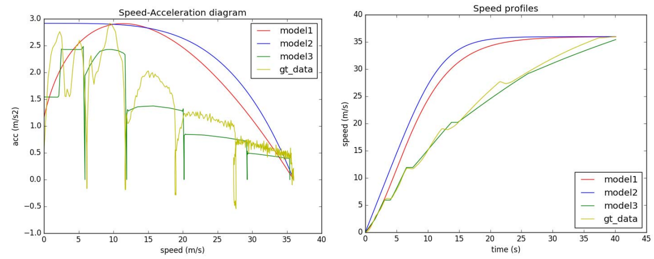

Fig. 8. Speed acceleration graph of Gipps model (model 1), IDM model (model2) and a vehicle-dynamics based model currently under development (model3), in comparison with real measurements (gt_data).

raise concerns about the capability of current traffic models to correctly predict the effect on traffic, emissions and on energy/fuel consumption of technologies having an impact on the vehicle dynamics. It is also shown that the calibration of the model against real data is not able to satisfactorily address this issue due to the intrinsic structural deficiencies of the existing models. Such deficiencies are so self-evident by the results provided that, although they are achieved on a limited sample of vehicles and drivers, they can be considered of general character.

In order to address these limitations there is need of new acceleration models where the vehicle characteristics, the driver profile, as well as their interaction, should be explicitly taken into consideration. These models should better capture relevant characteristics and factors, such as the heterogeneity in acceleration behavior due to variability in the capabilities and characteristics of the vehicles (e.g. engine, mass, transmission types) and the differences in behaviors between and within drivers. Similarly, the effect of gear-shifts that generate discontinuities in the speed-acceleration function that are present in the observations need to be captured. Experimental observations seem also to suggest that within gears, accelerations increase rapidly and then decrease until the discontinuity point introduced by gear-shifting. At speeds that are close to the desired speed, the acceleration reduces almost linearly with the speed and then drops when the desired speed is achieved.

Current work by the authors is focused on the implementation of such a concept. Fig. 8 demonstrates the speed – acceleration diagram of 3 models, one of which is currently under development by the authors and takes into account the driving style, the gear shifting logic and the characteristics of the vehicle. Current research focuses on the adaptation of this mode to micro-simulation needs in terms of accuracy and computational complexity.

Acknowledgments

The authors are grateful to B. Giechaskiel and the JRC Vehicle Emissions Laboratory (VELA) team for their support throughout the experimental activity.

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Biagio Ciuffo received the Ph.D. degree in transportation engineering from the Department of Transportation Engineering, University of Naples Federico II, in 2008. Then, he joined the European Commission Joint Research Centre, working at the assessment of traffic and transport related measures and policies. He is currently a Project Leader for different projects concerning the reduction of CO_2 emissions from road transport and the effect of automated/connected vehicles on traffic management. He is an Associate Editor of the IEEE TRANSACTIONS ON INTELLIGENT TRANSPORTATION SYSTEMS.

Michail Makridis received the Ph.D. degree in image processing and machine intelligence from the Democritus University of Thrace, Greece. Since 2012, he has been with the European Commission Joint Research Centre as a Researcher and a Science and Policy Officer. His interests are in intelligent transportation systems, simulation of vehicle dynamics and driver behavior, energy demand and emissions, image segmentation and classification, natural language processing, and sequential pattern mining. He is a Reviewer in international journals and author of various publications in the fields of traffic modeling and simulation, image processing, and machine learning.

Tomer Toledo was a Research Associate with the MIT Intelligent Transportation Systems Lab. He is currently an Associate Professor with the Faculty of Civil and Environmental Engineering and the Transportation Research Institute, Technion–Israel Institute of Technology. His research is in the areas of transportation systems modeling and analysis, including traffic simulation models and their calibration and validation, driving and travel behavior, and intelligent transportation systems.

Georgios Fontaras received the Ph.D. degree in mechanical and automotive engineering from the Aristotle University of Thessaloniki, Greece. He has worked for eight years as a Researcher at the Lab of Applied Thermodynamics, Aristotle University of Thessaloniki. In 2010, he joined the European Commission Joint Research Centre. His work is related to vehicle energy efficiency analysis and modeling, monitoring CO2 emissions from road vehicles, vehicle testing, and policy analysis. He has been steering the development of the VECTO simulator for the certification of Heavy Duty Vehicle CO2 emissions in Europe. He is one of the core developers of the CO2MPAS simulator which used for light duty vehicle CO2 type-approval.