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Calibration of Gipps' car-following model for trucks and the impacts on fuel consumption estimation

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Johana Cattin¹, Ludovic Leclercq¹, Florian Pereyron² ✉, Nour-Eddin El Faouzi¹

¹University of Lyon, ENTPE, IFSTTAR/LICIT, UMR_T 9401, 69518 Lyon, France

²Renault Trucks, Volvo Group, 69806 Saint-Priest, France

✉ E-mail: florian.pereyron@volvo.com

Abstract: Calibration of car-following models plays an important role not only in traffic simulation but also in the estimation of traffic-related energy consumption. However, the majority of calibration studies only focus on errors on position or speed, whereas these models are used to evaluate environmental parameters associated with road traffic (e.g. pollutant emissions, energy consumption). Then, this study focuses on the ability of Gipps' car-following model calibrated on trajectory parameters to estimate properly the fuel consumption of a heavy vehicle. First, the shape of one of the most used Goodness-of-Fit function, Theil's inequality coefficient, is investigated. It will be demonstrated that optimal domains are flat and large, and so many combinations of parameters could accurately reproduce the vehicle trajectory. Then, the authors found that Gipps model, calibrated via a multi-objective particle swarm optimisation is relevant to simulate the trajectory of a heavy vehicle, but fuel consumption estimation resulting of these trajectories exhibits large discrepancies. To solve this issue, it is proposed to add the fuel consumption estimation directly in the calibration process as a further dimension. The results show an improvement in the value of energy consumption estimation without increasing too much the error on the trajectory.

1 Introduction

The reduction of fuel consumption, and more generally pollutant emissions, is one of the major challenges of vehicle manufacturers. With the increase of communicating systems, new technologies such as intelligent transportation systems (ITS) and advanced driver assistance system (ADAS) play now an important role in the reduction of pollutant emissions. In order to reduce prototyping costs, it is important to have powerful and relevant simulation tools for project development phases.

There are different ways to estimate fuel consumption of a vehicle. If we consider an individual vehicle, the calculation of its energy consumption requires only the knowledge of its own kinematics. This can be done on real data but for prototyping new solutions on doing test at large scale it is very useful to boost the simulation. However, to estimate it in a road traffic environment, in order to assess the benefit of new driving strategies, for example, it is necessary to assess how vehicle kinematics derived from traffic simulation model is accurate enough for such an application.

The study of car-following models calibration has already a long history, but very few studies focus specifically on heavy duty vehicles (HDVs) behaviour [1, 2], although truck's reactions to traffic are different from those of cars as shown in [3–5]. For the truck's trajectory, one can observe that spacing would be larger, acceleration capabilities are smaller, speed profiles are more complex due to more complex engine chains. Inertia also modifies the driving behaviour of HDVs due to the important weights of vehicles. The main studies taking into account truck following behaviour focus on the differences in following reactions [2, 3, 5, 6] depending of the follower and the leader type (passenger car or HDV). Other existing studies which consider truck following behaviour describe the influence of heterogeneous traffic flow on traffic instability [7–9].

To model the heterogeneity of real road traffic, several modified car-following models were previously developed. Previous studies about truck-following rule were based either on specific mode formulation [3, 8], on quite complex existing car-following rules [3] or on new developed models based on the local linear mode tree approach, LOLIMOT [10, 11]. All of these studies used data from the Next Generation Simulation project. The trajectories used were collected on the Hollywood freeway (U.S.101) and on the

Berkeley Highway (I-80) in California. They were, respectively, 640 and 503 m long. Here, we want to assess if a simpler expression, the Gipps' model, with dedicated parameter settings can accurately reproduce truck's behaviour under different applications: urban or regional. This would be very useful in practice as the Gipps model is widely used in traffic simulation because it is a good compromise between accuracy and the number of parameters for calibration.

A second contribution of this paper is about the connection with fuel consumption. First, we want to know if a calibration based on traffic objective function provided accurate results when calculating the fuel consumption. This is important because it is a common practice to calibrate the model for traffic applications and then determinate the fuel consumption as an output. Second, we will determine the improvements related to a direct integration of fuel consumption in the calibration process through multi-objective (MO) optimisation.

The first part of the paper presents the data used for the study. Then, Gipps' car-following model is detailed and its parameters to calibrate are highlighted. The following section is about calibration method and a particular attention is given to the Goodness-of-Fit (GoF) function and indicators on which computing the error between measured and simulated data. Then, the results of the calibration of the Gipps' car-following model are presented and resulting trajectories are used to estimate the fuel consumption of the vehicle. Finally, a solution is proposed to improve the calibration results and particularly the results on fuel consumption estimation.

2 Data description

Data were recorded in Lyon (France), with a vehicle weighted at 19 tons and equipped with sensors measuring the truck speed and the spacing to the vehicle ahead. The route driven by the vehicle is about 80 km (Fig. 1). The data is sampled with a time step of 0.1 s. For each sub-cycle, a lot of information is available at each time step: the position of the vehicle, its speed, its acceleration, the fuel injected (the instantaneous fuel consumption) and the slope. The instantaneous fuel consumption is used to compute the cumulated fuel consumption along the sub-cycles, and the fuel consumption

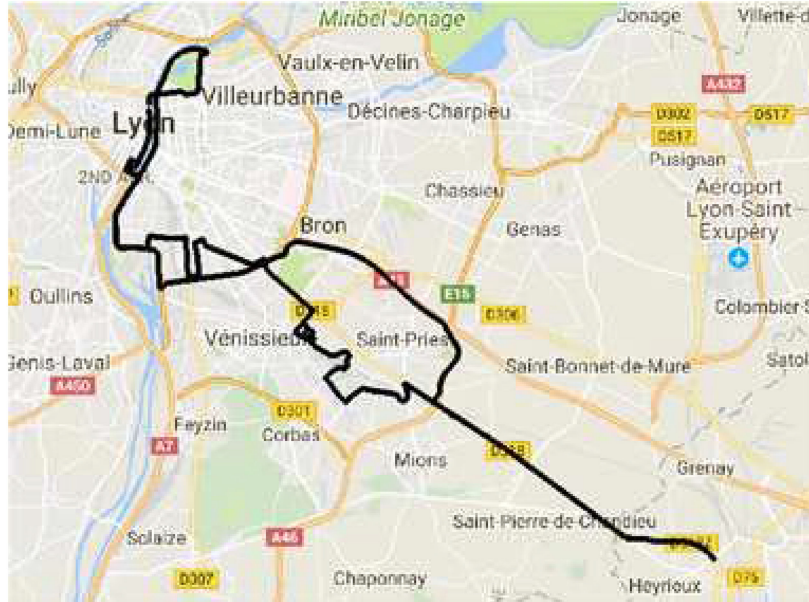


Fig. 1 Route driven by the vehicle

Table 1 Characteristics of the sub-cycles

no.	Urban					Regional				
	1u	2u	3u	4u	5u	1r	2r	3r	4r	5r
length, m	409	866	350	210	306	2634	1777	1771	1717	962
average speed, km/h	12	38	38	23	29	58	63	66	60	48
legal speed, km/h	50	50	50	50	50	90	90	90	90–70	90–70

expressed in $L/100$ km which will be, respectively, used in calibration and for comparison between the measure and the simulation.

Over the all route, the output of the sensor measuring the spacing is processed to extract sub-cycles with a situation following. First, the cycle is divided into sub-cycles separated by a stop (speed < 0.1 m/s). Then, sub-cycles in which there is no following situation (if the sensor has not detected a leader) are deleted. In the remaining sub-cycles, if some of them contain several following situations, they are divided into different sub-cycles. From the entire cycle, 35 sub-cycles have been created, with distances varying from 166 m to 2.6 km.

Among the extracted sub-cycles, ten cycles are presented in this paper. Five of the cycles are located in urban areas; the five others are regional cycles. The characteristics of those cycles, such as length, average and legal speeds in km/h, are presented in Table 1.

3 Gipps' car-following model

Gipps model was first introduced in 1981 [12]. This model is defined as a safe distance model because it is based on the choice of a safe following distance to avoid possible collision with the leader vehicle. The empirical model developed by Gipps consists of two components. The first represents the intention of a driver to achieve a certain desired speed, while the second reproduces the limitations imposed by the leader when trying to drive at the desired speed. The output of Gipps' car-following model is the speed. The expression of the speed is presented in (1) [13]. In the

rest of the paper, index n refers to the studied truck (the following vehicle), index $n - 1$ refers to its leading vehicle: (see (1)). Gipps' car-following model has six parameters to calibrate: a_n is the maximum acceleration rate of the follower; $S_{n-1} = L_{n-1} + \text{safetymargin}$ represents the length of the leader vehicle including a minimum safe distance; τ_n is the reaction time of the follower; V_n^{des} is its desired speed; b_n is its maximum braking rate; and b_{n-1} is the assumed braking rate of the leader. Gipps' model also includes a safety margin time θ [13, 14]. This parameter represents the ability of a driver to always stop safely if he begins to brake at $\tau_n + \theta$ after a change in the leader's behaviour. As demonstrated by Gipps [12], a good value for θ to ensure safety is $\tau_n/2$.

4 Calibration method: study of goodness-of-fit function and choice of calibration indicators

The calibration of car-following models aims at finding the set of parameters which would minimise the errors between the simulated trajectory of the truck and the measured one. The function computing the errors between the measure and the simulation will be named GoF function in the rest of the paper. Moreover, the trajectory of a vehicle can be described by different parameters: its position, the spacing to the vehicle ahead, its speed or its acceleration. The errors can be computed on each of these indicators, called Measure-of-Performance (MoP) in the rest of the paper.

$$\begin{aligned}
 v_n(t + \tau_n) &= \min \left\{ \begin{array}{l} v_n^a(t + \tau_n) \\ v_n^d(t + \tau_n) \end{array} \right\} \\
 &= \min \left\{ \begin{array}{l} v_n(t) + 2.5a_n\tau_n \left(1 - \frac{v_n(t)}{V_n^{\text{des}}} \right) \sqrt{0.025 + \frac{v_n(t)}{V_n^{\text{des}}}}; \\ b_n \left(\frac{\tau_n}{2} + \theta \right) + \sqrt{b_n^2 \left(\frac{\tau_n}{2} + \theta \right)^2 - b_n \left[2(x_{n-1}(t) - x_n(t) - S_{n-1}) - v_n(t)\tau_n - \frac{v_{n-1}(t)^2}{b_{n-1}} \right]} \end{array} \right\} \quad (1)
 \end{aligned}$$

Table 2 Range of variation of Gipps' car-following model parameters

Parameters	Min	Step	Max
τ_n , s	0.2	0.3	3.8
V_n^{des} , km/h – urban	40	2	50
V_n^{des} , km/h – regional	70	3	85
a_n , m/s ²	0.5	0.4	2.9
SafetyMargin, m	0.1	0.5	4.6
\hat{b}_{n-1} , m/s ²	-6.1	0.5	-0.1
b_n , m/s ²	-4.1	0.5	-0.1

Before calibrating Gipps' car-following model, a particular focus will be done on GoF function and MoPs. In the literature on car-following calibration, many GoF functions are used [14–19]. This paper will focus on Theil's inequality coefficient, described in (2):

$$U = \frac{\sqrt{(1/N) \sum_i^N (Y_i^{\text{obs}} - Y_i^{\text{sim}})^2}}{\sqrt{(1/N) \sum_i^N (Y_i^{\text{obs}})^2} + \sqrt{(1/N) \sum_i^N (Y_i^{\text{sim}})^2}} \quad (2)$$

with

$$\begin{cases} Y_i^{\text{obs}}, & \text{the measured MoP} \\ Y_i^{\text{sim}}, & \text{the simulated MoP} \end{cases}$$

In Theil's inequality coefficient $U = 0$ indicates a perfect fit between the measure and the simulation, whereas $U = 1$ indicates worst fit.

4.1 Choice of the MoPs: the shape of Theil's inequality coefficient

The different studies comparing the calibration of car-following models mainly focus on error on position or speed. It has been previously shown [20] that it is better to use MoP (the spacing or the position) instead of the speed when we want to minimise error on both spacing (or position) and speed. However, these studies were done by using a single MoP [15, 16, 20] or combined MoPs [21, 22], but not using a MO calibration. This solution is investigated here.

Prior looking for optimal parameter values, we first investigate the response of the GoF function to a large range of parameter values. Actually, if this function is flat, the optimal domain is large and so the calibration process will not lead to a narrow definition of optimal parameters. Moreover, because we want to focus on multiple objectives when calibrating the model, it is interesting to evaluate the intersection of optimal domains obtained independently for position, spacing, speed and acceleration. If this intersection is close to the union, it means that all independent process converges to the same consistent region for optimal parameters. If this intersection is void, it means that a single but MO calibration process is mandatory to determine a relevant set of optimal parameter values.

First, a surface grid of the Theil's inequality coefficient is done. For Gipps' car-following model, a range of variation of the parameters to calibrate is defined (Table 2). Then, trajectories are simulated for each possible combination of parameters and the error between the simulated trajectory and the measured one is computed with Theil's inequality coefficient. To study the shape of this function, the sizes of optimal domains are compared.

Optimal domains are defined for each of the variables that we want to optimise error on. Those variables are, as mentioned in previous paragraphs, the position of the follower, the spacing between the follower and the leader, the speed of the follower and its acceleration. The optimal domains are defined as follows: we search for the point which provides the minimum error on the variable, then, five optimal domains are defined per variable we want to optimise error on. The first one contains the points for

which the error is between the minimum error and the minimum error plus 10%. The second domain contains points for which the error is between the minimum error and the minimum error plus 20%, and so on until the minimum error plus 50%.

The number of points in each optimal domain, expressed as a percentage of the total number of tested points, is compared. First the evolution of the optimal domains size is studied. If the size of the domain increases a lot with the percentage of accepted error, it means that the optimal domain is quite flat, so a large range of parameters are acceptable.

The evolution of the size of the optimal domains is similar whatever the cycle of the category (urban or regional). This evolution is presented in Fig. 2. Fig. 2a illustrates the evolution for urban cycles and Fig. 2b illustrates the evolution for regional cycles of the size of optimal domains. The first axis represents the optimal domains for the four variables (position, speed, acceleration and spacing) and two intersection domains. The first intersection domain represents the common points of optimal domains in position, speed and acceleration. The second is for common points for optimal domains in spacing, speed and acceleration. The second axis corresponds to the percentage of accepted error, from 10 to 50%. The last axis (vertical) represents the percentage of points in the optimal domain.

For the optimal domains in position and spacing, the results are quite identical. The sizes of the optimal domains are only increasing slightly when the percentage of error is increasing. Moreover, these two domains are really close to each other even if the optimal domain for spacing is a bit larger. The optimal domains for speed and acceleration, respectively, for urban and regional cycle, are really sensitive to the percentage of accepted error. From 20%, their sizes increase quickly, so the GoF function is quite flat for these two variables.

It was previously demonstrated that it is preferable to use spacing or position as MoP [15, 16, 20]. This result is consistent with the precedent conclusion. As illustrated in Fig. 2, the optimal domain for spacing is really less flat than speed or acceleration optimal domains, which ensures to find a minimum more easily than for the other MoP. Calibrating the car-following model according to the error on speed or on acceleration could lead to many sets of parameters that could be considered as optimal. However, the final objective of the calibration method developed in this paper is to have a car-following model well calibrated to compute the fuel consumption of industrial vehicles: the error on speeds and accelerations must be minimised too. Moreover, we can observe in Fig. 2 that the intersection domains are small. This means that very few points are optimal for all MoPs. Therefore, MO calibration is needed for the application considered in this study: minimising errors between measurements and simulation not only for position, but also for speed and acceleration.

Two intersections of optimal domains are defined. The second intersection domain (spacing, speed and acceleration) is generally greater than the first one (position, speed and acceleration) because the optimal domain for position is a little smaller than the optimal domain for spacing. To ensure that the MO calibration algorithm will find the maximum of possible optimal points, it will be run with the three variables that allow the biggest intersection domain: spacing, speed and acceleration.

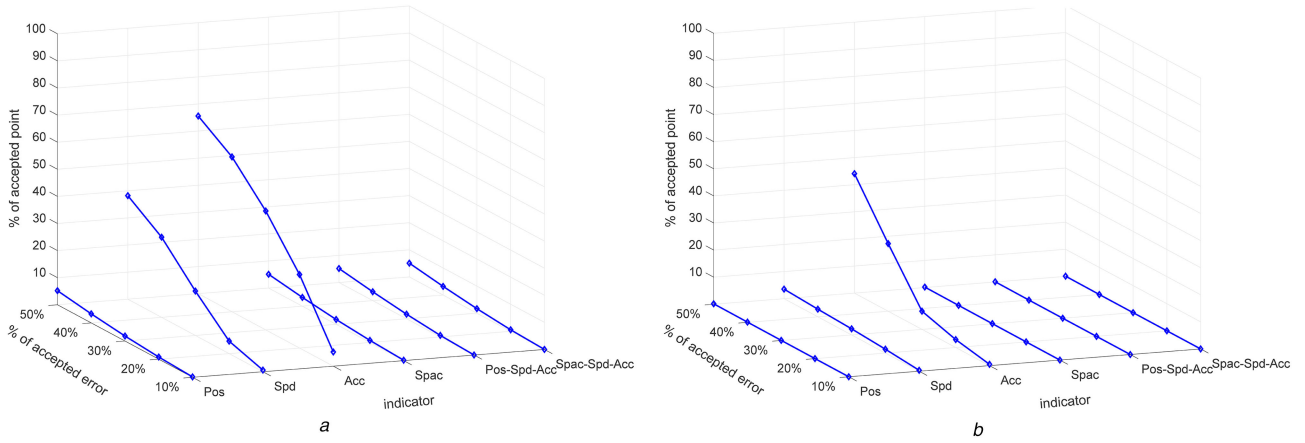


Fig. 2 Evolution of optimal domains for Gipps' car-following model for Theil's inequality coefficient
(a) Urban cycle, (b) Regional cycle

Table 3 Errors, for the ten cycles, on position, spacing, speed and acceleration

	Urban					Regional				
Theil's inequality coefficient										
no.	1u	2u	3u	4u	5u	1r	2r	3r	4r	5r
position, %	1.43	0.51	0.47	1.90	1.15	0.59	0.22	0.56	0.45	0.63
spacing, %	12.16	10.93	4.71	3.10	6.62	13.70	6.98	8.30	11.75	8.76
speed, %	10.43	3.10	1.96	6.04	2.13	2.65	2.32	3.30	3.01	3.66
acceleration, %	40.83	30.47	13.19	24.23	26.46	32.60	21.50	24.88	23.22	25.53
MAE										
no.	1u	2u	3u	4u	5u	1r	2r	3r	4r	5r
position, m	4.94	5.01	1.98	2.68	3.37	14.77	4.41	9.56	8.33	5.38
spacing, m	4.94	5.01	1.98	2.68	3.37	14.77	4.41	9.56	8.33	5.38
speed, km/h	2.10	2.13	1.33	2.43	1.09	2.53	2.19	2.93	2.18	2.34
acceleration, m/s ²	0.17	0.14	0.12	0.23	0.18	0.14	0.17	0.16	0.11	0.21

4.2 Multi-objective particle swarm optimisation

The Gipps' model presented in the previous section is calibrated using a method based on the particle swarm optimisation (PSO) algorithm. This global optimisation method was proposed in 1995 by Eberhart and Kennedy [23]. The method used here is the standard 'GBEST model' [24]. As demonstrated previously, the optimal domains are different depending on the MoP. Then, a MO calibration is mandatory to try reducing errors on spacing, speed and acceleration. This approach is interesting because new driving strategies are mainly used to reduce fuel consumption, and it is necessary in this way to simulate accurately not only position or spacing but also speed and acceleration.

The PSO algorithm is modified into a multi-objective PSO (MOPSO) allowing the calibration of several variables: spacing, speed and acceleration. The algorithm is described in the following text. The MOPSO algorithm provides a set of optimal parameters for Gipps' model, which dominate other possible parameters according to the dominance definition of Pareto [25] (see the Appendix for definitions).

At the beginning of the calibration, a set of N particles is defined randomly inside the upper and lower bounds defined. The MO calibration implies the use of an archive containing particles that dominate the swarm. In our case, the particles are the vectors of parameters of the Gipps' car-following model to calibrate. Each particle i is given a position x^i and a speed v^i . The position is the value of the coordinates of the vector. The speed is used to update the particle's position in the direction of the particle named GBEST g : the best position (the lowest error) reached since the beginning of the optimisation, and the best position PBEST reached by the particle itself, p^i . The speed at the initialisation phase is defined randomly. At each iteration, the position and the speed are updated according to (3) and (4), and the archive of dominating particles is updated to include new dominants. For the MO calibration, there is not one GBEST particle because there are several objectives. Then,

a GBEST particle is defined for each particle of the swarm. The choice is based on the RANDOM global guides' selection proposed by Alvarez-Benitez and Everson [26].

If the particle is part of the dominating archive, its GBEST is chosen randomly into the archive, if not, its GBEST is chosen randomly among the set of particles which dominates it, including the particles into the archive. This last choice is different from what is proposed in [26], where they only consider as a possible GBEST the particles in the archive which dominate the particle for which GBEST is computed.

$$x^i(k+1) = x^i(k) + v^i(k) \quad (3)$$

$$v^i(k+1) = K(v^i(k) + r_1 c_1 (p^i - x^i(k)) + r_2 c_2 (g - x^i(k))) \quad (4)$$

With $i \in [1, N]$, $k \in [1, \text{nb_iter} - 1]$, $K = 2 / |2 - \varphi - \sqrt{\varphi^2 - 4\varphi}|$, and $\varphi = c_1 + c_2$.

For convergence φ must be >4 [27], we chose $c_1 = c_2 = 2.05$. The number of particles and the maximum number of iterations are, respectively, defined equal to 50 and 500. r_1 and r_2 are random values between 0 and 1.

5 Results

5.1 Ability of Gipps' car-following model to reproduce truck's behaviour

The Gipps' car-following model has been calibrated using the MOPSO algorithm presented in Section 4.2. The GoF function is the Theil's inequality coefficient described in Section 4, the MoPs are the spacing between the leader and the follower vehicle, and the speed and the acceleration of the follower, a truck in our case. The results of the calibration of the cycles presented in this paper are summarised in Table 3.

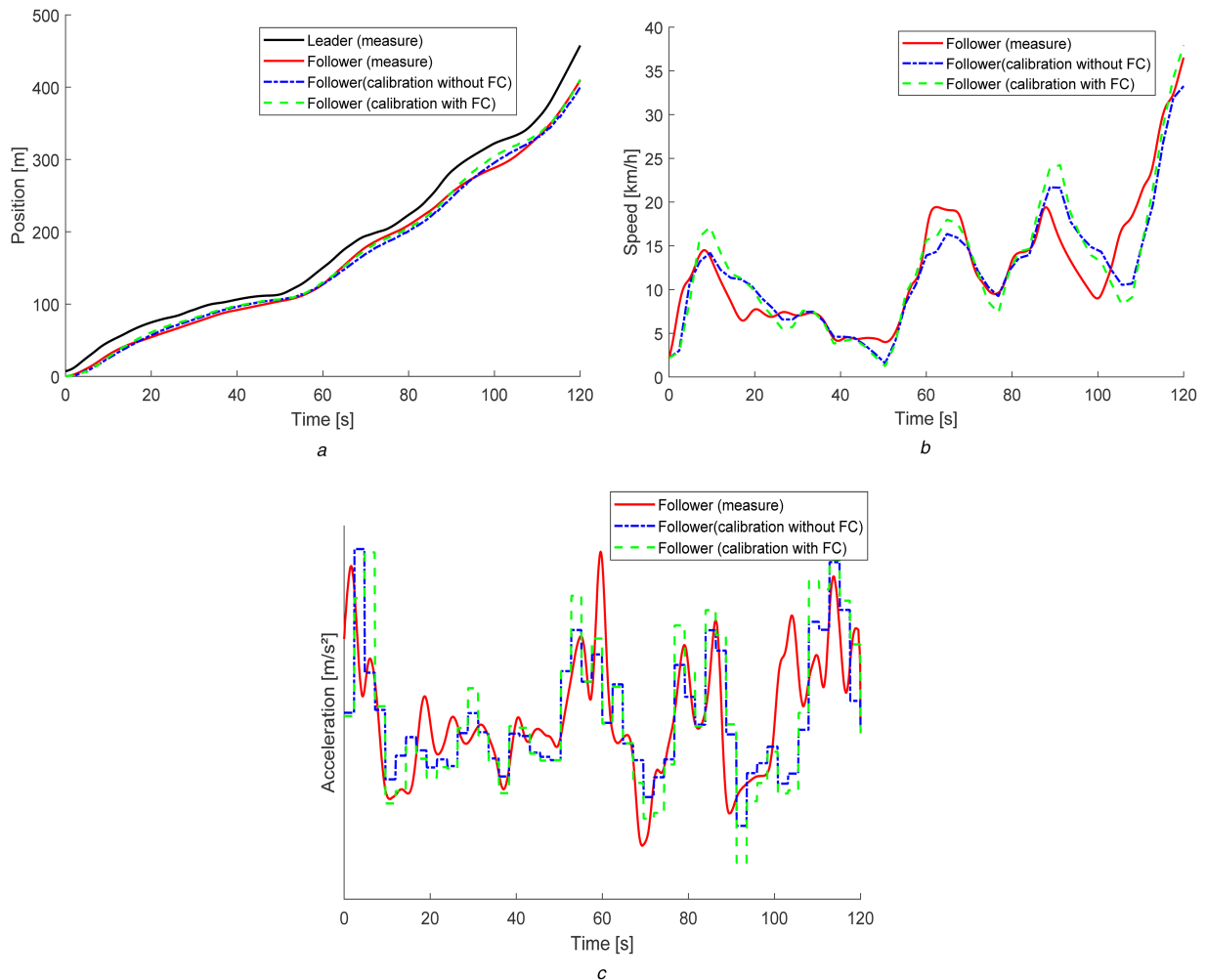


Fig. 3 Measured and simulated trajectory of the vehicle for cycle 1u
(a) Position, (b) Speed, (c) Acceleration

We can see that the calibration has provided good results. The errors on position and speed are very low for all of the cycles. The errors on acceleration are higher than on the other variables. This can be explained by the fact that Gipps' model output is the speed, which is derived to obtain acceleration. Moreover, the acceleration profile of a vehicle oscillates with a higher frequency than the speed, which made it more difficult to model accurately.

In [11], the author proposed a new model (LOLIMOT) to represent truck-following behaviour and compared it to Gipps' model calibrated with a genetic algorithm (GA) using the squared error as GoF function. The MoP used is the speed of the truck. The results presented by Aghabayk are expressed as the root mean squared error (RMSE, in km/h) of the speed. The results for a truck following a car are 3.27 and 6.84 km/h, respectively, for LOLIMOT and Gipps' model. For comparison, we compute the RMSE on the simulated speed defined. The results are 2.33 and 3.20 km/h in average, respectively, for urban and regional cycles.

In [8], the authors calibrated the intelligent driver model (IDM) for the four following combinations: car-truck, car-car, truck-car and truck-truck. IDM has been calibrated with a GA using Theil's inequality coefficient as GoF function. The MoP is the acceleration. The results presented in [8] are expressed using the mean absolute error (MAE). For the truck-car combination, the results are 5.75 m (3%), 4.32 km/h and 1.24 m/s², respectively, for the position, the speed and the acceleration. For comparison, the error on the simulated trajectories defined in this paper is computed again but with the MAE function. The results are 3.60 m (3.8%), 1.82 km/h and 0.17 m/s² in average for the urban cycles; for regional cycles results are 8.49 m (1.2%), 2.43 km/h and 0.16 m/s², respectively, for the position, the speed and the acceleration. The calibration method proposed in this paper provides better results

than the one in the previous studies. The MAE values for the ten cycles studied here are detailed in Table 3.

An example (cycle 1u) of the simulated trajectories compared to the measured ones is presented in Fig. 3.

5.2 Robustness to mean parameters

In the previous section we have seen that the Gipps' car-following model was calibrated on the ten selected cycles and results are pretty good. Here we will study the robustness of the model to the use of average parameters per category of cycles: urban and regional.

For each category, we define a unique set of parameters as the average of the optimal set of parameters of the cycles of the category. This set is then used to simulate the cycles of the category and the errors are computed. Table 4 shows the results of these simulations, the errors using optimal or average parameters are compared. We can see that the use of average parameters does not deteriorate too much the error values. Particularly, errors on position are still very good. The other errors increased, but their values are still acceptable. In practice, it is interesting to have a generic model well calibrated for different type of roads or different use cases. The robustness of Gipps model to the use of average parameters allows using it in a generic simulation tool.

5.3 Application to fuel consumption

The previous sections have allowed demonstrating that Gipps car-following model could be relevant to simulate the behaviour of a heavy vehicle. However, we would like now to assess if these simulated trajectories are enough precise to estimate the fuel consumption.

Table 4 Errors, for the ten cycles, on position, spacing, speed and acceleration, for optimal and averaged parameters

	Urban									
	Optimal parameters					Averaged parameters				
Theil's inequality coefficient										
no.	1u	2u	3u	4u	5u	1u	2u	3u	4u	5u
position, %	1.43	0.51	0.47	1.90	1.15	2.20	2.21	4.16	5.68	2.66
spacing, %	12.16	10.93	4.71	3.10	6.62	23.84	33.03	29.36	11.02	13.99
speed, %	10.43	3.10	1.96	6.04	2.13	10.01	5.79	7.56	8.16	4.49
acceleration, %	40.83	30.47	13.19	24.23	26.46	44.65	42.05	23.37	38.44	36.78
MAE										
no.	1u	2u	3u	4u	5u	1u	2u	3u	4u	5u
position, m	4.94	5.01	1.98	2.68	3.37	7.13	20.04	18.37	8.47	7.22
spacing, m	4.94	5.01	1.98	2.68	3.37	7.13	20.04	18.37	8.47	7.22
speed, km/h	2.10	2.13	1.33	2.43	1.09	2.34	3.63	5.33	4.04	2.27
acceleration, m/s ²	0.17	0.14	0.12	0.23	0.18	0.22	0.18	0.23	0.40	0.23

	Regional									
	Optimal parameter					Averaged parameters				
Theil's inequality coefficient										
no.	1r	2r	3r	4r	5r	1r	2r	3r	4r	5r
position, %	0.59	0.22	0.56	0.45	0.63	0.52	1.71	0.72	1.11	1.26
spacing, %	13.70	6.98	8.30	11.75	8.76	12.91	36.98	10.58	22.69	15.74
speed, %	2.65	2.32	3.30	3.01	3.66	3.64	4.20	3.81	3.28	3.75
acceleration, %	32.60	21.50	24.88	23.22	25.53	43.02	27.59	39.84	29.32	28.88
MAE										
no.	1r	2r	3r	4r	5r	1r	2r	3r	4r	5r
position, m	14.77	4.41	9.56	8.33	5.38	12.78	37.15	12.97	21.06	10.76
spacing, m	14.77	4.41	9.56	8.33	5.38	12.78	37.15	12.97	21.06	10.76
speed, km/h	2.53	2.19	2.93	2.18	2.34	3.71	4.31	4.28	2.93	2.66
acceleration, m/s ²	0.14	0.17	0.16	0.11	0.21	0.19	0.20	0.27	0.16	0.26

Table 5 Fuel consumption estimation relative errors between the simulation and the measure (in %), and corresponding MAE values

	Urban					Regional				
	1u	2u	3u	4u	5u	1r	2r	3r	4r	5r
no.										
fuel consumption relative error, %	-14.22	21.13	-8.09	-9.58	-1.04	3.24	4.07	4.34	9.87	-3.67
MAE, L	0.0088	0.0276	0.0062	0.0095	0.0137	0.0164	0.0111	0.0148	0.0229	0.0096

The tool used to estimate the fuel consumption is an internal tool used within Volvo Group. It takes as input the speed of the vehicle. The speed profiles generated with the calibrated Gipps' model are given as input to this tool which computes the corresponding fuel consumption (at each time step and the fuel consumption expressed in $L/100$ km). This tool also takes into account the slope along the cycle and the type of vehicle (engine, gearbox etc.).

The results of the simulations are presented in Table 5. It presents the errors in percentage between the total fuel consumption measured and the simulation expressed in $L/100$ km, and the corresponding MAE value.

The results of the fuel consumption estimation are not so good because they represent a significant gap for the total consumption over the cycles. The error values are closer to each other for regional cycles (between -3.67 and 9.87%) than for urban cycles where error goes from -14 to 21% .

Fig. 4 compares the cumulated fuel consumption measured and simulated. We can observe several differences in the data. The first one occurs between 20 and 50 s. This corresponds to a part of the sub-cycle 1u where the simulated acceleration is not accurately estimated compared to the measured one, and the speed is low (<10 km/h). The emissions are very sensitive to the acceleration in this range of speed and even if the errors on the car-following model look minimal for the spacing and the speed, they are too

important in acceleration. Two other differences occur at time $t = 60$ s and $t = 90$ s. At these moments, the simulated speed is far from the measured one. At time $t = 90$ s, the speed has been overestimated, which implies that the follower is too close to the leader and needs to decelerate more than in the measurement (until $t = 110$ s) to avoid collision. This longer deceleration causes a longer time during which the follower does not use fuel which can be observed in Fig. 4. This explains the gap at the end of the sub-cycle 1u.

As shown in [28] for passenger vehicles, we also see here that good calibration results from a traffic point of view do not necessarily imply accurate estimation for fuel consumption. However, car-following models or traffic models are always calibrated regarding to traffic indicators, and they are used to estimate energy consumption or pollutant emissions. As we can see in this study, this method can lead to bias in energy consumption value, particularly for HDVs.

To solve this problem, we propose to add the fuel consumption estimation into the calibration process as a fourth MoP.

5.4 Fuel consumption estimation, the fourth MoP

The calibration of Gipps' car-following model is done again but with four MoPs this time: the spacing between the truck and its leader, and the speed, the acceleration and the cumulated fuel consumption of the truck. The fuel consumption is estimated

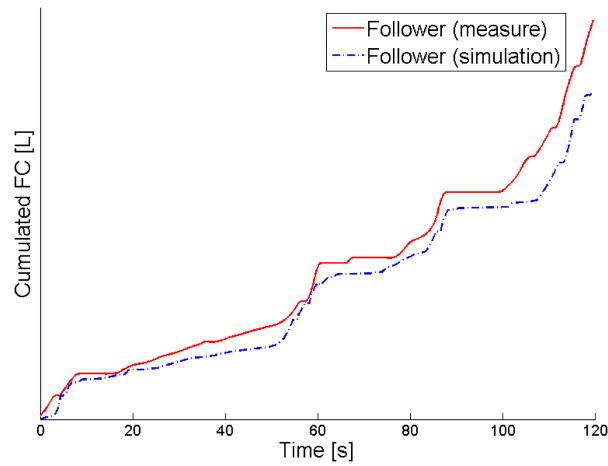


Fig. 4 Measured and simulated fuel consumption for cycle 1u

Table 6 Errors (Theil's inequality coefficient and MAE), for the ten cycles, on position, spacing, speed and acceleration, and relative error for fuel consumption between the simulation and the measure in %

	Urban					Regional				
Theil's inequality coefficient										
no.	1u	2u	3u	4u	5u	1r	2r	3r	4r	5r
position, %	1.49	0.70	0.45	1.26	1.05	0.54	0.19	0.62	0.48	0.67
spacing, %	13.82	13.82	4.78	2.05	6.12	12.71	6.48	9.44	13.22	9.27
speed, %	11.27	3.49	2.02	3.39	2.10	2.59	2.27	2.95	1.99	3.50
acceleration, %	41.29	31.56	14.30	25.58	26.75	31.56	21.69	24.16	23.25	24.79
fuel consumption, %	-6.90	9.82	4.43	1.56	0.22	2.50	2.58	0.71	7.91	3.13
MAE										
no.	1u	2u	3u	4u	5u	1r	2r	3r	4r	5r
position, m	4.83	13.07	2.19	2.69	12.16	40.09	5.58	10.09	12.90	5.45
spacing, m	4.83	13.07	2.19	2.69	12.16	40.09	5.58	10.09	12.90	5.45
speed, km/h	2.31	2.47	0.99	3.32	1.68	3.05	2.12	3.05	2.24	2.32
acceleration, m/s ²	0.20	0.13	0.13	0.27	0.18	0.12	0.16	0.16	0.11	0.20
fuel consumption, L	0.0034	0.0053	0.0030	0.0068	0.0057	0.0168	0.0062	0.0151	0.0057	0.0043

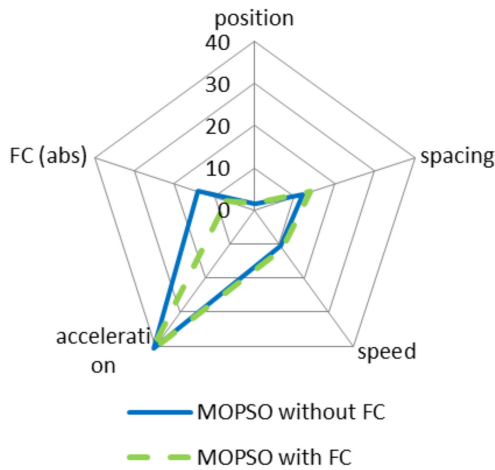


Fig. 5 Error evolution between calibration without and with fuel consumption estimation in MoPs

thanks to the tool mentioned in Section 5.3. Results are presented in Table 6.

We observe that the errors on position, spacing, speed or acceleration are really close to the errors presented in previous sections. However, the errors on fuel consumption estimations are reduced significantly.

It means that we can reduce the error on fuel consumption estimation without deteriorating the error on trajectory indicators. The optimal parameters domain from a traffic point of view is large and including another indicator in the calibration process helps to

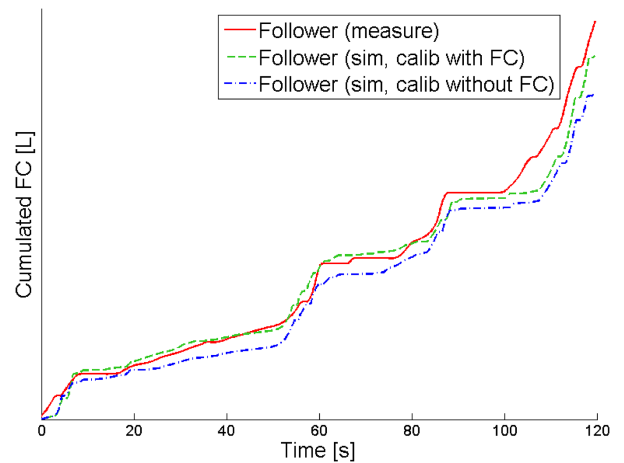


Fig. 6 Measured and simulated fuel consumption for cycle 1u

narrow it. Fig. 5 illustrates the fact that improvement of fuel consumption estimation does not affect other MoPs.

Fig. 6 presents the improvement of the fuel consumption estimation after the calibration in four dimensions. We can observe that the majority of the errors that have been previously highlighted in Section 5.3 has been corrected. By increasing the speed of the follower at time $t = 10$ s, the simulated fuel consumption is almost equal to the measured one between times $t = 20$ s and $t = 50$ s, without introducing a gap before. This is because the acceleration profile, between time $t = 10$ s and $t = 20$ s, is now better tuned for the calculation of emission. In the same way, at time $t = 60$ s, the simulated speed is higher and closer to the measured one which

causes that the simulated cumulated fuel consumption is close to the measured on until time $t = 105$ s. At $t = 90$ s, the same error occurs than previously, the vehicle speed is too high and it forces the follower to decelerate more to avoid collision with the leader. However, the vehicle accelerates more than in the previous calibration and because the first errors have been corrected, the final gap is lower.

6 Conclusion

This paper focuses on the calibration of the Gipps' car-following model on truck data. First, by studying the shape of the Theil's inequality coefficient, moreover, the importance of the definition of the MoPs is highlighted. It has been shown that the optimal domains in position, spacing, speed or acceleration are really different (the intersection of optimal domains is really small). Moreover, we have seen that the optimal domains in position or spacing are sharper than the ones in speed or acceleration, which implies that it should be easier to converge to an optimal set of parameters if we calibrate the Gipps' car-following model only on position or spacing than on speed or acceleration. The MO calibration (on spacing, speed and acceleration) has been chosen to find good parameters to represent truck's behaviour and dynamics.

The calibration of the Gipps' car-following model has been done using MOPSO with three MoPs: spacing, speed and acceleration, and it provides good results. The errors on position and speed are most of the time lower than 2% and 4%, respectively. The errors on the acceleration mainly fluctuates around 25%, and contrary to what was previously found in the literature [29], Gipps' model does not overestimate the acceleration value of the truck. Moreover, we have shown that the calibrated model is robust, because we can use average optimal parameters instead of optimal one without losing the ability of the model to reproduce the measured trajectory.

The calibrated model has then been used to generate simulated trajectories on which the fuel consumption has been evaluated. It has been shown that even if those trajectories were close to the measurement, the resulting energy consumption was not so good. To solve this issue, the fuel consumption evaluation has been added to the calibration process as a fourth MoP. Taking into account the fuel consumption estimation of the vehicle leads to better results than previously. Since GoF function is flat for the speed and the acceleration, we can reduce error value on fuel consumption without increasing too much the error on the other MoPs.

This study has shown, as in [28], that car-following models could be well calibrated from a traffic point of view but not from an energy consumption point of view. A solution is proposed to solve this problem.

This work points out an important issue in the way traffic simulation tools are used. Actually, car-following models are calibrated based on traffic data (macroscopic or microscopic) and they were originally used to evaluate road construction new control strategies or to predict traffic evolution. Their validity was mainly validated in this context. However, these models are now more and more used to estimate environmental parameters such as energy consumption, fine particles or CO₂ emissions and the effects of new driving strategies such as ITS and ADAS on the environment. A bias can be observed between real emissions and simulated emissions because the simulation tools are calibrated for traffic purposes. It is important to notice this phenomenon to calibrate the models in a proper way for emission estimations.

7 Discussion

This study was done considering only one case: the leading vehicle is a car and the following vehicle is a truck. However, the same results were demonstrated in the case of a car following a car in [28], and we can assume that it will be true for the two other following situations. Gipps' car-following model was here calibrated for a particular vehicle. The optimal parameters found could not be optimal for another vehicle, but the methodology of the calibration could be used for any other vehicle.

Moreover, because of the small number of available cycles, the validation of the model was not done on another set of cycle. However, the robustness of the model to the use of averaged parameters (per category) has been studied. This verification shows that the spacing and the acceleration are a little sensitive to the use of averaged parameters, whereas the errors on position and speed stay stable. A validation of the model would be done later on another set of cycles to complete the study.

8 References

- [1] Aghabayk, K., Sarvi, M., Young, W.: 'A state-of-the-art review of car-following models with particular considerations of heavy vehicles', *Transp. Res.*, 2015, **35**, (1), pp. 82–105
- [2] Nodine, E., Lam, A., Yanagisawa, M., *et al.*: 'Naturalistic study of truck following behavior', *Transp. Res. Rec.: J. Transp. Res. Board*, 2017, **2615**, pp. 35–42
- [3] Aghabayk, K., Sarvi, M., Young, W.: 'Including heavy vehicles in car-following model: modeling, calibrating and validating', *J. Adv. Transp.*, 2016, **50**, (7), pp. 1432–1446
- [4] Sarvi, M., Eitemai, O.: 'Exploring heavy vehicles car-following behaviour'. Proc. of the 34th Australasian Transport Research Forum (ATRF), Adelaide, South Australia, Australia, 2011, pp. 1–11
- [5] Aghabayk, K., Sarvi, M., Young, W.: 'Understanding the dynamics of heavy vehicle interactions in car-following', *J. Transp. Eng.*, 2012, **138**, (12), pp. 1468–1475
- [6] Sarvi, M.: 'Heavy commercial vehicles-following behaviour and interactions with different vehicle classes', *J. Adv. Transp.*, 2011, **47**, pp. 572–580
- [7] Yang, D., Jin, P., Pu, Y., *et al.*: 'Stability analysis of the mixed traffic flow of cars and trucks using heterogeneous optimal velocity car-following model', *Physica A*, 2014, **395**, pp. 371–383
- [8] Liu, L., Zhu, L., Yang, D.: 'Modeling and simulation of the car-truck heterogeneous traffic flow based on a nonlinear car-following model', *Appl. Math. Comput.*, 2016, **273**, pp. 706–717
- [9] Chen, D., Ahn, S., Bang, S., *et al.*: 'Car-following and lane-changing behavior involving heavy vehicles', *Transp. Res. Rec.: J. Transp. Res. Board*, 2016, **2561**, pp. 89–97
- [10] Aghabayk, K., Sarvi, M., Forouzideh, N., *et al.*: 'New car-following model considering impacts of multiple lead vehicle types', *Transp. Res. Rec.: J. Transp. Res. Board*, 2013, **2390**, pp. 131–137
- [11] Aghabayk, K.: 'Modelling heavy vehicle car-following in congested traffic conditions'. PhD thesis, Department of Civil Engineering, Institute of Transport Studies, Monash University, 2013
- [12] Gipps, P.G.: 'A behavioural car-following model for computer simulation', *Transp. Res. B: Methodol.*, 1981, **15**, (2), pp. 105–111
- [13] Wilson, R.E.: 'An analysis of Gipps' car-following model of highway traffic', *IMA J. Appl. Math.*, 2001, **66**, (5), pp. 509–537
- [14] Ciuffo, B., Punzo, V., Montanino, M.: 'Thirty years of Gipps' car-following model', *Transp. Res. Rec.: J. Transp. Res. Board*, 2012, **2315**, pp. 89–99
- [15] Punzo, V., Simonelli, F.: 'Analysis and comparison of microscopic traffic flow models with real traffic microscopic data', *Transp. Res. Rec.: J. Transp. Res. Board*, 2005, **1934**, pp. 53–63
- [16] Kesting, A., Treiber, M.: 'Calibrating car-following models by using trajectory data: methodological study', *Transp. Res. Rec.: J. Transp. Res. Board*, 2008, **2088**, pp. 148–156
- [17] Ciuffo, B., Punzo, V.: 'Verification of traffic micro-simulation model calibration procedures: analysis of goodness-of-fit measures'. Proc. of the 89th Annual Meeting of the Transportation Research Record, Washington, DC, USA, 2010
- [18] Punzo, V., Ciuffo, B., Montanino, M.: 'May we trust results of car-following models calibration based on trajectory data?'. Proc. of the 91st Transportation Research Board Annual meeting, Transportation Research Board of the National Academies, Washington, DC, USA, 2012
- [19] Treiber, M., Kesting, A.: 'A microscopic calibration and validation of car-following models – a systematic approach', *Proc. Soc. Behav. Sci.*, 2013, **80**, pp. 922–939
- [20] Punzo, V., Montanino, M.: 'Speed or spacing? cumulative variables, and convolution of model errors and time in traffic flow models validation and calibration', *Transp. Res. B: Methodol.*, 2016, **91**, pp. 21–33
- [21] Ossen, S., Hoogendoorn, S.: 'Calibrating car-following models using microscopic trajectory data: a critical analysis of both microscopic trajectory data collection methods and calibration studies based on these data', *Delft Univ. Technol.*, 2008, **vol. 21**
- [22] Kim, J., Mahmassani, H.: 'Correlated parameters in driving behaviour models: car-following example and its implication for traffic microsimulation', *Transp. Res. Rec.: J. Transp. Res. Board*, 2011, **2249**, pp. 62–77
- [23] Kennedy, J., Eberhart, R.: 'Particle swarm optimization'. IEEE. Conf. Neural Networks, Perth, Australia, Perth, Australia, 1995, **vol. 4**, pp. 1942–1948
- [24] Eberhart, R., Kennedy, J.: 'A new optimizer using particle swarm theory'. IEEE. Micro Machine and Human Science, Nagoya, Japan, 1995, pp. 39–43
- [25] Coelho Coelho, C.A., Lechuga, M.S.: 'MOPSO: a proposal for multiple objective particle swarm optimization'. IEEE. Evolutionary Computation, Honolulu, HI, USA, 2002, pp. 1051–1056
- [26] Alvarez-Benitez, J.E., Everson, R.M.: 'A MOPSO algorithm based exclusively on pareto dominance concepts'. Third Int. Conf. on Evolutionary Multi-Criterion Optimization, Guanajuato, Mexico, 2005, pp. 459–473

- [27] Eberhart, R.C., Shi, Y.: 'Comparing inertia weights and constriction factors in particle swarm optimization'. Proc. of the 2000 Congress on Evolutionary Computation, La Jolla, CA, USA, 2000, vol. 1, pp. 84–88
- [28] Vieira da Rocha, T., Leclercq, L., Montanino, M., *et al.*: 'Does traffic-related calibration of car-following models provide accurate estimations of vehicle emissions?', *Transp. Res. D: Transp. Environ.*, 2015, **34**, pp. 267–280
- [29] Rakha, H., Wang, W.: 'Procedure for calibration Gipps car-following model', *Transp. Res. Rec.: J. Transp. Res. Board*, 2009, **2124**, pp. 113–124

9 Appendix

Definition 1: Pareto optimality: $\mathbf{x}^* \in \Omega$ is Pareto optimal if $\forall \mathbf{x} \in \Omega$ and $I = \{1, \dots, k\}$ either

$$\forall i \in I, \quad f_i(\mathbf{x}) = f_i(\mathbf{x}^*)$$

or

$$\exists i \in I, \quad f_i(\mathbf{x}) > f_i(\mathbf{x}^*)$$

Definition 2: Pareto dominance: $\mathbf{u} = (u_1, \dots, u_k)$ is said to dominate in the sense of Pareto $\mathbf{v} = (v_1, \dots, v_k)$, ($\mathbf{u} \leq \mathbf{v}$) if and only if

$$\forall i \in \{1, \dots, k\}, \quad u_i \leq v_i$$

and

$$\exists i \in \{1, \dots, k\}, \quad u_i < v_i$$