Available online at www.sciencedirect.com

ScienceDirect

Transportation Research Procedia 3 (2014) 952 – 961

Transportation Research Procedia

www.elsevier.com/locate/procedia

17th Meeting of the EURO Working Group on Transportation, EWGT2014, 2-4 July 2014, Sevilla, Spain

Calibration of the Gipps car-following model using trajectory data

Luís Vasconcelos[a*], Luís Neto[a], Sílvia Santos[b], Ana Bastos Silva[b], Álvaro Seco[b]

[a]*Polytechnic Institute of Viseu, Campus Politécnico de Repeses, 3504-510 Viseu, Portugal*
[b]*University of Coimbra, Rua Luís Reis Santos, 3030-788 Coimbra, Portugal*

Abstract

One of the most important tasks in the microscopic simulation of traffic flow, assigned to the car following sub-model, is the modelling of the longitudinal movement of vehicles. The calibration of a car-following model is usually done at an aggregated level, using macroscopic traffic stream variables (speed, flow, density). There is an interest in calibration procedures based on disaggregated data. However, obtaining accurate trajectory data is a real challenge.
This paper presents a low-cost procedure to calibrate the Gipps car-following model. The trajectory data is collected with a car equipped with a datalogger and a LIDAR rangefinder. The datalogger combines GPS and accelerometers data to provide accurate speed and acceleration measurements. The LIDAR measures the distances to the leading or following vehicle.
Two alternative estimation methods were tested: the first follows individual procedures that explicitly account for the physical meaning of each parameter; the second formulates the calibration as an optimization problem: the objective function is defined so as to minimize the differences between the simulated and real inter-vehicle distances; the problem is solved using an automated procedure based on a genetic algorithm.
The results show that the optimization approach leads to a very accurate representation of the specific modeled situation but offers poor transferability; on the other hand, the individual estimation provides a satisfactory fit in a wide range of traffic conditions and hence is the recommended method for forecasting purposes.

Selection and peer-review under responsibility of the Scientific Committee of EWGT2014

Keywords: Car Following; Gipps; Acceleration; Reaction Time; Genetic Algorithm; Calibration.

* Corresponding author. *E-mail address:* vasconcelos@estv.ipv.pt

Selection and peer-review under responsibility of the Scientific Committee of EWGT2014
doi:10.1016/j.trpro.2014.10.075

1. Introduction

Microscopic modelling of traffic flows is based on the description of each individual vehicle composing the traffic stream. This implies modeling the actions – acceleration, deceleration and lane changes – of each driver in response to the surrounding traffic (Barceló, 2010). One of the most important tasks in the simulation, assigned to the car following sub-model, is the modelling of the longitudinal movement of vehicles. According to Treiber and Kesting (2013a) a car-following model is complete if it is able to describe all situations including acceleration in free flow conditions, following other vehicles in stationary and non-stationary situations, and approaching slow or standing vehicles, and red lights. A complete model has complex data requirements and numerous model parameters, and, therefore, the calibration and validation tasks are still major requirements and challenges in the use of simulation for practical purposes.

Traditional calibration approaches rely on the use of easily measurable macroscopic traffic data, such as counts and speeds at detectors. The most reliable methodological process consists of checking the values of model parameters that are better fitted to the fundamental relationships of speed, flow and density (Barceló, 2010). For example, Rakha *et al.* (2007) and Vasconcelos *et al.* (2014) suggested analytic calibration procedures for the Gipps' car following model (Gipps, 1981), and more specifically for the set of parameters that intervene in the steady-state operations. Another approach is to formulate the model calibration as an optimization problem in which a combination of parameter values that best satisfies an objective function is searched. The optimization procedure requires a large number of simulation runs (Ciuffo *et al.*, 2008) and it is usual to reduce the optimization complexity by selecting a sub-set of parameters either by engineering judgment or by more systematic techniques, such as sensitivity analyses or analyses of variance (Ciuffo *et al.*, 2013; Punzo and Ciuffo, 2009).

The optimization approach is useful for most practical applications as it gives satisfactory solutions at macroscopic level. However, as it formulates the objective function as a black-box model, without much concern for the physical meaning of each parameter, it may yield parameters that result in inaccurate representations of the traffic streams at the individual vehicle level. In fact, according to Hollander and Liu (2008), when the calibration problem is formulated as an optimization problem, it is unlikely to lead to a global optimum, due to the multidimensionality of the solution search space and the tendency of the observed data to exhibit various inconsistencies.

Casas *et al.* (2010) state that the most exact procedure to calibrate the car-following model is to conduct specific experiments in which accurate field data is recorded on the relative distances and speeds between pairs of leader-follower vehicles, and the simulation model is calibrated against this field data. Trajectory data can be obtained using instrumented vehicles (Brackstone *et al.*, 2002; Ranjitkar *et al.*, 2005) or from aerial images, collected either from tall buildings (Punzo *et al.*, 2011) or from helicopters (Ossen and Hoogendoorn, 2005). These types of experiments are expensive and seldom can be conducted in the current professional practice.

This research is focused on the microscopic calibration of the Gipps car-following model. It has three main objectives: *i*) to test a low-cost method to obtain trajectory data; ii) to understand how the road environment affects the car-following behavior; iii) to compare the effectiveness and applicability of two estimation methods, both based on trajectory data – with Method 1 (sequential calibration) each parameter is estimated individually having in mind its physical meaning; with Method 2 a set of parameters are automatically and simultaneously estimated using an optimization process based on a genetic algorithm.

The paper is organized as follows. Section 2 offers a review of the Gipps car-following model. Section 3 presents the system used to collect the field data. Section 4 describes Method 1 and presents the results of a set of field experiments, categorized by road type. Following that, Section 5 describes Method 2, presents the results of another set of experiments, and compares the resulting parameter values from the two methods. This paper finishes with an outline of the main conclusions in Section 5.

2. The Gipps car-following model

The Gipps' car-following model is the most commonly used model from the collision avoidance class of models. Models of this class aim to specify a safe following distance behind the leader vehicle. Gipps' model is mostly known for being the building block of the Aimsun microscopic simulator (Casas *et al.*, 2010). It consists of two components: acceleration and deceleration sub-models, corresponding to the empirical formulations illustrated by equations (1) and (2), which output the speed of each vehicle at a given time t in terms of its speed at the previous step.

$$v_n^{acc}(t+\tau) = v_n(t) + 2.5\,a_n\tau\left(1 - \frac{v_n(t)}{v_n^d}\right)\sqrt{0.025 + \frac{v_n(t)}{v_n^d}} \tag{1}$$

$$v_n^{dec}(t+\tau) = -\tau d_n + \sqrt{\tau^2 d_n^2 + d_n\left\{2\left[x_{n-1}(t) - x_n(t) - S_{n-1}\right] - \tau v_n(t) + \frac{v_{n-1}(t)^2}{d'_{n-1}}\right\}} \tag{2}$$

where τ is the reaction time, $v_n(t)$ and $v_{n-1}(t)$ are, respectively, the speeds of vehicles n (follower) and n - 1 (leader) at time t, v_n^d and a_n are respectively the follower's desired speed and maximum acceleration, d_n and d'_{n-1} are respectively the most severe braking that the follower wishes to undertake and his estimate of the leader's most severe braking capability ($d_n > 0$ and $d'_{n-1} > 0$), $x_{n-1}(t)$ and $x_n(t)$ are respectively the leader's and the follower's longitudinal positions at time t, and S_{n-1} is the "leader's effective length", that is, the leader's real length L_{n-1} added to the follower's desired inter-vehicle spacing at stop s_{n-1} (between front and rear bumpers).

If vehicle n has a large headway the minimum speed is given by Eq. (1) and the vehicle accelerates freely, tending asymptotically to the desired speed. In other cases the minimum speed is given by Eq. (2). This speed allows the follower to come to a stop, using its maximum desired deceleration d_n, without encroaching on the safety distance. In this derivation it is assumed that the leader brakes according to d'_{n-1} and that the follower cannot commence braking until a reaction time τ has elapsed. The expression implicitly allows for a safety margin (θ) in the reaction time that allows the follower not to brake always at his or her maximum desired rate. Gipps assumed for θ to be equal to $\tau/2$, and for this reason it does not appear in the above equation (Ciuffo *et al.*, 2012). The speed of vehicle n at time $t+\tau$ is given by the minimum of the expressions (1) and (2) above:

$$v_n(t+\tau) = \min\left\{v_n^{acc}(t+\tau), v_n^{dec}(t+\tau)\right\} \tag{3}$$

Then, the position of the vehicle n inside the current lane is updated taking this speed into the movement equation:

$$x_n(t+\tau) = x_n(t) + v_n(t+\tau)\tau \tag{4}$$

3. Data collection technique

The fundamental assumption to this research is that each of the behavior parameters that describe a given driver-vehicle unit has a well-defined physical meaning and therefore can be estimated by conducting specific experiments. This contrasts with the more conventional estimation methodologies that seek the set of parameters that best mimic a given traffic condition, regardless of the values obtained for each parameter.

To support the research real data was collected using a pair of instrumented vehicles. The leader vehicle is an 8-year-old Volkswagen Golf 1.9 TDi, the follower is a Renault Clio Sport Tourer Gasoline 90, each one equipped with a datalogger device from Race Technology Ltd (DL1 MK3) – Figure 1. The data loggers have a 6g 3-axis accelerometer and a 20Hz GPS that allows data to be referenced by time and position on the road. Positional accuracy is about 3 m (circular error probability) and the speed accuracy is better than 0.1 km/h. In addition to position, speed and accelerations, the data loggers allow the connection to external sensors. A LIDAR rangefinder (ULS, from Laser Technology Inc.) was connected to the follower's datalogger to provide real time distances to the leader vehicle. The data analysis was based on the Race Technology software which, with a maximum frequency of 20 Hz, allows the extraction of time series for any measured variable. The variables of interest to the calibration were the leader's position, speed and acceleration and the follower's position and speed. The space headway between the two vehicles was calculated from the GPS positional difference and combined with the LIDAR measurements, resulting in expected errors of less than 0.5 m, already accounting for the errors related to the handheld operation. Some experiments required a single vehicle and were conducted with the Renault Clio (follower). The total cost of this system was approximately 4000€ which makes it affordable to many research units.

Given the objectives of this work a single person was selected to be the follower driver. He was instructed to execute a series of maneuvers, either isolated or following the leading vehicle at his normal safe distance. These maneuvers were performed in two types of road environments: suburban arterial roads (70/90 km/h legal speed limit, no pedestrians and no on-street parking) and urban distributer roads (50 km/h legal limit, on-street parking, high density of crosswalks and, in some cases, informal pedestrian crossing).

Figure 1 – Data acquisition system: top-left – leader vehicle; bottom-left – leader's datalogger; right – handheld operation of the LIDAR on the follower vehicle, targeting the leader's license plate

4. Sequential estimation method

4.1. Maximum desired acceleration and deceleration (a and d)

As referred in section 2, the Gipps acceleration sub-model gives the speed to which a vehicle will accelerate during a time step, assuming free-flow conditions, and depends only on the desired speed v_d and on the maximum desired acceleration a. To obtain the field data required to estimate these parameters the subject driver was instructed to execute a set of elementary acceleration maneuvers: in each of these maneuvers, the driver immobilized the vehicle and then accelerated normally to its desired speed. The deceleration sub-model gives the speed that the vehicle can reach during the time interval (t, $t + \tau$), according to its own characteristics and the limitations imposed by the presence of the lead vehicle. The simplest situation that can be described by this model is the approximation to a stop line (modeled as a stopped vehicle with zero length), starting from the desired speed. This way, following the acceleration maneuver, the driver was instructed to have its speed stabilized before decelerating normally to a full stop (in some cases due to the presence of pedestrians in crosswalks, in other cases merely as a response to the passenger's request). This acceleration-deceleration process was performed 85 times (44 on arterial roads, 41 on distributor roads).

The estimation process consisted of plotting the theoretical time-series of acceleration, speed and distance and manually adjusting, for each case, the intervening parameters (a, d) so as to minimize the eye-measured difference to the corresponding measured data points in the time-speed and time-distance plots (the fitting to the acceleration plot is not viable since the Gipps model doesn't explicitly account for the gear shifts. Figure 2 shows the fitted speed and acceleration plots for one of the observations. The model can accurately reproduce typical acceleration maneuvers only by adjusting v_d and a; the deceleration maneuvers require the adjustment of the deceleration parameter d. The reaction time τ has also some influence on the deceleration profile but a constant value was assumed for all observations since its effect is almost negligible.

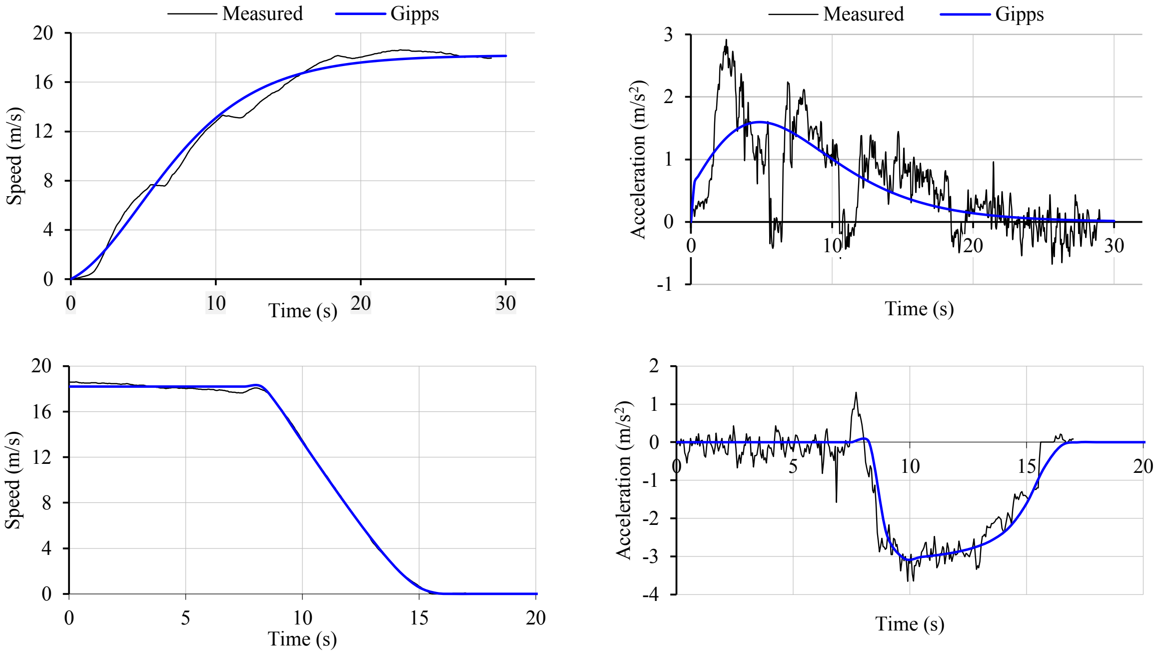

Figure 2 - Manual estimation of Gipps acceleration (top) and deceleration (bottom) parameters – Arterial road, case 8 of 44. Optimal parameters: a = 1.60 m/s^2, v_d = 18.2 m/s, d = 3.3 m/s^2

An independent-samples t-test was conducted to compare acceleration and deceleration values in arterial and distributor roads (Table 1). The results show no statistically difference at the 5% level of confidence for the acceleration values and thus this parameter was taken as the mean of the total sample (a = 1.77 m/s^2). Regarding the deceleration, the comparison of both data sets reveals a statistically significant difference in the means ($p < 0.05$), suggesting a more aggressive driving behavior on arterial roads. The mean values are d = 4.05 m/s^2 and d = 3.50 m/s^2 at arterial and distributer roads respectively.

Table 1 – Acceleration and deceleration values in arterial and distributor roads: t-test results

Variable	Mean Arterial	Mean Distributor	t-value	df	p	Valid N Arterial	Valid N Distributor	Std.Dev. Arterial	Std.Dev. Distributor	F-ratio	p
a	1,811	1,717	1,385	83	0,170	44	41	0,307	0,320	1,084	0,794
d	4,050	3,505	3,180	83	0,002	44	41	0,790	0,789	1,004	0,993

4.2. Reaction time and minimum spacing

These parameters' role in the deceleration sub-model is to return a safe following distance for a given combination of follower/leader vehicles' speeds. The simplest driving situation involving these parameters is the stationary car-following process. In fact, Rakha and Wang (2009) show that in steady-state conditions Eq. (2) can be simplified to give the space headway:

$$h_s = S + 1.5\tau v + \frac{v^2}{2}\left(\frac{1}{d} - \frac{1}{d'}\right), \forall v < v^{max} \quad (5)$$

According to this equation, h_s is given as a sum of three components:

- S - the length L of the leader vehicle added to the minimum desired space s between vehicles;
- $1.5\tau v$ – the distance travelled by the follower vehicle during the perception-reaction time, at constant speed;
- $v^2(1/d - 1/d')/2$ – the difference in the distances travelled during the deceleration by the two vehicles (as estimated by the follower).

Some traffic simulation applications do not require the detailed description of the vehicles' trajectory and thus the simplification $d = d'$ can be assumed, thus leading to a simplified calibration methodology (Vasconcelos *et al.*, 2014)

In order to obtain the field data necessary to estimate these parameters the subject driver was instructed to follow a lead vehicle in several arterial and distributer roads. The leader drove at relatively low speeds (below the follower's desired speed), thus assuring forced following conditions. The passenger in the follower vehicle was continuously measuring the spacing to the lead vehicle with the LIDAR, allowing a representative $h_s - v$ point to be taken for each stretch of road traveled with constant speed and spacing. The sample includes 64 measurements on arterial roads and 46 on distributor roads, including 11 measurements of the minimum spacing s (with $v = 0$) at traffic signals and priority junctions.

Figure 3 reveals the data points clustered in function of the road type, suggesting a more aggressive behavior on the arterial roads. It is also clear that the space headway increases with the speed in an exponential fashion, meaning that the third component of Eq. (5) has a significant value and therefore the abovementioned simplification $d = d'$ cannot be made at this level of detail. The parameters were estimated for each road type by manually fitting the two curves from Eq. (5) to the field data. Only three parameters were adjusted (S, τ and d') as the length of the leader vehicle was directly measured (L = 4.2 m) and the deceleration values were assumed to be the ones previously estimated.

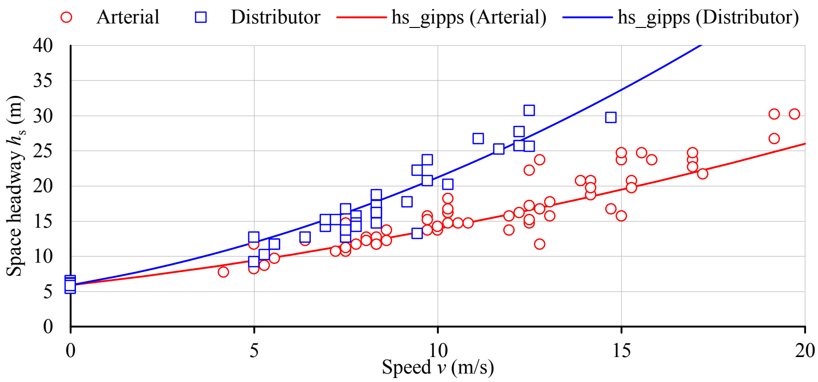

Figure 3 – Best fit curves for the field h_s – v measurements under steady-state conditions

The complete set of parameters for the two road types is listed on Table 2. Regarding the driver's desired speed, although no formal estimation method was followed, it was noticed that the subject driver, under free flow conditions, tends to slightly exceed the legal speed limits and therefore these parameters were set equal to 1.10 times the legal speed limit of each traveled road. It should be noted that under forced following conditions this parameter has a very limited influence in the driver behavior.

Table 2 - Parameters at each road type obtained with the sequential estimation method

Road Type	v_d (m/s)	a (m/s^2)	d (m/s^2)	d' (m/s^2)	s (m)	τ (s)
Arterial	27.5	1.77	4.05	4.92	5.9	0.40
Distributor	15.3		3.51	6.30		0.60

5. Sequential vs simultaneous estimation

Following the individualized and sequential estimation of the Gipps parameters (hereafter named Method 1), we were interested in understanding how useful they are to predict the driver behavior on different roads, taking as reference the results of the conventional estimation method based on optimization (Treiber and Kesting, 2013b) - Method 2. Five new circuits were selected – two in arterial roads and three in distributer roads. In each circuit, the leader performed a sequence of maneuvers that influenced the follower's behavior, given that it was not possible to overtake or use other lanes. The optimization framework was implemented in Matlab using the built-in genetic algorithm tool. The objective function was defined so as to minimize the difference between the measured and predicted time series of the space headway, given by the average root mean square error (RMSE). The resulting optimal parameters, listed on Table 3, are very variable among the different roads, even when comparing values within the same road group.

Table 3 – Optimal parameters at each road type obtained with the simultaneous estimation method (genetic algorithm)

Road Type	Road / Street	v_d (m/s)	a (m/s^2)	d (m/s^2)	d' (m/s^2)	S (m)	τ (s)
Arterial	EN 17	26,00	0,82	2,53	2,78	5,20	0,40
	EN 341	24,47	9,80	8,87	13,03	4,95	0,50
Distributor	Montes Claros	11,50	1,53	5,06	5,08	5,91	0,75
	Av. Dias Silva	13,05	1,06	2,87	3,06	7,24	0,79
	R. Brasil	18,03	1,42	2,87	3,69	4,89	0,82

The plots in Figure 4 compare the model predictions with the field measurements and indicate that Method 2 (Genetic Algorithm) is very effective at replicating the closing-in and shying-away patterns. This is not surprising since each run was simulated with its own set of optimal parameters. However, in practical applications it would be unrealistic to expect users to calibrate the model for each and every type of traffic situation (and in many cases it would even be impossible), as was done in this exercise. The real challenge of any simulation model is to make accurate predictions outside its calibration domain.

This way, in order to investigate the predictive and transferability power of the two alternative calibration methods, it was assumed a set of scenarios in which the optimal behavioral parameters of each circuit obtained by each method would be used to model the remaining circuits. The results (see Table 4) indicate that this approach has very variable results, sometimes resulting in poor fits. The simulation with the parameters from method 1 (individually estimated), provide a satisfactory fit at each circuit (for example, the simulation of EN 341 using the optimal parameters from EN 17 results in a RMSE value of 4.15, vis-à-vis the RMSE value of 3.00 obtained when the generic parameters from method 1 are used).

It can thus be concluded that Method 1, based on the physical meaning of each parameters, is much more robust and transferable, being recommended for forecasting purposes. Method 2 is preferable if the main objective is to accurately characterize an existing traffic condition (for example for demonstration or visualization purposes).

Table 4 – Comparison of the goodness-of-fit at each circuit using different sources of optimal parameters (RMSE values calculated when parameters specifically estimated for the road defined in the column are applied to the road specified in the row)

		Goodness of Fit (RMSE) for the different sets of parameters					
		Method 1 (parameters from Table 2)	Method 2 (parameters from Table 3)				
Road Type	Road / Street		EN 17	EN 341	Montes Claros	Av. Dias Silva	R. Brasil
Arterial	EN 17	3.48	3.08	3.22	--	--	--
	EN 341	3.00	4.15	2.69	--	--	--
Distributor	Montes Claros	2.97	--	--	1.35	4.52	2.94
	Av. Dias Silva	2.61	--	--	3.76	2.09	2.59
	R. Brasil	3.16	--	--	5.14	5.72	3.02

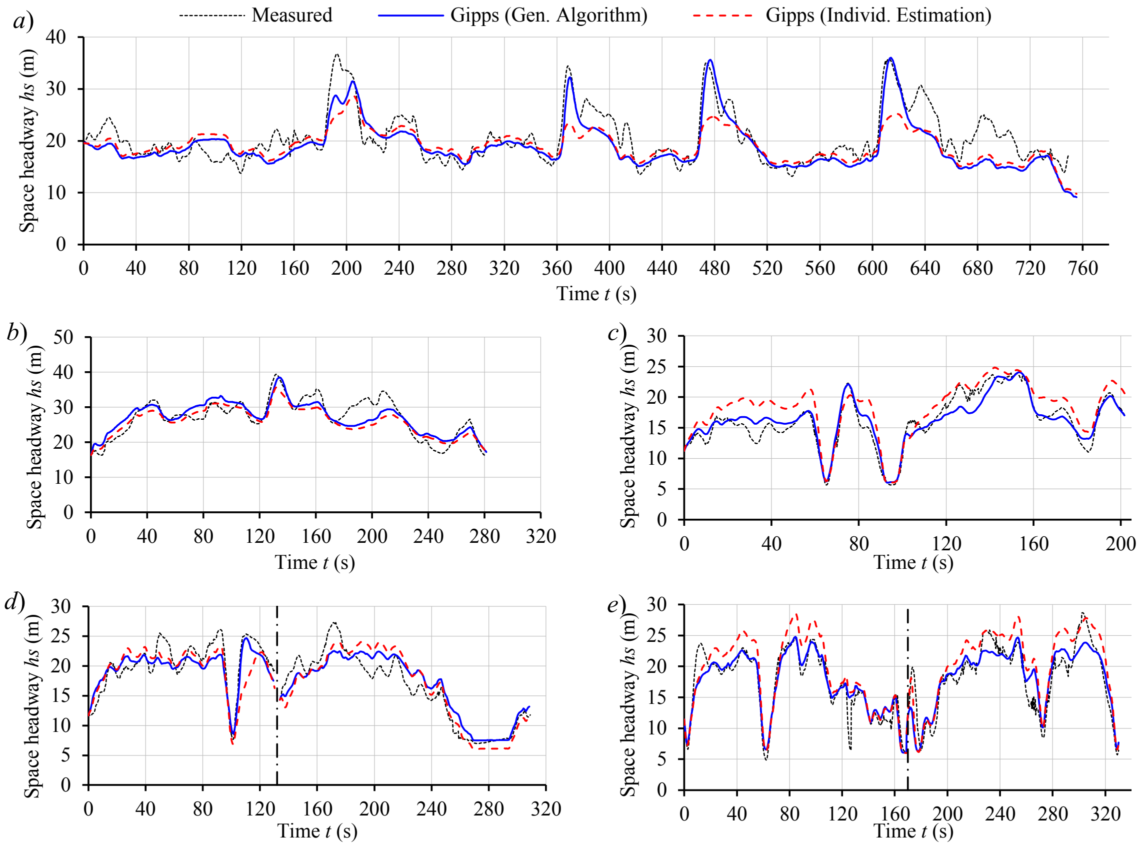

Figure 4 – Time series of the space headway (hs): a) N17, b) N341, c) Montes Claros, d) Av. Dias da Silva, e) R. Brasil. The vertical dashed lines in graphs d) and e) indicate a break in the time series corresponding to a direction change.

6. Conclusions

One of the most important facets of this research was to test a method to calibrate car-following models that can be easily replicated in the future by any research group. This method is adequately accurate, rather inexpensive, and simple to follow, requiring only two data loggers and a LIDAR rangefinder

Regarding the calibration results our sequential estimation method made it possible to realize that, in this set of cases, the desired acceleration parameter does not present a statistically significant difference between the two different road environments (arterial, distributor). On the other hand, it revealed a statistically significant difference in the deceleration parameters, suggesting a more aggressive driving behavior on arterial roads. Furthermore, while the estimated values for the minimum spacing proved to be the same in both environments, as anticipated, a substantial distinction between the reaction time parameters was noted, also suggesting a more aggressive behavior on arterial roads. The experiments have also shown that the space headway increases with the speed in an exponential fashion; the linear relation, sometimes assumed at the macroscopic level, is not valid for this degree of detail.

This research proves that calibration based on optimization is the most effective at replicating the closing-in and shying-away patterns of a specific run. However, simulating with the optimal parameters of a different circuit presents inconstant and, sometimes, poor results, whereas individually estimated parameters provide a satisfactory fit for every circuit. This way the optimization method is recommended for the accurate modelling of a specific traffic situation (for example for public presentations) whereas the sequential estimation method is recommended for forecasting purposes.

Nonetheless, there are some limitations of these estimation methods that justify future research efforts: first, only one person was used as a test driver and it is important to understand if the main conclusions continue to hold with different drivers; second, it would be interesting to see if the results from Method 2 can be improved by increasing the run lengths and by mixing driving environments (e.g. stop-and-go and free-flow conditions); finally, it would be important to understand if the subject drivers, being aware that their behaviors are being recorded, have a natural driving behavior or, on the contrary, it is necessary to observe unaware drivers.

Acknowledgements

This work has been carried out in the framework of projects EMSURE - Energy and Mobility for Sustainable Regions (CENTRO-07-0224-FEDER-002004) and AROUND (FCT project PTDC/SEN-TRA/122114/2010).

References

Barceló, J., 2010. Models, Traffic Models, Simulation, and Traffic Simulation, in: Barceló, J. (Ed.), *Fundamentals of Traffic Simulation*. Springer New York, pp. 1-62, DOI: 10.1007/978-1-4419-6142-6_1.

Brackstone, M., Sultan, B., McDonald, M., 2002. Motorway driver behaviour: studies on car following. *Transportation Research Part F: Traffic Psychology and Behaviour* **5**(1), p. 31-46, DOI: 10.1016/S1369-8478(02)00004-9.

Casas, J., Ferrer, J., Garcia, D., Perarnau, J., Torday, A., 2010. Traffic Simulation with Aimsun, in: Barceló, J. (Ed.), *Fundamentals of Traffic Simulation*. Springer New York, pp. 173-232, DOI: 10.1007/978-1-4419-6142-6_5.

Ciuffo, B., Casas, J., Montanino, M., Perarnau, J., Punzo, V., 2013. Gaussian Process Metamodels for Sensitivity Analysis of Traffic Simulation Models. *Transportation Research Record: Journal of the Transportation Research Board* **2390**(-1), p. 87-98, DOI: 10.3141/2390-10.

Ciuffo, B., Punzo, V., Torrieri, V., 2008. Comparison of Simulation-Based and Model-Based Calibrations of Traffic-Flow Microsimulation Models. *Transportation Research Record: Journal of the Transportation Research Board* **2088**, p. 36-44, DOI: 10.3141/2088-05.

Ciuffo, B.F., Punzo, V., Montanino, M., 2012. Thirty Years of Gipps's Car-Following Model: Applications, Developments, and New Features, *TRB 91st Annual Meeting*, Washington D.C.

Gipps, P.G., 1981. A behavioural car-following model for computer simulation. *Transportation Research Part B: Methodological* **15**(2), p. 105-111, DOI: 10.1016/0191-2615(81)90037-0.

Hollander, Y., Liu, R., 2008. The principles of calibrating traffic microsimulation models. *Transportation* **35**(3), p. 347-362, DOI: 10.1007/s11116-007-9156-2.

Ossen, S., Hoogendoorn, S., 2005. Car-Following Behavior Analysis from Microscopic Trajectory Data. *Transportation Research Record: Journal of the Transportation Research Board* **1934**, p. 13-21, DOI: 10.3141/1934-02.

Punzo, V., Borzacchiello, M.T., Ciuffo, B., 2011. On the assessment of vehicle trajectory data accuracy and application to the Next Generation SIMulation (NGSIM) program data. *Transportation Research Part C: Emerging Technologies* **19**(6), p. 1243-1262, DOI: http://dx.doi.org/10.1016/j.trc.2010.12.007.

Punzo, V., Ciuffo, B., 2009. How Parameters of Microscopic Traffic Flow Models Relate to Traffic Dynamics in Simulation. *Transportation Research Record: Journal of the Transportation Research Board* **2124**, p. 249-256, DOI: 10.3141/2124-25.

Rakha, H., Pecker, C., Cybis, H., 2007. Calibration Procedure for Gipps Car-Following Model. *Transportation Research Record: Journal of the Transportation Research Board* **1999**, p. 115-127, DOI: 10.3141/1999-13.

Rakha, H., Wang, W., 2009. Procedure for Calibrating the Gipps Car-following Model, *TRB 2009 Annual Meeting*. Transportation Research Board, Washington DC.

Ranjitkar, P., Nakatsuji, T., Kawamura, A., 2005. Experimental Analysis of Car-Following Dynamics and Traffic Stability. *Transportation Research Record: Journal of the Transportation Research Board* **1934**, p. 22-32, DOI: 10.3141/1934-03.

Treiber, M., Kesting, A., 2013a. Elementary Car-Following Models, *Traffic Flow Dynamics*. Springer Berlin Heidelberg, pp. 157-180, DOI: 10.1007/978-3-642-32460-4_10.

Treiber, M., Kesting, A., 2013b. Microscopic Calibration and Validation of Car-Following Models – A Systematic Approach. *Procedia - Social and Behavioral Sciences* **80**(0), p. 922-939, DOI: http://dx.doi.org/10.1016/j.sbspro.2013.05.050.

Vasconcelos, L., Seco, Á., Silva, A., 2014. Hybrid Calibration of Microscopic Simulation Models, in: Sousa, J.F., Rossi, R. (Eds.), *Computer-based Modelling and Optimization in Transportation*. Springer International Publishing, pp. 307-320, DOI: 10.1007/978-3-319-04630-3_23.