On-line calibration of car-following models exploiting input parameter correlation

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ABSTRACT

Car-following models have been extensively studied in the last decades. However, the calibration of these models requires further research, so that drivers' behavior could be simulated in high accuracy. The effectiveness of car-following models is closely related to the potentially best estimation of their parameters, mainly the calibration process. Default parameter values may be inappropriate for capturing driving behavior under various circumstances. In order to address this problem, an alternative methodological approach for calibration of car-following models is proposed in this research. Different sets of parameter values could be set for each time instant of the model, as traffic conditions are modified dynamically over the time. Optimal model parameters are closely related to input parameters and thus an on-line calibration is proposed. In addition, a static calibration is illustrated and is used as a reference benchmark for comparison. Real trajectory data was available from an experiment conducted in Naples and was used for a case study in this research. The results from static and on-line calibration of a well-known car-following model are also compared with the results from a previous work in which same data have been used. On-line calibration seems to be a promising solution for the development of flexible and reliable models.

1. INTRODUCTION

Simulation models do not always adequately reflect field conditions outside of the time period for which they have been calibrated [1-3]. Microscopic models often comprise different detailed models, including car-following, lane-changing and gap-acceptance models. In most cases, the parameters of these models are assumed to be stable, both across space and time, and also across drivers.

The online calibration of car-following models is a promising approach to capture the heterogeneity of driver behavior and traffic conditions. By continuously supplying a car-following model with surveillance data, an online calibration process could be applied in order to adapt model parameters to the current traffic state. In this view, the use of richer data, such as real-time Floating Car Data (FCD), based on traces of GPS positions, could be leveraged as a reliable and cost-effective way to gather accurate traffic data [4-5]. Calibration of car-following models [6] has been an issue for a long time [7], but nowadays it has received a new boost [8-9], in light of new data-collection techniques, mostly related to the increasing availability of trajectory data [10-12] which of course introduce other challenges [13].

The objective of this paper is to motivate, develop and demonstrate with real data a practical and simple approach for the online calibration of microscopic traffic simulation models, which considers dynamic parameters for individual drivers, in time and space. Firstly, a literature review is presented in the following section. Then, the overall methodological framework is presented. A case study setup to demonstrate the feasibility and superiority of the approach, over previous techniques, is then presented, followed by a discussion of the conclusions and future prospects.

2. LITERATURE REVIEW

Reliable representation of driving behavior is a crucial issue for traffic simulation. Appropriate simulation models are chosen according to the requirements of each application; when considering the modeling detail, traffic simulation models can be divided into microscopic, mesoscopic and macroscopic. Microscopic models provide the highest level of detail for advanced transport applications [14]. However, the traditional static calibration approach may not allow the incorporation of driving heterogeneity in the simulation.

Many car-following models predict a stable car-following behavior with a very small fluctuation around an equilibrium value. However, in reality these fluctuations are much larger than these models predict. Wagner [15] has attributed them not due to driver heterogeneity, but to an internal stochasticity of the driver itself. Randomness is thus incorporated in traffic flow and model calibration requires the flexibility to adapt to it. On the other hand, several empirical analyses performed by Ossen [16] showed a high degree of driver heterogeneity in car-following. Inter-driver differences could be described not only by different parameter values, but also different model specifications may be needed. All above researchers conclude that different optimal parameter values, as well as different optimal car-following models, should be applied to overcome this problem.

Static calibration requires a database with historical data. It could feed a simulation model with initial parameter values, which allow a good representation of a general traffic state [17]. However, dynamic calibration could take advantage of real-time data and adapt model parameters to the current traffic state.

Online calibration has been used in many macroscopic and mesoscopic modeling approaches [18-20]. The use of the Kalman Filter (and its extensions) for online parameter calibration has shown encouraging results [21]. However, in recent years there has been an increasing interest in online applications of microscopic traffic models. Moreover, Henclewood et al. [22] suggest that a real-time calibration algorithm should be included in online, data--driven microscopic traffic simulation tools.

Dynamic estimation of model parameters and especially reaction time has been attempted by e.g. [23-24]. Hoogendoorn et al. [23] and Lorkowski and Wagner [25] use the Unscented Kalman Filter (UKF), while Ma and Jansson [24] have proposed a dynamic model estimation method based on iterative usage of the Extended Kalman Filter (IEKF) algorithm. Ma and Andreasson [26] have suggested a dynamic car following data collection and noise cancellation based on the Kalman smoothing. However, according to Treiber et al. [27], smoothing the data had no significant influence on the calibration quality. Naturally, calibration and sampling issues in estimation car--following parameters have been studied extensively in the literature [28-29].

3. METHODOLOGY

3.1 Methodological framework

The overall methodological framework is presented in Fig. 1. The observations (e.g. speeds, distances, accelerations, etc.) collected up to time t are imported to an optimization algorithm and the optimal model parameters are estimated. Parameters values are forecasted and then model parameters from time t+1 are predicted. The predicted model parameters could be produced by a function of estimated parameter values from previous time instants and forecasted parameter values. This presupposes that correlations between model and input parameters have been identified. In the case study of this research predicted model parameters for time instant t+1 are considered equal to estimated parameters for time instant t. Then, predicted model parameters are input in the microscopic traffic model e.g. car-following model and outputs of the model are predicted from time t+1 onwards. When a new observation arises, the calibration procedure is iterated.

3.2 Measures of goodeness-of-fit

The performance of the models presented in this paper is evaluated using several goodness-of-fit measures: RMSN, RMSPE, MPE and Theil's U, Um and Us coefficients (for details and a discussion of these metrics, see [30]). Different measures are used so as the extent of the validation result could be quantified from different views. For example, the normalized root mean square error (RMSN) assesses the overall error and performance of each method estimating the difference between the observed and simulated values.

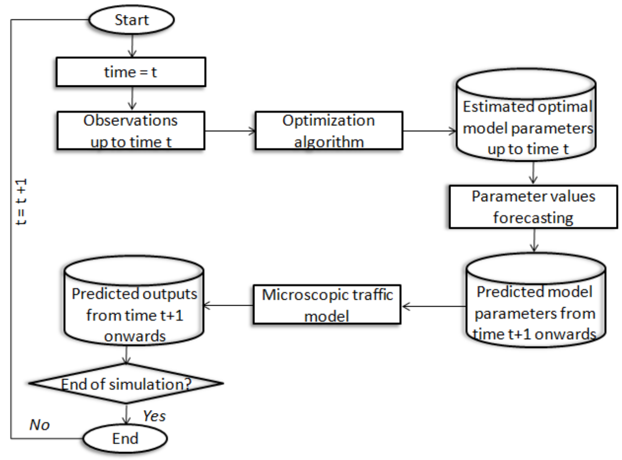

Figure 1: Methodological framework for on-line calibration

The root mean square percentage error (RMSPE) penalizes large errors more heavily than small errors and MPE indicates the existence of systematic under- or over-estimation in the simulated values. The measure of Theil's inequality coefficient U has been applied in transport model validation and includes three error proportions: the bias (U_m), the variance (U_s) and the covariance (U_c), whose sum is one. Values close to zero for U_m and U_s measures indicate an ideal fit, while values close to 1 suggest the worst fit.

$$RMSN = \frac{\sqrt{N \cdot \sum_{n=1}^{N} (Y_n^{obs} - Y_n^{sim})^2}}{\sum_{n=1}^{N} Y_n^{obs}}), \qquad RSMPE = \sqrt{\frac{1}{N} \cdot \sum_{n=1}^{N} (\frac{Y_n^{sim} - Y_n^{obs}}{Y_n^{obs}})^2}$$

$$MPE = \frac{1}{N} \cdot \sum_{n=1}^{N} (\frac{Y_n^{sim} - Y_n^{obs}}{Y_n^{obs}}), \qquad U = \frac{\sqrt{\frac{1}{N} \sum_{n=1}^{N} (Y_n^{sim} - Y_n^{obs})^2}}{\sqrt{\frac{1}{N} \sum_{n=1}^{N} (Y_n^{sim})^2} + \sqrt{\frac{1}{N} \sum_{n=1}^{N} (Y_n^{obs})^2}}$$

$$U^M = \frac{(\bar{Y}_n^{sim} - \bar{Y}_n^{obs})}{\frac{1}{N} \sum_{n=1}^{N} (Y_n^{sim} - Y_n^{obs})^2}, \qquad U^S = \frac{(\sigma^{sim} - \sigma^{obs})^2}{\frac{1}{N} \sum_{n=1}^{N} (Y_n^{sim} - Y_n^{obs})^2}$$

$$U^C = \frac{2(1-p)\sigma_{sim}\sigma_{obs}}{\frac{1}{N} \sum_{n=1}^{N} (Y_n^{sim} - Y_n^{obs})^2}$$

4. CASE STUDY

4.1 Experimental set-up

A series of data-collection experiments were carried out on roads surrounding the city of Naples, in Italy [11]. All data were collected under real traffic conditions in October 2002. All data were collected from the same platoon, namely the same four drivers by the same vehicles (vehicles 1, 2, 3, 4) moving in the same sequence (first vehicle 1 as the leader, followed by vehicle 2, which was in turn followed by vehicle 3, while the last vehicle was vehicle 4), but from different driving sessions, outlined in Table 1.

Table 1. Speed profile and experimental data

Data series	Length (s)	Summary statistics of speed (m/s)			
		min	max	mean	var
B1695	169.5	0.11	19.00	12.18	14.27
A358	35.8	3.35	13.22	9.10	12.16
A172	17.2	6.16	9.10	7.51	0.97
C168	16.8	9.74	12.86	11.18	0.50
C171	17.1	2.94	9.82	6.08	4.16

The driving routes and traffic conditions were differentiated among the datasets. Datasets with index A and C correspond to one-lane urban road, while datasets with index B to a two-lane extraurban highway. However, all selected roads have one lane per direction in order to avoid effects on driving behavior by lane changing. GPS receivers located on the vehicles were recording the coordinates X, Y, Z of each vehicle per 0.1s (i.e. in 10Hz). Thus, the speed of each vehicle ($v_1(t)$, $v_2(t)$,$v_3(t)$, $v_4(t)$) and the travelled distances for each vehicle could be calculated at each moment ($x_1(t)$, $x_2(t)$, $x_3(t)$, $x_4(t)$). In this research, data used are readily available observations from the field. No corrections and no interpolation have been performed. Therefore, only segments with consecutive measurements have been considered. A detailed description of the data could be found in Punzo et al. [11], who kindly provided the data for this research.

4.2 Gipps' model

The car-following model, used in Aimsun, is a safety distance model based on the model developed by Gipps [31-33]. The model suggests that the speed of a vehicle (n-1) is subject to three constraints included in Eq.1. First, the vehicle speed does not exceed the driver's desired speed (V_n). Second, the vehicle accelerates rapidly until it approaches the desired speed and then the acceleration is reduced almost to zero. If two vehicles are far apart, they behave as in the free flow condition. These two conditions are summarized in the first part of Eq. 1. The third condition is taken into account, when the vehicle is constrained by the vehicle in front. It is taken for granted that the following vehicle will adjust its velocity so as to keep a safe distance from the preceding vehicle. This condition is described by the second part of Eq. 1. Overall, according to the above restrictions, the speed of vehicle n at time (t + τ) could be calculated by the following formula:

$$u_n(t+\tau)=\min\left\{\begin{array}{l} u_n(t)+2.5\cdot a_n\cdot\tau\cdot(1-\frac{u_n(t)}{V_n})\cdot\sqrt{(0.025+\frac{u_n(t)}{V_n})} \\ \\ b_{n\cdot}\cdot\tau+\sqrt{(b_n{}^2\cdot\tau^2-b_n\left[2\cdot[x_{n-1}(t)-s_{n-1}-x_n(t)]-u_n(t)\cdot\tau-\frac{u_{n-1}(t)^2}{\hat{b}}\right])} \end{array}\right\} \quad (1)$$

where:

a_n: the maximum acceleration that the driver of vehicle n wishes to acquire (m/s^2).

b_n: the maximum braking that the driver of vehicle n wishes to apply in order to avoid a crash, $b_n<0$ (m/s^2).

$\hat{b}$: the estimated maximum braking that the driver of the preceding vehicle (n-1) wishes to apply (m/s^2).

$S_{n-1} = L_{n-1}$ + Safety, namely the size of the preceding vehicle (n-1) including its length and the safety distance at which vehicle n is unwilling to compromise even when at rest (m).

V_n: the speed at which the driver of vehicle n wishes to travel (m/s).

$x_n[t]$, $x_{n-1}[t]$: the location of the front side of the respective vehicle (n or n-1) at time t (m)

$v_{n-1}[t]$: the speed of the preceding vehicle (n-1) at time t (m/s)

$v_n[t]$: the speed of the following vehicle (n) at time t (m/s)

τ: the apparent reaction time (a constant for all vehicles) (s)

4.3 Correlation between optimal and input parameters

The optimal parameter values of Gipps' model have been defined for each observation of a data series using an optimization algorithm, Improved Stochastic Ranking Evolution Strategy (ISRES) algorithm [34] within the R software for statistical computing [35]. Each observation includes the input parameters v_2, v_3, x_2, x_3. The optimization algorithm calculates different parameter values for different input parameters. The concept that there is a correlation between optimal and input parameters is explored in this section.

In Figures 2 and 3, the optimal values of two parameters are plotted against the current speed v_3 of the vehicle. The output of the model is the speed of the vehicle in a next time instant. The desired speed of the driver is a parameter of the model and its optimal values should be higher than the current speed of the vehicle, as it could be observed in Fig. 2, regarding the available data. It is indicated as the majority of points form a diagonal line in this plot. Moreover, in Fig. 3 the optimal value of the maximum desired acceleration seems to be lower for higher speeds, when the current speed probably approaches the desired speed of the driver. As concerns as very low speeds corresponding probably to a stop and go situation, there is no clear image for the optimal values of parameters.

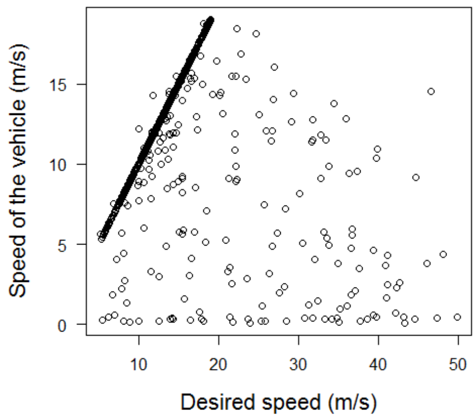

Figure 2: Optimal values of desired speed (a parameter of Gipps' model) against current speed of the vehicle

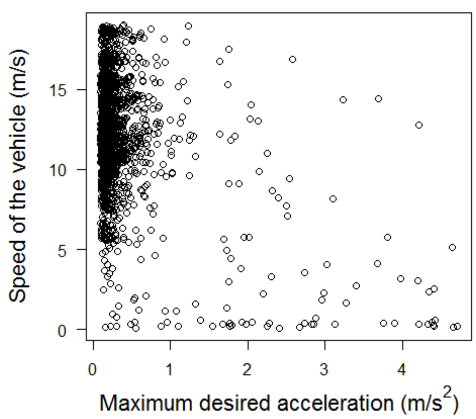

Figure 3: Optimal values of maximum desired acceleration (a parameter of Gipps' model) against current speed of the vehicle

Based on the fact that optimal parameter values are correlated to the input data of the model, an on-line calibration is definitely proposed. A unique model that produces the optimal parameters according to the input parameters is difficult to be developed due to the different nature of the data. Moreover, such a model should be able to consider interactions between model parameters, a fact that increases the complexity of the problem. On the other hand, an optimization algorithm per time instant could define effectively the optimal set of parameters. The proposed methodology is illustrated in the next section.

4.4 Calibration

4.4.1 Static calibration

Firstly, a static calibration is illustrated in order to be used as a reference benchmark for comparison with the proposed method. The longest data series (B1695, longer than 3 minutes) was used for model calibration. It is worth noting that -besides being the longest- this time series includes the most extensive range of speed values. The calibration process was fulfilled within the R software for statistical computing. In particular, the Improved Stochastic Ranking Evolution Strategy (ISRES) algorithm was used, which is included in the package "nloptr" and is appropriate for nonlinearly constrained global optimization [34].

The objective function that was set to be minimized is: RMSN{v_3^{obs}, v_3^{sim}}. The range of model parameters, shown in Table 2 has been defined in an earlier research [12]. In addition, as initial values for the optimization process, optimal values defined through a sensitivity analysis for Gipps' model and the same data [12]. In the sensitivity analysis interactions among model parameters had not been taken into account. However, these are considered in this optimization process.

Table 2. Optimization of model parameters using ISRES algorithm

Parameters of Gipps' model	Parameters range	Initial values	Optimal values
a (m/s^2)	[0.8, 2.6]	0.8	0.8
b (m/s^2)	[-5.2, -1.6]	-5.2	-3.2
V (m/s)	[10.4, 29.6]	14	14.4
s (m)	[5.6, 7.5]	5.6	5.9
$\hat{b}$ (m/s^2)	[-4.5, -3.0]	-3	-3.1
τ (s)	[0.4, 3.0]	0.4	0.4

4.4.2 On-line calibration

In online calibration an optimization process with the same characteristics (parameters range, initial values, objective function) is iterated per time instant, mainly per observation ($v_2(t_i)$, $v_3(t_i)$, $x_2(t_i)$ and $x_3(t_i)$), and not for the whole data series such as in static calibration. Therefore, a different optimal set of parameters is determined per time instant t_i in order to be characteristic of the current traffic conditions. In order to simplify the optimization problem, the apparent reaction time is considered equal to τ=0.4 sec (for a discussion and motivation of this choice, see e.g. [12]). The remaining five parameters are optimized per iteration.

4.4.3 Validation results

For static calibration the same set of parameters is always considered. In on-line calibration for each observation the optimal set of parameters is defined per each observation. When a new observation arises, the optimal set of parameters of the previous time instant is considered. The results are presented in Fig. 4 and 5. Dynamic calibration outperforms all the methods. Static calibration seems to overfit more to the training data B1695 than calibration with sensitivity analysis and thus produces higher error for dataseries used for validation.

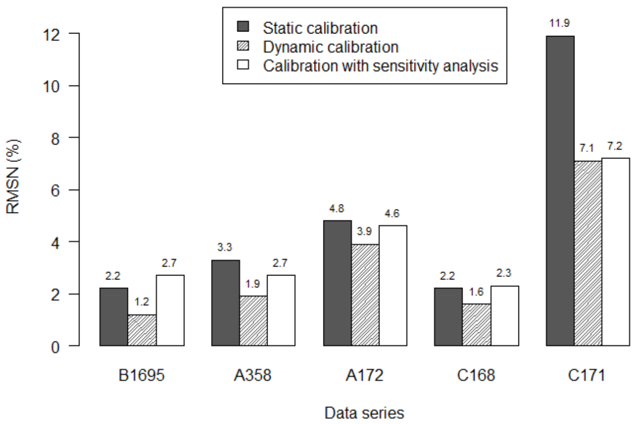

Figure 4. Comparison of static calibration, dynamic calibration and calibration with sensitivity analysis

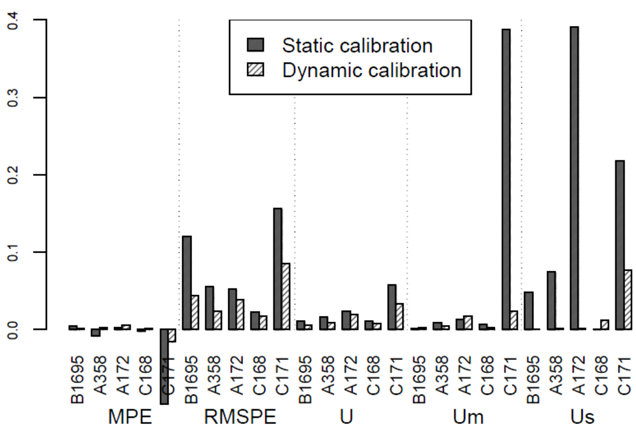

Figure 5. Comparison between static and dynamic calibration

5. CONCLUSIONS

The proposed method of calibration is flexible enough to adapt to different traffic conditions. Constraints of using a default set of parameters have been addressed. The validation to further data is essential. The proposed method should be applied to more car-following models or generally transportation models. Further research could lead to more general conclusions.

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