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CALIBRATION OF CAR-FOLLOWING MODELS WITH SINGLE- AND MULTI-STEP APPROACHES

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ABSTRACT

Microscopic traffic simulation models are applied in the analysis of transportation systems for years. Nevertheless, calibration (and validation) of microscopic sub-models such as car-following and gap-acceptance models is still a recent matter. The objective of the calibration is to adapt the simulation output to empirical data by adjusting the model's parameters. However, simulation results may vary from the underlying real-world data, despite the calibration. To analyze these deviations the present paper compares two different approaches of calibration using data from a single-lane car-following experiment on a Japanese test track. It is demonstrated that the results of the two methods differ significantly. A recommendation for the more appropriate method to use is given.

1 INTRODUCTION

At present about 100 different models for the simulation of traffic flow have been described in the literature (see (D. Chowdhury and Schadschneider 2000, Helbing 2001, K. Nagel and Woesler 2003) for an overview). The complexity of these models ranges from simple, low-parametric specifications like NEWELL's lower-order model (Newell 2002) or the cellular automaton model by NAGEL and SCHRECKENBERG (Nagel and Schreckenberg 1992) up to multi-regime models like WIEDEMANN's psycho-physical perception threshold model (Wiedemann 1974) or the model implemented in the MITSIM-lab (Ahmed 1999) open source simulator. Over the past years especially microscopic models became more and more important in analyzing and benchmarking transportation systems.

This paper will concentrate on microscopic car-following models. To describe the process of car-following a number of measurements are needed: For the objective vehicle, it's velocity $v(t)$ (as a function of time t) and acceleration $a(t)$ as well as the net distance $g(t)$ to the vehicle driving ahead must be known. Furthermore, measurements for the leading vehicle's speed $V(t)$ are necessary in order to describe the driver's reaction to the behavior of the vehicle in front. Additionally to these dynamics, the models depend on a set of parameters p_k, $k = 1 \dots M$, where M refers to the total number of parameters. Subsequently, these parameters will be handled to be time-independent or at least to vary to a lesser extent than the dynamics itself. Finally, in the case of non-deterministic car-following models, a yet to be described stochastic process ξ for generating acceleration noise with an amplitude of D must be introduced ($D = 0$ for deterministic car-following models).

With this at hand, a general car-following model can be defined as an inhomogeneous stochastic differential equation (SDE):

$$\dot{v} = F(g, v, V; p_k) + D\,\xi, \tag{1}$$

$$\dot{x} = v. \tag{2}$$

The headway or net distance to the leading vehicle in eq. (1) is defined by $g = X - x - \ell$, where ℓ is a generalized vehicle length, i. e. the physical length plus the average distance between two vehicles when standing behind each other at standstill. The variable x in eq. (2) describes the position of the following vehicle along the road whereas X denotes the position of the leading vehicle.

For a reliable application it is important to adapt a model to reality, that is to calibrate (and validate) it to a particular traffic situation. This results in an unique set of model parameters p_k (or ranges for each model parameter $p_{1...M}$ characterizing a group of different drivers) which suits best a certain traffic situation, e. g. dense inner-city traffic or free-flow traffic on highways. Usually, this calibration is carried out by a non-linear minimization (e. g. maximum-likelihood estimation, MLE) of the distance between the model and a certain realization, i. e. a measurement for a unique driver in a particular traffic situation. This realization is defined by the boundary condition of the lead vehicle's speed time-series $\hat{V}(t)$ and an empirical time-series $\{\hat{g}(t), \hat{v}(t), \hat{a}(t)\}$ for the following vehicle including the initial conditions $\{g(0) = \hat{g}(0), v(0) = \hat{v}(0), a(0) = \hat{a}(0)\}$. For the execution of the calibration, two different strategies have been followed so far.

1.1 Local Approach (Single-step Prediction)

For the first approach, empirical data are used to fit the model function $F(\cdot)$ directly (in the following called *local* fit), i. e. to maximize e. g. the following likelihood function:

$$\begin{aligned} E^{(\mathrm{lf})} &= \sum_{t=1}^{N} \log L\left(a^{(\mathrm{lf})}(t) - \hat{a}(t)\right) \\ &= \sum_{t=1}^{N} \log L\left(F\left(\hat{g}(t), \hat{v}(t), \hat{V}(t); p_k\right) - \hat{a}(t)\right), \end{aligned} \tag{3}$$

where the index t labels subsequent measurements in time and N denotes the number of data-points of the underlying time-series. Usually, velocities or headways are more sensitive to errors in a car-following model. Moreover, some data sets may not even include measured accelerations but provide accelerations derived from velocities by numerical methods. Hence, the objective function for the maximum-likelihood estimation in eq. (3) is rewritten to make use of velocities directly:

$$\begin{aligned} E^{(\mathrm{lf})} &= \sum_{t=1}^{N} \log L\left(v^{(\mathrm{lf})}(t) - \hat{v}(t)\right) \\ &= \sum_{t=1}^{N} \log L\left(\left(\hat{v}(t) + \Delta t \cdot F\left(\hat{g}(t), \hat{v}(t), \hat{V}(t); p_k\right)\right) - \hat{v}(t)\right), \end{aligned} \tag{4}$$

where Δt is the time-step size in the empirical data set. The error measure $E^{(\mathrm{lf})}$ in eq. (4) contains the difference of the velocities calculated by the model and the velocities from the empirical time-series: $\Delta v = v^{(\mathrm{lf})}(t) - \hat{v}(t)$. This is typically done in the approaches followed e. g. in (T. Toledo and Ben-Akiva 2009).

1.2 Trajectory Approach (Multi-step Prediction)

For the second approach, first a simulation is run in order to solve the differential equations (1) and (2) according to a given set of parameters p_k and in compliance with the initial boundary condition stated above as well as the boundary condition in time set by the lead vehicle. (In almost all microscopic car-following models it is sufficient to only specify the lead vehicle's speed $\hat{V}(t)$ as input parameter.) As a consequence, for the time period of the empirical data a dedicated simulation data set is generated.

The trajectory created in this way is denoted as $\{g^{(\mathrm{tf})}(t), v^{(\mathrm{tf})}(t), a^{(\mathrm{tf})}(t)\}$. In contrast to the local approach, these trajectory data are compared to the empirical time-series (hence the name *trajectory* fit):

$$E^{(\mathrm{tf})} = \sum_{t=1}^{N} \log L\left(v^{(\mathrm{tf})}(t) - \hat{v}(t)\right). \tag{5}$$

Here, in accordance to eq. (4), the index t labels subsequent measurements in time and N refers to the total number of data-points, too. The trajectory approach had been followed e. g. in (E. Brockfeld and Wagner 2003). In theory these two approaches should be equivalent (compare e. g. (Horbelt 2001)). However, in the examples below it has been found that this is not necessarily the case. Often, it is not clearly stated by the researchers which approach is chosen. Moreover, the terms in eqn. (4) and (5) look almost the same. In consequence, one cannot tell the difference between these two calibration approaches from inspecting the objective function only.

2 MODELS AND DATA SET

For the present paper, two car-following models have been analyzed by the different approaches of calibration: The intelligent driver model *IDM* (M. Treiber and Helbing 2002) and a simplified, *linear* approach proposed in (P. Wagner and Flötteröd 2012).

2.1 Intelligent Driver Model – IDM

The IDM is a deterministic model, i. e. the amplitude of the noise term ξ in eq. (1) must be set to zero: $D = 0$. According to eq. (6) the IDM is defined as follows:

$$\dot{v} = a\left[1 - \left(\frac{v(t)}{v_{\max}}\right)^{\delta} - \left(\frac{\theta + T\,v(t) + \frac{v(t)(v(t)-V(t))}{2\sqrt{ab}}}{g(t)}\right)^{2}\right]. \tag{6}$$

This model consists of six parameters p_k, $k = 1\ldots6$:

- $v_{\max}$: The maximum speed of the modeled vehicle;
- θ: The distance between vehicles when standing at standstill;
- T: The safe time headway;
- δ: The acceleration exponent;
- a: The maximum acceleration;
- b: The maximum deceleration (defined as a positive value).

Because some model parameters are not sufficiently sensitive they have been set to fixed values: $v_{\max} = 33.3\,\mathrm{m/s}$, $\delta = 4$. This corresponds to the default value defined in (M. Treiber and Helbing 2002).

2.2 Linear Model – LM

The linear model approach in (P. Wagner and Flötteröd 2012) is based on a classical time-series analysis (ARMAX-type models, where ARMAX indicates **a**uto-**r**egressive, **m**oving **a**verage with e**x**ternal factors). The velocity of a following vehicle $\{v_t\}_{t=\{1,\ldots,N\}}$ (with N the length of the time-series) can be described as:

$$v_t = \sum_{i=1}^{p} a_i\, v_{t-i\Delta t} + \varepsilon_t + \sum_{j=1}^{q} d_j\, \varepsilon_{t-j\Delta t} + b_1\, g_{t-\Delta t} + c_1\, V_{t-\Delta t}, \tag{7}$$

where $\varepsilon_{t-j\Delta t}$ is a sequence of correlated external noise terms and $g_{t-\Delta t}$ as well as $V_{t-\Delta t}$ denote the distance to the leader and the velocity of the vehicle in front at the time-step before, respectively. By defining $p = 1$,

$q = 0$ in eq. (7) a simplified model formulation is derived:

$$v_t = a_1 v_{t-1} + b_1 g_{t-1} + c_1 V_{t-1} + \varepsilon_t. \tag{8}$$

The model in eq. (8) consists of three parameters p_k, $k = 1 \ldots 3$ which don't seems to show an immediate physical meaning. In (P. Wagner and Flötteröd 2012) the following interpretation is provided:

$$\begin{aligned} T &= \frac{c_1}{b_1}, \\ \alpha &= 1 - a_1 - c_1, \\ \tau &= \frac{1 - a_1 - c_1}{b_1}. \end{aligned}$$

Here, T denotes the anticipation time, i. e. the time-horizon a driver uses to predict the future behavior of its leader. The parameter α describes a relaxation constant whereas τ represents the preferred headway to the vehicle in front. For the analysis in the present paper a version of the linear approach with an absolute term according to eq. (9) was chosen to improve the precision of fit:

$$v_t = a_1 v_{t-1} + b_1 g_{t-1} + c_1 V_{t-1} + d_1 + \varepsilon_t. \tag{9}$$

2.3 Time-series Data

The data used for analyzing the two calibration approaches were taken from a 20 minutes driver experiment on a Japanese test track recorded in October 2001 (G. S. Gurusinghe and Tanaboriboon 2003). The test track is a single lane circuit with a length of 3 km (2×1.2 km straight segments and 2×0.3 km bend segments). The recorded time-series data comprise nine different drivers in car-following mode performing different driving patterns, e. g.:

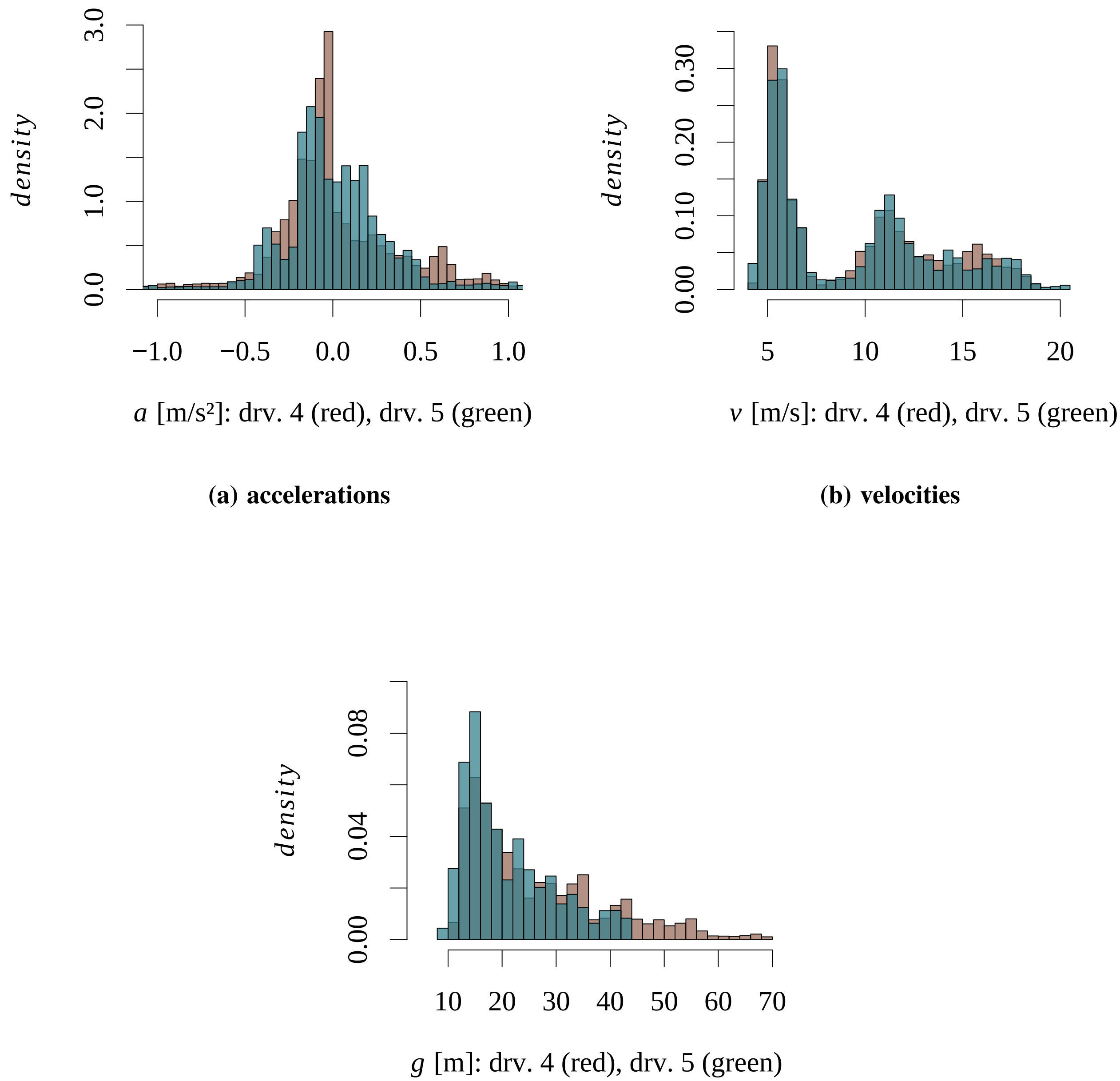
- Driving at several but constant levels of speed up to 80 km/h for a defined time interval;
- Varying speeds (regularly increasing/ decreasing speed);
- Emulating a number of acceleration/ deceleration processes (as typically found at intersections).

Figure 1 depicts quite different driving manners applied in the experiment by two subsequent sample drivers (driver 4 and 5). Driver 4 (red) shows a more or less delayed reaction compared to it's leader. This behavior demands longer headways (fig. 1 c, red bars above $g = 45$ m), a longer range of time without any acceleration utilized (fig. 1 a, higher red bars around $a = 0.0\,\mathrm{m/s^2}$) and a need for greater accelerations in order to keep up with the leading vehicle (fig. 1 a, red bars above $a = 0.5\,\mathrm{m/s^2}$). Driver 5 responds better (or more adaptive) to it's leader. This driving manner is characterized by smaller headways (fig. 1 c, no green bars above $g = 45$ m, higher green bars (light green marks) for $5\,\mathrm{m} < g < 15\,\mathrm{m}$) and lower accelerations (fig. 1 a, higher green bars (light green marks) for $0.1\,\mathrm{m/s^2} < a < 0.5\,\mathrm{m/s^2}$). The differences in velocity between the two drivers (fig. 1 b) are smaller. This results from the limited velocity of around 80 km/h in the empirical data set.

All vehicles were equipped with a differential global positioning system (DGPS) storing the position of each car in 0.1 s time-steps. The speeds of the vehicles have been quantified independently by a real-time kinematic system (RTKS). The other parameter like acceleration and net headway between vehicles were derived from the stored vehicle's positions. According to (G. S. Gurusinghe and Tanaboriboon 2003), the accuracy of the DGPS based location determination is about 1 cm. The speeds measured have got an error of less than 0.2 km/h. Thus, these time-series data are particularly suitable for the analysis of car-following behavior and the calibration of car-following models.

2.4 Application

Dependent on the times-series used an appropriate distribution need to be defined for the error-measures $E^{(\mathrm{lf})}$ resp. $E^{(\mathrm{tf})}$ in eqn. (4) and (5). For the local method, the difference of the velocity calculated by the



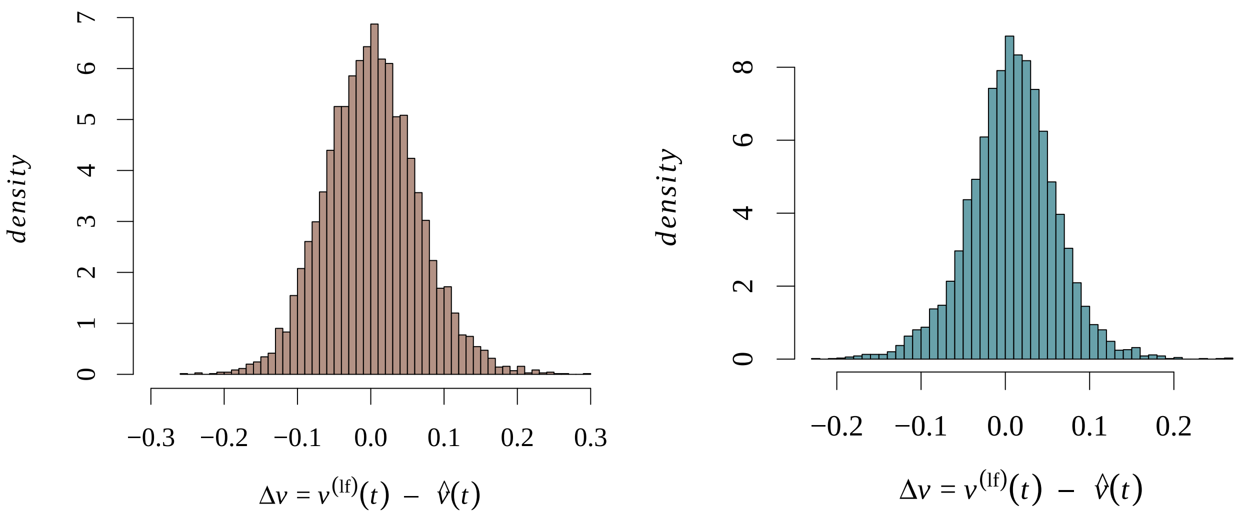
(a) accelerations

(b) velocities

(c) headways

Figure 1: Distribution of accelerations (a), velocities (b) and headways (c) applied by driver 4 (red) and driver 5 (green). Darker green indicates an underlying red bar whereas lighter green signifies the absence of such an underlying red bar.

IDM model equation and the speeds found in the empirical time-series described above $\Delta v = v^{(\mathrm{lf})}(t) - \hat{v}(t)$ seems to be distributed according to $L \propto \exp\left(\text{-}\Delta v^2/2\,\sigma^2\right)$, where σ is the variance of the normal distribution. Figure 2 graphically represents histograms for the difference of the calculated and empirical velocity for two different drivers. Here, the fundamental shape of the probability density function for a GAUSSian



(a) driver 4 **(b) driver 5**

Figure 2: Histogram for the difference of modeled (IDM) and empirical velocity $\Delta v = v^{(\mathrm{lf})}(t) - \hat{v}(t)$ for driver 4 (a) and 5 (b).

distributed stochastic variable can be seen in each sub-figure. (For the different behavior of the drivers concerning car-following refer to sec. 2.3.) This applies for both tested car-following models and also for the case of the trajectory approach.

Note that indeed the likelihood functions in eqn. (4) and (5) do not obey a real normal distributions. This is due to the fact that accelerations, velocities and headways are always bounded. Therefore, truncated versions of the probability functions should be used in principle. However, the parameter estimation seems to be quite robust against the details of the likelihood function $L(\Delta v)$ – at least in the case of the empirical data and car-following models used here.

To run the simulation for the trajectory method, the differential equations (1) and (2) need to be solved under the initial boundary condition and the boundary condition in time set by the lead vehicle for a specific set of parameters p_k. In the present paper, a simple Euler forward scheme is used, i. e. the following equations have to be iterated:

$$v^{(\mathrm{tf})}(t+\Delta t) = v^{(\mathrm{tf})}(t) + \Delta t\, F(g^{(\mathrm{tf})}(t), v^{(\mathrm{tf})}(t), \hat{V}(t); p_k) + \sqrt{\Delta t}\, D\, \xi(t), \tag{10}$$

$$g^{(\mathrm{tf})}(t+\Delta t) = \frac{\Delta t}{2}\left(\hat{V}(t) + \hat{V}(t+\Delta t) - v^{(\mathrm{tf})}(t) - v^{(\mathrm{tf})}(t+\Delta t)\right). \tag{11}$$

Following the definition above the parameter Δt denotes the time-step size of the Euler scheme. Here, equation (11) is necessary because the dynamic variable $g^{(\mathrm{tf})}(t+\Delta t)$ has to be computed from the change of the coordinates of the lead and following vehicle.

3 RESULTS AND INTERPRETATION

In the first step, both, the IDM and the linear car-following model were applied to the empirical time-series for the local and the trajectory calibration approach. Then, the resulting parameters of the trajectory approach $p_k^{(\mathrm{tf})}$ were used to create synthetic data. For these data the underlying model parameters are known (and constant by definition). In the second step, the calibrations for the local and the trajectory approach were repeated with this synthetic data set.

As an example, table 1 presents the resulting model parameters p_k (in column "estimate") for driver 5 and the IDM model applied to the empirical time-series for the respective calibration approach (lf = *local* fitting, tf = *trajectory* fitting). Additionally, some test statistics derived from the MLE are given. Note that the last parameter σ is not part of the car-following model itself but refers to the variance of the underlying likelihood function for the error-measures $E^{(\mathrm{lf})}$ resp. $E^{(\mathrm{tf})}$ (cf. eqn. (4) and (5)). The estimated parameters look more or less realistic. Nevertheless, acceleration a seems to be quite low for the local or single-step approach, whereas deceleration b has a huge magnitude for the trajectory or multi-step approach. The calibration tasks for the two different approaches have been carried out for both drivers and models.

Table 1: Calibrated parameters for driver 5 and IDM applied to the empirical time-series.

	p_k		estimate	std.-error	t-value	signif. level
lf	T	[s]	1.2313	0.0159	77.4304	0.0000
tf	T	[s]	0.8227	0.0212	38.7759	0.0000
lf	θ	[m]	2.6447	0.0500	52.8700	0.0000
tf	θ	[m]	10.7198	0.4206	25.4850	0.0000
lf	a	[m/s^2]	0.2227	0.0076	29.3177	0.0000
tf	a	[m/s^2]	1.5213	0.0194	78.5980	0.0000
lf	b	[m/s^2]	2.9613	0.0290	102.1166	0.0000
tf	b	[m/s^2]	7.0945	0.7952	8.9213	0.0000
lf	σ	[m/s]	0.0514	0.0006	84.0384	0.0000
tf	σ	[m/s]	0.6400	0.0079	81.3791	0.0000

In theory, the local and the trajectory calibration approach should be equivalent and lead to similar outcomes (cf. (Horbelt 2001)). In the present case, however, at least some model parameters differ substantially. Table 2 contains the differences between the two calibration approaches for any driver and model. The columns Δp contain the perceptual disparity of the trajectory calibration approach for the respective driver and model related to the value of the local fit. For the IDM the parameter θ (distance between vehicles at standstill) varies significantly for both drivers, whereas all other parameters differ much less for driver 4. For driver 5 the parameters for acceleration a and deceleration b differ to a much greater extent in comparison to driver 4. In case of the linear model the sign changes for all parameters except the absolute term δ for driver 4. Moreover, parameter β differs to a vast extent. For driver 5 the sign changes

Table 2: Deviations of model parameters p_k between local (lf) and trajectory (tf) approach for empirical data.

IDM		
p_k	Δp drv. 4	Δp drv. 5
T	94%	67%
θ	690%	405%
a	190%	683%
b	51%	240%

linear model		
p_k	Δp drv. 4	Δp drv. 5
α	-89%	102%
β	-3863%	-136%
γ	-415%	15%
δ	479%	453%

for parameter β as well. The other parameter, γ and δ also differ significantly, whereas parameter α has almost the same magnitude for the different calibration approaches.

Figures 3 and 4 graphically represent these calibration results for a selected time range of the empirical data set for driver 4 and 5. The calibration results derived from the local approach (solid lines) almost perfectly fit the empirical time-series data (black solid line with circles). There are very low deviations between the two different models for both drivers. For the trajectory approach (dashed lines), however, significant differences between the empirical data and the fitted curves can be seen for both models. This emphasis once more the deviations between the two approaches presented in table 2. Furthermore, even the shapes of the trajectory curves differ between the two models at certain times: e. g. between 560 and 570 seconds for driver 4 and 580 and 590 seconds for driver 5.

For a further investigation of these deviations the accelerations, velocities and headways created by the simulation for the trajectory approach were taken as a "synthetic" time-series. In this way, the underlying parameters are a priori known and constant. Table 3 shows the resulting model parameters p_k again for driver 5 and the IDM model applied to this synthetic input. Here, the first row "data" contains the "true" value for each parameter derived from the first trajectory calibration run. Underneath, the results for the local (lf) and trajectory (tf) fitting of the synthetic data are presented. Again, the calibration for the synthetic data was carried out for both drivers and models.

Table 3: Calibrated parameters for driver 5 and IDM applied to the empirical time-series.

	p_k		value/ estimate	std.- error	t-value	signif. level
data	T	[s]	0.8227			
lf	T	[s]	0.9057	0.0007	1209.9162	0.0000
tf	T	[s]	0.8171	0.0006	1286.4422	0.0000
data	θ	[m]	10.7198			
lf	θ	[m]	9.7808	0.0083	1176.0091	0.0000
tf	θ	[m]	11.8066	0.0237	497.4898	0.0000
data	a	[m/s^2]	1.5213			
lf	a	[m/s^2]	1.4396	0.0015	933.5420	0.0000
tf	a	[m/s^2]	1.5798	0.0023	677.0998	0.0000
data	b	[m/s^2]	7.0945			
lf	b	[m/s^2]	6.3250	0.0551	114.7104	0.0000
tf	b	[m/s^2]	6.3377	0.0124	511.5440	0.0000

Table 4 summarizes the results for calibrating the synthetic data set for each model and driver. For the IDM car-following model the parameter differ for the two drivers to only a smaller extent. The trajectory approach seems to perform better especially with regard to the accelerations a and decelerations b. For

Table 4: Deviations of model parameters p_k between local (lf) and trajectory (tf) approach for synthetic data.

	IDM			
p_k	drv. 4		drv. 5	
	lf	tf	lf	tf
T	103%	98%	91%	101%
θ	70%	117%	110%	91%
a	94%	100%	106%	96%
b	70%	109%	112%	112%

	linear model			
p_k	drv. 4		drv. 5	
	lf	tf	lf	tf
T	79%	88%	105%	116%
θ	87%	107%	28%	76%
a	79%	126%	-22%	-67%
b	87%	112%	-36%	59%

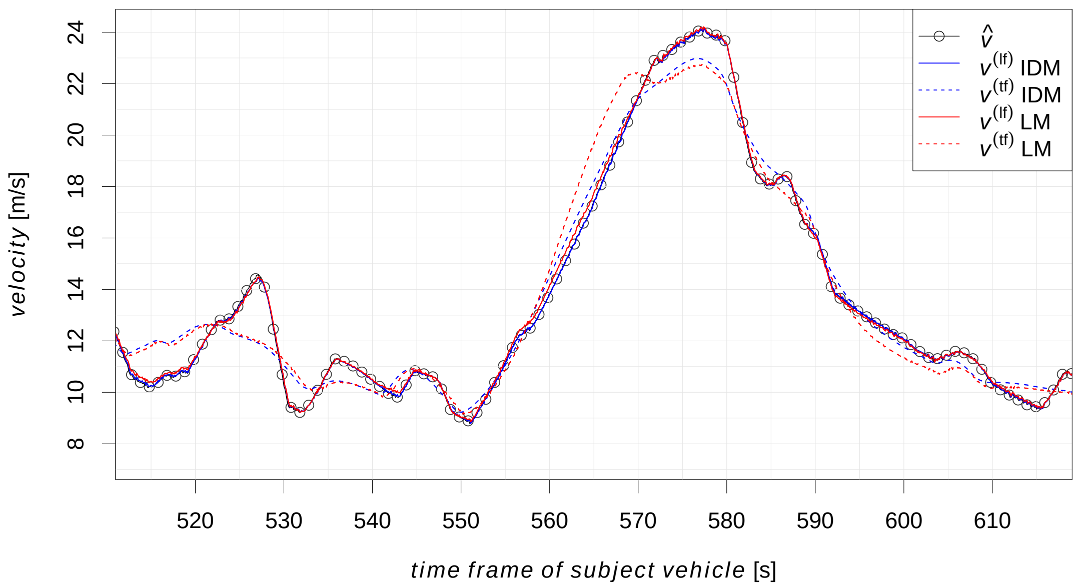


Figure 3: Sample section for calibration results for the linear model (red) and IDM (blue) for driver 4.

Figure 4: Sample section for calibration results for the linear model (red) and IDM (blue) for driver 5.

the simpler (and weaker) linear model the trajectory approach definitely performs better. For driver 5 only poor results can be seen for the local approach reproducing the synthetic input data.

4 CONCLUSION

The weaker performance of the local approach cannot easily be explained. Apparently, the determination of the trajectory contains more information than what is comprised in a car-following model's acceleration or velocity function alone. Note that the two different methods for computing the model's answer to the behavior of a leading vehicle are in fact quite different: While the trajectory approach definitely includes a memory (the auto-correlation function of this acceleration does only decay after several seconds), the local approach is memory-less. Here, the objective function (acceleration, velocity or headway) may fundamentally change in the next 0.1 s, while in the trajectory approach a variation of these values takes some time. This delay is due to the objective function being directly linked to the speeds and net distances from the previous time-step. Speeds and net distances themselves cannot change very rapidly in a car-following model. However, this seems to be only a part of the full answer and should be explored into more detail in future.

So, the conclusion of this paper is: Do not only do a calibration, but in addition (or maybe as the one and only approach) run a simulation with the best-fitting parameters and see what happens. Since running the simulation is the final goal of any calibration endeavor, it seems that this approach in fact is the better one. This will become important especially in the case with lane changing models that still present a big challenge for any calibration approach.

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