Empirical Analysis of Two-Leader Car-Following Behavior*

Serge P. Hoogendoorn* and Saskia Ossen**
Transportation and Traffic Engineering Section
Delft University of Technology
Delft
The Netherlands
* e-mail: S.P.Hoogendoorn@CiTG.TUDelft.NL (corresponding author)
** e-mail: S.J.L.Ossen@TUDelft.nl

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Several researchers have proposed that drivers do not just respond to the vehicle directly ahead, but also to the second, and even the third, fourth or fifth vehicle ahead. Little empirical evidence for this hypothesis has however been presented so far.
We provide empirical evidence showing that drivers are not only reacting on the vehicle directly ahead, but also the 'second leader'. This is achieved by analyzing vehicle trajectory data collected by observing a motorway traffic flow from a helicopter. These microscopic data enable estimation of individual car-following models.
The extent to which this multi-anticipatory behaviour occurs turns out to be considerable: on average, the sensitivity with respect to stimuli coming from the second vehicle is half the sensitivity of the first vehicle ahead. For some vehicle triples, even higher sensitivities to the behaviour of the second leader than to the behaviour of the first have been observed. The estimation results show large differences in car-following behaviour between the different drivers. These differences can in part be explained by the vehicle-type composition of the considered vehicle triples. Trucks drivers show different behaviour than person-car drivers; drivers following a truck show dissimilar car-following behaviour than drivers following a person-car.
Although not being a benchmarking study aimed at providing the best model of car-following behaviour, the research presented in this article shows that including multiple leaders can improve modelling of driving behaviour considerably.

Keywords: Car-following models, vehicle trajectories, stimulus-response models

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1. Introduction

In the last years, research has focused on development, calibration and validation of models capturing the way in which drivers interact with other vehicles in the traffic flow. Despite the increased complexity of the models, few have succeeded in providing a real improvement over the simple models developed in the fifties and sixties. For instance, a recent benchmarking study revealed that the most complex traffic flow models were not able to predict car-following behaviour more accurately than the relatively simple ones (Brockfeld et al., 2004).

There are many research directions in which improvements of driving models can be found. For one, Ossen and Hoogendoorn (2005) established that the inter-driver differences of the parameters describing car-following behaviour are considerable, which need to be incorporated correctly for a microscopic model to accurately predict driving behaviour. For two, it has been suggested that driver behaviour adapts to the prevailing traffic conditions (Dijker and Bovy, 1998; Daganzo, 2002 and Zhang and Kim, 2001). Drivers who have been driving in congestion for a long time may loose motivation to efficiently follow the vehicle directly ahead. From a modelling perspective, this would imply that the car-following parameters are changing according to the history of the driver.

Thirdly, several researchers have suggested that driving behaviour cannot be described adequately by just considering the vehicle directly in front. Rather, drivers anticipate on traffic conditions further downstream by considering not only the vehicle directly ahead, but also the vehicle in front of its 'leader'. For instance, the well known car-following model of Gazis et al. (1961) was extended by Bexelius (1968) to include multi-leader stimuli in the equations describing the response behaviour of a driver. More recently, Lenz et al. (1999) extend the model of Bando et al. (1995) to include multiple vehicle interactions. In doing so, they show how the reaction to multiple vehicles stabilizes the dynamic behaviour of the model, while retaining the fundamental macroscopic properties of the traffic flow. Moreover, the multi-anticipative car-following model is able to describe synchronized traffic flow conditions. Treiber et al. (2004) take a similar view and extend the Ideal Driver Model (IDM) with multi-vehicle interaction behaviour.

The aforementioned studies are generally based on rather non-scientific arguments: "... from everyday experience one knows that drivers often observe two ore more vehicles ahead." (Lenz et al., 1999). Empirical evidence showing that these models indeed provide a better description of car-following was however lacking.

Recent innovations in the field of data collection have made it possible to collect detailed, microscopic vehicle data. Hoogendoorn and Schreuder (2005) describe a system enabling automated collection of vehicle trajectory data from an airborne observation platform. The collected data consist of vehicle trajectories having a temporal resolution of 0.1 s and a spatial resolution of a few centimetres.

This contribution focuses on specifying and estimating parameters of a simple two-leader car-following model using empirical vehicle trajectories collected from two busy motorways. In doing so, we investigate if drivers also react to the second leader (i.e. two vehicles ahead). We study whether the prediction error reduces, and whether the estimated car-following parameters (sensitivity and reaction time) are plausible. It is emphasized here that we do not aim to establish the most realistic model describing car-following behaviour, but only aim at empirically investigating multi-anticipatory car-following behaviour.

In section 2, a short introduction of car-following theory will be given. This section is followed by a description of the methodology used to identify the parameters of the multi-leader model of Bexelius (section 3) and the data that are used to this end (section 4). Section 5 discusses the estimation results, which is followed by the conclusions and a description of the future research directions (section 6).

2. Car-following theory and modeling

A microscopic model provides a description of the movements of individual vehicles. These movements are the result of the characteristics of drivers and vehicles, the interactions between drivers, and between the driver and road characteristics, external conditions and the traffic regulations and control. In general, two types of driver tasks are distinguished: longitudinal tasks (acceleration, maintaining speed, distance-keeping relative to leading vehicle) and lateral tasks (lane changing, overtaking). This contribution considers the former.
The term *car-following model* is used here for the general class of dynamic microscopic models describing the longitudinal behaviour of a driver in relation to the driver(s) in front. Driver i, following driver i+1, may for instance react on (changes in) the spacing between the vehicles, or his or her relative speed. Many models have been proposed to describe this longitudinal behaviour.
It is beyond the scope of this contribution to provide a comprehensive overview of all models. We will focus upon so-called stimulus response models (GHR models to be specific) and the multi-anticipatory generalizations of these models towards multiple vehicle interactions due to (Bexelius, 1968). The latter is done for the sole purpose of gaining more insight into the car-following process by statistical analysis of microscopic trajectory data.

2.1 Gazis-Herman-Rothery models

Despite the fact that many researchers correctly argue that more realistic descriptions of car-following behaviour exist, in this manuscript we focus on so-called *stimulus response models*. The main reasons for doing so is the straightforward statistical analyses that can be used to establish the parameters of the model, and the fact that these models are easily interpreted and understood.

2.1.1 GHR model specification
A well-known car-following model is given by the following equation (Gazis et al., 1961):

$$a_i(t) = \frac{d}{dt} v_i(t) = \kappa_1 \left(v_{i-1}(t - T_r) - v_i(t - T_r) \right) \tag{1}$$

where κ_1 denotes the so-called *sensitivity* and $T_r > 0$ denotes the reaction time. Equation (1) is generally referred to as the *Gazis-Herman-Rothery (GHR) model*, and describes the retarded or delayed reaction to the relative speed $v_r^{(1)} = v_{i-1} - v_i$ with respect to the vehicle ahead. The sensitivity κ_1 is generally described as a function of speed, and the distance headway:

$$\kappa_1 = \kappa_1^0 \frac{v_i^m(t)}{(x_{i-1}(t - T_r) - x_i(t - T_r))^l} \tag{2}$$

For the data used in the ensuing of the manuscript, empirical analyses have so far shown no evidence that a non-constant specification of the sensitivity provides a considerably better description of the car-following data (Ossen and Hoogendoorn, 2005). In the remainder we therefore assume that the sensitivity is constant (i.e. $m = l = 0$). It is recognized here that this assumption may not be valid when considering varying traffic regimes (free-flow, congestion, saturated flow, etc.), as argued plausibly by (Brackstone and MacDonald, 1999). In the remainder, data collected during a period of stop-and-go traffic (with average speeds of 5.7 m/s) are used.

2.1.2 Empirical analyses

The GHR model has been analyzed thoroughly using empirical data. In many cases, macroscopic data was used to identify the model parameters. Amongst the more reliable studies (Brackstone and MacDonald,1999) were those using microscopic data for model calibration and validation (see Chandler et al., 1959; Herman and Potts, 1959; Hoefs, 1972; Treiterer and Myers, 1974 and Ozaki, 1993).

The calibration of Chandler et al. (1959) model was performed using data collected from wire-linked vehicles to examine the responses of 8 test subjects to a 'realistic' speed profile of a lead vehicle (which varied from 10 to 80 mph), over 30 min on a test track. The analysis of the resulting data, assuming the presence of terms linear in both the relative speed and the distance headway led to two conclusions. Firstly that the distance headway contributed little to the following relationship and hence could be rejected (producing a sub case of the GHR model with $l = m = 0$), and secondly, that the sensitivity κ_1 showed a high variation between subjects (0.17±0.74 s) as did T_r (1.0±2.2 s).

Wire-linked experiments were also performed by Herman and Potts (1959) to calibrate another special case of the GHR model (with $m = 0$ and $l = 1$). The experiment was conducted in 3 tunnels in New York. They found a reaction time of 1.2 s, and a sensitivity value of 19.8 ft/s.

Treiterer and Myers (1974) used airborne film footage of a flow breakdown to monitor the paths of a large number of vehicles, from which they extracted the required measurements. Again assuming that behaviour may in some way be different according to what the driver is required to do, they split their analysis to separately consider the acceleration and deceleration phases of car-following, determining that two differing relationships could exist (acceleration and deceleration); for deceleration, $m = 0.7$ and $l = 2.5$, for acceleration $m = 0.2$ and $l = 1.6$ were found to be optimal.

Lastly, Ozaki (1993) used 90 min of data extracted from video film taken of a motorway from the 32nd floor of a city office building. This gave a 160-m field of view, and data were obtained on the passage of a total of 2000 vehicles. It should be noted that with such a small field of view it would only have been possible to extract a time-series for each vehicle of less than 10 s.

2.2 Bexelius multi-anticipatory car-following model

Several researchers have proposed that follower *i* may not only respond to vehicle *i*-1 directly ahead, but may also respond to other drivers or conditions further upstream or in other traffic lanes. Following this line-of-thought, a straightforward model incorporating this assumption is (Bexelius, 1968):

$$a_i(t) = \kappa_1\left(v_{i-1}(t-T_r) - v_i(t-T_r)\right) + \kappa_2\left(v_{i-2}(t-T_r) - v_i(t-T_r)\right) \\ = \kappa_1 v_r^{(1)}(t-T_r) + \kappa_2 v_r^{(2)}(t-T_r) \tag{3}$$

In equation (3), κ_1 and κ_2 describe the sensitivity with respect to leader 1 (vehicle directly ahead) and leader 2 (two vehicles away). Note that we have assumed that the reaction time T_r is equal for both stimuli. The motivation for this is two-fold: for one, using one reaction time yields a model that is in line with traditional car-following models. For two, in estimating the model, problems may be avoided since the second term would in fact be conveying the response of leader 1 to leader 2 (i.e. serial correlation between lagged signals). This is shown by the model estimation approach verification in the next section.

2.2.1 Multi-vehicle generalization

Equation (3) can be easily generalized to include the reaction to multiple vehicles ahead as follows:

$$a_i(t) = \sum_{j=1}^{n} \kappa_j\left(v_{i-j}(t-T_r) - v_i(t-T_r)\right) = \sum_{j=1}^{n} \kappa_j v_r^{(j)}(t-T_r) \tag{4}$$

For the present study, this generalization is not pursuit further. This holds equally for including driver response to vehicles in adjacent lanes or stimuli coming from behind, although it is generally believed that the latter will be only minor due to the anisotropic nature of a traffic flow.

2.2.2 Model stability

The stability of the two-leader model was analyzed by Bexelius (1968). For the linear model, it can be proven that the car-following is (asymptotically) stable if it satisfies the following condition Bexelius (1968):

$$2T_r \leq \frac{\kappa_1 + 4\kappa_2}{\left(\kappa_1 + 2\kappa_2\right)^2} \tag{5}$$

This means that small disturbances tend to dissolve when propagating through a vehicle platoon. In the remainder of the manuscript, we will briefly come back to these stability issues when assessing the parameter estimates.

3. Model identification

This section discusses estimation of the parameters of the two-leader model equation (3) by multivariate linear regression. The approach that is taken is similar to the estimation of the GHR model using microscopic data described in Ossen and Hoogendoorn (2005). The data used for model identification are time-series of relative speeds and accelerations during a certain time interval. Since the observations of successive instants will be correlated, the issue of serial correlation and its implications is discussed as well. Furthermore, verification of the approach is discussed briefly.

3.1 Multivariate linear regression and reaction time estimation

The statistical analysis of model (3) using the empirical trajectory data (Hoogendoorn and Schreuder, 2004) is straightforward. First, the vehicle following triples (i,i-1,i-2) are determined from the data. Secondly, for each vehicle in the triple the location and speed is determined; for vehicle i (the follower), the acceleration a_i is determined from the successive speed changes. We refer to figure 3 for a couple of examples.
Next, we will fix the reaction time T_r to a fixed value and determine the data points used for multivariate regression

$$y_k := a(t_k), \quad x_k^{(1)}(k) := v_r^{(1)}(t_k - T_r), \quad x_k^{(2)}(k) := v_r^{(2)}(t_k - T_r) \tag{6}$$

where $t_k = hk$ are the time instants at which the data is available. The next step is to determine the regression coefficients of the simple linear multivariate regression model:

$$y_k = \kappa_1 x_k^{(1)} + \kappa_2 x_k^{(2)} + \varepsilon_k \tag{7}$$

which can be achieved by standard regression tools. Note that the mean prediction error resulting when using the estimates $\hat{\kappa}_1$ and $\hat{\kappa}_2$

$$e = e(T_r) = \frac{1}{n}\sqrt{\sum_k \left(y_k - \hat{\kappa}_1 x_k^{(1)} + \hat{\kappa}_2 x_k^{(2)}\right)^2} = \frac{1}{n}\sqrt{\sum_k \left(\varepsilon_k\right)^2} \tag{8}$$

is a function of the reaction time T_r. The remaining optimization problem is to find the reaction time that minimizes the prediction error, i.e.

$$\hat{T}_r = \arg\min_{T_r>0} e(T_r) \tag{9}$$

This is achieved in a very straightforward way: the error is determined for all reasonable reaction times and the one yielding the smallest prediction error $e(T_r)$ is selected. Please note that due to the temporal resolution of 0.1 s, only multitudes of 0.1 s will be considered in this search, i.e. no data interpolation was considered in the analysis.

3.2 Autocorrelation and its consequences

Generally speaking, common sources for autocorrelation in multivariate regression are the omission of explanatory variables, misspecification of the mathematical model, interpolation of observations (e.g. due to smoothing) and misspecification of the error term. When data are auto correlated, the autocorrelation-coefficient

$$\rho = \mathrm{cov}(\varepsilon_k, \varepsilon_{k-1}) \tag{10}$$

will generally *not be equal to zero*.
Considering our model equation (7), the errors are not uncorrelated but satisfy the following expression:

$$\varepsilon_k = \rho\varepsilon_{k-1} + \nu_k \quad \text{where} \quad |\rho| \leq 1 \tag{11}$$

where ν_k is a random error fulfilling the classical linear model assumption.
When the errors are auto correlated, the model will remain linear and the estimates of the model parameters will remain unbiased as long as $E(\varepsilon_k) = 0$. However, *variance estimates* of

the parameters are known to be biased and underestimated considerably. As a result, the *t*-statistic will be inflated and the *t* and *F* tests will *not be suitable*.
Since it is known that the parameter values are unbiased, the autocorrelation-coefficient ρ can be determined as follows (Cochrane and Orcutt, 1949):

1. obtain the parameter estimates of the multivariate linear model equation (7);
2. determine the errors $\varepsilon_k = y_k - \hat{\kappa}_1 x_k^{(1)} - \hat{\kappa}_2 x_k^{(2)}$;
3. determining ρ directly by equation (10).

The *Durbin-Watson test* (see Durbin, 1970) can then be applied to test if the estimate of the autocorrelation-coefficient significantly differs from zero.
If $\rho \neq 0$ we need to transform the linear model to determine correct values for the parameter variance estimates. Without going into detail, we recall that the following model eliminates the autocorrelation from the statistical analyses (see Cochrane and Orcutt, 1949):

$$\tilde{y}_k = \kappa_1 \tilde{x}_k^{(1)} + \kappa_2 \tilde{x}_k^{(2)} + \nu_k \tag{12}$$

with

$$\tilde{y}_k = y_k - \rho y_{k-1} \tag{13}$$

$$\tilde{x}_k^{(i)} = x_k^{(i)} - \rho x_{k-1}^{(i)} \quad \text{for} \quad i = 1, 2 \tag{14}$$

Using the model equation (12)-(14), standard techniques from multivariate linear regression can be applied.

3.3 Estimation approach verification

The estimation approach was verified by using synthetic data. These data were established by applying the two-leader model using different parameter settings. Furthermore, white noise was added to the acceleration, affecting speeds and positions of the simulated vehicles. Figure 1 shows an example where the estimation approach has been applied to synthetic data.
From the verification of the estimate approach it turns out that the *estimates are unbiased*. Table 1 depicts the results from this verification analysis. The table shows that the mean absolute error is small, and depends on the variance of the added noise.
At this point, let us note one might argue that an *indirect multiple vehicle interaction effect* may be present. This indirect effect would be caused by the fact that leader 1 reacts to leader 2, and thus than the follower reacting to leader 1 thus reacts to leader 2 indirectly (i.e. by sequential application of equation (1)). The verification of the estimation approach shows that this is not the case, and that approach correctly estimates the parameter values also in the case the underlying data stems from a single-leader car-following model.

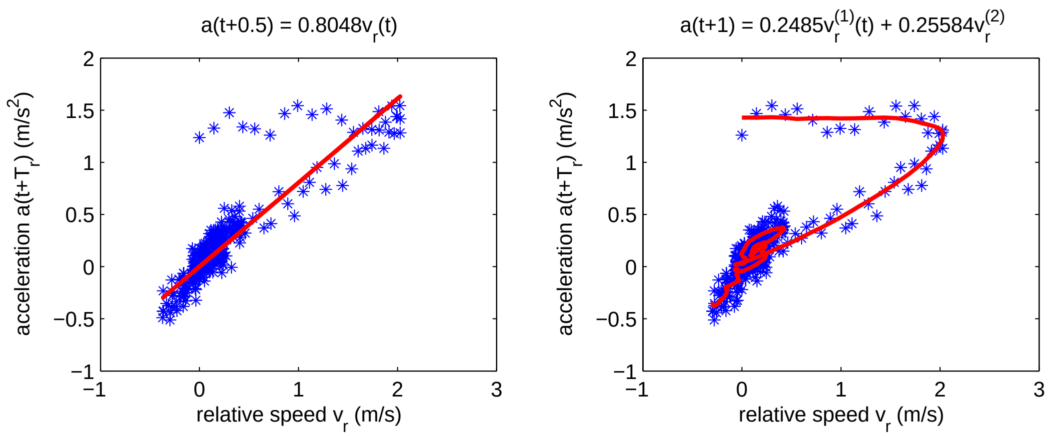


Figure 1. Results from application of the estimation approach to synthetic data. The data was generated by application of the two-leader car-following model with $\kappa_1 = \kappa_2 = 0.25$. White noise was added to the computed acceleration; the standard deviation of the noise equalled 0.01 m/s^2.

Table 1. Mean absolute error for parameter estimates using synthetic data to which different levels of noise were applied.

Parameter:	T_r	κ_1	κ_2
Value used for simulation:	1.0	0.5	0.0
Error standard dev.		Mean absolute error	
0.01	0.000	0.008	0.005
0.1	0.029	0.031	0.021
0.4	0.082	0.060	0.041

Table 2. Mean absolute error for parameter estimates using synthetic data to which different levels of noise were applied.

Parameter:	T_r	κ_1	κ_2
Value used for simulation:	1.0	0.25	0.25
Error standard dev.	Mean absolute error		
0.01	0.013	0.015	0.005
0.1	0.067	0.037	0.015
0.4	0.138	0.075	0.035

4. Data collection

To perform the data analysis, vehicle trajectory data was collected using a new data collection approach (Hoogendoorn and Schreuder, 2005) using an air-borne observation platform (a helicopter), mounted with a high-frequency digital camera and frame grabber. Using image processing software, vehicles are detected from the scene and tracked. This yields trajectory data covering approximately 500 m of roadway stretch; the spatial resolution is smaller than 40 cm, while the temporal resolution is 0.1 s. Besides the trajectories of all vehicles present, the system also determined the vehicles' *lengths and widths* that can for instance be used to

determine the vehicle type. Vehicles driving in both roadway directions were detected and tracked. Only one direction is considered in the remainder of this contribution.
The data were collected during the afternoon peak hour at the three-lane A15 motorway to the South of the Dutch city of Rotterdam. Figure 2 shows a subset of the 935 collected vehicle trajectories for a ninety second period. During the entire period in which data was collection, congestion was heavy.

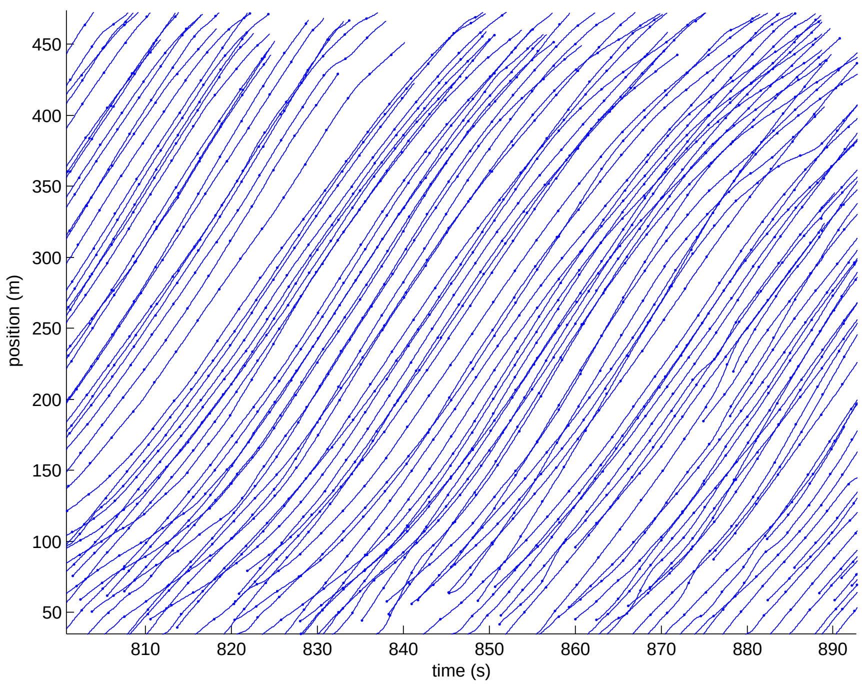


Figure 2. Example subset of vehicle trajectories for data collected at A15 site. The small dots represent time instants which are 2.5 second apart.

A total of 535 vehicle triples were selected for further statistical analyses. These triples satisfied certain criteria. For one, only triples have been considered the composition of which did not change during the observation period. For two, the triples have been observed for at least 15 seconds (150 observation points). The triples have been observed for periods ranging from the aforementioned 15 seconds up to 54 seconds. Figure 3 shows some examples of trajectories of vehicle triples.

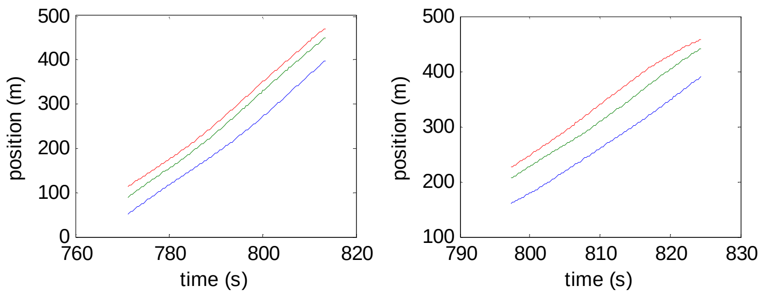


Figure 3. Examples of trajectories of vehicle triples. Only trajectories of fixed triples are considered, i.e. triples of which the composition does not change.

5. Estimation results

This section discusses the results of parameter estimation of both the single-leader model equation (1) and the two-leader model equation (3).

5.1 Statistical testing and autocorrelation

The Durbin-Watson test revealed that autocorrelation could not be neglected. On average, the autocorrelation-coefficient ρ was 0.9. As a result, the modified model equation (12)-(14) was used to test the statistical significance of the model estimates. The results discussed in the ensuing pertain to models for which the parameter estimates κ_1 and κ_2 turned out to be *statistically different from zero* at 95% confidence. Of the 535 vehicle triples deemed useful for estimation purposes, for 518 vehicle triples statistically significant parameter estimates could be established.

5.2 Example estimation results

Figure 4 shows an example of the model after model identification. The figure depicts both measured and predicted acceleration as a function of the relative speed with respect to the leader directly ahead. The figure clearly shows the differences between the predictions stemming from the one-leader car-following model (left) and the two-leader car-following model (right). Studying the estimation results shows that the sum of the sensitivities of the two-leader model is approximately equal to the sensitivity of the single-leader model. Furthermore, the sensitivity estimate κ_1 is *smaller than* the sensitivity κ_2, meaning that the reaction to the second leader is even stronger than to the vehicle directly ahead. Please note that the latter is rather uncommon; for most triples, κ_1 is larger than κ_2.

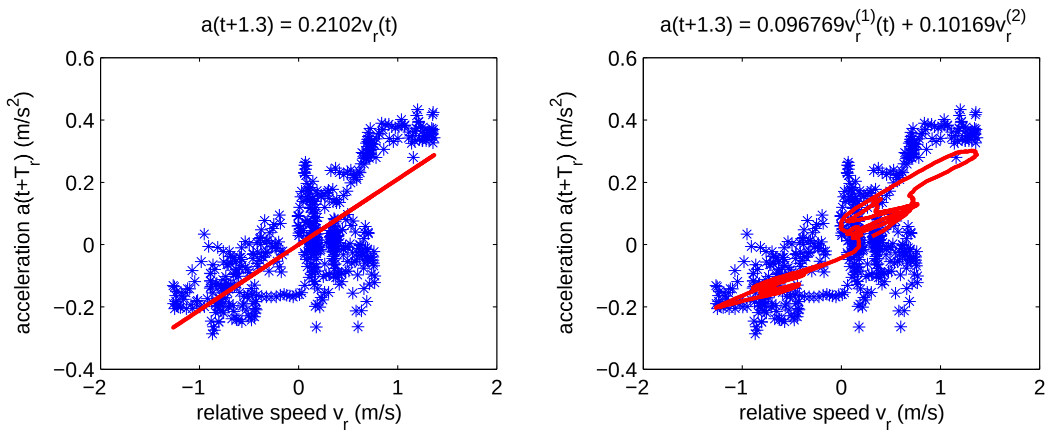
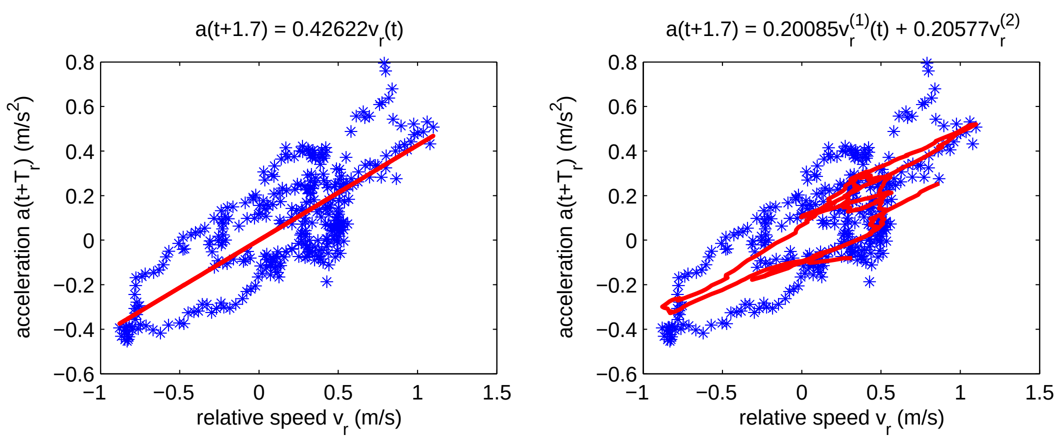


Figure 4. Estimation results for traditional single-leader car-following model (left) and proposed two-leader car-following model (right). The latter is in fact a projection for all values of the relative speed of the second leader.

Figure 5 shows more examples of model estimation results. Looking at the parameter estimates provides some insights into possible parameter values as well as their variability. There are clear differences in the optimal values of the sensitivities κ_1 and κ_2; in some cases, the sensitivity κ_2 with respect to the second leader is even larger than the sensitivity κ_1 with respect to the first. Also note that different values for the reaction times are found.



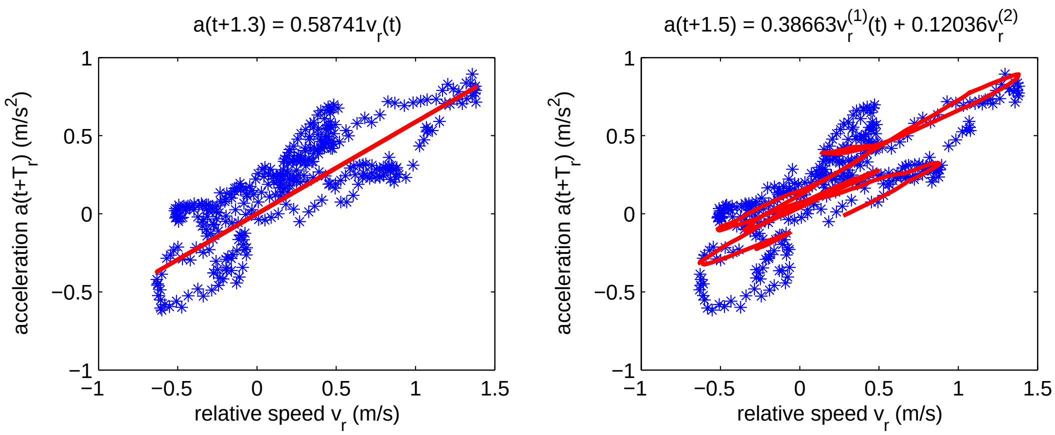


Figure 5. Other examples of model estimation for three car-following triples.

5.3 Parameter distributions

To gain more insight into the inter-driver differences, let us consider the distributions of the parameter estimates. Table 3 shows an overview of model estimation results. The estimates of the standard deviation of the parameters (both the one-leader and the two-leader models) show the large variability in parameter values. This is an interesting and important observation, since it may indicate an important direction in which microscopic simulation models can be improved, i.e. by more effectively include differences between drivers into the microscopic simulation.

From table 3 we can furthermore conclude that the proposed two-leader model outperforms the one-leader model, with an average improvement of 9% in terms of the mean absolute error. Also recall that the parameters in the two-leader car-following model appeared to be significant at 95% confidence.

We see that the parameter values appear to be consistent. The sum of the sensitivities κ_1 and κ_2 of the two-leader model is comparable to the sensitivity κ_1 of the one-leader model. Regarding the two-leader model, we see that the sensitivity κ_1 to the relative speed with respect to the leader is two times larger than the sensitivity κ_2 with respect to the second leader. The correlation between the two parameters estimates κ_1 and κ_2 is -0.31 (not shown in table).

Table 3. Overview of model estimation results.

Model	**Sample size**	**Error**	**Reaction time**	**Sensitivity**	
			***T_r* (st.dev)**	**κ_1 (st.dev)**	**κ_2 (st.dev)**
One-leader	518	0.051	1.36 (0.28)	0.278 (0.139)	
Two-leader	518	0.047	1.54 (0.49)	0.180 (0.126)	0.087 (0.086)
				0.267 (0.127)	

Another interesting observation can be made with respect to the reaction time. From table 3 we can conclude that the reaction time in the two-leader model (1.54 s) is larger than the reaction time in the one-leader model (1.36 s). At this point, it is interesting to note that the inclusion of multiple vehicle interactions has a stabilizing effect on the traffic flow dynamics

(Lenz et al., 1999). The stability reducing effect of the increased reaction time is hence counteracted by the inclusion a driver's response to the second leader. The extent to which this occurs can be determined via stability analysis.
Figure 6 shows that the averages of the parameter estimates yield a stable system. This can be seen by substituting the parameter estimates depicted in table 3 into the stability criterion equation (5).

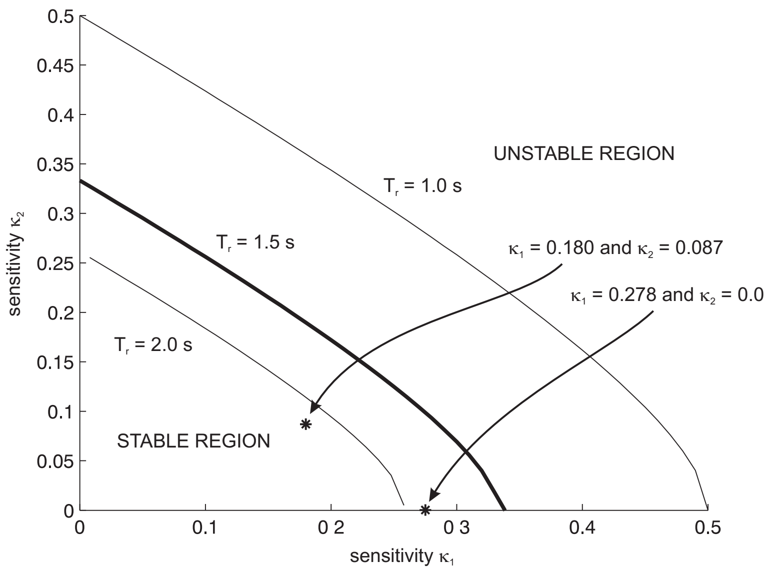


Figure 6. Stability regions for different reaction times T_r. *The figure shows that the mean parameter estimates (one-leader and two-leader model) both yield an asymptotically stable system. The figure also shows how the stable region increases when the reaction time reduces.*

Figure 7 shows the distributions of the sensitivity parameters for the two models. Note that the distribution of the sensitivity parameter of the one-leader model is similar to the sum of the sensitivities of the two-leader model. Again also notice the large variability in the parameter estimates.

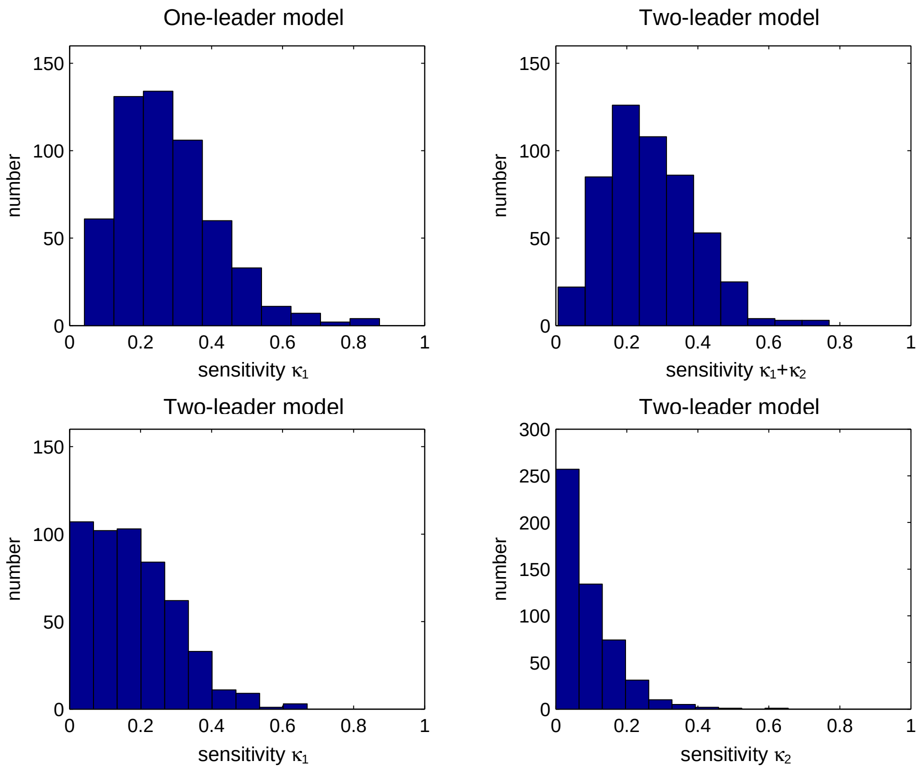


Figure 7. Distributions of parameter estimates for one-leader car-following model (Gazis et al,1961) and the two-leader car-following model (in line with the model of (Bexelius,1968)).

5.4 Analysis of vehicle triple composition

To gain more insight into the reasons for the large inter-driver differences in car-following parameters, the dependence of the estimates on the composition of the vehicle triples was studied. More specifically, we consider:

1. Driver behaviour of person-cars and trucks;
2. Driver behaviour in case the first leader is either a person-car or a truck.

With respect to the first case, we investigate if we can determine statistical differences in the car-following behaviour of the two vehicle types, which would reflect the differences in vehicle characteristics and driver behaviour. The second case is interesting since it would reveal if drivers following a truck are to a lesser extent reacting to the vehicles in front of the truck (second leader) than drivers following a person-car. This is expected, since drivers will generally not be able to look beyond a truck when being directly behind it. Table 4 shows the result of both analyses.

Let us first consider the case where the first leader is either a person-car or a truck. From the parameter estimates, we see that on average, the sensitivity κ_2 is larger when the first leader is a person-car (0.094) compared to the situation that the first leader is a truck (0.054). As mentioned before, this result is as expected, since drivers are more likely to look beyond a person-car than beyond a truck. At the same time, the sensitivity κ_1 with respect to the first leader is

somewhat larger when the first leader is a truck than in case the first leader is a person-car. Also notice that the sum of both sensitivities is slightly smaller when the first leader is a truck, which may be explained by the drivers' awareness of the lesser deceleration capabilities of the truck in front of him or her. Also note that the reaction time is slightly less in the case of following a truck, which can be explained along the same line of thought.
Secondly, we compare the differences between following person-cars and trucks. As it turns out, the reaction time of truck drivers is smaller than the reaction time of person-cars. This can be explained by differences in driver experience between the two driver types. At the same time, the *relative sensitivity* $\kappa_2/(\kappa_1 + \kappa_2)$ to the second vehicle ahead is much larger in case of truck drivers (0.37) than in case of person-cars (0.29); the total sensitivity $\kappa_1 + \kappa_2$ is nevertheless much smaller, which can be explained by smoother driving of the truck drivers.

Table 4. Overview of model estimation results for different compositions

Composition of vehicle triple			**Sample size**	**Error**	**Reaction time**	**Sensitivity**	
Follower	**1st leader**	**2nd leader**			T_r **(st.dev)**	κ_1 **(st.dev)**	κ_2 **(st.dev)**
*	*	*	518	0.047	1.54 (0.48)	0.190 (0.127)	0.089 (0.088)
*	P	*	426	0.049	1.53 (0.44)	0.185 (0.129)	0.094 (0.090)
*	T	*	67	0.033	1.57 (0.64)	0.219 (0.116)	0.054 (0.068)
P	*	*	428	0.047	1.54 (0.46)	0.198 (0.128)	0.090 (0.086)
T	*	*	65	0.043	1.51 (0.56)	0.138 (0.110)	0.082 (0.101)

* mixed
P person-cars
T trucks (articulate and non-articulate)

Note that the results are in line with earlier work pertaining to the headway distributions (Hoogendoorn and Bovy, 1998). Here, it was also found that the car-following behaviour (in terms of headway distributions) depends on the composition of the vehicle pair.

6. Conclusions and future work

This manuscript presents new estimation results of stimulus-response car-following models based on empirical vehicle trajectories. The main contribution of the work is the empirical evidence of the much argued assumption that drivers are not only considering the vehicle directly ahead, but also the 'second leader' (two vehicles ahead). The extent to which this occurs is considerable. On average, the sensitivity with respect to the first leader is only two times larger that the sensitivity with respect to the second leader. For some vehicle triples, we even observe a higher sensitivity to the behaviour of the second leader than to the behaviour of the first (strong anticipation behaviour). Comparison the estimation results from the different vehicle triples shows large differences in driving behaviour between the vehicles.
These observations indicate interesting directions in which microscopic simulation models may be substantially improved. For one, an improvement is anticipated upon including multiple vehicle interactions into the microscopic modelling. This has been argued by several researchers before, but using the empirical trajectory data, empirical evidence is now provided. For two, inclusion of the large differences in driving behaviour may improve accuracy of microscopic simulation considerably.

In this contribution it is also shown that the extent to which drivers react to the second leader depends on the type of vehicle that is following as well as the type of vehicle that is followed. For instance, drivers following a truck on average show a weaker reaction to the second leader than drivers following a person-car, which can be explained by noticing that drivers cannot easily look beyond a truck. In a similar way, truck drivers show a relative strong reaction on the second leader. This is explained by the high vantage point of truck drivers and the increased ability to look further ahead.
The next step in the research entails a further analysis of the properties of the resulting traffic flow model, yielding insight into the impact of differences in individual car-following behaviour in the properties of the traffic flow. Future research is also directed towards benchmarking different single leader and multi leader car-following models as well as developing more advanced ones. Additionally, the research will focus on changing driving behaviour (behavioural adaptation) when different traffic conditions are experienced using the microscopic traffic data.

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References

Bando, M., et al. (1995). Dynamical Model of Traffic Congestion and Numerical Simulation. *Physical Review*, vol. 51, pp. 1035-1042.

Bexelius, S. (1968). An extended model for car-following. *Transportation Research*, vol. 2, no. 1, pp. 13-21.

Brackstone, M. and McDonald, M. (1999). Car-Following: A Historical Review. *Transportation Research Part F*, vol. 2, pp. 181-196.

Brockfeld, E. and Kühne, R. et al. (2004). Calibration and validation of microscopic traffic flow models. *Transportation Research Board Annual Meeting* Pre-Print CD-Rom, Washington D.C., Transportation Research Board.

Cochrane, D. and Orcutt, G.H. (1949). Application of Least Squares Regression to Relationships Containing Auto correlated Error Terms. *Journal of the American Statistical Association*, vol. 44, pp. 32-61

Daganzo, C.F. (2002). A Behavioral Theory of Multi-Lane Traffic Flow. Part I: Long Homogeneous Freeway Sections. *Transportation Research B*, vol. 36, no. 2, pp. 131-158.

Dijker, T. and Bovy, P.H.L., et al. (1998). Car-Following under Congested Conditions: Empirical Findings. *Transportation Research Record*, vol. 1644, pp. 20-28.

Durbin, J. (1970). Testing for Serial Correlation in Least-Squares Regression When Some of the Regressors Are Lagged Dependent Variables. *Econometrica*, vol. 38, pp. 410-421.

Gazis, D.C., Herman, R. and Rothery, R.W. (1961). Nonlinear follow-the-leader models of traffic flow. *Operation Research*, vol. 4, no. 9, pp. 545-567.

Herman, R., and Potts, R.B. (1959). Single Lane Traffic Theory and Experiment. In: *Proceedings of the Symposium on Theory of Traffic Flow*, Research Labs, General Motors, New York, Elsevier, pp. 147-157.

Hoefs, D.H. (1972). *Entwicklung einer Messmethode uber den Bewegungsablauf des Kolonnenverrkehrs*. Universitat (TH) Karlsruhe, Germany.

Hoogendoorn, S. P. et al. (2002). Microscopic Traffic Data Collection by Remote Sensing. *Transportation Research Records*, vol. 1855, pp. 121-128.

Hoogendoorn, S.P. and Bovy, P.H.L. (1998). A new estimation technique for vehicle-type specific headway distributions. *Transportation Research Record*, vol. 1646, pp. 18-28.

Hoogendoorn, S.P., and Schreuder, M. (2005). Tracing Congestion Dynamics with Remote Sensing: Towards a robust method for microscopic traffic data collection. *Transportation Research Board Annual Meeting*, Pre-print CD-rom.

Lenz, H., Wagner, C.K. and Sollacher, R. (1999). Multi-anticipative car-following model. *The European Physical Journal B*, vol. 7, pp. 331-335.

Ossen, S., and Hoogendoorn, S.P. (2005). Car-following behaviour analysis from microscopic trajectory data. *Transportation Research Board Annual Meeting*, pre-print CD-ROM. Accepted for presentation.

Ozaki, H. (1993). Reaction and anticipation in the car following behaviour. In: *Proceedings of the 13th International Symposium on Traffic and Transportation Theory*, pp. 349-366.

Treiber, M., Kesting, A. and Helbing, D. (forth coming). Multi-anticipative driving in microscopic traffic models. Submitted to *Physical Review E*.

Treiterer, J. and Myers, J.A. (1974). The hysteresis phenomenon in traffic flow. In: *Proceedings of the Sixth International Symposium on Transportation and Traffic Theory*, Sydney, pp. 13-38.

Zhang, H.M. and Kim, T. (2001). A car-following theory for multiphase vehicular traffic.