Microscopic Traffic Flow Properties in Emergency Situations

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Emergency situations (e.g., evacuations following a disaster) have been shown to affect traffic flow operations substantially. However, the best way to model the adaptation effects in longitudinal driving behavior underlying this impact had not been made clear. Furthermore, the macroscopic consequences of the adaptation effects in longitudinal driving behavior had also not been made clear. This study sought to clarify these modeling issues and macroscopic consequences by estimating parameter values and model performance of the intelligent driver model with the data obtained through a driving simulator study. In addition, this paper presents the results of a case study that used a microscopic simulation program and the parameter values obtained through the estimation of the intelligent driver model. Results show that emergency situations have a substantial influence on parameter values and performance of the intelligent driver model. Furthermore, results show that the adaptation effects represented in parameter values and model performance have a substantial influence on macroscopic flow characteristics. A discussion of results and recommendations for future research are provided.

Emergency situations have been shown to have a substantial impact on traffic flow operations. For example, in the United States, the events of Hurricanes Georges in 1998 and Floyd in 1999 precipitated the country's two largest evacuations and perhaps its two largest traffic jams (*1*). Hurricane Rita also led to massive traffic congestion as well as fuel supply problems. These hurricanes revealed that emergency response agencies were not as prepared for such scenarios as had been previously assumed.

However, because emergency situations have a low rate of occurrence, experience in how to cope with them is sparse. In this context, Hoogendoorn et al. showed that emergency situations have a substantial influence on empirical longitudinal driving behavior (*2*). They observed that emergency situations lead to a substantial increase in speed, acceleration, and deceleration and a reduction in the distance from the lead vehicle.

To investigate whether evacuation strategies (e.g., lane reversal) are effective, simulation studies must be performed. For example, a large number of evacuation studies recently investigated the efficacy of evacuation strategies by using well-established dynamic traffic simulation models developed for day-to-day traffic applications (*3*). Many of studies used microscopic simulation models. In those models, mathematical models are used to approximate longitudinal and lateral driving behavior.

However, the best way to model the adaptation effects in longitudinal driving behavior established in Hoogendoorn et al. has not been made clear (*2*). To what extent are these adaptation effects in longitudinal driving behavior represented in changes in parameter values and performance of mathematical models of longitudinal driving behavior? Furthermore, the extent to which the adaptation effects in longitudinal driving behavior affect traffic flow operations has also not been made clear.

This paper therefore reports the results of estimations of an often-used car-following model, namely the intelligent driver model [IDM (*4*)] by using the data reported in Hoogendoorn et al. (*2*). These estimations used the calibration approach for joint estimation reported in Hoogendoorn and Hoogendoorn (*5*). This paper shows that emergency situations have a substantial influence on parameter values and the performance of IDM.

Furthermore, this paper reports the results of a simulation study that used the microscopic simulation model reported in Schakel et al. (*6*). That study simulated an emergency situation with an increasing traffic demand by using the parameters of IDM reported in this paper. These results were compared with those under normal driving conditions with an increasing traffic demand.

The next section briefly introduces IDM and is followed by a brief report on the state of the art in modeling of longitudinal driving behavior in an emergency situation (*4*). A presentation of the methodology comes next and briefly describes the data, the method used for the estimation of the parameter values, and the performance of IDM and presents the setup of the simulation study. Then the results are presented. The paper ends with a discussion section in which conclusions are drawn and recommendations for future research are provided.

MODELING LONGITUDINAL DRIVING BEHAVIOR IN EMERGENCY SITUATIONS

Description of IDM

Car following can be regarded as a subtask of the longitudinal vehicle interaction task. This vehicle interaction subtask has received significant attention among those who study or have responsibility for traffic flow. Several mathematical microscopic models have been developed that aim to mimic driving behavior under a wide range of conditions so that they can be used in microscopic simulation

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and in guiding the design of advanced vehicle control and safety systems (*7*).

These models are called microscopic because they capture traffic flow at the level of individual vehicles. They describe traffic flow through behavioral rules of those vehicles. Therefore, they are by definition built on specifications of driving behavior (*8*). These models have been used for research on the influence of vehicle, road, and driver characteristics; external conditions, and traffic regulations.

IDM (*4*) was developed because earlier models had unrealistically small acceleration and deceleration times [e.g., Bando et al. (*9*)] and because more high-fidelity models, like that of Leutzbach and Wiedemann (*10*), had too many parameters. Furthermore, Treiber et al. conjectured that most models do not adequately incorporate traffic flow phenomena such as traffic instabilities and hysteresis (*4*). The number of parameters and the belief that the model replicates several traffic flow phenomena fairly well were the reasons for choosing this car-following model.

Acceleration in IDM is a continuous function incorporating different driving models for all speeds in both freeway and city traffic (*4*). In addition to the following distance Δx and speed v, IDM also takes relative speed Δv into account. IDM acceleration is given by

$$a(t) = a_{\max}\left[1 - \left(\frac{v(t)}{v_0}\right)^{\delta} - \left(\frac{s^*(v(t), \Delta v(t))}{\Delta x(t)}\right)^2\right]$$

$$s^*(v(t), \Delta v(t)) = s_0 + v(t)T + \frac{v(t)\Delta v(t)}{2\sqrt{a_{\max} b_{\max}}}$$

and $a[1 - (v/v_0)^{\delta}]$ is the free-flow acceleration and $-a(s^*/\Delta x)^2$ is the deceleration strategy. The latter becomes relevant when the distance Δx from the lead vehicle is not significantly larger than the desired distance s^* from the lead vehicle. The free-flow acceleration is characterized by free speed v_0, maximum acceleration $a_{\max}$, and the component δ. This component characterizes how acceleration decreases with speed. The variable t is the time instant.

Desired distance s^* from the lead vehicle is composed of a minimal stopping distance ("jam distance") s_0, and a speed-dependent distance vT, which corresponds to following the lead vehicle with a constant desired time headway T and a dynamic contribution that is active only in nonstationary traffic conditions. The dynamic contribution implements an intelligent driving behavior that, in normal situations, limits braking decelerations to maximum deceleration $b_{\max}$ (*11*).

Car-Following Modeling in Emergencies

No research on the influence of emergency situations on parameter value changes in current car-following models was found. Hamdar and Mahmassani, however, took a step forward in the incorporation of adaptation effects in longitudinal driving behavior attributable to emergency situations (*12*). They devised a model to capture longitudinal driving behavior under extreme conditions through modification of the safe-distance model devised by Gipps (*13*). Hamdar and Mahmassani used the Gipps model in their research to show that an acceptable degree of stability resulted when the model's safety constraints were relaxed (*12*).

Hamdar and Mahmassani stated that, in relation to acceleration under emergency situations, drivers are more willing to apply higher acceleration rates than under normal driving conditions; these higher acceleration rate cause irregularities and possible instabilities in traffic flow patterns (*12*). The variable a_i was drawn from a truncated Gaussian-shaped distribution to deal with unrealistically high and low volumes. In relation to maximum deceleration, Hamdar and Mahmassani assumed that the value of this parameter can increase in absolute value because, under extreme conditions, drivers tend to have higher braking rates or an increased use of emergency braking (*12*). In their modification of the Gipps model, they also altered the variable representing desired speed. In emergency situations, the true value of this parameter was drawn from a probabilistic mixture of two Gaussian distributions in which the means were, respectively, higher and lower than the suggested mean in the model's original formulation (*13*).

This paper, however, uses IDM to describe and predict adaptation effects in longitudinal driving behavior as well as to establish the effects of these adaptation effects on traffic flow operations (*4*). The next section describes the research method. It starts with a brief description of the data used for the parameter estimations, which is followed by a presentation of the used estimation method. The section ends with a description of the setup of the simulation study.

RESEARCH METHOD

Data Collection

To estimate parameter values and determine model performance of IDM (*4*), the data obtained through the driving simulator experiment presented in Hoogendoorn et al. were used (*2*). This driving simulator experiment had a multifactorial design with two experimental groups (no emergency situation versus emergency situation) and three (within-subjects) conditions with an increasing level of urgency. Participants could earn a maximum reward of €30 under the condition that they would reach their destination safely in time. During the test trials, three messages were shown on the simulator screen, including "On time" and "You are running out of time!" These messages were accompanied by the remaining reward and represented the three within-subject conditions (*2*).

The test trials took place on a virtual motorway with two lanes in the same direction. No speed limit was set. The length of the test trial was 18.9 km. The behavior of the other traffic was derived from a pilot study and consisted of an increase in speed, acceleration, and deceleration rates along with a reduction in the distance from the lead vehicle. During the test trials in the control as well as in the experimental group, two stop-and-go waves were simulated. Speed v, acceleration a, deceleration b, and distance s from the lead vehicle of the participants were measured at 10 Hz.

The research population consisted of 38 employees and students of Delft University of Technology (21 male and 17 female). The age of the participants varied from 21 to 56, with a mean age of 30.41 [standard deviation (SD) = 5.30]. Driving experience varied from 3 to 29 years, with a mean of 10.31 years (SD = 6.41).

Estimation of IDM

The approach used to estimate the parameters of IDM is a derivation of an approach to estimation of statistical parameters that enables the statistical analysis of the model estimates and cross comparison of models of differing complexity (*4*). This approach, explained in depth in Hoogendoorn and Hoogendoorn, allows simultaneous use of multiple trajectories, through which the estimation results are improved when the information in individual trajectories is limited

(*5*). Further, it allows for inclusion of prior information on parameter values that are to be estimated.

The approach also allows for statistical analysis of the model estimates, including the standard error and the correlation of the parameter estimates. Furthermore, one can easily test whether a specific model outperforms other models by using a likelihood ratio test. A nice property of this approach is that it takes the number of parameters of the model into account as well as performance.

The objective of the approach is to estimate the parameter vector $\vec{\theta}_i$ of the car-following model for driver *i.* This vector therefore describes the behavior of driver *i* by using the data. Therefore, the maximum-likelihood procedure first proposed in Hoogendoorn and Ossen was amended by enabling the use of prior information on the parameter distribution (*14*).

If one assumes a set of N trajectories for an equal number of drivers $i = 1, 2, \ldots, N,$ then the driving behavior of each of these drivers can be described by a driver-specific set of parameters $\vec{\theta}^{(i)}$. Given the observed trajectory data, the likelihood $L^{(i)}(\vec{\theta}^{(i)})$ of observing this trajectory can be determined given that the car following is described by the set of parameters $\vec{\theta}^{(i)}$. In combining the trajectories, one can easily determine the joint likelihood L_{mult} of observing the trajectories of drivers $i = 1, 2, \ldots, N$:

$$L_{\text{mult}}\left(\vec{\theta}^{(1)}, \ldots, \vec{\theta}^{(N)}\right) = \prod_{i=1}^{N} L^{(i)}\left(\vec{\theta}^{(i)}\right)$$

With this expression, one can also determine the likelihood that all drivers in the considered driver population $[L_{\text{mult}}(\bar{\theta})]$ can be described by the same parameter set:

$$L_{\text{mult}}\left(\bar{\theta}\right) = \prod_{i=1}^{N} L^{(i)}\left(\bar{\theta}\right)$$

The preceding equation therefore assumes that the behavior of all drivers is governed by the same parameter vector. If one assumes that the parameters $\vec{\theta}^{(i)}$ are drawn from some random distribution with mean Θ and covariance matrix Σ, then

$$\sum\left(\bar{\theta}\right) = \Theta$$

and

$$\text{var}\left(\bar{\theta}\right) = \frac{1}{\sqrt{N}}\Sigma$$

This expression allows, from the joint estimation results, construction of the mean and covariance of the distribution underlying the individual parameters. This construction also allows one to determine whether changes in parameter values are significantly influenced by adverse conditions through the performance of statistical tests (e.g., *t*-tests for independent samples and for paired samples).

This section discussed the data analysis method used to estimate the parameter values and model performance of IDM (*4*). The next section presents setup of the simulation study.

Setup of Simulation Study

The simulation study used the simulation software package OpenTraffic, an open-source simulation package developed in Java (*6*). The study used a road length of $x = 6{,}000$ m and a simulation time $t = 7{,}200$ s with time steps of 0.2 s. Starting at $x = 2{,}500$ m, vehicles were able to merge onto the main carriageway.

Six loop detectors were placed, at $x = 1{,}000$, 1,500, 2,000, 2,500, 3,000, and 3,500 m (before and after the on-ramp). The traffic demand q was set to values of 3,000, 5,000, and 3,000 vehicles per hour (vph) at $t = 0$, 3,600, and 7,200, respectively. This demand was interpolated at each minute. The demand of the on-ramp was set to a constant value of 2,000 vph.

Only one vehicle class was applied (cars). Furthermore, the study used the parameter settings of IDM obtained through the estimation approach described earlier (*4*). The lane-changing model used was the one described in Schakel et al. (*6*).

Two scenarios with differing parameter settings were studies. The first scenario (control condition) simulated individual driving behavior and traffic flow operations given normal driving conditions, while the second scenario (experimental condition) used the parameter settings established for an emergency situation.

This section described the setup of the simulation study aimed at showing the influence of an emergency situation on traffic flow operations. The next section presents the results of both the estimations and the simulation study.

RESULTS

Parameter Values and Performance of IDM

This section discusses the extent to which emergency situations lead to parameter value changes and changes in model performance of IDM (*4*).

To determine the influence of emergency situations on parameter values of IDM, parameter values of the control group (no emergency situation) were compared with those of the experimental group (emergency situation) for this model. The parameter values maximum acceleration a_{max}, maximum deceleration b_{max}, free speed v_0, and desired time headway T were estimated separately by driver and by longitudinal position, and then the mean, minimum, and maximum values and the SDs were calculated.

In Table 1, the mean values, SDs, and ranges for the parameter values of IDM in an emergency situation are presented. This table shows the descriptive statistics of the parameter values for both the

TABLE 1 Parameter Values of IDM for Control Group (No Emergency Situation) and Experimental Group (Emergency Situation)

Parameter	Mean	SD	Min.	Max.
Control group				
Max. acceleration a_{max} (m/s^2)	0.94	0.68	0.35	2.03
Max. deceleration b_{max} (m/s^2)	0.87	0.34	0.57	1.18
Free speed v_0 (m/s)	29.97	4.02	25.87	34.01
Desired time headway T	0.78	1.06	0.07	2.99
Experimental group				
Max. acceleration a_{max} (m/s^2)	1.46	0.65	0.80	2.14
Max. deceleration b_{max} (m/s^2)	0.97	0.21	0.70	1.18
Free speed v_0 (m/s)	35.27	3.07	32.38	39.51
Desired time headway T	0.25	0.68	0.09	0.45

NOTE: SD = standard deviation; min. = minimum; max. = maximum.

control group (no emergency situation) and the experimental group (emergency situation).

In IDM, maximum acceleration a_{max} represents the maximum acceleration a driver is willing to apply (*4*). As an illustration, Figure 1, *a* and *b*, shows the estimation results for the parameter a_{max} obtained by fitting IDM to the observations of the driving simulator for the control group (no emergency situation) and the experimental group (emergency situation).

Figure 1 shows that for both groups the parameter value a_{max} fluctuates considerably over time. In both groups, the two stop-and-go waves do not seem to have a substantial influence on the mean parameter value of a_{max}. Furthermore, the figure shows that the variability between drivers is quite substantial, as indicated by the large SDs. In Figure 1, *a* and *b*, the bold blue line represents the estimate of the parameter values, while the thin lines indicate the expected value plus or minus SD. The four vertical dotted lines represent the start and end of the stop-and-go waves.

Comparison of the two groups from the data in Table 1 and Figure 1 shows that overall a_{max} is larger in the experimental group than in the control group. The overall mean value of a_{max} in the control group was 0.94 m/s^2, while, in the experimental group, it was 1.46 m/s^2. When one compares the value of a_{max} in the control group with values normally used in simulations, one may conclude that the values are quite similar (*11*). Overall, the variation between drivers was smaller in the experimental group than in the control group.

A *t*-test for independent samples showed that the difference in a_{max} between the control group and the experimental group was significant ($p < .05$). One can therefore conclude that a_{max} in emergency situations is significantly larger than in normal driving conditions.

Table 1 also includes descriptive statistics for maximum deceleration b_{max}, which in IDM represents the maximum deceleration a driver is willing to apply (*4*). As an illustration, Figure 1, *c* and *d*, shows the estimation results for the parameter maximum deceleration b_{max} obtained by fitting IDM to observations of the driving simulator

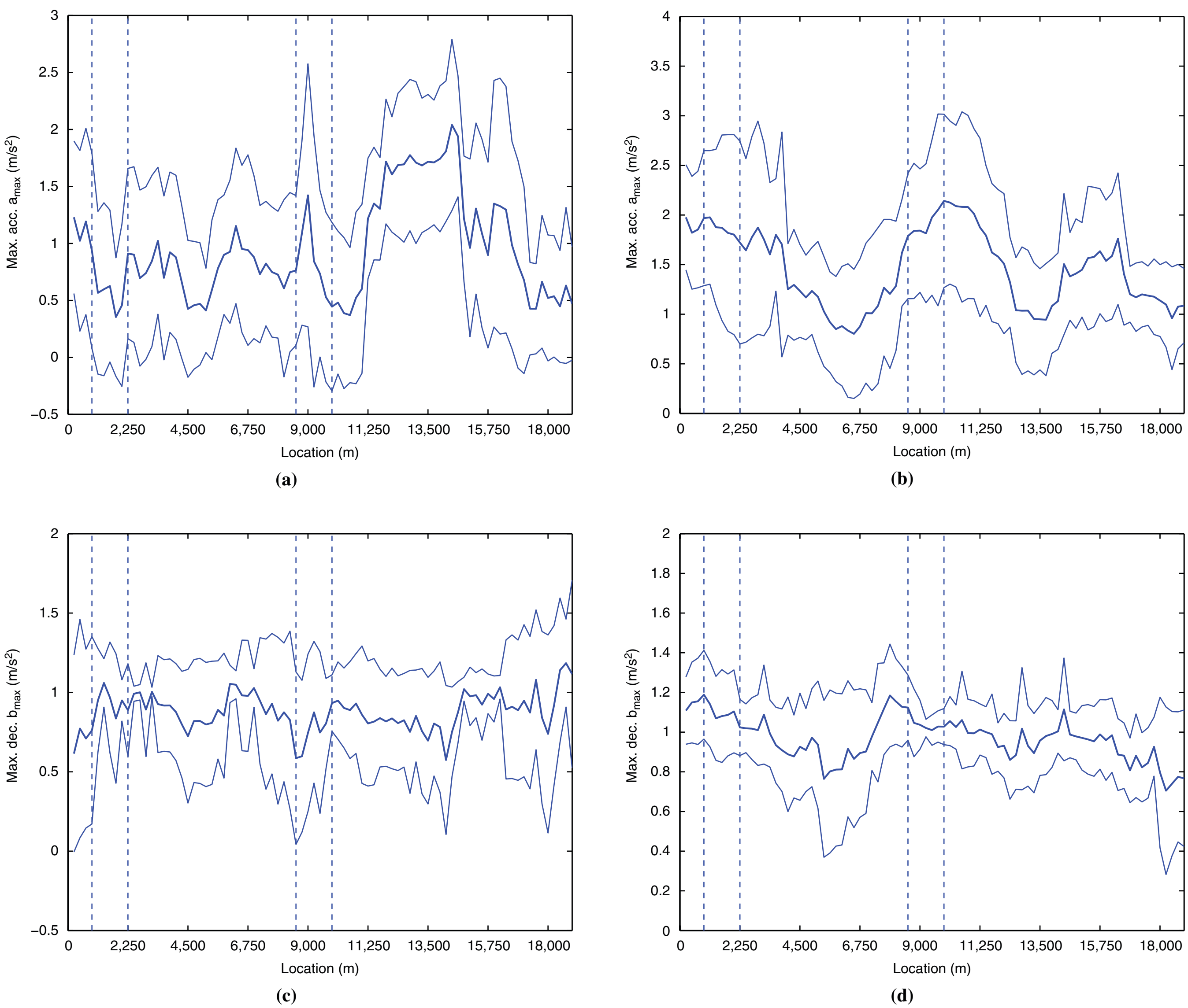

FIGURE 1 IDM parameter estimates: maximum acceleration a_{max} for (*a*) control group and (*b*) experimental group; maximum deceleration b_{max} for (*c*) control group and (*d*) experimental group (*4*) (max. acc. = maximum acceleration; max. dec. = maximum deceleration).

for the control group (no emergency situation) and the experimental group (emergency situation).

Figure 1 shows that for both groups the parameter value b_{max} fluctuates considerably over time. This fluctuation is a strong indication of a substantial degree of variability within drivers. As was the case with maximum acceleration a_{max}, maximum deceleration b_{max} also shows substantial differences between drivers, as indicated by the large SDs. In both groups, the two stop-and-go waves do not seem to have a substantial influence on the mean parameter value of b_{max}. In Figure 1, *c* and *d*, the bold blue line also represents the estimate of the parameter values, while the thin lines indicate the expected value plus or minus SD. Again, the four vertical dotted lines represent the start and end of the stop-and-go waves.

Comparison of the two groups from the data in Table 1 and Figure 1 shows that overall b_{max} is larger in the experimental group than in the control group. The overall mean value of b_{max} in the control group was 0.87 m/s^2, while, in the experimental group, it was 0.97 m/s^2. When one compares the value of b_{max} in the control group with the values normally used in simulations, one can conclude that b_{max} is somewhat lower (*11*). Overall, the variability between drivers was smaller in the experimental group than in the control group.

A *t*-test for independent samples showed that the difference in b_{max} between the control group and the experimental group was significant ($p < .05$). One can therefore conclude that b_{max} in emergency situations is significantly larger than in normal driving conditions.

Table 1 also includes descriptive statistics for free speed v_0. As an illustration, Figure 2, *a* and *b*, shows the estimation results for the parameter free speed v_0 obtained by fitting IDM to the observations of the driving simulator for the control group (no emergency situation) and the experimental group (emergency situation). Figure 2 shows that for both groups the parameter value of free speed v_0 remains fairly constant over time. Furthermore, the figure shows a relatively small SD, which is an indication of a small degree of variability between drivers in relation to the v_0 parameter of IDM. In both groups, the two

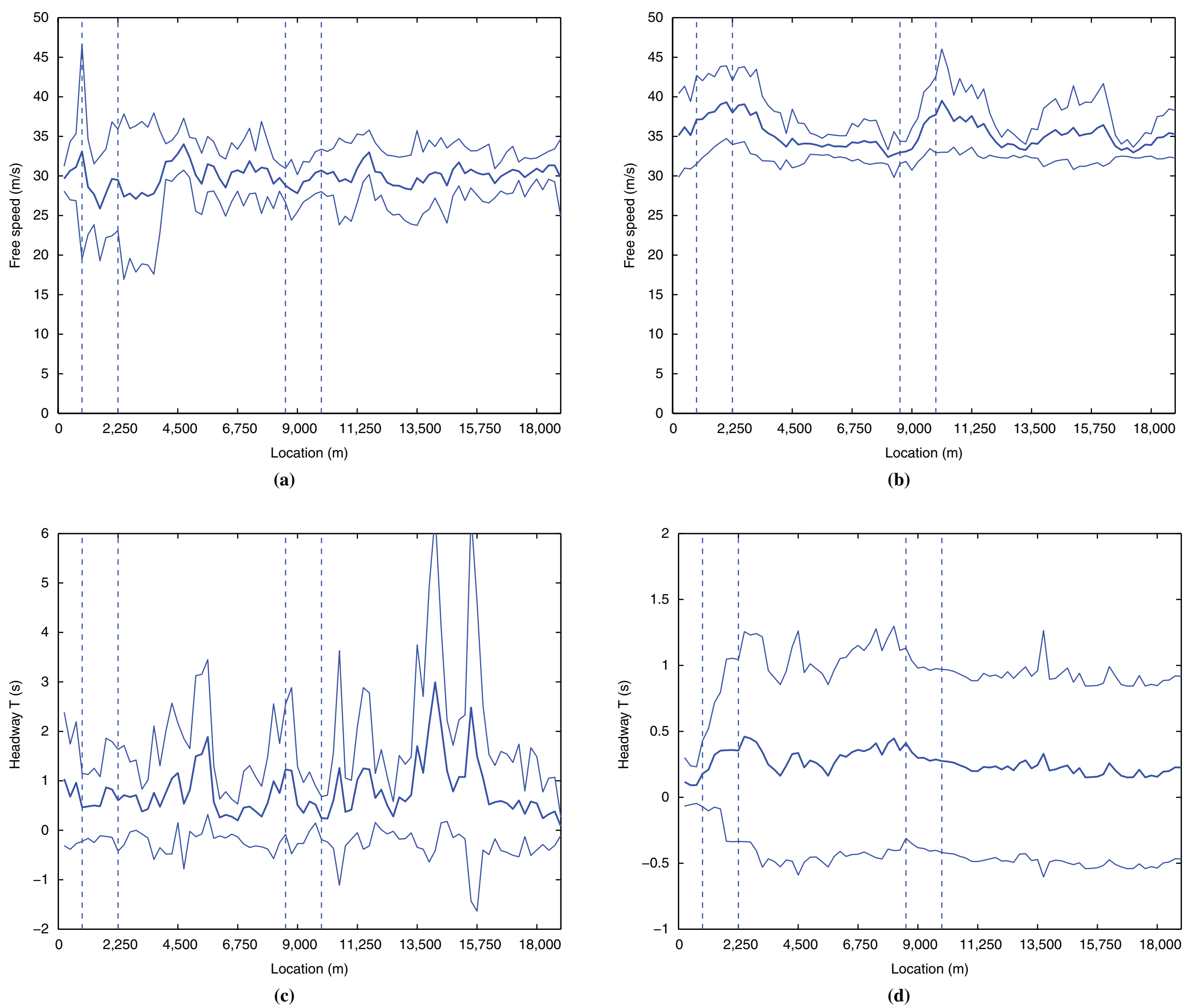

FIGURE 2 IDM parameter estimates: free speed v_0 for (*a*) control group and (*b*) experimental group; desired time headway *T* for (*c*) control group and (*d*) experimental group (*4*).

stop-and-go waves do not seem to have a substantial influence on the mean parameter value of v_0. In Figure 2, *a* and *b*, the bold blue line represents the estimate of the parameter values, while the thin lines indicate the expected value plus or minus SD. The four vertical dotted line represent the start and end of the stop-and-go waves.

Comparison of the two groups from the data in Table 1 and Figure 2 shows that overall v_0 is larger in the experimental group than in the control group. The overall mean value of v_0 in the control group was 29.97 m/s, while, in the experimental group, it was 35.27 m/s. Again, overall, the variability between drivers was smaller in the experimental group than in the control group.

An independent samples *t*-test showed that the difference in v_0 between the control group and the experimental group was significant ($p < .05$). One can therefore conclude that v_0 in emergency situations is significantly higher than in normal driving conditions.

Finally, Table 1 also includes descriptive statistics for desired time headway *T*, which in IDM represents the dynamic component of desired distance from the lead vehicle. This parameter determines the extent to which desired distance from the lead vehicle is dependent on the speed of the following vehicle. Again, as an illustration, Figure 2, *c* and *d*, shows the estimation results for the parameter desired time headway *T* obtained by fitting IDM to the observations of the driving simulator for the control group (no emergency situation) and the experimental group (emergency situation).

Figure 2 shows that, especially in the control group, the parameter value of *T* fluctuates considerably over time. This fluctuation is a strong indication of a substantial degree of variability within drivers in relation to *T* in normal driving conditions. In the experimental group, the fluctuations over time were considerably smaller. Figure 2 also shows that the variability between drivers is relatively large in both groups. Furthermore, the two stop-and-go waves do not seem to have a substantial influence on the mean parameter value of *T*. In Figure 2, *c* and *d*, the bold blue line also represents the estimate of the parameter values, while the thin lines indicate the expected value plus or minus SD. Again, the four vertical dotted lines represent the start and end of the stop-and-go waves.

Comparison of the two groups from the data in Table 1 and Figure 2 shows that overall *T* is substantially smaller in the experimental group than in the control group. The overall mean value of *T* in the control group was 0.78 s, while, in the experimental group, it was 0.25 s. Again, overall, the variation between drivers was smaller in the experimental group than in the control group.

An independent samples *t*-test showed that the difference in *T* between the control group and the experimental group was significant ($p < .05$). One can therefore conclude that *T* in emergency situations is significantly smaller than in normal driving conditions.

To gain insight into the performance of IDM, the estimated model was compared with a null model (i.e., the model assuming zero acceleration). In other words, in the null model, the parameter values were set to zero to allow a good comparison of performance of the estimated model. Figure 3, *a* and *b*, shows that, for IDM in both the control and the experimental groups, the estimated models outperform the null model. Furthermore, the figure shows that performance of the estimated model in both the control group and the experimental group increases during the segments in which a stop-and-go wave is present. (In the figure, the blue line represents the log likelihoods of the estimated model, while the red line represents the log likelihoods of the null model. The four vertical dotted lines represent the start and end of the stop-and-go waves.)

When one compares the log likelihoods of IDM of the control group with those of the experimental group, one can see that their performance was quite similar. However, overall performance of IDM was somewhat lower in the experimental group than in the control group. An independent samples *t*-test showed that this difference was significant ($p < .05$).

This section demonstrated that emergency situations have a substantial influence on parameter values of IDM (*4*). A substantial increase in maximum acceleration a_{max}, maximum deceleration b_{max}, and free speed v_0 and a reduction in desired time headway *T* can be observed. Comparison shows a substantial variability between drivers, with the magnitude of the variability differing between normal driving conditions and driving in an emergency situation. Furthermore, one can conclude from the results that performance of IDM (*4*) is substantially and significantly lower in an emergency situation than in normal driving conditions. Car following seems to be, to a lesser extent, a determinant of longitudinal driving behavior.

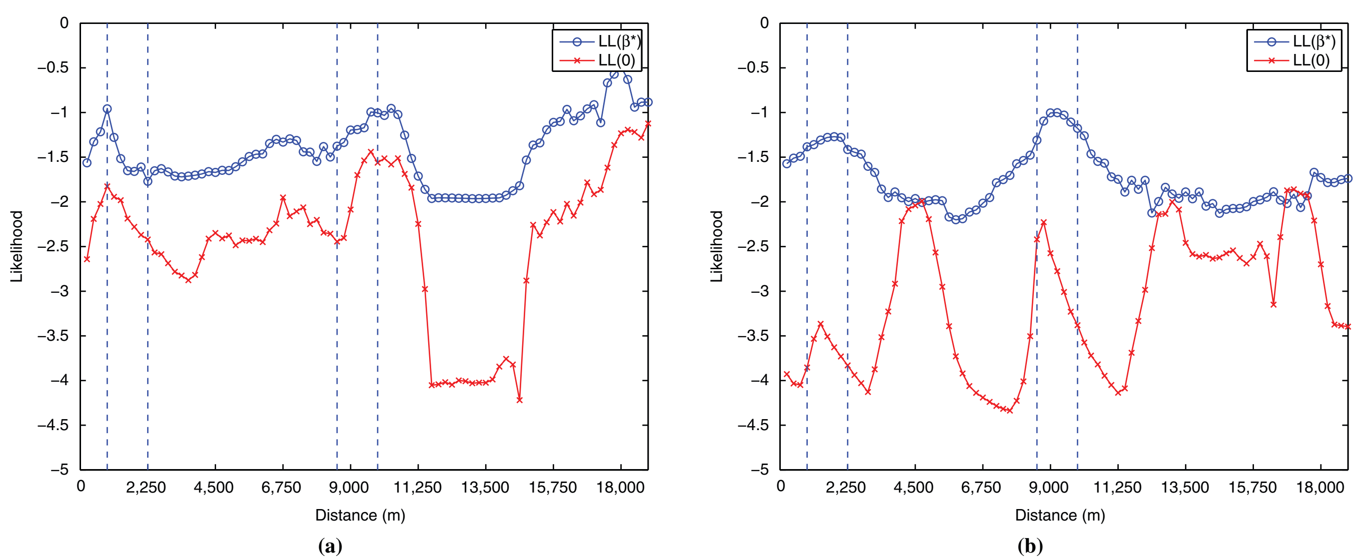

FIGURE 3 Performance of model compared with null model (zero acceleration) for IDM: (*a*) control group and (*b*) experimental group (*4*).

Macroscopic Consequences of Emergency Situations

By using the simulation setup presented in the section on research methodology and the parameter values reported in the preceding section, the speeds at the six detectors can be compared. In Figure 4, the speeds at each of the six detectors are plotted for normal driving conditions [blue markers (dark gray)] and an emergency situation [red markers (light gray)].

Some clear differences between the two scenarios can be observed. As noted earlier, the on-ramp starts at $x = 2{,}500$ (Figure 4*d*). In normal driving conditions, at all the detectors before and after the on-ramp substantial reductions in speed occur. Similar reductions occur during the emergency situation. However, in the emergency scenario, congestion begins at a substantially later time instant. Figure 4 also makes clear that the congestion is less severe in the emergency situation than in normal driving conditions. This difference is probably attributable to the substantially lower value of the desired time headway T and the higher maximum acceleration a_{max} and maximum deceleration b_{max}. At detector $x = 3{,}500$ (Figure 4*f*), one can see that speeds in the emergency situation are higher than under normal driving conditions. These higher speeds may be assumed to be the result of the higher value of free speed v_0 in the emergency situation.

Figure 5 shows the flow–density plots for normal driving conditions [blue markers (dark gray)] and an emergency situation [red markers (light gray)]. Again, the two scenarios exhibit some striking differences. The figure clearly shows that overall densities are much lower in the emergency situation. Most striking, however, is the difference in capacity: under normal driving conditions, capacity is situated around 2,000 vph, but in the emergency situation, this value increases to around 2,500 vph. One may assume that this difference is attributable to the substantially lower value of desired headway T in the emergency situation.

It can therefore be concluded that emergency situations have a substantial influence on macroscopic characteristics of traffic flow. Overall congestion sets in at a later time instant, while capacity in an emergency situation is substantially higher than under normal driving conditions, given the parameter values reported in here.

DISCUSSION OF RESULTS

Emergency situations have been shown to have a substantial impact on traffic flow operations. However, the best way to model the established adaptation effects in longitudinal driving had not been made clear [Hoogendoorn et al. (*2*)]. Furthermore, the macroscopic consequences on traffic flow of the adaptation effects in longitudinal driving behavior during an emergency situation had also not been made clear. The macroscopic consequences of the adaptation effects in longitudinal driving behavior on traffic flow were also yet unclear. Therefore, this paper reported the results of the estimation of parameter values and performance of IDM by using the data obtained through the driving simulator study reported in Hoogendoorn et al. (*2*).

This research showed that emergency situations have a substantial influence on the parameter values of IDM (*2*). For instance, emergency

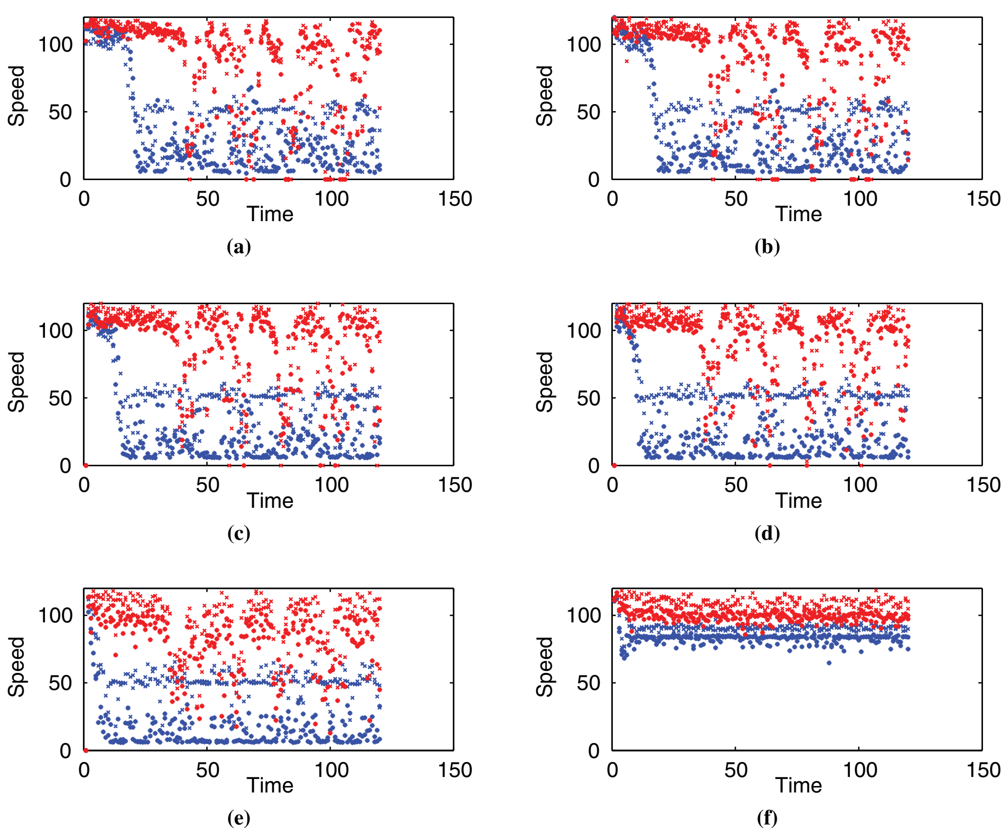

FIGURE 4 Speed–time plots for each of six detectors: (*a*) x = 1,000 m, (*b*) x = 1,500 m, (*c*) x = 2,000 m, (*d*) x = 2,500 m, (*e*) x = 3,000 m, and (*f*) x = 3,500 m.

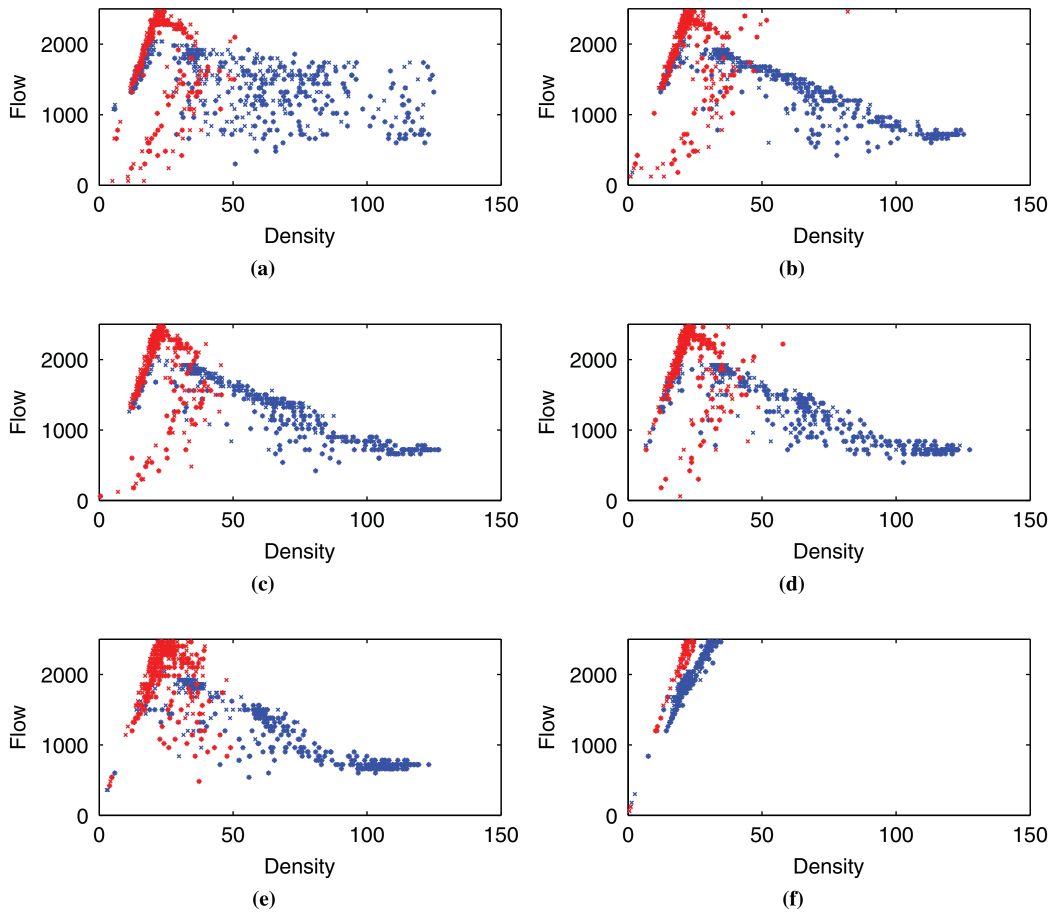

FIGURE 5 Flow–density plots for each of six detectors: (*a*) *x* = 1,000 m, (*b*) *x* = 1,500 m, (*c*) *x* = 2,000 m, (*d*) *x* = 2,500 m, (*e*) *x* = 3,000 m, and (*f*) *x* = 3,500 m.

situations were accompanied by an increase in maximum acceleration a_{max}, maximum deceleration b_{max}, and free speed v_0 and a reduction in desired time headway T. This study also showed that model performance in an emergency situation was significantly lower than in normal driving conditions. Car following seems to be to a lesser extent a determinant of longitudinal driving behavior in an emergency situation.

Finally, the paper showed that emergency situations have a substantial influence on macroscopic flow characteristics. Two simulation scenarios at an on-ramp showed that overall speeds are higher during an emergency situation and that congestion begins at a later time instant. Furthermore, this research showed that capacity is substantially higher during this adverse condition.

IDM in its current formulation, however, does not account for driver heterogeneity. As the results of the parameter value estimations indicate, differences within, as well as between, drivers are substantial. These differences may be caused by the influence of human factors such as mental workload and situational perception on driving behavior. The authors therefore recommend that human factors be incorporated into IDM, preferably on the basis of a well-grounded theoretical framework, such as the task–capability interface model by Fuller (*15*). This adaptation of IDM should incorporate both conscious adaptation effects (compensation effects) in driving behavior and the knowledge that car following becomes to a lesser extent a determinant of longitudinal driving behavior (performance effects).

Furthermore, the parameters of IDM were estimated here by using driving simulator data. The extent to which these data can be regarded as valid for this specific situation has yet to be investigated. The authors therefore recommend additional research to determine the validity of using a driving simulator to replicate an emergency situation.

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