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## **LONGITUDINAL DRIVING BEHAVIOR UNDER ADVERSE WEATHER CONDITIONS**

### **Adaptation Effects, Parameter Value Changes and Model Performance in case of Fog**

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### **ABSTRACT**

Adverse weather conditions have been shown to have a substantial impact on traffic flow operations. It is however unclear which adaptation effects in actual longitudinal driving behavior underlie this impact nor to what extent current mathematical models of car-following behavior are adequate in incorporating these adaptation effects. A driving simulator experiment with a repeated measures design was performed to investigate the influence of fog on adaptation effects in longitudinal driving behavior as well as to gain insight into parameter value changes and model performance of the Helly model and the Intelligent Driver Model under this adverse weather condition. From the results it followed that fog led to substantial adaptation effects in longitudinal driving behavior. A decrease in speed as well as in acceleration could be observed. Furthermore, a substantial increase in actual distance to the lead vehicle was observed. From the model estimation results of the Helly model and Intelligent Driver Model using a calibration approach for joint estimation it followed that sensitivity factors, maximum acceleration and deceleration decreased substantially after the start of the adverse weather condition. Parameters representing headway increased substantially. Furthermore, it followed from the results that the estimated models decreased in performance after the start of the adverse weather condition. It is concluded that it is essential to develop car-following models able to adequately incorporate these adaptation effects following adverse weather conditions.

### **KEYWORDS**

Adverse weather conditions, fog, longitudinal driving behavior, adaptation effects, car-following model performance

# INTRODUCTION

Adverse conditions have shown to have a substantial impact on traffic flow operations. These conditions can be defined as conditions following unplanned events with a relatively high impact and a low probability of occurring. Examples of these adverse conditions are evacuations due to man-made or naturally-occurring disasters (e.g. earthquakes, flooding and terrorist' attacks), incidents (e.g. car-accidents and road works), but also adverse weather conditions (e.g. fog, heavy rain, black ice and snow).

From research, it follows that adverse weather conditions indeed have a substantial impact on traffic flow operations. In this regard Jones et al. (1970) reported that heavy rain reduced freeway capacity by 14 to 19%. This reduction is supported by Chung et al. (2006). In their research using precise rainfall data with detector data at five highly congested sections at the Tokyo Metropolitan Expressway, it was concluded that freeway capacity was reduced by 4 to 7% in case of light rain and up to 14% in case of heavy rain.

Fog has been shown to have a substantial impact on traffic flow operations as well. Though studies on the influence of this adverse weather condition are scarce (Chin et al. (2002)), from research performed by Agarwal et al. (2006) it followed that fog, resulting in impaired visibility, led to capacity reductions between 10 and 12%. However, little is known about what adaptation effects in actual longitudinal driving behavior underlie this impact on traffic flow operations.

When quantifying these adaptation effects, mathematical models of car-following behavior can be developed or existing models can be adjusted. Little knowledge is however available with regard to what extent existing car-following models are adequate in quantifying adaptation effects in case of adverse weather conditions, represented by changes in parameter values and model performance.

This contribution therefore focuses on the theory and modeling of adaptation effects in longitudinal driving behavior in case of adverse weather conditions (i.e. fog) in relationship with car-following behavior. Insight is gained into adaptation effects in actual longitudinal driving behavior in case of adverse weather conditions as well as into the extent in which car-following models, represented by the Helly model (Helly (1959)) and the Intelligent Driver Model (Treiber et al. (2000)) are adequate in incorporating these adaptation effects. The adequacy of these car-following models was examined by focusing on parameter value changes as well as model performance. These models were chosen as they are relatively easy to estimate and as the parameters in these models are easy to interpret.

The aforementioned was realized by performing a driving simulator experiment with a repeated measures design. In this experiment fog was simulated in the experimental condition. Speed, acceleration, deceleration and distance to the lead vehicle were measured through registered behavior in the Advanced Driving Simulator of Delft University of Technology. The parameter value changes as well as model performance of the Helly model (Helly (1959)) and the Intelligent Driver Model (Treiber et al. (2000)) were investigated using a new calibration approach for joint estimation (Hoogendoorn & Hoogendoorn (2010)).

In the next section a brief state-of-the-art is presented with regard to adaptation effects in actual longitudinal driving behavior in case of adverse weather conditions. Furthermore in this state-of-the-art the general principle of car-following models is discussed, followed by an in-depth discussion of the Helly model and the Intelligent Driver Model. This state-of-the-art is followed by a presentation of the research method. In this section an introduction to the Advanced Driving Simulator is provided, followed by a presentation of the experimental design, measures and

the data analysis method. Next, the results are presented. Finally, these results are discussed in the Conclusion section.

## **STATE-OF-THE-ART**

### **Adaptation effects in actual longitudinal driving behavior in case of adverse conditions**

In the previous section it became clear that adverse weather conditions have a substantial impact on traffic flow operations. However, research regarding the underlying adaptation effects in actual driving behavior due to these conditions is scarce.

Hogema (1996) studied in this regard the influence of rain on driving behavior. In his research, periods were selected which had at least five hours of moderate rain in a row. For each lane mean speed and the percentage of vehicles with a time headway of  $< 1s$ ,  $3s$  and  $5s$  were collected. With regard to mean speed and mean time headways ANOVAs were performed using the factors Weather, Lane, Volume category and Carriageway. A main effect of the factor Weather was found, showing that mean speed in case of rain was 11 km/h lower than under dry conditions.

Furthermore, mean speed seemed to decrease further as a function of volume level. Also, it was found that mean speed was higher in the left lane than in the right lane. There was an interaction effect between Volume category and Weather and also between Volume category, Lane and Weather. The decrease in speed due to rain was larger in the lowest traffic volume, especially in the left lane. For the percentage of vehicles with a mean time headway  $< 1s$  there also was a main effect of Weather, showing that this percentage was smaller than in case of dry conditions. The time headway with regard to the percentage of vehicles with a time headway of  $3s$  showed a similar, but smaller effect. No effect of Weather was found with regard to vehicles with a time headway of  $5s$  or smaller.

A study performed by Chung et al. (2006) also investigated the influence of rain on driving behavior. In this research it was found that median free-flow speeds decreased from 77.7 km/h during dry conditions to 71.4 during conditions in which 5-10 mm rain per hour had fallen.

In research performed by Eisenberg & Warner (2005) it was shown that snow also has a considerable impact on driving behavior. In their research regarding the effect of snowfall on vehicle collisions, injuries and fatalities it was shown that snowy days had fewer fatal crashes than dry days ( $IRR = 0.93$  at a confidence interval of 95%). There were however more non-fatal injury crashes and property-damage only crashes. The authors state that compared to dry days, drivers seem to adjust their speed enough to influence the severity of outcomes.

Finally, some studies have shown that fog also has a substantial influence on adaptation effects in actual longitudinal driving behavior. Traffic studies generally show that headway is reduced in fog (e.g. White & Jeffery (1980)). Although it might be hypothesized that a reduction in visibility due to fog may lead to a compensatory reduction in speed in order to decrease accident risk, there is some contradictory evidence available.

In Sumner et al. (1977) for example, the effect of reduced visibility due to fog in a motorway situation was studied. The authors found that drivers did adjust their speed to the situation. However, in case of more than half of the drivers studied, speed adjustments applied in these situations were insufficient to enable them to stop within the visibility distance.

In this regard, in research performed by Broughton et al. (2007) using a driving simulator, car-following decisions under three visibility conditions (fog) and two speeds were investigated. The results showed that some remarkable differences between drivers could be observed. At higher speeds, fog separated participants into a group that stayed within the visibility range of the lead vehicle from another group that lagged beyond this visibility range. Finally, also large individual differences were found in Caro et al. (2009) with regard to the following distance in case of reduced visibility due to fog. Foggy conditions also increased response times when the outline of the vehicle was barely visible or not visible at all.

From the scarcely available research it can be concluded that adverse weather conditions have an influence on adaptation effects in actual longitudinal driving behavior. However, especially with regard to fog, this literature review yields some contradictory results. With regard to fog in some studies it was found that drivers decrease their speed while increasing their headway in order to reduce accident risk, while other studies found large individual differences between drivers. Some drivers even drove faster than under normal visibility conditions. Differences between these studies may possibly be caused by differences in the investigated sample and differences in external circumstances. This stresses the need to perform research using an experimental design and a representative sample.

In the aforementioned the influence of the adverse weather condition fog on adaptation effects in actual longitudinal driving behavior was discussed. In the next section a discussion of car-following models is presented. This discussion is only a brief overview of existing car-following models. For a more elaborate overview of car-following models can be referred to Brackstone & McDonald (1999).

## Car-following models

Car-following can be regarded as a subtask of the longitudinal vehicle interaction subtask. This vehicle interaction subtask has received a lot of attention in the traffic flow community. In this regard numerous mathematical microscopic models have been developed aiming to mimic driving behavior under a wide range of conditions and to use them in microscopic simulation as well as to guide the design of advanced vehicle control and safety systems (Brackstone & McDonald (1999)). These models are called microscopic as they capture traffic flow on the level of individual vehicles. Therefore and in contrast with macroscopic models they are by definition built on driving behavior specifications (Boer (1999)). Generally speaking, car-following models relate acceleration of a driver-vehicle combination  $a_i$  at time  $t$  as a function of speed of the vehicle  $v_i$ , speed of the lead vehicle  $v_{i-1}$ , net distance to the lead vehicle  $s_{i-1}$  and acceleration of the lead vehicle  $a_{i-1}$ :

$$a_i(t) = f_{cf}(v_i, v_{i-1}, s_{i-1}, a_{i-1}) \quad (1)$$

Each mathematical model of car-following behavior has its own distinctive control objective. For example, the Gipps model (Gipps (1981)) assumes that drivers want to reach and maintain a safe distance to the lead vehicle, while in the model formulated by Tampere (Tampere (2004)) it is assumed that drivers want to attain a desired distance to the lead vehicle and that they want to synchronize their speed with the speed of the lead vehicle.

In this regard car-following models can roughly be divided into three types:

1. safe-distance models

2. stimulus response models
3. psycho-spacing models

Safe-distance models assume that drivers choose their headway such that collisions can be avoided, for instance in case of emergency braking. Among these types of models are for example the models by Pipes (1953) and Forbes et al. (1959).

Stimulus-response models are dynamic models which describe the reactions of drivers as a function of changes in relative distance and speed. An example of a stimulus-response model is the model formulated by Helly (1959). This model will be elaborated upon in the ensuing of this contribution.

Furthermore, with regard to these stimulus-response models a distinction can be made between models which only incorporate the behavior of the direct lead vehicle (simple car-following models) and models which also take into account traffic conditions further downstream (multi-anticipative car-following models).

The aforementioned models have a rather mechanistic character. In the models is not taken into account that drivers are not able to observe stimuli within certain perceptual thresholds due to observation errors related to for example radial motion observation. This drawback of safe-distance models and stimulus-response models was corrected in so-called psycho-spacing models. In these models car-following behavior is described on a relative speed-spacing plane ( $\Delta v, s$ ) plane. Perhaps the most well-known example of psycho-spacing models is the model formulated by Leutzbach & Wiedemann (1986). For a more elaborate discussion of psycho-spacing models can be referred to Brackstone et al. (2002)

In this contribution only simple stimulus response car-following models are considered, represented by the Helly model (Helly (1959)) and the IDM (Treiber et al. (2000)). In the Helly model the driver reacts with changes in acceleration  $a_i$  at time  $t$  to speed differences  $\Delta v_i$  with the lead vehicle as well as to differences between the actual distance  $x_i$  and the desired distance  $S_i$  to the lead vehicle. These stimuli are moderated by the sensitivity parameters  $\alpha$  and  $\gamma$ . The model also incorporates reaction time of the driver  $T_r$ . The model is expressed in the following equation:

$$a_i(t) = \alpha \Delta v_i(t - T_r) + \gamma(x_i(t - T_r) - S_i) \quad (2)$$

Furthermore, this model assumes that desired distance to the lead vehicle  $S_i$  is linearly dependent on speed  $v_i$ . Also, a minimal stopping distance  $s_0$  when the vehicle is stationary is incorporated in the model:

$$S_i = s_0 + h_{min} v_i \quad (3)$$

The IDM describes the acceleration of driver  $i$  at time  $t$  as a function of the distance to the lead vehicle  $s_i$ , speed  $v_i$ , free speed  $v_0$  and relative speed  $\Delta v_i$  using the following expression:

$$\frac{d}{dt} v_i = a \left( 1 - \left( \frac{v_i}{v_0} \right)^4 - \left( \frac{s^*(v_i, \Delta v_i)}{s_i - 1} \right)^2 \right) \quad (4)$$

The desired gap  $s^*$  is expressed in the following equation:

$$s^*(v_i, \Delta v_i) = s_0 + Tv_i - \frac{v_i \Delta v_i}{2\sqrt{ab}} \quad (5)$$

In this equation  $T$  denotes the change in desired distance with every additional unit of speed, while  $s_0$  denotes the distance to the lead vehicle when stationary. Furthermore, in the model two tendencies are assumed. The first tendency is that drivers accelerate with  $a$  as a function of the difference between their own speed and the speed of the lead vehicle:

$$a(v_i) = a_i \left[ 1 - \left( \frac{v_i}{v_0^{(i)}} \right)^\delta \right] \quad (6)$$

The second tendency is that drivers, when the vehicle comes too close to the lead vehicle, tend to brake with a deceleration  $b$  of:

$$b(s_i, v_i, \Delta v_i) = -a^{(i)} \left( \frac{s^*(v_i, \Delta v_i)}{s_i} \right)^2 \quad (7)$$

In the aforementioned the basic idea of car-following models was briefly explained, followed by a more in-depth discussion of the Helly model and the IDM. In the next section the research method is presented.

## RESEARCH METHOD

From the previous sections it follows that it is unclear which adaptation effects in actual longitudinal driving behavior underlie the discussed impact on traffic flow operations in case of adverse weather conditions. Furthermore it is unclear to what extent current models of car-following behavior, represented by the Helly model and the Intelligent Driver Model are adequate in incorporating adaptation effects under adverse weather conditions. With regard to the extent in which these models are adequate in incorporating adaptation effects in case of fog no research was found at all. This leads to the following research questions:

1. Which adaptation effects in actual longitudinal driving behavior can be observed in case of the adverse weather condition fog?
2. To what extent are adaptation effects in actual longitudinal driving behavior due to the adverse weather condition reflected in parameter value changes in the Helly model and the Intelligent Driver Model?
3. To what extent is performance of the Helly Model and Intelligent Driver Model affected by the adaptation effects due to the adverse weather condition?

In this regard a driving simulator experiment with a Repeated Measures design was performed among 19 participants. Adaptation effects in actual longitudinal driving behavior were measured through registered behavior in the driving simulator. These adaptation effects were analyzed through paired samples t-test, while the extent in which the Helly model and Intelligent Driver Model are adequate in incorporating these adaptation effects was determined through a new calibration approach for joint estimation (Hoogendoorn & Hoogendoorn (2010)). In the next section however a brief introduction to the Advanced Driving Simulator is provided.



**Figure 1: The Advanced Driving Simulator used in the experiment**

## **The Advanced Driving Simulator**

The fixed base driving simulator (Figure 1) consists of three screens placed at an angle of 120 degrees, a drivers seat mock-up as well as hardware and software interfacing of this mock-up to a central computer system. From the drivers seat the view consists of a projection of 210 degrees horizontally and 45 degrees vertically. The software was developed by StSoftware.

For the purpose of the experiment a driving environment was developed consisting of three segments. The first segment was a short test drive through a suburban area to accustom participants to driving in a driving simulator and to investigate whether they would suffer from simulator sickness.

The other two segments were used in the experiment: an experimental and a control condition. In the experimental condition fog was generated (Figure 2) while in the control condition normal visibility conditions were applied.

The test trials took place on a virtual freeway with two lanes in the same as well in the opposite direction. The speed limit was set to 100 km/h. The length of the three segments combined was 10.8 km. In the experimental condition the lead vehicles were programed to show adaptation effects, consisting of a decrease in speed and an increase in headway.

As a driving simulator was used to measure adaptation effects in actual longitudinal driving behavior, some remarks regarding the validity of driving simulators are in order. In research performed by Reimer et al. (2006) behavior in the driving simulator was compared with real-life behavior using self-reports. Significant relationships were found with regard to accidents, speeding, overtaking and behavior at traffic signs. The authors state that driving simulators are adequate instruments to measure driving behavior. Validity issues of driving simulators with regard to driving behavior at intersections were examined in Yan et al. (2008). From the results followed that driving simulators are assumed to possess relative validity, meaning that observed behavioral responses converge in the same direction as is real-life.

## **Experimental Design and Participants**

All participants participated in the experimental condition as well as in the control condition, rendering up a complete within-subjects design. The conditions were counterbalanced across



**Figure 2: Fog in the Advanced Driving Simulator**

subjects, meaning that the order in which the conditions were offered to the participants was varied. For each condition longitudinal driving behavior was measured through two averaged measurement periods.

Participants were recruited among Dutch female and male drivers between the age of 23 and 65 years old. Participants had to be in the possession of a drivers license for a period of at least 5 years, since from research by Sagberg & Bjørnskau (2006) follows that risk perception of inexperienced drivers differs significantly from experienced drivers. Another restriction was that the participants were excluded when they indicated being prone to simulator sickness.

The research population consisted of 19 employees and students of Delft University of Technology (13 male and 6 female participants). The age of the participants varied from 24 to 40 years with a mean age of 30.50 years ( $SD = 4.00$ ). Driving experience varied from 5 to 17 years with a mean of 8.67 years ( $SD = 3.30$ ).

## **Measures and Data Analysis of Adaption Effects**

Adaptation effects in actual longitudinal driving behavior were measured through registered behavior in the Advanced Driving Simulator. Speed, acceleration, deceleration and distance to the lead vehicle were measured at a sampling rate of 10 samples per second. In order to test if the experimental condition differed significantly from the control conditions, paired-samples t-tests were performed. Due to the a priori character of the test, they were performed with the conventional Type I error of .05. This means that a confidence interval was used of 95%.

## **Estimation of changes in parameter values and model performance of the Helly model and the IDM**

Estimation of the Helly model and the IDM for the entire sample was achieved through a joint Maximum Likelihood estimation approach (Hoogendoorn & Hoogendoorn (2010)). In this section the approach is briefly explained. For a more elaborate discussion of the approach is referred to Hoogendoorn & Hoogendoorn (2010).

Parameters to be determined with regard to the Helly model and the Intelligent Driver Model are indicated by the vectors:

$$\vec{\theta}_i = \{a, b, v_0, T\} \quad (8)$$

$$\vec{\theta}_i = \{\alpha, \gamma, h_{min}, T_r\} \quad (9)$$

To estimate the joint parameters, a Maximum Likelihood approach was amended. The driving behavior of individual drivers, described by the parameter set was used to determine the likelihood using the following equation:

$$\tilde{L}(\vec{\theta}) = \prod_{k=1}^k p(\vec{e}_i(t_k)) \quad (10)$$

Joint likelihood could then be determined through observation of the trajectory of the sample:

$$L_{mult}(\vec{\theta}^{(1)}, \dots, \vec{\theta}^{(N)}) = \prod_{i=1}^N L^{(i)}(\vec{\theta}^{(i)}) \quad (11)$$

To investigate the changes in parameter values during the experiment, trajectories were divided into overlapping segments with a length of 1 km.

## RESULTS

### Adaptation effects in actual longitudinal driving behaviour

Descriptive statistics with regard to speed, acceleration, deceleration and distance to the lead vehicle were first calculated. Next, paired samples t-tests were performed. The results indicate a significant decrease in mean speed in the experimental condition ( $M = 54.68$  km/h,  $SD = 1.68$ ) compared to the control condition ( $M = 77.68$  km/h,  $SD = 1.48$ ),  $t(18) = 10.01, p < .05$ .

Furthermore, the results indicate a significant decrease in acceleration in the experimental condition ( $M = .28m/s^2, SD = .18$ ) compared to the control condition ( $M = .40m/s^2, SD = .10$ ),  $t(18) = 2.10, p < .05$ . Mean deceleration in the experimental condition ( $M = -.39m/s^2, SD = .12$ ) did however not differ significantly from deceleration in the control condition ( $M = -.41m/s^2, SD = .13$ ),  $t(18) = -.46, p > .05$ .

Finally, mean distance to the lead vehicle increased significantly in the experimental condition ( $M = 36.54m, SD = 32.15$ ) compared to the condition with normal visibility ( $M = 12.28m, SD = 28.55$ ),  $t(18) = 9.32, p < .05$ . These results are an indication for a strong change in longitudinal driving behavior after the start of the adverse weather condition. In other words: substantial adaptation effects in actual longitudinal driving behavior to fog can be observed. Drivers decrease their speed and acceleration while increasing their distance to the lead vehicle. A possible explanation for this observed behavior is that drivers reduce speed and increase headways in order to decrease accident risks.

## Parameter estimation results and model performance

Figure 3 shows the estimation results obtained by fitting the Helly model to the observations of the driving simulator. From the figure it can be observed that estimates of the sensitivity factor  $\alpha$  decreased significantly in the adverse weather condition, namely from around  $1.1s^{-1}$  in the normal visibility condition to around  $0.45s^{-1}$  in fog. This means that in case of fog drivers may become less sensitive to speed differences with the lead vehicle. The aforementioned is less clear with regard to the sensitivity factor  $\gamma$ . After an increase just before the start of the adverse weather condition, the value of this parameter sharply decreases.

Most striking, however, is the gradual increase in  $h_{min}$ . Here, an increase can be observed from an average of around  $1.5s$  in the normal visibility condition to a very high value of around  $3.7s$  in the adverse weather condition. This is an indication for strong adaptation effects in longitudinal driving behavior.

Figure 4 shows the estimation results obtained by fitting the IDM to the observations of the driving simulator. From the figure it can be observed that the maximum acceleration  $a$  decreases substantially after the start of the adverse weather condition. This is also the case for maximum deceleration  $b$ .

Free speed  $v_0$  seems to increase just before the start of the adverse weather condition and then decreases again. This may be due to the fact that the model is not very sensitive to  $v_0$ , given that it is sufficiently high. Also, the drivers were in a situation of car-following, making estimations of free speed unreliable. Again, most striking is the substantial increase in minimum headway. After a slight decrease the value of this parameter increases drastically.

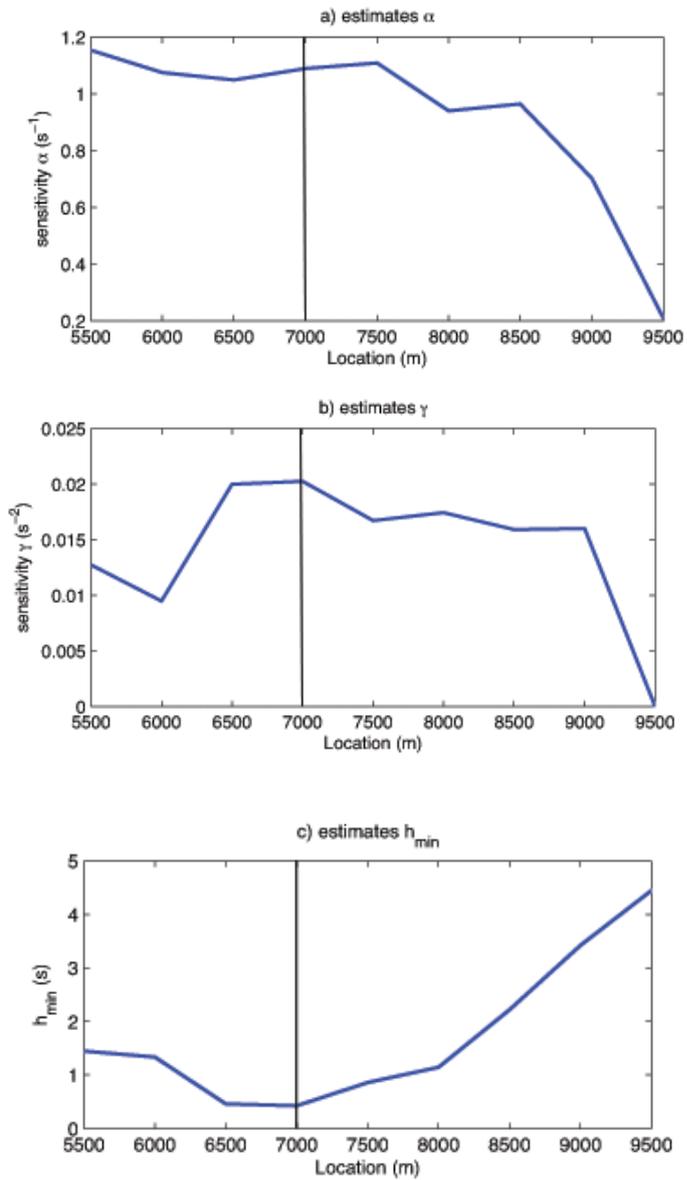
To gain insight into the performance of the Helly model and the IDM the estimated model was compared to a null model (i.e. the model assuming zero acceleration). From Figure 5 it can be observed that the performance of the estimated models of the Helly model and the IDM when compared to the null model is quite similar. Also both estimated models outperform the null model. However, some differences can be observed from the figure. On average the Helly model seems to perform slightly better than the IDM.

In general from the figure it can be observed that after the start of the adverse weather condition, the differences between the estimated model and the null model decrease. This means that the estimated model starts to perform less well compared to the null model. Furthermore, with regard to the Helly model as well as the IDM it can also be observed that the log-likelihoods of the estimated models as well as the null models decrease after the start of the adverse weather condition. This means that the models less adequately incorporate longitudinal driving behavior in case of this adverse weather condition.

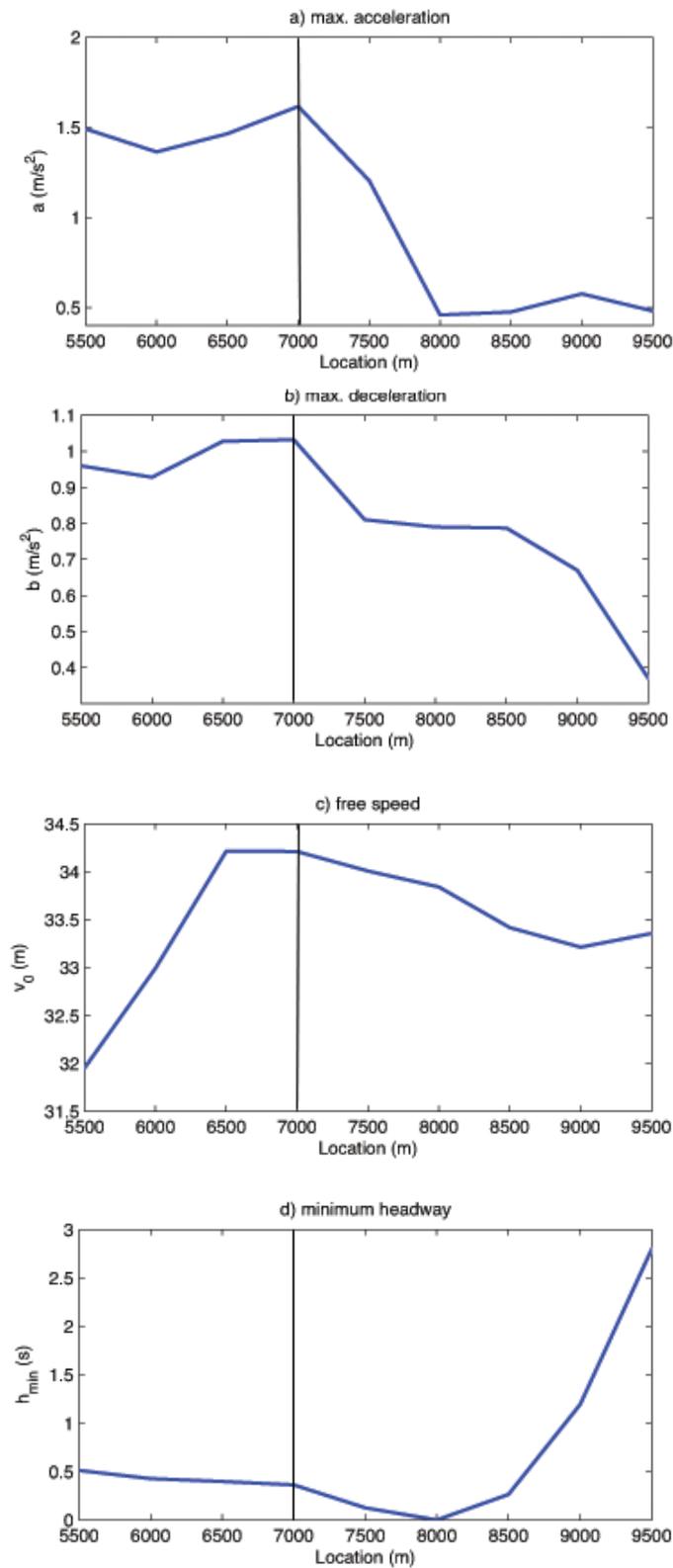
## CONCLUSIONS

In this driving simulator experiment with a repeated measures design the influence of the adverse weather condition fog on adaptation effects in actual longitudinal driving behavior was investigated. Also it was investigated to what extent current mathematical models of car-following behavior, represented by the Helly model and the IDM, are adequate in incorporating longitudinal driving behavior in case of fog.

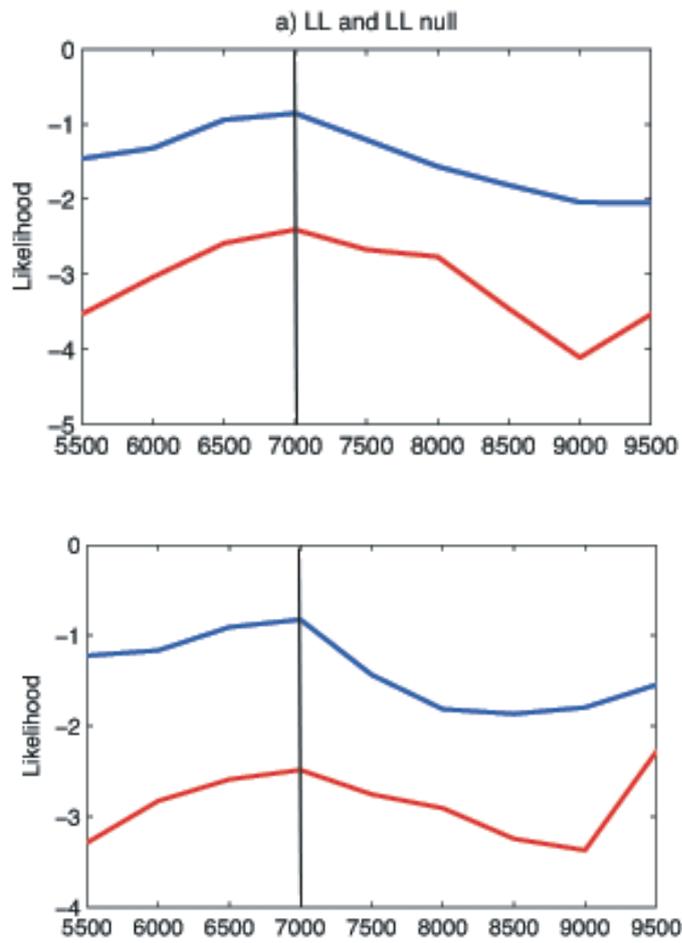
With regard to the influence of fog on adaptation effects in actual longitudinal driving behavior the results from the driving simulator experiment indicated a significant decrease in mean speed and mean acceleration after the start of the adverse weather condition. Furthermore the results



**Figure 3: Parameter estimates for the Helly model. The vertical line indicates where the adverse weather condition started.**



**Figure 4: Parameter estimates for the IDM. The vertical line indicates where the adverse weather condition started.**



**Figure 5: Performance of the models compared to the null model (zero acceleration) for the Helly model (top) and the IDM (bottom)**

indicated a significant increase in distance to the lead vehicle in the experimental condition. The effect of fog on deceleration was not significant. These findings are in line with existing research (e.g. White & Jeffery (1980)). However, large individual differences as reported by for example Caro et al. (2009) were not found.

The aforementioned stresses the need for the development of car-following models that are able to adequately incorporate longitudinal driving behavior under adverse weather conditions. From the estimation results with regard to the Helly model followed that sensitivity toward speed differences with the lead vehicle  $\alpha$  decreased substantially. This was to a lesser extent also the case for the sensitivity toward the difference between the actual and the desired distance to the lead vehicle  $\gamma$ . Most striking was however the gradual increase in minimum headway  $h_{min}$ . The aforementioned changes in parameter values may be explained through the decreased visibility of the lead vehicle in case of fog. As the driver gradually increases headway in order to decrease accident risks, speed differences with as well as distances to the lead vehicle become harder to perceive, leading to a decrease in the sensitivity toward speed differences with the lead vehicle and the difference between the actual and the desired distance to the lead vehicle.

This conclusion can also be drawn with regard to the substantial decrease in the value of the maximum acceleration  $a$  and maximum deceleration  $b$  in the IDM. As minimum headway increases during fog, it can be assumed that drivers have difficulty in estimated speed differences with and distances to the lead vehicle, leading to a reduction in the parameter value of  $a$  and  $b$ .

The value of free speed  $v_0$  increased after the start of the adverse weather condition. This may be due to the fact the IDM is not very sensitive to this parameter, given that it is sufficiently high and that drivers were in car-following mode.

With regard to model performance it followed from the results that the Helly model and the IDM performed quite similar. Performance of the estimated models exceeded performance of the null models, showing the added value of these models. However, after the start of the adverse weather condition the log-likelihood values of the estimated models gradually decreased. The difference with the null models also decreased. This shows that model performance deteriorated after the start of the adverse weather condition. This may be explained by the fact that due to a reduction in visibility of the lead vehicle, car-following may become to a lesser extent a determinant of longitudinal driving behavior. This may also be supported by the parameter value changes of  $h_{min}$ ,  $\alpha$  and  $\gamma$  in the Helly model and  $a$ ,  $b$  and  $T$  in the IDM. Although a substantial change could be observed, the values of these parameters do not stabilize.

The aforementioned stresses the need to develop models of longitudinal driving behavior, which are adequate in describing and predicting longitudinal driving behavior under adverse weather conditions. Future research will therefore focus on the development of such models. In this regard will also be investigated through additional experiments if parameters in current car-following models converge when driving in fog for a longer period of time. Moreover, future research will investigate transients between normal driving conditions and driving in case of adverse weather conditions. Because in the current estimation approach overlapping segments were used in order to estimate parameter value changes, transients may be confounded.

Furthermore, recently it has become clear that lateral driving behavior also has a substantial impact on traffic flow operations. Therefore future research will also incorporate the influence of adverse weather conditions on lateral driving behavior.

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