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**Longitudinal Driving Behavior under Adverse Conditions: A Close Look at Psycho-spacing Models**

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**Abstract**

Adverse weather conditions have been shown to have a substantial impact on traffic flow operations following substantial adaptation effects in driving behavior. In quantifying these effects psycho-spacing models may be used. In this contribution it was examined to what extent adverse weather conditions influence the position of action points in the relative speed-spacing plane in these models, the relationship between speed of the lead vehicle and relative speed at the action points and acceleration as well as jumps in acceleration. In this regard a driving simulator experiment with a Repeated Measures design was performed in which fog was simulated in the experimental condition. Using a new data analysis technique followed from the results that substantial differences were present with regard to the position of action points. Furthermore a substantial influence of fog on the relationship between speed of the lead vehicle and relative speed at the action points was found. Finally, a substantial influence of this adverse weather condition on acceleration and jumps in acceleration was established. Furthermore, a large degree of driver heterogeneity was observed with regard to the position of action points as well as automobile acceleration and heterogeneity. It is recommended to develop a data driven stochastic car-following model based on psycho-spacing theory.

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**Keywords:** adverse weather conditions, fog, car-following behavior, psycho-spacing models, action points, acceleration, heterogeneity.

**1. Introduction**

Adverse conditions have been 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, incidents on the freeway but also adverse weather conditions.

In this regard, heavy rain has been reported to reduce freeway capacity by 14 to 19% (Jones & Goolsby, 1970). Furthermore, in research using precise rainfall data with detector data at five highly congested sections at the Tokyo...
Metropolitan Expressway, it was concluded that rain reduced freeway capacity by 4 to 7% in case of light rain and up to 14% in case of heavy rain (Chung et al., 2006).

Fog has been shown to have a substantial influence on traffic flow operations as well. Though studies on the influence of this adverse weather conditions are scarce (Chin & Franzese, 2002), it has been shown that fog leads to capacity reductions between 10 and 12% (Agarwal et al., 2006) following substantial adaptation effects in longitudinal driving behavior.

When quantifying adaptation effects in longitudinal driving behavior, mathematical models of car-following behavior can be developed. Numerous mathematical models have been developed aiming to mimic driving behavior under a wide range of conditions and to use them in microscopic driving simulations as well as to guide the design of advanced vehicle control and safety systems. As car-following models capture traffic flow on the level of individual vehicles, they are by definition built on driving behavior specifications.

However, most current models of car-following behavior incorporate a finite reaction time as the only human element. For example, drivers are assumed to react to small changes in speed of the lead vehicle, even at large headways. Drivers are assumed to perceive stimuli related to the lead vehicle, no matter how small. To adjust for these drawbacks, psycho-spacing models were developed. The differing versions of these models have independently been developed by a number of researchers since the 1960s. Perhaps the earliest contributions were due to Michaels (1963) and also Todosiev (1963).

Basically in these models driving behavior is controlled by four different perceptual: a minimum and maximum threshold for desired spacing and a threshold for positive and negative relative speeds. These thresholds serve to delineate a relative speed - spacing plane \((\Delta v, s)\) in which the driver of a following vehicle would be unable to notice any change in his dynamic conditions and would seek to maintain a constant acceleration \(a\) (Brackstone, Sultan, & MacDonald, 2002). On crossing one of these thresholds, a driver will perceive that an unacceptable situation has occurred and will adjust his longitudinal driving behavior through a change in the sign of his acceleration. In the remainder of this contribution these points in the \((\Delta v, s)\) plane are referred to as action points. The driver will maintain this acceleration until another threshold is crossed, producing the typical spirals in the \((\Delta v, s)\) plane (Fig. 1).

However, although the basis and structure of this model is well known and much supporting research is available little has been attempted regarding its further expansion (Brackstone, Sultan, & MacDonald, 2002). This is especially the case when drivers have to perform their driving task under adverse conditions. This contribution therefore focuses on the theory and prospective modeling of adaptation effects in car-following behavior in case of the adverse weather conditions (i.e. fog) in relationship with the aforementioned psycho-spacing models.

From the available research (e.g. Evans & Rothery, 1977) it can be assumed that car-following patterns closely resemble the ones predicted by psycho-spacing theory. It can however be assumed that the effect of adverse weather conditions will vary to a large extent within and between drivers as expressed by the shape and location of the perceptual thresholds. It can therefore be conjectured that the aforementioned deterministic perceptual thresholds in the original formulation of the model (e.g. Leutzbach & Wiedemann, 1986) do not hold in reality.

Furthermore, it can also be assumed that speed of the lead vehicle \(v_2\), contrary to what is assumed in the original formulation of the model, also has an influence on the position of the action points. This is in accordance with the so-called Fechner-Weber law (e.g. Shen & Jung, 2006), in which it is hypothesized that for an individual to be able to perceive a change a stimulus must change by a set percentage (typically 7 to 10%). In other words: action points at higher speeds of the lead vehicle \(v_2\) will be positioned at larger positive and negative values of \(\Delta v\) than is the case at lower values \(v_2\). Furthermore, it can be assumed that in case of fog this set percentage will increase substantially compared to normal visibility conditions.

![Figure 1 Basic psycho-spacing model](image)
Furthermore, it is assumed in the original formulation of the model that on crossing one of the aforementioned thresholds, a driver will change his longitudinal driving behavior by changing the sign of his acceleration, typically in the order of $0.2 \text{ m/s}^2$. It can however be assumed that a relationship exists between $\Delta v$, $s$ and acceleration $a(t)$ at the action points. This relationship can be assumed to be less pronounced in the adverse weather condition as the driver is less able to adequately perceive $\Delta v$ and $s$. The aforementioned will also be the case for changes in acceleration before and after an action point $\Delta a$, as it can be assumed that these 'jumps' in acceleration are also determined by the location of the action points in the $(\Delta v, s)$ plane.

The aforementioned leads to the following research questions:

1. To what extent does the adverse weather condition fog influence the position of action points in the $(\Delta v, s)$ plane?
2. To what extent does the adverse weather condition fog influence the relationship between speed of the lead vehicle $v_2$ and relative speed $\Delta v$ at the action points?
3. To what extent does the adverse weather condition fog influence acceleration $a(t)$ at the action points?
4. To what extent does the adverse weather condition fog influence so-called 'jumps' in acceleration $\Delta a(t)$ at the action points?

In order to answer these research questions a driving simulator experiment with a Repeated Measures design (counterbalanced across subjects) was performed consisting of a normal visibility condition and a condition in which fog was induced. In this experiment 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 first research question was answered by estimating action points in the $(\Delta v, s)$ plane using a new data analysis technique described in Hoogendoorn, Hoogendoorn, & Daamen (2011). Next, cumulative distribution functions were constructed after which the distributions of action points were compared using a Kolmogorov-Smirnov test. The second research question was answered by comparing cumulative distribution functions between the two conditions at four different classes of lead vehicle speed $v_2$ also using a Kolmogorov-Smirnov test. Finally, the third and fourth research questions were answered by estimating four different models using a Multivariate Regression Analysis method.

In the next section the research methodology is presented. In this section an introduction to the Advanced Driving Simulator is provided. Furthermore in this section the experimental design, participants as well as the data analysis method are discussed. In the next section the results are presented followed by an in-depth discussion of these results.

2. Research Methodology

2.1 The Advanced Driving Simulator

The fixed-base driving simulator consists of three screens placed at an angle of 120 degrees, a driver’s seat mock-up and hardware and software interfacing of this mock-up to a central computer system. From the driver’s 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 a participant would suffer from motion sickness.

The other two segments were used in the experiment: an experimental and a control condition. In the experimental condition fog was generated, while in the control condition normal visibility conditions were applied (Figure 2). The test trials took place on a virtual 2 x 2 lane motorway. The speed limit was set to 120 km/h. The length of the three segments combined was 10.8 km.

The behavior of the lead vehicles was derived from actual longitudinal driving behavior of participants in a pilot study. This means that the lead vehicles showed adaptation effects to the adverse weather condition, consisting of a decrease in speed and acceleration and an increase in headway. Speed, acceleration, deceleration and distance to the lead vehicle were measured at a sampling rate of 10 samples per second.
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. Simulator and real-life behavior in the driving simulator have been compared with real-life behavior using self-reports (Reimer et al. (2006). 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.

2.2 Experimental design and participants

All participants participated in the experimental condition as well as in the control condition, rendering up a complete within-subject design. Furthermore, the order in which the participants were exposed to the conditions was varied between participants (counterbalancing across subjects).

Participants were recruited among Dutch female and male drivers between the age of 23 and 65 years old. The research population consisted of 25 employees and students of Delft University of Technology (13 male and 12 female participants). The age of the participants varied from 24 to 45 years with a mean of 32.65 years ($SD = 4.23$). Driving experience varied from 6 to 18 years with a mean of 8.44 years ($SD = 4.48$).

2.3 Data analysis method

The first research question, regarding the influence of the adverse weather condition fog on the position of action points in the psycho-spacing model in the $(\Delta v, s)$ plane, was answered through a new data analysis technique (Hoogendoorn, Hoogendoorn, & Daamen, 2011). This approach is very briefly explained in the ensuing.

The basic assumption of the proposed method is that trajectories are represented by non-equidistant periods in which acceleration is constant. This means that speed $v(t)$ is a continuous piecewise function of time, given the time instants $t_j$ for $j=0,\ldots,M$ at which the acceleration changes. Given these time instants, we aimed at finding the points $y_k$ which describe the value of the piecewise linear function at the time instants $t_j$. Respectively the vector of fixed time instants and the vector of function values are denoted by:

$$t = \{t_j\}$$

$$y = \{y_j\}$$

The resulting piecewise linear function that can be constructed using these vectors is denoted by:

$$f(t,y)$$
Finding the optimal values for \( y_j \) can then be mathematically described by:

\[
\hat{y}_j(\tilde{t}) = \arg\min_{k=1}^{n} \left( f(t_k, \tilde{t}, \hat{y}) \right) v^{obs}(t_k))_2
\]

where \( t_k \) denotes the time instants where the vehicle data is measured and \( v^{obs} \) denotes the observed speed values.

The remaining problem was to find the required number \( M \) of time instants \( t_j \) and their optimal positions. This was achieved in a very straightforward way. Setting \( M \) to a fixed value, we determine:

\[
\tilde{t} = \arg\min_{k=1}^{n} \left( f(t_k, \hat{y}(\tilde{t}) \ v^{obs}(t_k))_2 \right)
\]

The problem was solved using standard least squares optimization approaches. This was done for different values of \( M \), until the improvement in the error is less than some threshold value \( \varepsilon_o \). In illustration, Figure 3 shows an example of applying the approach to trajectory data collected on a Dutch motorway. This figure shows how the proposed method approximates the observed noisy individual vehicle speed profiles using a piecewise linear function (implying constant acceleration between the action points). In this manner action points can be identified.

![Figure 3](image1.png)

Figure 3  Example showing application results of the estimation approach. The top graph shows the raw data collected, while the bottom graph shows the estimation results. The crosses show the location of the identified points.

Next the distributions of action points in a \((\Delta v, s)\) plane were generated for the control condition as well as the experimental condition. Here action points with small accelerations \((-0.01 > a(t) < 0.01)\) were excluded from the analysis. Also the distribution of action points in the \((\Delta v, s)\) plane was generated by excluding small ‘jumps’ in acceleration. This exclusion of action points was applied in order to ensure that only ‘reasonable’ actions were included in the analysis.

To make the distributions more insightful, cumulative distribution functions for \( \Delta v \) and \( s \) were constructed. To test for normality a Lilliefors test with a Monte Carlo approximation was performed. From these analyses followed that the null hypothesis of normality was rejected. Therefore the distribution of the normal and the adverse weather condition were compared using a Kolmogorov-Smirnov test at a confidence level of 95%.

The second research question with regard to the extend in which these changes in the location of the action points due to the adverse weather condition are represented by changes in the relationship between speed of the lead vehicle \( v_2 \) and relative speed \( \Delta v \) at the action points was answered by was dividing speed of the lead vehicle \( v_2 \) into four different classes, namely: 40 to 60, 60 to 80, 80 to 100, and 100 to 120 km/h. These classes were chosen as they yield a relatively adequate representation of the distribution of speed of the lead vehicle. Furthermore, a distinction was made between positive and negative relative speeds \( \Delta v \). Next, cumulative distribution functions were constructed. Here also, normality was tested using a Lilliefors test with a Monte Carlo approximation. As was the
case with the first research question the null hypothesis of normality was rejected. Therefore, here also the distributions were compared using a Kolmogorov–Smirnov test.

The third research question regarding the extent in which acceleration $a(t)$ is influenced by the adverse weather condition at the action points in the $(\Delta v, s)$ plane was answered using a Multivariate Regression Analysis method for the control condition as well as the experimental condition. In this analysis the following two models, which in the ensuing will be referred to as Model 1 and Model 2, were fitted:

$$a = b_1 \Delta v + b_2 s$$

$$a = b_1 \frac{v}{\sqrt{s}} + b_2 v$$

These relations assume that acceleration $a$ is a linear function of relative speed $\Delta v$ which implies that the larger the relative speed, the larger the chosen acceleration. Furthermore, the model shows that the magnitude of the acceleration $a$ at the action points reduces for larger values of $s$. Note that this relation does not describe if a driver will accelerate or not. Instead, it describes the (average) acceleration the driver chooses to accelerate at a certain relative speed and distance. Next the estimated parameters as well as the errors were compared between the condition providing an indication of the influence of the adverse weather condition on the acceleration choice of the driver as well on as driver heterogeneity.

Finally, the extent in which the adverse weather condition fog influences the 'jumps' in acceleration $\Delta a(t)$ at the action points was compared between the control and the experimental condition. In this regard, the same steps were followed as was the case for the fourth research question. However, here the following two models were fitted using the Multivariate Regression Analysis method, which in the ensuing of this contribution will be referred to as Model 3 and Model 4:

$$a = b_1 \Delta v + b_2 s$$

$$a = b_1 \frac{v}{\sqrt{s}} + b_2 v$$

3. Results

The first research question was: "To what extent does the adverse weather condition fog influence the position of action points in the $(\Delta v, s)$ plane?". Using the approached discussed in the aforementioned (Hoogendoorn, Hoogendoorn, & Daamen, 2011), action points were determined for the control condition as well as the experimental condition. In Figure 4 the results are presented when excluding action points at small accelerations. Furthermore in the figure the results are presented when excluding action points with small jumps in acceleration.

The picture that emerges from this figure for the different graphs is quite similar. Firstly, in all four graphs an overlap in acceleration reductions and acceleration increases can be observed. Though this might seem strange, this can be explained by the fact that speed differences with the leader are not the only determinant of acceleration changes. However, a strong bias can be observed with regard to these overlapping regions when comparing the distributions between acceleration increases and acceleration reductions.
Furthermore, a clear difference between the control condition and the experimental condition can be observed. The action points in the experimental condition are much more scattered than is the case in the control condition. The fact that such large differences can be observed can also be regarded as an indication in favor of the hypothesis that due to a large degree of inter-driver and intra-driver heterogeneity the assumption of deterministic perceptual thresholds is unrealistic. Secondly, it becomes clear from Figure 4 that in the experimental condition (even at small values of $s$) drivers mostly seem to react to larger values of $\Delta v$.

![Figure 4](image1.png)

Figure 4 Distribution of action points for the control condition (a) and the experimental condition (b) when excluding small accelerations (left) and small jumps in acceleration (right).

![Figure 5](image2.png)

Figure 5 Cumulative distribution functions of delta $v$ (left) and $s$ (right) for the normal visibility (red line) and the adverse weather condition (blue line).

This is much less the case in the control condition, where drivers also seem to react to smaller values of $\Delta v$. This may be due to the fact that drivers are unable to adequately perceive small speed differences with their lead vehicle in case of the adverse weather condition, making corrections to larger values of $\Delta v$ necessary. This is in accordance with the constructed cumulative distribution functions in Figure 5. Furthermore, the result showed that the difference between the two distributions is statistically significant as from the Kolmogorov-Smirnov test followed that $p<.05$ for $\Delta v$ as well as for $s$.

The second research question was: "To what extent does the adverse weather condition fog influence the relationship between speed of the lead vehicle $v_2$ and relative speed $\Delta v$ at the action points?" In this regard cumulative distributions functions were constructed for the experimental as well as the control condition for the
aforementioned four classes of lead vehicle speed $v_2$. The results are presented in Figure 6. Mean values as well as standard deviations are reported in Table 1.

**Table 1 Mean values and standard deviations negative and positive relative speed at action points per speed class lead vehicle for the control condition and the experimental condition (fog)**

<table>
<thead>
<tr>
<th>Speed Class</th>
<th>Negative Mean</th>
<th>SD</th>
<th>Positive Mean</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>40-60 km/h (normal)</td>
<td>-1.0052</td>
<td>0.9900</td>
<td>1.0621</td>
<td>1.0947</td>
</tr>
<tr>
<td>60-80 km/h (normal)</td>
<td>-1.8253</td>
<td>1.5555</td>
<td>1.5897</td>
<td>1.3204</td>
</tr>
<tr>
<td>80-100 km/h (normal)</td>
<td>-1.7890</td>
<td>2.1998</td>
<td>3.5445</td>
<td>3.1200</td>
</tr>
<tr>
<td>100-120 km/h (normal)</td>
<td>-3.2336</td>
<td>3.3469</td>
<td>4.2592</td>
<td>3.0250</td>
</tr>
<tr>
<td>40-60 km/h (fog)</td>
<td>-2.6377</td>
<td>2.1121</td>
<td>2.1746</td>
<td>1.3405</td>
</tr>
<tr>
<td>60-80 km/h (fog)</td>
<td>-3.7027</td>
<td>3.8184</td>
<td>2.8300</td>
<td>2.0325</td>
</tr>
<tr>
<td>80-100 km/h (fog)</td>
<td>-2.4376</td>
<td>2.1305</td>
<td>3.0649</td>
<td>2.7540</td>
</tr>
<tr>
<td>100-120 km/h (fog)</td>
<td>-4.1481</td>
<td>3.3048</td>
<td>3.7586</td>
<td>3.5972</td>
</tr>
</tbody>
</table>

Overall, it can be observed from the figures and tables that there is a difference between the magnitude of positive and negative $\Delta v$ at the action points for all classes of $v_2$. This is the case for the control as well as for the experimental condition as positive mean values of $\Delta v$ are larger than negative mean values. This is an indication for the fact that perceptual thresholds, contrary to the original formulation of the model (Leutzbach & Wiedemann, 1986) are not symmetric.

Furthermore, it can be observed that for the control condition as well as the experimental condition higher values of $v_2$ were accompanied by larger values of $\Delta v$ as indicated by higher mean values at the higher classes of $v_2$. This contradicts the assumption of the original formulation of the model. As was mentioned before, in this formulation it is assumed that the perceptual thresholds with regard to $\Delta v$ are dependent on spacing $s$.

Relative speed $\Delta v$ at the action points seems to be dependent on $v_2$. This is illustrated by the fact that values of positive as well as negative values of $\Delta v$ are larger at higher speed classes. This supports the notion that in order for a change to be noticed by individuals, a stimulus must change by a set percentage (typically between 7 and 10%) (e.g. see Shen & Jung (2006)). Also it can be observed that the standard deviations for the different classes of lead vehicle speed increase at higher values of $v_2$. This is an indication that driver heterogeneity increases at larger values of $v_2$ and therefore supports the hypothesis that the assumption of deterministic perceptual thresholds assumed in the original formulation of the model is unrealistic. The differences between the two conditions was statistically significant as from the Kolmogorov-Smirnov test followed that $p<.05$. 

![Figure 6 Cumulative distribution functions of positive and relative speed for the control condition (first and third graph and the experimental condition)](image)
Table 2 Results MRA for the control condition and the experimental condition

<table>
<thead>
<tr>
<th>Model</th>
<th>$b_1$</th>
<th>$b_2$</th>
<th>Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model 1 (normal)</td>
<td>0.2009</td>
<td>-0.0002</td>
<td>215.4991</td>
</tr>
<tr>
<td>Model 2 (normal)</td>
<td>0.7777</td>
<td>0.0994</td>
<td>215.2825</td>
</tr>
<tr>
<td>Model 3 (normal)</td>
<td>0.2201</td>
<td>-0.0020</td>
<td>322.0517</td>
</tr>
<tr>
<td>Model 4 (normal)</td>
<td>0.7812</td>
<td>0.1116</td>
<td>316.4544</td>
</tr>
<tr>
<td>Model 1 (fog)</td>
<td>0.1022</td>
<td>-0.0003</td>
<td>225.9876</td>
</tr>
<tr>
<td>Model 2 (fog)</td>
<td>0.3795</td>
<td>0.0551</td>
<td>223.0240</td>
</tr>
<tr>
<td>Model 3 (fog)</td>
<td>0.1608</td>
<td>0.0002</td>
<td>346.0627</td>
</tr>
<tr>
<td>Model 4 (fog)</td>
<td>0.6628</td>
<td>0.0770</td>
<td>341.6662</td>
</tr>
</tbody>
</table>

The third research question was: "To what extent does the adverse weather condition fog influence acceleration $a$ at the action points?". In Table 2 the results of the Multivariate Regression analysis of Model 1 and 2 are presented for the control condition as well as for the experimental condition.

In the table the error, defined as the sum of the residuals is also reported. As an illustration, Model 2 is depicted in Figure 7. This figure merely represents the model and does not represent the observed accelerations. Overall, it can be concluded that, for the control condition as well as the experimental condition, drivers accelerate less strong at larger values of $s$ in response to speed differences with the lead vehicle. From these results, it can also clearly be observed that the parameter values of $b_1$ as well as $b_2$ decreased substantially in the experimental condition compared to the control condition. This means that drivers in the experimental condition did react with less strong accelerations $a$ in response to speed differences with the lead vehicle $Δv$. The fact that these relations change substantially due to the adverse condition can be regarded as an indication for a substantial degree of driver heterogeneity. Furthermore, it can be observed that in the experimental condition compared to the control condition, the error increases substantially. This also means that driver heterogeneity increases substantially in the experimental condition compared to the control condition.

The fourth research question was: "To what extent does the adverse weather condition fog influence so-called 'jumps' in acceleration $Δa$ at the action points?" The results of the Multivariate Regression analysis with regard to Model 3 and 4 for the control condition as well as the experimental condition are presented in Table 2. As an illustration, the results are also presented in Figure 7.

Overall, it can be observed from the figure as well as the table that 'jumps' in acceleration at the action points are larger at smaller values than at larger values of $s$. This can even more strongly be observed in the experimental condition. This means that drivers in the experimental condition did react with smaller 'jumps' in acceleration than in the control condition. This is also reflected in the values of the parameter values $b_1$ and $b_2$ in Table 2.

Furthermore, it can be observed from this table regarding Model 3 and 4 that here also the error increases substantially when comparing the two conditions. This fact as well as the observation that parameter values changed substantially between the two conditions also give way to the conclusion that driver heterogeneity is substantial.

From the results of the fourth and the fifth research question it furthermore becomes clear that the assumption of the original formulation of the model is not correct. In this formulation it was assumed that at the action points drivers change the sign of the acceleration, typically in the order of $0.2m/s^2$. From the results of the Multivariate Regression analysis can however be observed that acceleration at the action points changes depending on the location of these points in the $(Δv,s)$ plane. Furthermore, it can be concluded that, when the values of the parameters $b_1$ and $b_2$ in the models are observed, acceleration $a$ depends to a large degree on $Δv$ as compared to $s$. This means that although spacing $s$ is relevant for the decision whether to accelerate or not, it is less relevant for the actual acceleration $a$ a driver chooses at the action point. Furthermore, it becomes clear from the aforementioned that the relationship between $Δv$ and acceleration $a$ at the action points is influenced by external circumstances, like adverse weather conditions.
4. Discussion

Adverse weather conditions have been shown to have a substantial impact on traffic flow operations. In quantifying the adaptation effects possibly underlying this impact on traffic flow operations, mathematical models of car-following models can be developed. It is however unclear which model can best be used in order to describe these adaptation effects.

A likely candidate with regard to the description of these adaptation effects are psycho-spacing models (e.g. Leutzbach & Wiedemann, 1986). However, little has been attempted regarding the further expansion of these models. In this regard in this contribution the effect of an adverse weather condition (i.e. fog) on the position of action points in the \((\Delta v, s)\) plane was analyzed. Furthermore the relationship between speed of the lead vehicle \(v_2\) and relative speed \(\Delta v\) in case of normal visibility and adverse weather conditions was determined. Finally, the influence of the adverse weather condition on acceleration \(a\) as well as on 'jumps' in acceleration \(\Delta a\) at the action points was analyzed.

From the estimation of the action points in the \((\Delta v, s)\) plane followed that large differences in the position of the action points were present when comparing the normal visibility condition with the adverse weather condition. Firstly, action points were much more scattered in the adverse weather condition. Furthermore, compared to the normal visibility condition, in the adverse weather condition drivers mostly seem to react to larger values of \(\Delta v\). This may be due to the fact that drivers are less able to adequately perceive small speed differences with the leader in the adverse weather condition. These differences between the aforementioned conditions can furthermore be regarded as an indication that the assumption of the deterministic perceptual thresholds in the original formulation of the model is unrealistic.

From the analysis of the relationship between speed of the lead vehicle \(v_2\) and relative speed \(\Delta v\) at the action points it followed that there was a difference between the magnitude of positive and negative values of \(\Delta v\) at the action points, as mean positive values of \(\Delta v\) were larger than negative values. This was the case for the different speed classes in the normal visibility as well as in the adverse weather condition. It was concluded that perceptual thresholds, contrary to what is assumed in the original formulation of the model, are asymmetric (see also Misener et al., 2000). Furthermore it followed from the analysis that in the normal visibility condition as well as in the adverse...
weather condition higher values of $v_2$ were accompanied by larger values of $\Delta v$ as indicated by higher mean values of $\Delta v$ at higher speed classes of the lead vehicle $v_2$. This contradicts the assumptions in the original formulation of the model but supports the hypotheses of the so-called Weber-Fechner law.

Furthermore, it could be observed that values of $\Delta v$ at the action points in the different speed classes of the lead vehicle were larger in the adverse weather condition compared to the normal visibility condition. As drivers seem to be less able to adequately perceive small speed differences with the lead vehicle, especially values of $v_2$ they react to larger values of $\Delta v$. Also it was investigated to what extend the adverse weather condition fog has an influence on acceleration $a$ in relation with $\Delta v$ and $s$ at the action points. From the Multivariate Regression Analysis it was concluded that overall, drivers react with a less strong acceleration in case of the adverse weather condition compared to the normal visibility condition. This was also the case with regard to the 'jumps' in acceleration $\Delta a$.

The fact that acceleration $a$ and also $\Delta a$ seems to be mainly dependent on $\Delta v$, contradicts the assumptions made in the original formulation of the model, as in this formulation it is assumed that drivers just change the sign of their acceleration, typically in the order of 0.2m/s$^2$. This relationship also seems to be influenced to a large degree by external circumstances.

Also it was concluded from the results that the error of the fitted models increased significantly when comparing the normal visibility condition with the adverse weather condition. This is an indication that with regard to the effect of $\Delta v$ and $s$ on $a$ a substantial degree of driver heterogeneity can be observed. This was especially the case in the adverse weather condition. This also implies that the assumption of deterministic perceptual thresholds is unrealistic.

The aforementioned expresses the need for developing a data driven stochastic model based on the principles of psycho-spacing theory. In this model the decision whether or not to execute an action can be dependent on $\Delta v$ and $s$, while the acceleration chosen at these action points must be dependent on $\Delta v$. Furthermore in this model the relationship between perceptual thresholds with regard to $\Delta v$ and speed of the lead vehicle $v_2$ has to be taken into account. Finally, external circumstances, like adverse conditions, have to play an important role in the decision whether or not to accelerate as well as in the actual choice of acceleration at these action points. In this contribution it is therefore recommended to incorporate these determinants in a stochastic optimal control approach.

References


