

Empirical Research and Modeling of Longitudinal Driving Behavior Under Adverse Conditions

Raymond Gerard Hoogendoorn

Delft University of Technology, 2012

This thesis is part of the research program
"Traffic and Travel Behavior in Case of Exceptional Events"
sponsored by the Dutch Foundation of Scientific Research MaGW - NWO



Cover illustration: Fabienne Alexandra Hoogendoorn

Empirical Research and Modeling of Longitudinal Driving Behavior Under Adverse Conditions

Proefschrift

ter verkrijging van de graad van doctor

aan de Technische Universiteit Delft,

op gezag van de Rector Magnificus prof. ir. K.C.A.M. Luyben,

voorzitter van het College voor Promoties,

in het openbaar te verdedigen op 5 juli 2012 om 10.00 uur

door

Raymond Gerard HOOGENDOORN

Master of Science in Psychology

geboren te Nederland, Rotterdam

Dit proefschrift is goedgekeurd door de promotoren:

Prof. dr. K.A. Brookhuis en

Prof. dr. ir. B. van Arem

Samenstelling promotiecommissie :

Rector Magnificus prof. ir. K.C.A.M. Luyben

Prof. dr. K.A. Brookhuis

Prof. dr. ir. B. van Arem

Prof. dr. H.J. van Zuylen

Prof. ir. L.H. Immers

Prof. dr. H.S. Mahmassani

Prof. dr. R.L. Bertini

Dr. M.H. Martens

voorzitter

Technische Universiteit Delft, promotor

Technische Universiteit Delft, promotor

Technische Universiteit Delft

Technische Universiteit Delft

Northwestern University

Portland State University

Universiteit Twente

This thesis is the result of a Ph.D. study carried out from 2009 to 2012 at the Faculty of Civil Engineering and Geosciences, Department of Transport and Planning, Delft University of Technology

TRAIL Thesis Series no. T2012/3 , the Netherlands TRAIL Research School

TRAIL

P.O. Box 5017

2600 GA Delft

The Netherlands

Phone: +31 15 278 6046

Fax: +31 15 278 4333

E-mail: info@rsTRAIL.nl

ISBN 978-90-5584-158-5

Copyright © 2012 by Raymond Gerard HOOGENDOORN.

All rights reserved. No part of the material protected by this copyright notice may be reproduced or utilized in any form or by any means, electronic or mechanical, including photocopying, recording or by any information storage and retrieval system, without written permission from the author.

Printed in the Netherlands

*"Ab esse ad posse valet, a posse ad esse non valet consequentia."
(From reality one can be certain of a possibility, from a possibility one cannot be certain of a reality).*

Preface

Adverse conditions have been shown to have a major impact on society. Examples of these conditions are emergency situations (e.g., evacuations following a life-threatening disaster), adverse weather conditions (e.g. heavy rain, fog) and freeway incidents (e.g. vehicle crashes in the other driving lane). Besides a substantial damage to society (e.g. economic losses, casualties, etc.), these conditions have been shown to have a substantial impact on traffic flow operations. For example, freeway incidents have been shown to lead to freeway capacity reductions up to 30%!

However, very little knowledge was available on the changes in driving behavior actually underlying this impact nor was any knowledge available on the possible causes of these changes in driving behavior. How do drivers actually change their speed, acceleration and following distance in case of an emergency situation? What are the causes of these changes? Is it panic? Emotions? Or is there a change in the demand the driving task makes on the capabilities of a driver?

Furthermore, very little knowledge was available on how these changes in driving behavior are represented in current mathematical models of longitudinal driving behavior. Are these models, which are used in simulation software packages, adequate? Do they account for differences within as well as between drivers?

The aforementioned inspired us to write this dissertation, which entails empirical longitudinal driving behavior and modeling of longitudinal driving behavior (driving behavior in the same lane) in case of emergency situations, adverse weather conditions and freeway incidents.

I would like to take this opportunity to thank the organizations that made the work presented in this dissertation possible. I especially want to acknowledge the Dutch Foundation of Scientific Research MaGW-NWO for sponsoring the project "Traffic and Travel Behavior in Case of Exceptional Events".

I also want to express my sincere gratitude to all the people who contributed to this dissertation. Firstly I want to thank my promoters Karel Brookhuis and Bart van Arem. They provided me with many pieces of advice on how to best perform my research and on how to best incorporate my findings in my dissertation. I also would like to thank Winnie Daamen for her useful comments on the many papers we wrote together.

A special thanks goes out to Serge Hoogendoorn. Without him this dissertation would not have existed at all. So...thank you so much!

Furthermore, I would also like to thank my former roommates Ramon Landman, Mignon van den Berg, Mahtab Joueiai and Guus Tamminga for their willingness to keep listening to me rambling on about the ideas I had. Thank you guys! I also would like to thank Allert Knapper for our many fun and interesting talks and for his help with the driving simulator.

And last, but certainly not least, I would like to thank my family. Patries, Fabienne, Serge, Sascha, mum and Piet... thank you for being there for me and especially putting up with me. Fabbie, you're the most important person in the world to me!

And to all the people who contributed in one way or another to this dissertation and I forgot to mention.... Thank you!!

Yours sincerely,

-Reem, 9 March 2012

Contents

Preface	i
1 Introduction	1
1.1 Context of research	3
1.2 Research scope	4
1.3 Research questions	5
1.4 Scientific and societal relevance	7
1.4.1 Scientific relevance	7
1.4.2 Societal relevance	8
1.5 Dissertation outline	8
I Empirical Longitudinal Driving Behavior and Adverse Conditions	13
2 State-of-the-art Empirical Driving Behavior Under Adverse Conditions	15
2.1 Introduction	15
2.2 The structure of adverse conditions	16
2.3 A classification of driving tasks	18
2.3.1 Michon's hierarchical model of driving tasks	18
2.3.2 Action-based and task-based classifications	19
2.4 Empirical adaptation effects and adverse conditions	20
2.4.1 Emergency situations	20
2.4.2 Adverse weather conditions	21
2.4.3 Freeway incidents	23
2.5 Determinants of longitudinal driving behavior under adverse conditions	24

2.5.1	Static determinants: Personal characteristics of drivers	25
2.5.2	Dynamic determinants: Activation level, distraction, mental workload, emotions and panic	27
2.6	Introducing a theoretical framework	33
2.7	Conclusions	37
3	Research Methodology	39
3.1	Aim and structure of this chapter	39
3.2	An introduction into validity and controllability	40
3.3	Data collection method of longitudinal driving behavior and mental workload .	41
3.3.1	Empirical longitudinal driving behavior	41
3.3.2	Mental workload	46
3.4	Experimental set-up	50
3.4.1	The Advanced driving simulator	50
3.4.2	Experimental designs	51
3.4.3	The driving environments	52
3.4.4	Measures	57
3.4.5	Participants	59
3.4.6	Data analysis methods	60
3.5	Conclusions	62
4	Empirical Longitudinal Driving Behavior in Case of Adverse Conditions	63
4.1	Aim and structure of this chapter	63
4.2	Emergency situations	63
4.3	Adverse weather conditions	67
4.4	Freeway incidents	70
4.5	Conclusions	73
5	Mental workload and Driver Characteristics Under Adverse Conditions	75
5.1	Aim and structure of this chapter	75
5.2	Mental workload and driver characteristics in case of emergency situations . . .	76
5.2.1	Influences on physiological indicators of mental workload	76

5.2.2	Influence of driver characteristics	79
5.3	Mental workload and driver characteristics in case of adverse weather conditions	80
5.3.1	Influences on physiological indicators of mental workload	80
5.3.2	Influence on subjective estimates of effort	82
5.3.3	Influence of driver characteristics	82
5.4	Mental workload and driver characteristics in case of freeway incidents	82
5.4.1	Influences on physiological indicators of mental workload	82
5.4.2	Influence on subjective estimates of effort	86
5.4.3	Influence of driver characteristics	86
5.5	Conclusion	88

II Modeling of Longitudinal Driving Behavior Under Adverse Conditions 93

6 Driving Behavior Modeling and Adverse Conditions: a State-of-the-art 95

6.1	Aim and structure of this chapter	95
6.2	An introduction to car-following models	96
6.3	Continuous car-following models	97
6.3.1	Stimulus-response models	97
6.3.2	Safety distance models	99
6.3.3	Multi-anticipative car-following models	101
6.4	A look at psycho-spacing models	101
6.5	Variability in continuous car-following models and psycho-spacing models . .	103
6.6	Car-following models and adverse conditions	105
6.7	Conclusions	106

7 Data Analysis Methods 109

7.1	Aim and structure of this chapter	109
7.2	Estimating parameter values and model performance in continuous car-following models	110
7.2.1	Estimation of continuous car-following models	110
7.2.2	A closer look at the proposed method	110

7.3	Estimation of action points and acceleration in psycho-spacing models	114
7.3.1	Determining action points	114
7.3.2	Determining acceleration at action points	116
7.4	Conclusions	117
8	Continuous Car-following Models and Adverse Conditions	119
8.1	Aim and structure of this chapter	119
8.2	Parameter value changes and model performance under emergency situations .	120
8.2.1	Parameter value changes in case of an emergency situation	120
8.2.2	Model performance in case of emergency situations	128
8.3	Parameter value changes and model performance in case of adverse weather conditions	129
8.3.1	Parameter value changes in case of adverse weather conditions	129
8.3.2	Model performance in case of adverse weather conditions	136
8.4	Parameter value changes and model performance in case of freeway incidents .	137
8.4.1	Parameter value changes in case of freeway incidents	137
8.4.2	Model performance in case of freeway incidents	141
8.5	Conclusions	142
9	Psycho-spacing Modeling in Case of Adverse Conditions	145
9.1	Aim and structure of this chapter	145
9.2	Microscopic traffic data	146
9.3	Estimating the positions of action points	148
9.3.1	Emergency situations	148
9.3.2	Adverse weather conditions	152
9.3.3	Freeway incidents	152
9.4	Acceleration at action points in case of adverse conditions	157
9.4.1	Emergency situations	159
9.4.2	Adverse weather conditions	161
9.4.3	Freeway incidents	162
9.5	Conclusions	165

10 A Stochastic Psycho-spacing Model through Bayes Net Modeling	169
10.1 Aim and structure of this chapter	169
10.2 Bayesian networks	171
10.3 A simple Bayesian network for car-following	172
10.4 Marginal and joint probabilities through parameter learning	175
10.5 Extending the Bayesian network with adverse conditions	177
10.5.1 Evidence of an emergency situation	180
10.5.2 Evidence of adverse weather conditions	182
10.5.3 Evidence of a freeway incident	185
10.6 Conclusions	188
 III Conclusions and Recommendations	 191
11 Conclusions and Recommendations	193
11.1 Summary of research aims and approaches	193
11.1.1 Empirical adaptation effects in longitudinal driving behavior under adverse conditions	194
11.1.2 Determinants of longitudinal driving behavior under adverse conditions	197
11.1.3 Mathematical modeling of longitudinal driving behavior under adverse conditions	198
11.2 Main findings	200
11.2.1 Empirical adaptation effects	200
11.2.2 Determinants of longitudinal driving behavior under adverse conditions	200
11.2.3 Mathematical modeling of longitudinal driving behavior under adverse conditions	201
11.3 Conclusions	203
11.3.1 Empirical driving behavior under adverse conditions	203
11.3.2 Modeling of driving behavior under adverse conditions	205
11.4 Practical implications	208
11.5 Reflections	209
11.6 Recommendations for future research	210

References	213
About the author	225
List of publications and conference proceedings by the author	227
Summary	231
Samenvatting	237
TRAIL Thesis Series	243

Chapter 1

Introduction

The ability of transport systems to deal with adverse conditions has become increasingly important. Adverse conditions, in this dissertation defined by conditions following an unplanned event with a high impact and a low probability of occurring, have been shown to have a considerable impact in terms of economic losses, casualties, medical costs, loss of production capabilities, material and immaterial costs. Examples of adverse conditions are emergency situations (, due to man-made or naturally occurring disasters), adverse weather conditions (e.g., heavy rain, thick fog, snow, black ice, etc.) and freeway incidents (e.g., vehicle crashes).

Emergency situations have been shown to have considerable impacts on traffic flow operations. For example, in the U.S. the events of the hurricanes Georges in 1998 and Floyd in 1999 precipitated the two largest evacuations and perhaps its two largest traffic jams (Urbina & Wolshon, 2003). Hurricane Rita created substantial problems as well, as massive traffic congestion as well as fuel supply problems occurred (Litman, 2006). The aforementioned revealed the fact that emergency response agencies were not as prepared for such scenarios as had been previously assumed.

Emergency situations are often accompanied by adverse weather conditions, complicating the impact emergency situations in itself have on traffic flow operations. In Pisano and Goodwin (2002) for example, it was conjectured that adverse weather conditions impact roadway mobility by increasing delay (i.e., variability in travel time), reduced speed, increasing speed variance and decreasing roadway capacity. The authors mention that the Oak Ridge National Laboratory estimated that capacity of U.S. freeways and principle arterials reduced more than 11% due to fog, snow and ice in 1999.

The effect of adverse weather conditions on traffic flow operations is supported by Van Arem et al. (1993). In their research the effect of different roadway and weather conditions on maximal occupancy and capacity was investigated. Strong indications were found of a dependence of maximal occupancy and capacity on weather conditions. Also Jones et al. (1970) reported a substantial influence of adverse weather conditions on traffic flow operations. Here it was concluded that heavy rain reduced freeway capacity by 14 to 19%.

This influence of rain is also supported by recent research. Chung et al. (2006) used precise rainfall data with detector data at five highly congested sections at the Tokyo Metropolitan

Expressway and concluded that rain reduced roadway capacity ranging from 4 to 7% in case of light rain and up to 14% in case of heavy rain (Figure 1.1). Also reductions in free-flow speed were found between 4.5% in case of light rain and 8.2% in case of heavy rain. Ibrahim and Hall (1994) investigated the influence of heavy rain on flow occupancy and speed-flow relationships. It was estimated that in case of heavy rain conditions, freeway capacity reduced around 10%.

Finally, in Saberi and Bertini (2010) significant differences were found between speed and flow under different rainfall conditions. However, during congested periods, the flow and speed differences were not significant.

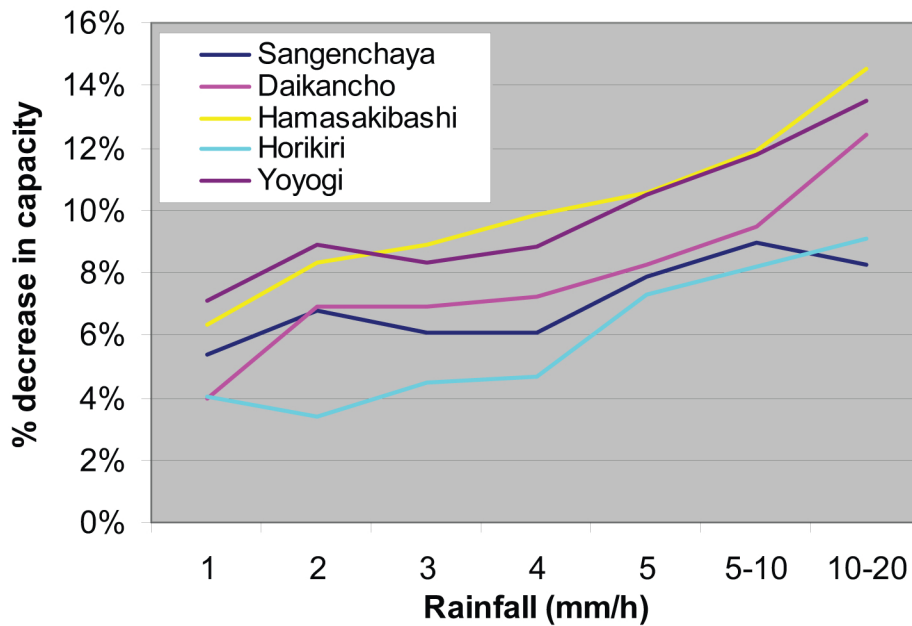


Figure 1.1: Freeway capacity reductions on the Tokyo Metropolitan Expressway in case of rain (Chung et al., 2006).

Fog has been shown to have a substantial impact on traffic flow operations as well. In research performed by Agarwal et al. (2006) loop detector data were used along with weather data in order to determine the influence of fog on freeway capacity. In their research it was shown that fog, resulting in impaired visibility, led to local roadway capacity reductions between 10 and 12%.

The impact on traffic flow operations is not restricted to emergency situations and adverse weather conditions. Freeway incidents have also shown to lead to substantial changes in traffic flow operations. Knoop et al. (2008) indicated that freeway incidents led to substantial capacity reductions in the lane where the crash occurred. However, also capacity reductions up to 30% could be observed in the lanes opposite from where the crash occurred. This capacity reduction may be due to rubbernecking, although no causal relationship could be established.

The aforementioned examples show to what extent adverse conditions affect traffic flow operations, thereby complicating the effects these conditions in itself have on society. Therefore, more effective and innovative strategies are needed in order to limit the impact of adverse con-

ditions, since both the infrastructure as well as behavior of road users are impacted considerably by these conditions.

However, since adverse conditions have a low rate of occurring, little experience is available on how to cope with them. In order to investigate whether strategies are effective, simulation studies must be performed. For example, recently a large number of evacuation studies investigated the efficacy of evacuation strategies using well-established dynamic traffic simulation models developed for day-to-day traffic applications (Pel, Bliemer, & Hoogendoorn, 2011). Many of these studies make use of microscopic simulation models, such as PARAMICS (Cova & Johnson, 2003), CORSIM (Williams et al., 2007), VISSIM (Han & Yuan, 2005) and INTEGRATION (Mitchell & Radwan, 2006). In these microscopic simulation models mathematical models are used in order to approximate driving behavior. In order to adequately perform these studies, it is crucial that insight is available into the influence adverse conditions have on empirical driving behavior as well as into the extent in which this influence is reflected in the aforementioned mathematical models of driving behavior.

In this thesis we therefore present extensive empirical analyses of driving behavior under adverse conditions. We also analyze the determinants of driving behavior under these conditions. This analysis is performed as this might provide us with insight into which strategies might be most effective in order to optimize traffic flow operations under adverse conditions.

However, insight into which adaptation effect in empirical driving behavior under adverse conditions may be observed, does not provide us with insight into the extent in which current mathematical models of driving behavior are adequate in describing adaptation effects in driving behavior due to adverse conditions. Therefore this thesis also presents extensive analyses on the representation of the adaptation effects in driving behavior under adverse conditions in several often used mathematical models of driving behavior.

1.1 Context of research

The research presented in this thesis is part of a research program called: 'Traffic and Travel Behavior in Case of Exceptional Events' sponsored by the Dutch Foundation of Scientific Research MaGW-NWO.

The general research objective of this program is the development of behavioral theories, conceptual and mathematical models in order to predict the transportation system's response to adverse conditions described in terms of the series of effects and the impact of actions undertaken by network managers. Furthermore, insight into the dynamic interactions between stakeholders, processes and networks is achieved in this project. This insight is the basis for developing efficient and robust designs, traffic and mobility management paradigms.

The research projects focus on the following five topics:

- Travel behavior modeling under adverse conditions, including information, guidance and control;
- Driving theory and modeling under adverse conditions;

- Multi-scale (mixed micro-macroscopic) and multi-modal transportation network modeling;
- Robust traffic and mobility management in case of adverse conditions;
- Development of a Multi-user Driving and Travel Simulator Laboratory.

On the level of driving behavior theory and modeling, empirical investigations in the past have considered changes in roadway capacity due to bad weather conditions or in case of an incident. The lack of individual driving behavior data has however precluded understanding driving behavior in such and other circumstances. New insights had to be gained by deploying innovative data collection techniques, enabling a thorough understanding of adaptation effects in driving behavior due to adverse conditions.

Theories relating the characteristics of the adverse conditions and drivers to adaptation effects in driving behavior have to be established and empirically underpinned, enabling the prediction of traffic flow operations in more generic cases (incidents, bad weather conditions, evacuations, etc.). These are essential in order to describe and manage flow operations, but also to improve design and control.

1.2 Research scope

The previous section discussed the context of this thesis. The aim of the present section is to discuss, limit and motivate the research scope.

The analyses presented in this thesis focus on longitudinal driving behavior on freeways under adverse conditions. Within these adverse conditions only emergency situations, adverse weather conditions and freeway incidents are considered. These adverse conditions were chosen as each can be assumed to have a different effect on empirical longitudinal driving behavior as well as to have a different effect on determinants of adaptation effects in longitudinal driving behavior.

Another motivation for choosing these three specific adverse conditions is that these might occur simultaneously. For example, it can easily be imagined that traffic crashes occur during an emergency situation following a man-made or naturally occurring disaster. Also it can be assumed that some emergency situations are accompanied by adverse weather conditions leading to a reduction in visibility.

In this dissertation we focus on interactions between drivers moving in the same lane, i.e., how do drivers execute their longitudinal driving task in case of an adverse condition? This choice is motivated by the fact that dynamics in traffic flow on freeways are largely determined by interactions between vehicles in the same lane. For example, Ossen (2008) conjectured that longitudinal driving behavior of individual drivers determines to a large extent the equilibrium as well as the dynamic characteristics of traffic flow.

Finally, this dissertation only considers driving behavior on freeways. Driving behavior in case of adverse conditions on the secondary road network was not considered.

1.3 Research questions

The main research objective of this thesis is to establish insight into longitudinal driving behavior in case of adverse conditions and develop mathematical models describing this behavior.

Although it may be assumed that adverse conditions have a substantial impact on longitudinal driving behavior of individual drivers, little information is available as to what extent this behavior is influenced. To this end the following research question is answered in this thesis:

1. *What are the effects of adverse conditions on longitudinal driving behavior?*

In our theoretical as well as in our empirical analyses of longitudinal driving behavior, we will show that adverse conditions have a substantial and significant influence on longitudinal driving behavior. The answer to this research question however does not provide us with insight into the causes of changes in longitudinal driving behavior under adverse conditions. In this regard the following research question is answered:

2. *Which determinants are responsible for longitudinal driving behavior under adverse conditions?*

We will introduce a new theoretical framework on the relationship between adverse conditions and longitudinal driving behavior grounded on the Task-Capability-Interface (TCI) model by Fuller (2005). In this adaptation of the TCI model (Fuller, 2005), it is assumed that adverse conditions have an influence on the interaction between driver capabilities and task demands. For example, in the framework it is assumed that perception of a freeway incident leads to distraction, in turn leading to a reduction in driver capability. This reduction in driver capability causes an imbalance between driver capability and task demands resulting in an increase in mental workload of the driver. The driver will try to resolve this imbalance, thus reducing his or her mental workload, by influencing those factors over which he or she has direct control (compensation effects). When the driver is unable to sufficiently resolve the imbalance, a deterioration in driving task performance will be the result (performance effects).

In the context of this theoretical framework, we show empirically that adverse conditions have a substantial and significant influence on mental workload. Furthermore we show that driver capabilities (e.g., age, driving experience) influence the effect adverse conditions have on mental workload.

After having established that adverse conditions have a substantial influence on longitudinal driving behavior and mental workload we focus on modeling of longitudinal driving behavior under adverse conditions. To this end, the following research question was formulated:

3. *To what extent is driving behavior under adverse conditions adequately represented in current mathematical models of driving behavior?*

In the theoretical framework it is assumed that adverse conditions lead to compensation as well as performance effects in longitudinal driving behavior due to an interaction between driver capabilities and task demands. It is however not clear to what extent these effects are adequately represented in continuous car-following models. In this dissertation we will show that adverse conditions lead to substantial changes in parameter values and model performance of an often used car-following model, namely the Intelligent Driver Model (IDM) (Treiber, Hennecke, & Helbing, 2000). In the IDM acceleration is a continuous function of the following distance of a vehicle and speed as well as the speed difference with the lead vehicle.

We conjecture in this thesis that most continuous models have a rather mechanistic character, as they insufficiently incorporate human elements. In order to correct for this drawback, psycho-spacing models were developed in the past. Michaels (1963) provided the basis for the first psycho-spacing model based on theories borrowed from perceptual psychology (Leutzbach & Wiedemann, 1986).

Basically, in these models longitudinal driving behavior is controlled by perceptual thresholds. These thresholds serve to delineate a relative speed - spacing plane, in which the driver of a following vehicle does not respond to any change in his dynamic conditions and would seek to maintain a constant acceleration (Brackstone, Sultan, & McDonald, 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 dissertation these points in the relative speed - spacing plane are referred to as action points. The driver will maintain this acceleration until another threshold is crossed, producing the typical spirals in the relative speed - spacing plane.

In our analyses we show that adverse conditions have a substantial influence on the position of action points in the relative speed - spacing plane. Furthermore, we show that adverse conditions influence the sensitivity to relative speed and spacing of acceleration as well as 'jumps' in acceleration at the action points considerably.

As compensation and performance effects are caused by an interaction between driver capabilities and task demands, it can be assumed that these effect vary considerably within and between drivers dependent on for example the external circumstances (i.e., adverse conditions) and characteristics of the drivers (i.e., age, driving experience, activation level and level of distraction). In this context from the analyses it follows that the degree of variability between as well as within drivers indeed is considerable. We show this for the continuous car-following models as well as for the psycho-spacing models.

As adverse conditions lead to substantial changes in parameter values and model performance in continuous car-following models and as action points in psycho-spacing models show a large degree of variability, in this dissertation we take a first step towards modeling of longitudinal driving behavior under adverse conditions using a Bayesian network modeling approach.

In sum, in this thesis we try to obtain new empirical insights into longitudinal driving behavior as well as the determinants of the observed behavior. As it is important to be able to predict the macroscopic consequences of adaption effects in longitudinal driving behavior due to adverse conditions, we also focus on modeling of these adaptation effects in longitudinal driving behavior.

1.4 Scientific and societal relevance

The contributions of the research presented in this thesis can be divided into scientific contributions and also into practical contributions. In this section therefore the scientific relevance as well as the societal relevance is discussed.

1.4.1 Scientific relevance

Many scientific contributions of this dissertation are present in the field of traffic engineering as well as traffic psychology.

One important contribution of this dissertation is the introduction of a theoretical framework for driving behavior in case of adverse conditions. From this theoretical framework it follows that adverse conditions lead to substantial adaptation effects in longitudinal driving behavior.

In order to empirically underpin this theoretical framework we show in Chapter 4 that emergency situations, adverse weather conditions and freeway incidents indeed lead to substantial adaptation effects in longitudinal driving behavior. For example, we will show that emergency situations lead to a considerable increase in speed, acceleration and deceleration rates, along with a substantial reduction in the distance to the lead vehicle.

In Chapter 5 we continue with the empirical underpinning of the theoretical framework. In this chapter we show that adverse conditions lead to a considerable change in mental workload of the driver and that personal characteristics of drivers (i.e., age and driving experience) moderate the influence adverse conditions have on mental workload.

Besides these scientific contributions in the field of traffic psychology, we also contribute to the field of traffic engineering. In Chapter 8 we provide evidence for the presence of substantial changes in parameter values and model performance in an often used car-following model, namely the Intelligent Driver Model (Treiber et al., 2000) following an adverse condition. These findings support our theoretical framework in two ways.

Firstly, we will argue that the changes in parameter values in the Intelligent Driver Model can be regarded as evidence for the existence of compensation effects as proposed in the theoretical framework. For example, we show that emergency situations are accompanied by an increase in the parameter representing maximum acceleration in the IDM. Secondly, we will argue that the reduction in model performance of the IDM is an indication for the existence of performance effects.

Furthermore, we contribute to the existing body of knowledge in the field of traffic engineering by showing that action points in psycho-spacing models display a large degree of variability and are substantially influenced by the presence of an adverse condition. We show that the assumption of deterministic perceptual thresholds assumed in the original formulation of the model (Leutzbach & Wiedemann, 1986) is unrealistic. In Chapter 9 it is shown that adverse conditions lead to a substantial change in the position of action points in the relative speed - spacing plane. Furthermore, we show that acceleration as well as so-called 'jumps' in acceleration (the difference in acceleration before and after an action point) are influenced by adverse conditions and also show a large degree of variability.

As large differences within and between drivers are established, we also contribute to the existing body of knowledge in the field of traffic engineering by introducing a new stochastic car following model using a Bayesian network modeling approach. We show that this model describes and predicts longitudinal driving behavior relatively well under normal driving conditions as well as under adverse weather conditions.

As becomes clear from this section, this dissertation adds to the body of knowledge in the field of traffic engineering as well as in the field of traffic psychology. Through an interdisciplinary approach we relate changes in psychological constructs (driver capabilities, task demands, mental workload) as well as changes in empirical longitudinal driving behavior to changes in parameter values, model performance and the position of action points in psychospatial models. This is one of the core contributions of this dissertation.

1.4.2 Societal relevance

As was stated in the aforementioned, adverse conditions can have considerable societal impacts in terms of casualties, economical and medical costs, loss of production capabilities, material and immaterial costs.

We conjectured that the impact of adverse conditions on society is complicated by its effect on traffic flow operations. This, as well as the recent increases in the frequency of both man-made and naturally occurring disasters (e.g., September 11th and the tsunami in Japan), have therefore required micro- and macroscopic traffic simulation models to account accurately for the effects of adverse conditions in addition to normal driving situations.

The acquired knowledge on empirical longitudinal driving behavior under adverse conditions can be used in order to improve the way in which longitudinal driving behavior is modeled in microsimulation tools. Implementation of the findings of this thesis in microsimulation tools is important as in general, it can be stated that when assumptions on longitudinal driving behavior in microscopic simulators become more realistic, the effects of traffic management measures intending to minimize the impact of adverse conditions on traffic flow operations, can be more accurately predicted thus providing opportunities for a more efficient use of the existing infrastructure.

For example, the effects of incidents in the other driving lane on longitudinal driving behavior can possibly be mitigated through placing screens around the incidents. Also Advanced Driver Assistance Systems (ADAS) may prove to be beneficial. However, in order to determine the efficacy of such measures simulation studies using adequate parameter settings are crucial.

1.5 Dissertation outline

To answer the research questions presented in Section 1.3 this thesis is organized into three parts:

1. Empirical driving behavior under adverse conditions
2. Modeling of driving behavior under adverse conditions

3. Conclusions and recommendations

These three parts are organized according to the scheme presented in Figure 1.2. In the next part of this section the different components of the scheme are discussed in more detail.

Part I: Empirical driving behavior under adverse conditions

This part of the dissertation starts in Chapter 2 with a comprehensive state-of-the-art on empirical driving behavior under adverse conditions. This state-of-the-art discusses changes in driving behavior under adverse conditions as well as the determinants of driving behavior under these conditions. However, before empirical driving behavior under adverse conditions can be investigated, it is necessary to gain more insight into the structure of adverse conditions as well as into the structure of the driving task.

Next in this chapter available literature on empirical longitudinal driving behavior in case of emergency situations, adverse weather conditions and freeway incidents is presented. Furthermore in this chapter the available research on possible determinants of longitudinal driving behavior under adverse conditions is discussed.

From the available research it can be assumed that adverse conditions have a substantial influence on empirical longitudinal driving behavior. Furthermore, it can be assumed that mental workload, moderated by age and driving experience, plays an important role as a possible determinant of behavior during adverse conditions. However, we show that current knowledge on the influence of adverse conditions on empirical longitudinal driving behavior as well as the possible determinants of this behavior is fairly limited.

Although it may be assumed that mental workload and driver characteristics have an influence on empirical longitudinal driving behavior in case of adverse conditions, this does not inform us how these conditions are related to empirical driving behavior. To this end, in Chapter 2 we propose a new theoretical framework describing the relationship between adverse conditions and changes in longitudinal driving behavior based on the Task-Capability-Interface model by Fuller (2005).

In order to empirically underpin the theoretical framework, we performed three extensive driving simulator experiments. These driving simulator experiments intended to investigate the influence of adverse conditions (i.e., emergency situations, adverse weather conditions and freeway incidents) on longitudinal driving behavior and mental workload (moderated by age and driving experience).

In Chapter 3 we start with a general introduction into the concepts of validity and controllability in relation to data collection methods. This introduction is followed by an overview of the available data collection methods of empirical longitudinal driving behavior and mental workload.

Furthermore, we discuss in Chapter 3 the experimental design of the three driving simulator experiments. Also, an introduction to the Advanced Driving Simulator as well as some validity issues are provided. The chapter concludes with a description of the participants as well as the data-analysis methods used in order to establish the significance of the observed effects.

Next, in Chapter 4 the results of the three driving simulator experiments with regard to the influence of adverse conditions on longitudinal driving behavior are presented. From the results of these experiments clear indications were found of a strong influence of adverse conditions on longitudinal driving behavior.

This chapter is followed by a presentation of the results of the influence of adverse conditions on mental workload, moderated by age and driving experience in Chapter 5. In this chapter we show that adverse conditions have a significant influence on mental workload, measured through physiological indicators of mental workload as well as through subjective estimates of effort expenditure.

Part II: Modeling of driving behavior under adverse conditions

In this part of the dissertation we start with a detailed overview of current continuous car-following models in Chapter 6. In this chapter we show that most current continuous car-following models have a rather mechanistic character. For example, the only human element incorporated in most of these models is a finite reaction time.

Therefore in the ensuing of Chapter 6 we turn to the discussion of psycho-spacing models. These models incorporate perceptual thresholds within which drivers are assumed to not notice and therefore respond to changes in their dynamic conditions. As it can be assumed that adverse conditions have a substantial influence on perception (e.g., through perceptual distortion following an increase in mental workload) it can be assumed that these models provide a better description of longitudinal driving behavior under adverse conditions.

In the theoretical framework we propose that adverse conditions lead to compensation and performance effects in longitudinal driving behavior due to an interaction between driver capability and task demands. In order to investigate whether these effects are reflected in parameter values as well as model performance in continuous car-following models, we used a new calibration approach for joint estimation. This approach is discussed in depth in Chapter 7. In this chapter we also introduce a new data analysis technique used to estimate action points in a psycho-spacing model.

In Chapter 8 we show that adverse conditions indeed lead to substantial changes in parameter values in a continuous car-following model, i.e., the Intelligent Driver Model (Treiber et al., 2000). We argue that these changes in parameter values reflect compensation effects proposed in the theoretical framework introduced in Chapter 2. Moreover, it is established that in general adverse conditions lead to a reduction in model performance of continuous car-following models. In Chapter 8 we argue that this reduction in model performance is an indicator of performance effects proposed in the theoretical framework introduced in Chapter 2. We assume as well that this reduction in model performance is a consequence of the fact that human elements are insufficiently incorporated in these continuous car-following models. Therefore we turn to the presentation of the estimation of so-called action points in psycho-spacing models in Chapter 9.

In Chapter 9 it is shown that adverse conditions lead to substantial changes in the position of action points. Furthermore, we show that the degree of variability with regard to the position

of action points is substantial between as well as within drivers. It is conjectured that car-following patterns closely resemble the ones predicted by psycho-spacing theory. However, due to the degree of variability the assumption of deterministic perceptual thresholds assumed in the original formulation of these models does not hold in reality. Furthermore, we will show that adverse conditions have a substantial influence on acceleration as well as the 'jumps' in acceleration at the action points. Also the degree of variability with regard to acceleration at the action points differs substantially between the conditions.

In order to capture variability in longitudinal driving behavior under normal and also under adverse conditions, we propose a new stochastic car-following model based on psycho-spacing theory in Chapter 10. In this chapter we introduce a new approach to modeling longitudinal driving behavior under adverse conditions using a Bayesian network modeling approach. A Bayesian network is designed and parameters in the net are learned using the data from the experiments as well as using empirical trajectory data. In this chapter we show that this approach describes and predicts longitudinal driving behavior under adverse conditions relatively well.

Part III: Conclusions, Synthesis, Implications and Recommendations

The previous chapters focus on empirical longitudinal driving behavior as well as on the modeling of longitudinal driving behavior under adverse conditions. We show that adverse conditions have a substantial influence on longitudinal driving behavior as well as mental workload (moderated by age and driving experience). Furthermore, we show that adverse conditions lead to substantial changes in parameter values and model performance of continuous car-following models as well lead to substantial changes in the position of action points and acceleration at these action points. Finally we introduce a new car-following model based on psycho-spacing theory using a Bayesian network modeling approach.

In Chapter 11 we draw conclusions from the findings in this dissertation. In this chapter we provide a brief summary of the research objectives and aims of this dissertation as well as provide a summary of the main findings. We continue in this chapter with the conclusions of this dissertation and discuss the implications of the findings. The chapter finishes with reflections on the performed research and the provision of recommendations for future research.

In the present chapter we provided an extensive introduction to this dissertation. We showed that adverse conditions have a substantial influence on traffic flow operations. Furthermore, we discussed the context of this dissertation as well as the research scope, the research questions, the scientific and societal relevance as well as provided a detailed dissertation outline.

In the next part we turn to empirical longitudinal driving behavior under adverse conditions. We start with a presentation of the state-of-the-art, in which we discuss the available research on the influence of adverse conditions on empirical longitudinal driving behavior and on the determinants of changes of longitudinal driving behavior under adverse conditions. Also in this chapter the theoretical framework is introduced.

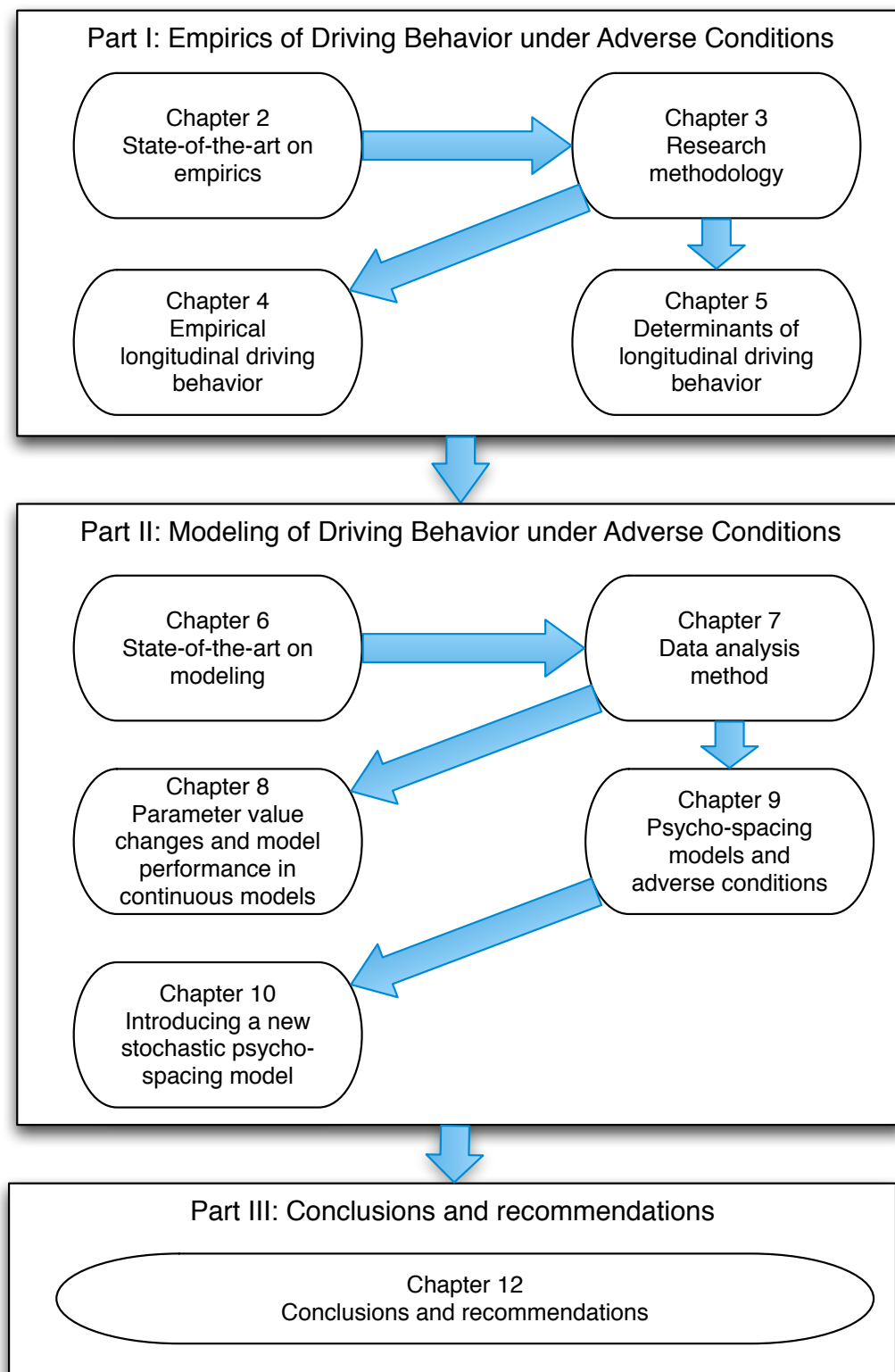


Figure 1.2: Schematic presentation of the thesis outline.

Part I

Empirical Longitudinal Driving Behavior and Adverse Conditions

Chapter 2

State-of-the-art Empirical Driving Behavior Under Adverse Conditions

2.1 Introduction

Adverse conditions (i.e., emergency situations, adverse weather conditions, freeway incidents) have a substantial influence on traffic flow operations. Little information is however available about which empirical adaptation effects in longitudinal driving behavior (driving behavior in the same lane) underlie this impact on traffic flow operations.

In this chapter the state-of-the-art on empirical longitudinal driving behavior under adverse conditions is presented. Also in this chapter we discuss the available research on determinants of adaptation effects in longitudinal driving behavior in case of adverse conditions as well as introduce a new theoretical framework. This theoretical framework aims at providing insight into the way the selected adverse conditions are related to adaptation effects in longitudinal driving behavior.

However before doing so, more insight into the nature of adverse conditions as well as the structure of the driving task is necessary. To this end, Section 2.2 provides several classifications of adverse conditions. In this section two different approaches to adverse conditions are discussed, namely a structural and a more dynamic approach. We continue with a presentation of the structure of the driving task in Section 2.3.

In Section 2.4 we present the available research on empirical longitudinal driving behavior under adverse conditions. Here we discuss research pertaining to the influence of emergency situations, adverse weather conditions and freeway incidents on longitudinal driving behavior. Based on this overview we conclude that adverse conditions may be assumed to have a substantial influence on longitudinal driving behavior. This however does not inform us through which determinants this influence of adverse conditions is exerted. Why do drivers change their longitudinal driving behavior in case of adverse conditions? Is this a result of personal characteristics of drivers, mental workload or panic?

In this regard, we continue with a discussion of possible determinants of adaptation effects in longitudinal driving behavior under adverse conditions in Section 2.5. In this context we start

with an overview of the influence of personal characteristics on longitudinal driving behavior under adverse conditions. This section is followed by a presentation of the influence of mental workload and distraction as well as emotions and panic on longitudinal driving behavior under adverse conditions.

We show that personal characteristics as well as mental workload may be assumed to have a substantial influence on empirical longitudinal driving behavior in case of adverse conditions. This does however not provide indications how adverse conditions actually exert their influence over longitudinal driving behavior.

In this context, we introduce a theoretical framework based on the Task-Capability-Interface model by Fuller (2005). This framework is introduced in Section 2.6. This theoretical framework aims at providing insight into the relationship between adverse conditions and longitudinal driving behavior through driver capabilities and task demands.

2.2 The structure of adverse conditions

It is intrinsic to human nature to modify behavior in order to suit new conditions. Looking at behavioral adaptation, adverse conditions show a remarkable degree of consistency (Leach, 1994). This consistency lies in the behavior of the people who find themselves in a situation which can be qualified as being threatening.

Adverse conditions can be described in terms of their properties as well as through modeling of their impact on human behavior before, during and after the event. In other words: a distinction can be made between a structural (static) and a dynamic (temporal) approach. In the next section the structural approach is discussed, followed by a discussion of the dynamic approach to adverse conditions.

In Barton (1969) the properties of adverse conditions in terms of four different dimensions are described, namely scope, preparedness, speed and duration of the impact. Scope refers to the geographical impact of a condition and includes the extent of the damage incurred on both lives and property. Preparedness refers to the preparedness of individuals to respond and react effectively to the consequences before, during and after the adverse condition has occurred. Speed refers to the speed of onset of the condition, while duration refers to the actual duration of the condition (whether it is relatively sharp or of a longer period with possible recurring episodes).

More recent attempts regarding a structural approach to adverse conditions have tried to incorporate the actual impact of the conditions on individuals. An example is the classification designed by Gleser et al. (1981). They distinguished the degree to which an individual is threatened, the bereavement felt by the individual, the length of suffering by the individual, the amount of geographical displacement required, the proportion of the community affected and the underlying cause of the adverse condition.

This structural approach to adverse conditions is however limited in understanding human behavior as a temporal dimension is ignored in this approach. Glass (1959) therefore distinguished between four dynamic phases:

- pre-impact;
- warning;
- recoil;
- post-impact.

These phases range from the moment a condition is likely to occur (pre-impact) to the phase in which a condition has already occurred (post-impact). A more detailed model was proposed by Powell and Rayner (1952). Their model consisted of seven stages: warning, threat, impact, inventory, rescue, remedy and recovery. In this model the warning and threat phases are equivalents to the pre-impact and warning phase in the model by Glass (1959), while their impact and inventory phase equate with the periods of impact and recoil described by Tyhurst (1951).

These models assume that each condition always goes through all of these stages. However, some stages may be repeated, for example in case of recurring adverse conditions. The value of these models lies in the fact that the aforementioned authors stated that each phase is accompanied by a specific behavioral response. This is illustrated in Figure 2.1 (Hoogendoorn et al., 2009). This framework was based on the theory described in Leach (1994).

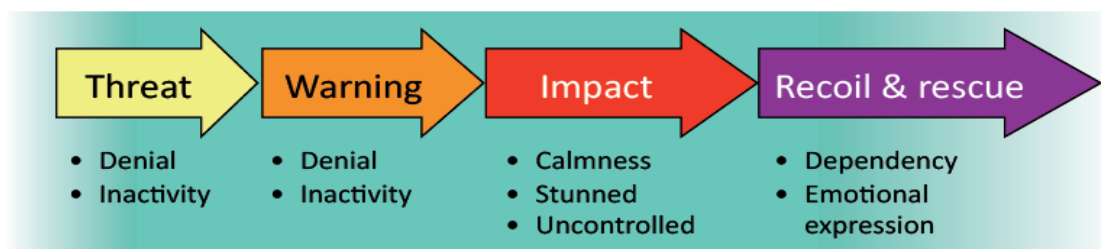


Figure 2.1: Different phases in adverse conditions and their most prevalent behavioral responses (Hoogendoorn et al., 2009).

As to the influence of adverse conditions on driving behavior, this thesis primarily focuses on the phases ranging from the warning phase to the impact phase, as we are mainly interested in the effects of adverse conditions on driving behavior shortly before and during the adverse condition.

Furthermore in this dissertation we focus on three different adverse conditions, namely: emergency conditions due to man-made or naturally occurring disasters, adverse weather conditions and freeway incidents. We chose these adverse conditions as we assume that these conditions each have a different effect on longitudinal driving behavior and as we assume that the underlying mechanisms differ between these conditions as well. For example, emergency situations may be assumed to be governed by a sense of urgency of drivers, while adverse weather conditions and freeway incidents may be assumed to be governed by respectively a reduction in visibility and distraction.

However, before more insight can be gained into the influence of adverse conditions on longitudinal driving behavior as well as into the possible determinants of this behavior, more insight is needed into the structure of the driving task. Therefore the following section focuses on this topic.

2.3 A classification of driving tasks

2.3.1 Michon's hierarchical model of driving tasks

With regard to the structure of the driving task, Michon (1985) made a distinction between a strategic, a maneuvering and a control level (see Figure 2.2).

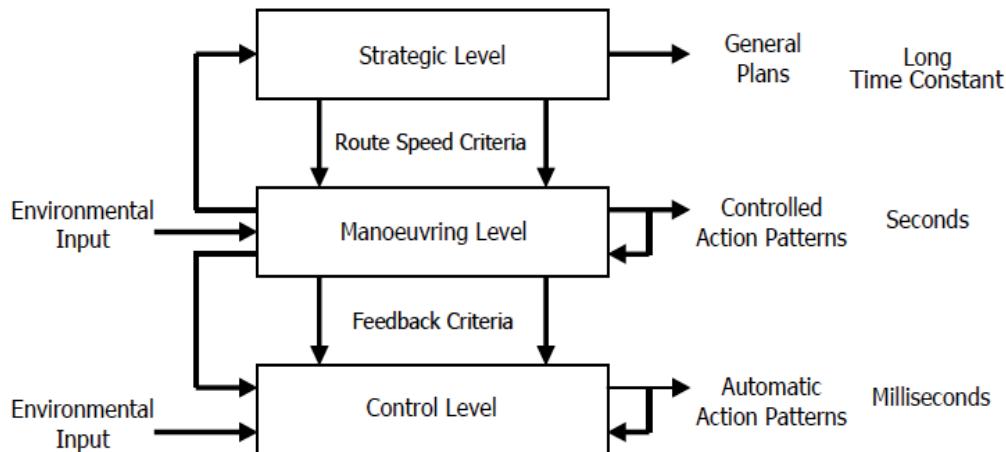


Figure 2.2: The hierarchical structure of the road-user task (Michon, 1985).

In this hierarchical control model the strategic level consists of the general planning stage of a trip, including the selection of a destination, route choice, mode choice plus an evaluation of the costs and risks involved. At the maneuvering level however, drivers exercise maneuvers allowing them to negotiate the directly prevailing circumstances. This incorporates actions as obstacle avoidance, gap acceptance, lane changing, turning and overtaking. Finally the control level incorporates automatic action patterns (e.g. pressing the braking pedal).

These levels are hierarchical as they are assumed to influence each other in a top-down manner. However, it has also been suggested that not only top-down influences can be observed (Schaap, Van der Horst & Van Arem, 2008). For example, a closed lane may force driver to make changes on a strategic level.

The hierarchical control model by Michon (1985) bears a strong resemblance with the hierarchical model of behavior by Rasmussen et al. (1987). Their taxonomy distinguished between three different levels, namely:

- knowledge based behavior;
- rule based behavior;
- skill based behavior.

These different levels of behavior are applicable to driving behavior and refer to the level of skill as well as the degree of conscious control that is exerted. For example, skill based behavior refers to internalized behavior which is automatically executed. Hale et al. (1990) combined the levels proposed by Rasmussen et al. (1987) with those of Michon (1985) (see Table 2.1).

Table 2.1: Examples of combining the hierarchical control model by Michon (1985) and Rasmussen's levels of behavior (Rasmussen et al., 1987).

	Strategic	Tactical	Operational
Knowledge-based	Navigating an unfamiliar area	Controlling a skidding vehicle	Novice drivers
Rule-based	Route choice for familiar routes	Overtaking	Driving an unfamiliar vehicle
Skill-based	Following daily route	Negotiating familiar intersection	Vehicle handling on curves

Table 2.2: Taxonomy of the driving task (Hoedemaker, 1999).

	Roadway subtasks	Vehicle interaction subtasks
Longitudinal	Speed choices (free speed)	Car-following
Lateral	Lane choice, lane keeping	Lane changing, merging

2.3.2 Action-based and task-based classifications

Following these hierarchical models of (driving) behavior, Hoedemaker (1999) distinguished between an action-based and a task-based categorization of the driving task. The action-based categorization (Minderhoud, 1999) distinguishes between a navigation subtask, a maneuvering subtask and a control subtask. While in the navigation task drivers prepare their journey, in the maneuvering task they interact with other traffic as well as with the road system. With regard to the control task, drivers perform the elementary tasks that enable them to maneuver the vehicle safely and efficiently (Janssen, Wierda & Van der Horst, 1992).

The task-based categorization distinguishes between roadway subtasks as well as vehicle interaction subtasks (Hoedemaker, 1999). The former consists of decisions of drivers regarding the guidance of the vehicle over the available infrastructure in a proper and comfortable manner, while the latter refers to the decisions of drivers necessary to guide the vehicle around other traffic (Ossen & Hoogendoorn, 2007).

With regard to the vehicle interaction subtask, longitudinal as well as lateral vehicle interaction subtasks can be distinguished. Longitudinal vehicle interaction subtasks consist of acceleration, deceleration, synchronization of the speed with the speed of the lead vehicle and maintaining a desired distance from the lead vehicle, while lateral vehicle interaction subtasks consist of lane changing, merging and overtaking (see Table 2.2).

Longitudinal vehicle interaction subtasks have been shown to play a substantial role in the formation and propagation of congestion (Boer, 1999). With regard to this task two different regimes can be observed:

- free flow;
- congested driving.

In the free-flow regime, the vehicle of the driver is not restricted by the presence of other traffic. In this case acceleration of the driver-vehicle combination is mainly determined by desired speed. In congested driving, the vehicle of the driver however is restricted by the presence of other traffic. In other words: there is to a certain extent hindrance from other vehicles. Here, acceleration of the driver-vehicle combination is determined by the prevailing speed, the presence of the lead vehicle(s), the speed of the lead vehicle, acceleration of the lead vehicle and net distance from the lead vehicle. When studying congestion, unconstrained driving (free-flow) is less important (Van Winsum, 1999).

As longitudinal vehicle interaction subtasks have been shown to play a substantial role in the formation and propagation of congestion and as unconstrained driving has been shown to be less important in studying these traffic flow phenomena, this dissertation primarily focuses on car-following behavior in case of emergency situations, adverse weather conditions and freeway incidents.

2.4 Empirical adaptation effects and adverse conditions

This section discusses the available research on the influence of emergency situations, adverse weather conditions and freeway incidents on longitudinal driving behavior. In Section 2.4.1 we start with a presentation of the available research on emergency situations due to man-made or naturally occurring disasters on longitudinal driving behavior. This section is followed by a presentation of the available research regarding the influence of adverse weather conditions (heavy rain, fog, snow) on longitudinal driving behavior in Section 2.4.2, followed by an overview of the available research on the influence of freeway incidents in Section 2.4.3.

2.4.1 Emergency situations

Research on the influence of emergency situations on longitudinal driving behavior was not yet available. However, in a number of evacuation studies using microscopic simulation models, model parameters describing car-following behavior have been adjusted for emergency situations. In research reported in Tu et al. (2010) it was for example assumed that drivers during an emergency situation express anxious behavior due to a mentally demanding situation.

Tu et al. (2010) subscribe to the assumptions made in Hamdar and Mahmassani (2008). In their research it is assumed that driving behavior under emergency situations ("extreme conditions") is characterized by an aggressive driving style. Based on this assumption, they hypothesize that longitudinal driving behavior under emergency conditions is characterized by:

- An increase in speed together with higher acceleration and deceleration rates;
- A high variance in speed;
- A decrease in headways in order to force other drivers to accelerate or move out of the way;
- An increase in emergency braking and rubbernecking;

- An increase in the intensity with regard to speed and braking rates over time.

From the aforementioned it can be concluded that research on empirical adaptation effects in longitudinal driving behavior is not available. The available research is solely based on the assumption that in case of emergency situations drivers will express anxious or aggressive behavior, leading to substantial adaptation effects in driving behavior.

2.4.2 Adverse weather conditions

Problems associated with driving in conditions of reduced visibility (heavy rain, fog, snow) have been relatively well documented. In Northern Europe, Scandinavia and in mountainous areas elsewhere in Europe, a considerable portion of road accidents has adverse weather (e.g., fog, strong winds, snow and ice) as a primary or a contributing cause (Thordarson & Olafsson, 2008). However, research regarding the underlying adaptation effects in empirical longitudinal driving behavior in case of these conditions is scarce.

With regard to adaptation effects in longitudinal driving behavior in case of heavy rain, Martin et al. (2000) report speed reductions ranging from 10% in wet conditions to 25% in case of 'slushy' conditions.

In Ibrahim and Hall (1994) a dummy variable technique was used in order to analyze the effects of adverse weather conditions. From these analyses it followed that heavy rain led to free flow speed reductions between 5 and 10 km/h.

Hogema (1996) studied the influence of rain on driving behavior as well. In his research, periods were selected which had at least five hours of moderate rain in a row. For each lane separately, mean speed and the percentage of vehicles with a time headway of <1s, 3s and 5s was collected. With regard to mean speed and mean time headway an ANalysis Of VAriance (ANOVA) was performed using the factors Weather, Lane, Volume category, and Carriageway. A main effect of 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 even further as a function of volume level. Also mean speed in case of rain 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 (see also Figure 2.3).

The reduction 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 on vehicles with a time headway of 5s or larger.

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 km/h during conditions in which 5-10 mm rain per hour had fallen.

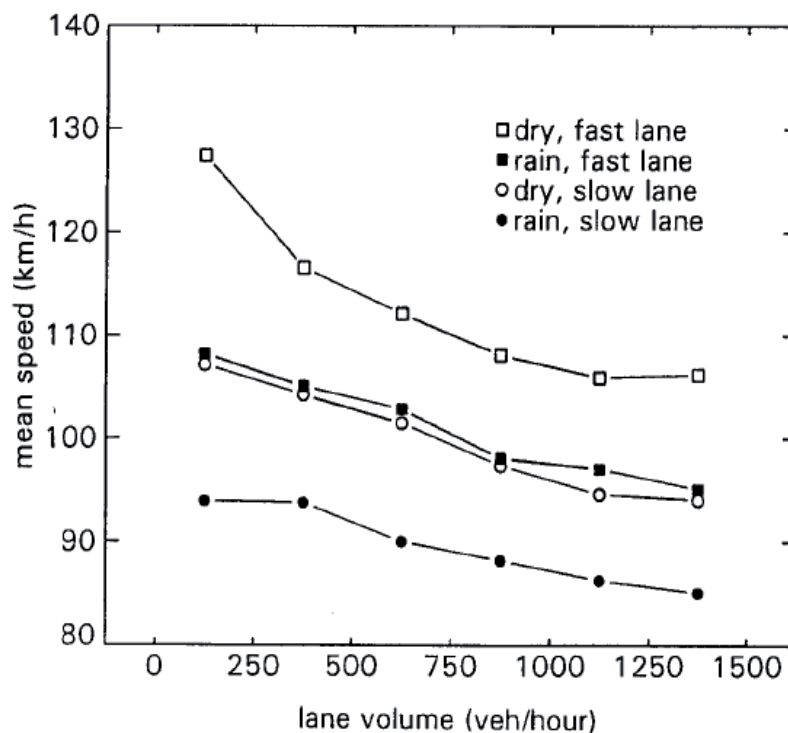


Figure 2.3: Mean speed as a function of traffic volume, weather and lane (Hogema, 1996).

Fog also has a substantial impact on driving behavior. Traffic studies generally show that time headway increases in foggy conditions (Bulte, 1985; White & Jeffery, 1989). Although it might be hypothesized that a reduction in visibility due to fog may lead to a compensatory reduction in speed in order to reduce accident risks, this hypothesis is not confirmed by the prevailing research.

Sumner et al. (1977) studied the effect of reduced visibility due to fog on driving behavior in a motorway situation. They found that drivers did adjust their speed to the situation. However, speed adjustments applied in these situations were in case of more than half of the drivers studied insufficient to enable them to stop within the visibility range. In another study, reported in Snowden et al. (1998), it was found that due to a lessening of visual cues regarding the perception of speed, some drivers drove faster than normal in case of fog.

In a study 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 remarkable differences between drivers. 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.

The fact that large individual differences exist in driving behavior in case of fog was supported by Caro et al. (2009). From their research it followed that large individual differences were present with regard to time headway in case of reduced visibility due to fog, making inferences with regard to capacity difficult. Furthermore, foggy conditions increased response times substantially when the outline of the vehicle was barely visible or not visible at all.

Snow also has an impact on driving behavior, though quantitative research is scarce. Re-

search regarding the effect of snowfall on vehicle collisions, injuries and fatalities has shown that snowy days had fewer fatal crashes than dry days ($IRR = 0.93$ at a confidence level of 95%). There were however more non-fatal injury crashes and property damage-only crashes (Eisenberg & Warner, 2005). Compared to dry days, drivers seem to adjust their speed enough to impact the severity of crashes.

Finally, speed reductions in case of heavy snow were also found by Ibrahim and Hall (1994). They found in their research that heavy snow leads to free flow speed reductions between 38 and 50 km/h.

From the available research it can be concluded that adverse weather conditions have a substantial impact on longitudinal driving behavior. In case of rain drivers tend to reduce their speed and increase their time headway. With regard to fog however, driver show large individual differences. Most drivers seem to decrease their speed while increasing their headway. Some drivers however drive even faster than normal, probably due to a lessening of visual cues regarding speed. Finally, from the available research it can be concluded that snow also leads to substantial changes in longitudinal driving behavior, namely a reduction in speed.

However, the research reported in this section has some drawbacks. Firstly it can be observed that research mainly focuses on speed reductions as an indicator of adaptation effects in longitudinal driving behavior under adverse weather conditions. Changes in spacing, acceleration, deceleration and relative speed are not considered. Secondly the research reported in this section did not make use of a proper experimental design as these studies did not take place under controlled conditions. Therefore it is not possible to draw inferences with regard to the observed adaptation effects in longitudinal driving behavior as confounding variables might have a substantial influence.

2.4.3 Freeway incidents

Little research is available on the influence of freeway incidents on empirical adaptation effects in longitudinal driving behavior. Research performed by Knoop et al. (2008) has shown a substantial influence on longitudinal driving behavior in case of an accident on the freeway. Data collected with a helicopter was used to describe longitudinal driving behavior at incidents in the other driving lane.

The results show that average speed dropped when drivers approached an incident site. After they had passed the incident site, they started to accelerate again. At the point where the drivers had the best view of the accident, minimum speed in the left lane was only 6.2 m/s. After the incident was out of sight, they accelerated to a minimum of 18.9 m/s.

Furthermore, it followed from the results that mean time headways increased substantially to around 3.2s, while normal headways were around 1.9s. Reaction times increased from a normal reaction time of around 1.3s to 3.9s at the incident site. The 'normal' indicators of longitudinal driving behavior were derived from literature. In addition, reaction times typically were centered around two values, namely 2 and 5 seconds. From a Kolmogorov-Smirnov test it followed that reaction times at the incident location differed significantly from reaction times under normal conditions.

From the available research it may be concluded that freeway incidents have a substantial influence on longitudinal driving behavior. Speed and acceleration decrease substantially at the incident site, while time headway substantially increases. After the drivers have passed the incident, they start to accelerate again.

However, the available research on the influence of freeway incidents is scarce. Only one contribution was found on the influence of this adverse condition on longitudinal driving behavior. Furthermore in this contribution by Knoop et al. (2008) use was made of a relatively short trajectory with only few vehicles. Also it is concluded that the observed increase in reaction time is due to the fact that drivers are distracted by perception of the incident in the other driving lane. However, it is not clear whether this increase in reaction time can solely be attributed to the incident, or whether this effect is a result of hysteresis (see also Hoogendoorn, Hoogendoorn et al., 2011). Hysteresis entails that behavioral differences can be observed between the deceleration and the acceleration phase in a stop-and-go traffic condition. In literature it is for example assumed that strong differences exist in the degree of anticipation towards behavior of the lead vehicle between these two phases.

In order to make inferences with regard to the actual causes of the observed adaptation effects in longitudinal driving behavior at freeway incidents it is crucial to use an experimental design, as this allows for a large degree of controllability.

2.5 Determinants of longitudinal driving behavior under adverse conditions

In the previous section we presented the available research on the influence of adverse conditions (i.e., emergency situations, adverse weather conditions and freeway incidents) on empirical longitudinal driving behavior. We concluded that research on the influence of these conditions is scarce and has not been performed using controlled conditions.

Nevertheless, from the available research it may be assumed that emergency situations, adverse weather conditions and freeway incidents do have a substantial influence on longitudinal driving behavior. This does however not inform us through which determinants adverse conditions exert their influence.

In this sense, a distinction can be made between static and dynamic determinants of adaptation effects in empirical longitudinal driving behavior. Static determinants are causes of adaptation effects in longitudinal driving behavior in case of adverse conditions which remain constant over a longer period of time, while dynamic determinants change over a relatively short time span.

In the context of static determinants of adaptation effects in empirical longitudinal driving behavior under adverse conditions, we focus on personal characteristics of drivers. Personal characteristics are for example gender, age, driving experience, socio-economic status and ethnicity.

Next we focus on dynamic determinants of adaptation effects in empirical longitudinal driving behavior in case of adverse conditions. Here we discuss the available research on activation level, distraction, mental workload emotions and panic.

2.5.1 Static determinants: Personal characteristics of drivers

With regard to personal characteristics we distinguish gender, age, driving experience, socioeconomic status and ethnicity. The aim of this section is therefore to investigate whether personal characteristics of drivers have an influence on longitudinal driving behavior in case of adverse conditions.

Gender

No specific research on the influence of gender on longitudinal driving behavior in case of adverse conditions (emergency situations, adverse weather conditions and freeway incidents) was found. However, some research on the influence of gender on driving behavior in general was found.

Gender has consistently been reported to be related to risk behavior, i.e., male drivers are more willing to take risks than female drivers. Yagil (1998) reported that male drivers express a lower motivation to comply with traffic rules, especially the younger individuals. She also found male drivers to perceive traffic violations as less dangerous than female drivers. Whissell and Bigelow (2003) did a study suggesting that accidents were typically a function of gender.

Ulleberg (2002) did a cluster analysis to identify subgroups of risky drivers among adolescents. He reported that males with high sensation seeking scores constituted to the majority of one such group. Finally, Rosenbloom and Wolf (2002) reported a risky shift in males' detection of danger on a road compared to female drivers.

Gender differences were also found in aberrant (deviant) driving behavior (Rimmo & Hakamies-Blomqvist, 2002). It was shown using a factor analysis that aberrant driving behavior was differently related to gender.

From the aforementioned it can therefore be concluded that gender may be assumed to have a substantial influence on empirical longitudinal driving behavior in case of adverse conditions. This conclusion can be drawn as gender has been shown to have an influence on risk behavior of drivers.

Age

Here also, no specific research on the influence of age on longitudinal driving behavior in case of adverse conditions was found. As was the case with gender, some research on the influence of age on driving behavior in general was available.

In literature, a higher age has often been connected to a decline in driving performance. Although a number of aspects related to human performance of the driving task change with age, such as response times, channel capacity and processing time needed for decision making and movement ranges / times, most of these are extremely variable between individuals (Koppa, 1998). In other words: although overall a decline can be assumed with regard to those aspects needed to adequately perform the driving task with higher age, large differences between individuals can be observed.

This is however not the case for visual performance, in which an accelerated impairment can be observed after the age of 50. Some of these changes in visual performance (needed to adequately perform the driving task) are related to aging of the eye, while others relate to changes in neural processing.

Allen and Reimer (2006) found in their research that strategies for capturing visual information are affected by age and the complexity of the driving environment. Older drivers' eye scanning differed significantly from younger drivers, which revealed a perceptual narrowing phenomenon when the driving task increased in complexity. This led to a decline in the performance of the driving task by older drivers.

Besides a decline in visual performance, also a decline in cognitive performance of older drivers can be observed. Older drivers seem to experience more problems in information processing, the use of filtering mechanisms and in rapid decision-making (Koppa, 1998). This is supported by research by Freund et al. (2008) in which pedal errors among older drivers were examined. From the results it followed that pedal errors were mainly caused by executive dysfunctions of older drivers.

It can therefore be concluded that age may be assumed to have an influence on empirical longitudinal driving behavior under adverse conditions.

Driving experience

As was the case with gender, driving experience also has been connected with risk perception during driving tasks in general. Again no specific research on the influence of this personal characteristic was found.

From research performed by Sagberg and Bjørnskau (2006) it follows that risk perception of novice drivers differs substantially from more experienced drivers. Research also suggests that less experienced drivers use different search strategies and that this might contribute to increased accident liability in novice drivers (Crundall, Underwood, & Chapman, 1999). In their experiment, hit rates of peripheral targets decreased when hazards occurred and the eccentricity increased in which an effect was found on driving behavior. This means that novice drivers experience a perceptual narrowing phenomenon, leading to a less effective visual search strategy.

In research performed by Underwood (2007) it was shown that driving experience was related to the size of the effective visual field during a driving task. More experienced drivers recalled (and as is assumed perceived) more details with regard to incidental events than novice drivers did.

Socio-economic status and ethnicity

No research was found on the influence of socio-economic status on driving behavior in general. This was however not the case for ethnicity, although research is scarce. From research by Porter and England (2000) it follows that risky driving behavior (i.e., red-light running) was significantly associated with ethnicity. This study showed that non-caucasian drivers showed a larger degree of risky driving behavior than caucasian drivers.

The aforementioned leads to the conclusion that no specific research on the influence of personal characteristics on longitudinal driving behavior under adverse conditions is available. However, research was found on the influence of gender, age, driving experience and ethnicity on driving behavior in general. In research, gender, driving experience and ethnicity has consequently been associated with risky driving behavior while age was related to a change in driving performance. It can therefore be assumed that personal characteristics also have a substantial influence on longitudinal driving behavior under adverse conditions.

2.5.2 Dynamic determinants: Activation level, distraction, mental workload, emotions and panic

With regard to dynamic determinants of adaptation effects in empirical longitudinal driving behavior under adverse conditions, we distinguish activation level, mental workload, distraction, emotions and panic. Overall it can be concluded that no specific research on the influence of these determinants on longitudinal driving behavior under adverse conditions was found. However, research on the influence of these determinants on driving behavior in general was available.

Activation level

Activation level can be defined as the individual's degree of energy mobilization (Cannon, 1915). During energy mobilization different physiological systems are activated, depending on the type of activity an individual is engaged in. According to literature the relationship between activation level and driver capability can be described by an inverted U-curve. High and low activation levels are both associated with low driver capability. It is well-established that activation level influences driver capability (Brown, 1982). Research on the influence of activation level on longitudinal driving behavior under adverse conditions was not available. However research on the influence of activation level on driving behavior in general was found.

Research has shown that activation level, or arousal, is associated with drivers' stress reactions as well as with the driving environment. In a study by Matthews et al. (1996) the hypothesis was tested whether activation level is associated with driving performance. Eighty young adult participants performed a simulated test drive concurrently with a reasoning task. The data indicated that performance was characterized by adaptive mobilization of effort in order to meet the changing task demands. Drivers with a high activation level adapted to high levels of demand fairly efficiently, but were at risk of performance reduction when the task required little effort.

Furthermore, in an experimental study Matthews et al. (1998) assessed multiple dimensions of vulnerability to driver stress by a questionnaire that was validated in previous field studies and related those dimensions to performance in a driving simulator. It was shown that activation level had a significant influence on alertness, indicated by a reduction in reaction times to pedestrian hazards.

In Brodsky (2001) the effects of music tempo on activation level, driving performance and vehicular control was investigated using a driving simulator. In this contribution it was found

that music tempo invoked a higher activation level within the participants. The study found that music tempo leading to a higher activation level consistently affected both simulated driving speed and speed estimates. Furthermore, music tempo affected the frequency of virtual traffic violations.

From the aforementioned it can be concluded that activation level can be assumed to have a substantial effect on longitudinal driving behavior under adverse conditions. This conclusion can be drawn as activation level has been shown to have a substantial influence on driving performance as well as compensatory behavior (speed increases) under normal driving conditions.

Distraction, mental workload, situational awareness and perceptual distortion

Activation level is closely related to distraction and mental workload. Driver distraction has been defined as a process or condition that draws the driver attention away from the driving task (Sheridan, 2004).

In general, a lack of attention to relevant events is one of the main causes of traffic accidents (Rumar, 1990). The result of distraction is an impaired capacity to process relevant information because of perceptual inefficiency or inadequate response selection. Attention is necessary for conscious perception, but engaging in events unrelated to the driving task could also directly affect decision processes producing incorrect or late response selections (LaBerge, 1995).

Distraction influences mental workload. Mental workload can be defined as the specification of the amount of information processing capacity that is used for task performance (De Waard, 1996).

Wickens (2002) formulated the so-called Multiple Resources Theory (MRT). The MRT tries to explain attentional interference at central processing levels. In this theory, human performance is based on a general pool of mental effort or undifferentiated resources. The theory emphasizes the demands made by tasks on the limited resources of individuals. When task demands exceed the mental resources available to the individual, task performance will suffer as a consequence.

Concerning dual processes Horrey et al. (2009) distinguished between three components, which might be able to predict the interference between a time-shared pair of tasks:

- resources demand component;
- resources conflict component;
- resource allocation component.

Regarding the resources demand component, a task can be either automated, easy or difficult independently of which resources are demanded for the task at hand. In the resources conflict component, two tasks are compared to the extent in which they share demands on common levels of three dimensions (Wickens, 2002):

- stages of processing;

- codes of processing;
- modalities of processing.

The concept of multiple resources is connected to these three dimensions (De Waard, 1996). The first dimension is the processing stage. Here perception (including encoding), central, and response processing can be distinguished. The second dimension is the modality of input and response. Auditory, visual and tactile modalities draw on different resources. Wickens (2002) argues that cross-modal time-sharing can be better performed than intra-modal timesharing. The third dimension is the processing code. The processing code can be either verbal or spatial (Waard, 1996).

The aforementioned does not inform us which performance of the multiple tasks (e.g., the driving task versus arguing with your spouse) will deteriorate. In this regard the level of engagement (Horrey et al., 2009) plays a substantial role. The level of engagement is reflected by the cognitive strategy used by the individual (deep versus shallow processing). This means that tasks with a low level of engagement will suffer more in performance compared to the tasks with a higher level of engagement.

Mental workload refers mostly to the resources demand and resources conflict components, thus characterizing the demand imposed by tasks on the limited mental resources of an individual (Moray, 1988). This demand can conceptually be associated with one of two regions of task demand level (Hollands & Wickens, 1999). The first region is one in which the demand is less than the capacity of the resources available. The second region is one in which the demand exceeds the capacity of the resources. Here, performance will deteriorate. This distinction between these two regions is often referred to as 'the redline of mental workload' (Grier et al., 2008).

It has been shown that mental workload substantially influences driving behavior. Brookhuis et al. (1991) showed that telephone conversations while driving led to a significant effect on mental workload. In their research effects were found on subjective indicators (measured on an effort scale) as well as on objective indicators of mental workload (heart rate indices). The observed increase in subjective and objective indicators of mental workload was accompanied by effects on driving behavior. Significant effects were found on rearview mirror checking, the adaptation of speed to the speed of the lead vehicle and braking in reaction to decelerations of the lead vehicle.

These findings are also supported by recent research reported in Tornros and Bolling (2006) and Makishita and Matsunaga (2008). In Tornros and Bolling (2006) mental workload increased when participants engaged in telephone conversations during a driving task in a low, medium as well as in a high complexity environment.

In Makishita and Matsunaga (2008) an experiment was performed in which reactions of drivers in various age groups were examined in order to assess the influence of mental workload. In their research experiments were performed on a simulated street in order to identify drivers with large reaction times and drivers whose reaction times are strongly affected by mental workload while driving. The results show that a secondary task (mental calculations) increased average reaction times for all age groups. This secondary task increased the differences between

age groups and individuals and increased differences in the drivers' individual performance. Especially reaction times of elderly drivers were affected substantially.

Horrey et al. (2009) performed an experiment in order to establish the extent in which concurrent driving tasks and in-vehicle activities with different levels of engagement influenced driving performance. From the results it followed that the performance of dual tasks decreased driver performance as well as subjective estimates of driving performance. Furthermore the authors concluded that a substantial discrepancy could be observed between the subjective estimates of performance and actual driving performance.

One way in which mental workload may influence longitudinal driving behavior under adverse conditions is through situational awareness. Situational awareness can be defined as the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning and the projection of their status in the near future (Endsley, 2000). This three-stage construct can be understood in terms of the following features. Firstly, it involves cognition and working memory, rather than action and response (Wickens, 2002). Secondly, situational awareness is relevant to dynamic evolving situations. Thirdly, the content of the product of situational awareness is distinct from the process of maintaining situational awareness.

It can be assumed that the complexity of the challenge of moving the vehicle safely and efficiently through space influences situational awareness. In aviation for example, it has been shown that the spatial complexity of the pilot's task influences situational awareness substantially (Wickens, 2002).

No research was found on the influence of situational awareness on longitudinal driving behavior under adverse conditions. However, research on the influence of situational awareness on driving behavior in general was found. In research performed by Kass et al. (2007) it has for example been shown that distractions during a driving task caused drivers to commit more driving infractions due to a decreased situational awareness.

Situational awareness is closely related to perceptual narrowing. The theory of perceptual narrowing suggests that as the level of demand increases at the fovea, there will be a corresponding decrease in the visual area around the fovea from which peripheral information can be extracted (Crundall et al., 1999). In literature, crossing the aforementioned 'redline of mental workload' is often associated with perceptual narrowing or distortion. Leach (1994) states that perceptual distortion is a common psychological reaction in situations in which mental workload exceeds the resources available to the individual. The most frequently reported form of perceptual distortion is perceptual narrowing, which occurs in vision.

Perceptual narrowing seems to appear as a manifestation of a restriction in attention. A narrowing of awareness occurs coupled with an intensification of attention to only one task. While this intensification enables a person to better concentrate on the selected task, there is no guarantee that the selected task is the most appropriate one under the specific circumstances. This one task may overwhelm the individual, blocking out other information needed for effective functioning and limiting the number of alternative responses available. In Baddeley (1996) was reported that one way in which adverse conditions affect performance is through its influence on the subject's breadth of attention.

The influence of perceptual narrowing on driving behavior is supported by research. In an experiment performed by Silber et al. (2005) dexamphetamine was administered to participants before they had to perform a simulated driving task. Dexamphetamine is a drug, which induces perceptual narrowing. The results of the experiment show that participants who experienced perceptual narrowing made more signaling mistakes, failed more often to stop at a red traffic signals and showed longer reaction times.

From the aforementioned it can be concluded that mental workload, situational awareness and perceptual distortion are closely related, as mental workload can be assumed to influence perception. For example, maintaining a high and accurate level of situational awareness is a resource-intensive cognitive process. As situational awareness needs attentional resources, a high mental workload will lead to less spare capacity in order to maintain a high sense of situational awareness.

Research on the influence of distraction, mental workload, situational awareness and perceptual distortion on longitudinal driving behavior under adverse conditions is not yet available. However, as substantial and significant effects of these psychological constructs were established on driving behavior in general, a substantial influence on longitudinal driving behavior under adverse conditions can be assumed.

Emotions

Another possible dynamic determinant of longitudinal driving behavior under adverse conditions are emotions. In Taylor (1964) it was proposed that the level of emotional tension (stress) guides the driver. Emotions can be defined as the individual evaluation of an emotional relevant event. Consequently, each emotional experience varies in time and between individuals.

In literature emotions have been consistently linked with risk taking behavior (e.g., Rundmo (2002)). According to Taylor (1964), the driving task is self-paced governed by the level of emotional tension or anxiety the driver wishes to tolerate. The Risk Homeostasis Theory (RHT) developed by Wilde (1982) proposes that drivers tend to target a specific level of risk, in which safety levels remain relatively constant.

This theory is however not uncontested. For example, earlier Summala and Naatanen (1974) already stated that drivers try to avoid risk by regulating their behavior according to a perception of zero risk, while Wilde (1982) conjectures that drivers seek a specific risk level. However in both approaches it is assumed that risk level is a number to be defined by the level of exposure (Vaa, 2001).

In literature however, no trace can be found of this weighing' procedure. Tversky and Kahneman (1974) show that people put much weight into their own experiences. One considered small sample may be viewed as representative of a much larger population. Tversky and Kahneman (1974) are however not referred to in Wilde (1982). Vaa (2001) concludes in this context that a target level of risk cannot be a number, a thought or imagination that is brought with you consciously and which is put into some weighing procedure when, for example, is decided at which speed should be driven. Vaa (2001) continues by stating that the RHT model does not grasp or mimic the varied dynamics of thinking and feeling.

Research has shown that the driving task has an influence on emotions of the driver. In Parkinson (2001) for example, it was shown that negative emotions (e.g., anger, anxiety) occur more often during driving tasks than during non-driving tasks. Especially negative emotions seem to be correlated to goal incongruent circumstances occurring during the driving task (for example the occurrence of congestion while you are pressed for an important appointment). Especially circumstances affecting the perceived safety of the driver seem to cause negative emotions (Mesken, Hagenzieker, Rothengatter, & Waard, 2007).

Qualitative research as to the question which sources of negative emotions during a driving task can be identified was conducted in Cahour (2008). This research suggests that the main sources of negative emotions during a driving task are: interactions with other drivers, the physical environment (e.g., adverse weather conditions), perceived control over the vehicle, the presence of passengers and the perception of accidents.

The fact that the driving task in itself leads to changes in the emotional state of the driver however does not inform us which influence emotions have on driving behavior. In Stephens and Groeger (2006) it was investigated if emotions influenced driving behavior in a driving simulator. During a test drive participants had to report which emotions they experienced. Three different emotions could be derived from the data: frustration, calm and anger. It was concluded that individuals who experienced anger accelerated faster.

Research conducted by Sullman et al. (2007) has shown that negative emotions were one of the best predictors of inefficient driving behavior, while positive emotions were related to more efficient driving behavior.

The available research on the influence of emotions on driving behavioral has some methodological shortcomings. Firstly, research is insufficiently based on theoretical models of behavior. Exceptions are two experiments on the influence of aggression on driving behavior (Knee, Neighbors, & Vietor, 2001; Neighbors, Vietor, & Knee, 2002). In their research it was attempted to explain the influence of aggression on driving behavior using the Self Determination Theory (SDT) (Deci & Ryan, 1985). In the SDT the emphasis lies on emotional regulation in interpersonal contexts. It is assumed in the SDT that motivational orientations influence reactions within social contexts (Knee et al., 2001).

Research on the influence of emotions on longitudinal driving behavior under adverse conditions is scarce. In this regard in Hoogendoorn, Waterink et al. (2011) studied to what extent emotions influence longitudinal driving behavior in case of an incident in the other driving lane in the context of the Somatic Marker Hypothesis (SMT) (Damasio, Everitt, & Bishop, 1996).

In the SMT (Damasio et al., 1996) emotions are defined as changes in both body and brain states in response to a stimulus. Physiological changes are communicated to specific cortical regions where there are transformed into subjective representations of emotions. In the SMT (Damasio et al., 1996) it is conjectured that emotions enable individuals to make a distinction between pleasure and pain and are therefore essential in decision-making.

From the results of the experiment reported in Hoogendoorn et al., (2011), it followed that perception of a serious car accident led to a significant change in emotions as well as to significant changes in longitudinal driving behavior. However, from multiple regression analyses it

followed that emotions did not significantly predict changes in longitudinal driving behavior. It was concluded that emotions in general do not have a significant influence on longitudinal driving behavior in case of adverse conditions.

Panic

It could be that in case of adverse conditions more specific emotions do have an influence on driving behavior. An often mentioned candidate is panic. However, there are some considerable definition problems regarding this psychological construct. In general panic can be defined as a psychological state which leads to behavior in which judgements and reasoning deteriorate so far as it often results in destructive behavior.

There are four basic elements that characterize panic (Leach, 1994). The first is that panic coincides with a time or space restriction to escape. The resources and means to escape are scarce and dwindling while the demand for these resources is increasing. The second element is that people will become aggressively concerned with their own survival and any altruism is destroyed. The third element is that behavior shown by the individual in response to the circumstances is irrational and illogical. Finally, the fourth element of panic is that the behavior shown is highly contagious and waves of panic are assumed to spread out.

However, panic has been shown to be quite an uncommon reaction to adverse conditions. Panic seems to be rare and not a typical reaction to these circumstances (Johnson, 1988; Keating, 1982; Sime, 1983). Systematic studies of a variety of different emergencies and disasters have each emphasized a lack of panic. Examples of adverse conditions in which panic was not substantially present are the atomic bombing of Japan in 1945 (Janis, 1952) and the King's Cross Underground fire of 1987 (Donald & Canter, 1990). More recently, in an analysis of the behavior of evacuees from the World Trade Center on September 11th, classic panic actions of people behaving in an irrational manner was observed in just 0.8% of the cases (Blake, Galea, Westeng, & Dixon, 2004). Furthermore, observed behavior seemed to contradict the aforementioned basic elements of panic. Anti-social or selfish behavior was rare and did not spread out to other individuals. Pro-social behavior (helping and cooperation) instead of individual competitive and selfish behavior was common.

From the reported research in this section it can be concluded that presently panic does not offer a feasible explanation for possible adaptation effects in driving behavior in case of adverse conditions as substantial definition problems can be observed. Furthermore, panic in case of adverse conditions seems to be rare.

2.6 Introducing a theoretical framework

In the previous sections we presented the available research on static and dynamic determinants of adaptation effects in longitudinal driving behavior under adverse conditions. We showed that personal characteristics, activation level, distraction and mental workload can be assumed to have a substantial influence on longitudinal driving behavior under adverse conditions. This does however not inform us how these elements exert their influence on longitudinal driving behavior. In this sense in this section we introduce a new theoretical framework grounded on the Task-Capability-Interface model by Fuller (2005).

In the Task-Interface-Capability model driving task difficulty comes forth from the dynamic interface between the demands of the driving task and the capability of the driver. Fuller (2005) mentions that driver capabilities are restricted by biological personal characteristics of the driver as well as by experience.

However, these capabilities due to biological personal characteristics (e.g., age, gender, ethnicity) and driving experience alone do not determine the total temporal capabilities of the driver, as more dynamic variables play a substantial role as well. In the proposed theoretical framework we assume that the dynamic elements activation level and distraction have a substantial influence on driver capability.

In the previous section we showed that activation level can be assumed to have a substantial impact on longitudinal driving behavior under adverse conditions. Activation level was defined as the individual's degree of energy mobilization (Cannon, 1915). Another important determinant influencing driver capability is distraction. It can be assumed that in case of distraction (e.g., due to mobile telephone conversations while driving) driver capability will reduce (Brookhuis et al., 1991). Driver capability is therefore influenced by many endogenous and exogenous variables. In this regard Brookhuis and De Waard (2001) assume that driver capabilities may vary between as well as within drivers.

Driving task demands are also related to a multitude of elements. Elements that may play a vital role are visibility (e.g., in case of adverse weather conditions), the complexity of the road design, behavior of other road users, etc. Important elements in task demand are however the elements over which the driver of the vehicle has direct control. These conscious actions of the driver are in the ensuing referred to as compensation effects.

Here, speed of the vehicle is clearly the most significant element: the faster a driver is moving, the less time is available to perceive stimuli, process information and make decisions. As Taylor (1964) regards the driving task as self-paced, driving task demand is in a fundamental way under the control of the driver through speed selection.

Driver capabilities as well as task demands are assumed to interact. In this regard three main regions can be distinguished (Fuller, 2005):

- where driving capabilities exceed demands, the task is not difficult, or even too easy;
- when demands of the task at hand equal the capabilities of the driver, the task is difficult;
- when task demands exceed the capabilities of the driver, the driver is assumed to fail the task.

When drivers fail the driving task, a loss of control can be observed as a consequence. Thus in essence, task difficulty is inversely proportional to the difference between the task demand and the capability of the driver. According to Fuller (2005), at the threshold where task demand begins to exceed the capability of the driver, a fragmented degradation of the driving task is to be expected. Fuller (2005) continues by stating that with a static level of capability, any event that increases task demand will therefore reduce this critical difference, increase task difficulty and potentially influence driving task performance.

According to Fuller (2005) the concept of task difficulty is closely related to mental workload. Brookhuis and De Waard (2001) defined mental workload as the proportion of mental capacity that is needed for task performance, determined by the interaction between the capability of the driver and the task itself.

In sum, changes in driver capability or task demands are expected to lead to compensatory changes in driving behavior (see also Brookhuis et al., 1991). When these compensatory reductions are insufficient in order to balance task demand with driver capability, performance will suffer. Stanton and Young (2001) showed that situational awareness decreased as mental workload increased.

In Figure 2.4 the Task-Capability-Interface model is applied to longitudinal driving behavior under adverse conditions. As was assumed in the TCI model (Fuller, 2005), driver capabilities are influenced by personal characteristics as well as by activation level and distraction. Task demands are determined by external circumstances (e.g., a reduction in visibility) as well as by factors of the driving task over which the driver has direct control.

In the theoretical framework, emergency situations are assumed to have an influence on the activation level of the driver. It is easy to imagine that when the level of urgency during an emergency situation increases, activation level of the drivers will also increase. Drivers can be assumed to experience arousal due to the time pressure they experience with regard to evacuating the location in time. This increase in activation level will increase driver capability, leading to an imbalance between driver capability and task demands, resulting in an increase in mental workload of the driver.

In case of adverse weather conditions task demands can be assumed to increase due to for example decreased visibility in case of fog or decreased friction in case of black ice (see also Fuller (2005)). As was the case with emergency situations, an imbalance will occur between driver capability and task demand, again resulting in an increase in mental workload.

In case of freeway incidents (e.g., car-accidents in the other driving lane), drivers may become distracted. In the theoretical framework it is assumed that distraction will lead to a reduction in driver capability, again leading to an imbalance between driver capabilities and task demands.

In order to correct for this imbalance in task difficulty, a driver will show compensatory behavior by influencing task demand. For example, in case of emergency situations drivers will increase their speed in order to increase task demand, while in case of adverse weather conditions they will reduce speed in order to reduce task demand.

However, when this compensatory behavior of the drivers is not sufficient to restore a situation of homeostasis, performance effects in longitudinal driving behavior may be observed. It can for example be assumed that drivers will follow the lead vehicle less adequately. In other words: a reduction in the performance of the car-following task may be the result.

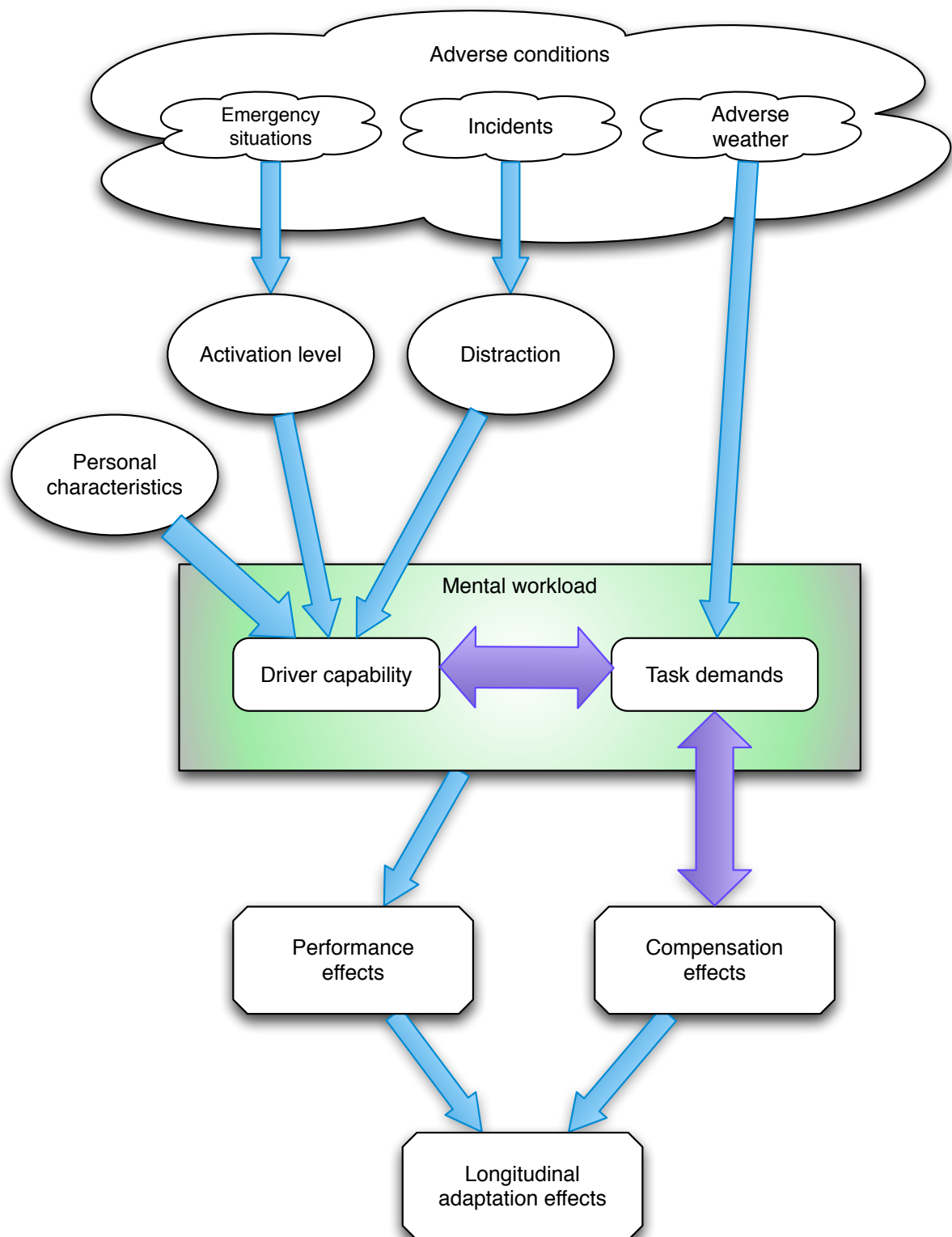


Figure 2.4: Theoretical framework of adaptation effects in longitudinal driving behavior under adverse conditions.

2.7 Conclusions

This chapter started with a presentation of the structure of adverse conditions as well as the structure of the driving task. We continued with a presentation of the available research on empirical longitudinal driving behavior under adverse conditions. In these sections we discussed the available research related to emergency situations, adverse weather conditions as well as freeway incidents.

Overall we conclude that research on the influence of emergency situations, adverse weather conditions and freeway incidents is scarce and sometimes even non-existent. For example, the research performed on emergency situations in connection with empirical longitudinal driving behavior is solely based on assumptions.

The scarcely available research in general does not make use of full experimental designs. For example, the available research lacks the use of control groups or control conditions, making inferences with regard to the observed adaptation effects difficult. Observed adaptation effects may be due to the presence of confounding variables. For example, the observed adaptation effects may be caused by traffic composition, differences in the personal characteristics of the drivers, etc. Therefore it remains unclear whether the observed effects in empirical longitudinal driving behavior can solely be attributed to the adverse conditions. Nevertheless, we assume that emergency situations, adverse weather conditions and freeway incidents have a significant and substantial influence on empirical longitudinal driving behavior.

The assumption of substantial and significant adaptation effects in empirical longitudinal driving behavior due to emergency situations, adverse weather conditions and freeway incidents does not inform us through which determinants the influence of adverse conditions is exerted on longitudinal driving behavior. Although no research on the possible determinants of adaptation effects in longitudinal driving behavior under adverse conditions was found, some likely candidates can be selected.

One of these likely candidates are personal characteristics of the drivers. Here we distinguished gender, age, driving experience, socio-economic status and ethnicity. From the available research it follows that gender, age, driving experience and ethnicity can be assumed to have a substantial influence on driving behavior in general. Also more dynamic constructs may be assumed to have a substantial influence on driving behavior in general as well. A large number of studies was reported showing the influence of mental workload on driving behavior. Emotions and panic were also discussed as possible candidates. It was stated that these psychological constructs have considerable definition problems and that overall research was performed without making use of experimental designs and objective measurement methods. Furthermore panic showed to be quite a rare phenomenon in case of adverse conditions.

The aforementioned selection of likely determinants of longitudinal driving behavior under adverse conditions does not provide us with insight into how these determinants actually influence longitudinal driving behavior under adverse conditions. To this end we proposed a theoretical framework based on the Task-Capability-Interface model by Fuller (2005).

This theoretical framework is aimed at explaining the relationship between emergency situations, adverse weather conditions and freeway incidents and empirical longitudinal driving

behavior. It is assumed that these conditions have an influence on activation level, distraction or task demands, leading to an imbalance between task demands and driver capabilities. The driver will try to resolve this imbalance by exerting direct control over his driving behavior (compensation effects). When these actions are insufficient to resolve this imbalance, a driver will experience an increase in mental workload leading to a reduction in performance (performance effects).

More insight is needed into the extent to which the proposed theoretical framework provides an adequate explanation of adaptation effects in empirical longitudinal driving behavior under adverse conditions. Therefore it is crucial to gain more insight into adaptation effects in empirical longitudinal driving behavior in case of emergency situations, adverse weather conditions and freeway incidents. Furthermore insight is necessary into the elements influencing driver capability and task demands. It is needed to determine the (moderating) influence of personal characteristics of drivers as well as to determine the influence of adverse conditions on mental workload of drivers.

Therefore three driving simulator experiments were performed intended to investigate the influence of emergency situations (i.e., flooding), adverse weather conditions (i.e., fog) and freeway incidents on empirical longitudinal driving behavior as well as on mental workload. In order to investigate the influence of personal characteristics we examined the influence of age as well as driving experience.

In the next chapter, the research methodology applied in these three driving simulator experiments is discussed. In this chapter we provide an overview of available data collection methods of empirical longitudinal driving behavior as well as mental workload. We continue with a presentation of the experimental setups used in the three driving simulator experiments. We provide a brief introduction to the Advanced Driving Simulator, present the experimental designs and the developed driving environments as well as discuss the applied measurement methods. We conclude with a description of the research samples and the data analysis methods.

Chapter 3

Research Methodology

3.1 Aim and structure of this chapter

In the previous chapter we discussed several classifications of adverse conditions, followed by a discussion on the structure of the driving task. Next we presented the available research on the influence of emergency situations, adverse weather conditions and freeway incidents on empirical longitudinal driving behavior. We concluded that the available research is scarce and in case of emergency situations even non-existent. The research that was available does not make use of full experimental designs, making the attribution of observed adaptation effects in driving behavior to the adverse conditions difficult due to the possible presence of confounding variables.

Furthermore, we investigated possible determinants of adaptation effects in longitudinal driving behavior under adverse conditions. We concluded that research on the determinants of adaptation effects in longitudinal driving behavior under adverse conditions was not available. We did however show that personal characteristics of drivers as well as activation level, distraction and mental workload may be assumed to have a substantial influence on driving behavior in general. Therefore we assume in this thesis that these elements have an influence on longitudinal driving behavior under adverse conditions as well.

The fact that these elements may be assumed to have an influence on longitudinal driving behavior under adverse conditions does not inform us how they exert their influence on this behavior. To this end we introduced a new theoretical framework based on the Task-Capability-Interface model by Fuller (2005).

In order to empirically underpin this theoretical framework, three extensive driving simulator experiments were performed intending to investigate the influence of emergency conditions, adverse weather conditions and freeway incidents on longitudinal driving behavior and mental workload (moderated by age and driving experience). This chapter provides a description of the research methodology.

This chapter starts with an overview of the concepts of validity and controllability in Section 3.2. Next, we provide an overview of the available data collection methods in Section 3.3. In

this section, the available data collection methods with regard to empirical longitudinal driving behavior as well as mental workload are discussed.

In this context, we also provide an elaborate introduction to the Advanced Driving Simulator owned by Delft University of Technology, Department Transport and Planning. In this section validity of driving simulators is discussed in-depth.

Next, in Section 3.4 the research methods used to investigate the influence of emergency conditions, adverse weather conditions and freeway incidents on longitudinal driving behavior and mental workload are presented.

Next, we continue with a presentation of the set up of the three driving simulator experiments. These three driving simulator experiments are intended to simulate respectively an emergency situation due to flooding, adverse weather conditions (i.e. fog) and freeway incidents (i.e., a vehicle crash in the other driving lane).

In this section the developed driving environments as well as the experimental designs are presented followed by a description of the used measurement methods and participants. Finally, the data analysis methods are discussed and a conclusion section is provided.

3.2 An introduction into validity and controllability

Validity has no single agreed definition. In general however, it refers to the extent in which a construct, conclusion or measurement is well-founded and corresponds accurately to real life. With regard to data collection methods, validity is the degree in which the method measures what it claims to measure.

In general, the following types of validity can be distinguished, namely:

- test validity (construct validity, content validity, criterion validity);
- experimental validity (conclusion validity, internal validity, external validity);
- diagnostic validity.

These types of validity are briefly explained in the ensuing. We will only focus on test validity and experimental validity as diagnostic validity is mainly applicable in clinical fields, such as medicine.

A species of the genus test validity is construct validity. Construct validity refers to the extent to which operationalizations of a construct actually do measure what is intended. As longitudinal driving behavior cannot be regarded as a construct, this type of validity is less important. This type of validity however plays an important role in the measurement of mental workload.

Another type of test validity is content validity. Content validity is a non-statistical type of validity that involves the systematic examination of the content of the data collection method in order to determine whether it covers a representative sample of the behavior domain to be measured (Anastasi & Urbina, 1997). This element of validity is particularly important with

regard to the measurement of longitudinal driving behavior under adverse conditions. In this context, face validity is often used as an indicator for content validity. Face validity is an estimate of whether a test appears to measure a certain criterion; it does not guarantee that the test actually measures phenomena in that domain.

Finally we discuss criterion validity as a type of test validity. Criterion validity involves the correlation between the data collected with the data collection method and a criterion variable (or variables) taken as representative of the construct. In other words, it compares the data with other measures or outcomes (the criteria) already held to be valid. In the context of longitudinal driving behavior under adverse conditions this element of test validity is less important.

Besides test validity we also distinguished experimental validity. One aspect of experimental validity of a study is statistical conclusion validity. This is the degree to which conclusions reached about relationships between variables are justified. This involves ensuring adequate sampling procedures, appropriate statistical tests, but also reliable measurement procedures. Conclusion validity is only concerned with whether there is any kind of relationship at all between the variables being studied.

A second aspect of experimental validity is internal validity. This is an inductive estimate of the degree to which conclusions about causal relationships are justified using the data collection method in question. This element is highly important in choosing the appropriate data collection method.

Finally we discuss external validity as an aspect of experimental validity. External validity concerns the extent to which the results of a study can be held to be true for other cases, for example to different people, places or times. In other words, it is about whether findings can be validly generalized.

As was mentioned before not only validity plays an important role in the choice of the appropriate data collection method, but also controllability. It is very important to possess a high degree of experimental control in order to reduce the risk of confounding variables.

In this section the constructs of validity and controllability were briefly discussed. In the next section an overview is provided of the available data collection methods for empirical driving behavior and mental workload. In this section, extra attention is paid to the use of driving simulators as data collection methods of empirical driving behavior.

3.3 Data collection method of longitudinal driving behavior and mental workload

3.3.1 Empirical longitudinal driving behavior

Several data collection methods are available in order to measure longitudinal driving behavior. The following data collect methods can be distinguished:

- instrumented vehicles;

- remote sensing;
- driving simulator experiments.

These data collection methods differ in their degree of validity as well as in their controllability of the independent variables. Validity and the level of controllability can be regarded as communicating vessels. Data collection methods with a high level of controllability do not seldom have a lower degree of external validity compared to data collection methods with a lower level of controllability. In Figure 3.1 the relationship between external validity and controllability is displayed (see also Anund and Kircher (2009)).

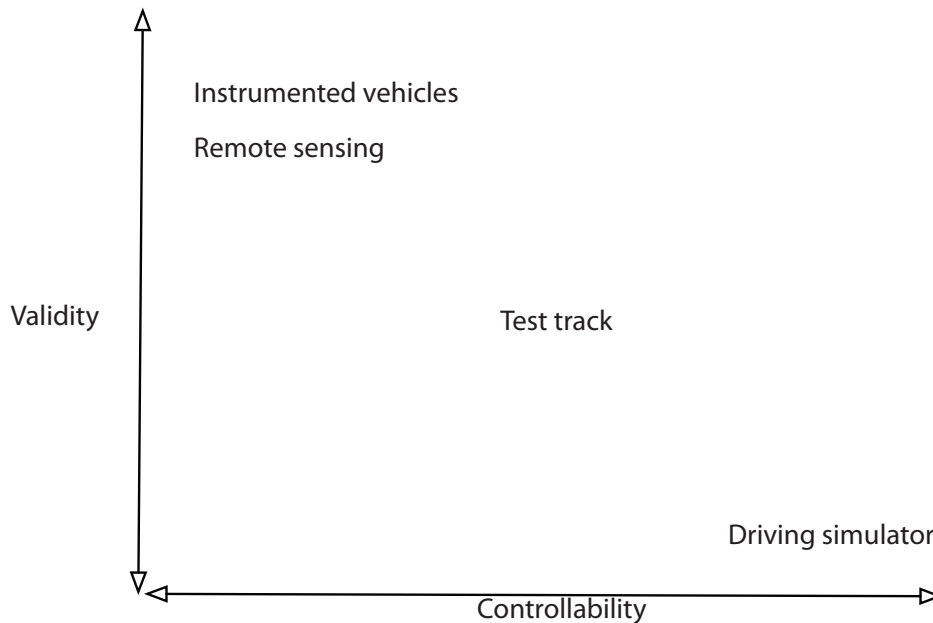


Figure 3.1: External validity and controllability of measures of empirical longitudinal driving behavior (Anund et al., 2009).

This figure clearly shows that data collection methods with a high level of validity are accompanied by a low level of controllability. For example, instrumented vehicles are assumed to have a high level of validity. However, due to the nature of this data collection method the level of controllability is limited.

In the next subsection the use of instrumented vehicles, remote sensing and driving simulators as data collection methods of empirical driving behavior is discussed. Driving simulators on the other hand have a high level of controllability. However this is accompanied by a relatively low level of validity. In the subsection on driving simulators an in-depth discussion on the validity of driving simulators is provided. However, in the next subsection we start with a brief discussion of instrumented vehicles.

Instrumented vehicles

When using an instrumented vehicle in order to collect data, a vehicle is equipped with several devices measuring for example speed, acceleration and distance to the lead vehicle. For example, in Brackstone and McDonald (1999) a vehicle was equipped with an optical speedometer

and a radar rangefinder. Furthermore, also a Video-Audio Monitoring system was installed in the car, allowing for insight into macroscopic traffic phenomena. It also allowed for registration of the behavior of the drivers.

A specific data collection method in which instrumented vehicles are used is naturalistic driving observation. Naturalistic driving observation consists of observing, in an unobtrusive way, driving behavior in naturalistic setting - that is, during everyday life driving - out of experimental context (Stutts et al., 2005; Sayer, Devonshire, & Flanagan, 2007; Dingus et al., 2006). In naturalistic driving observation, data is typically recorded non-stop during the whole observation period. After the observation an in-depth analysis of driving behavior is applied. The external validity of naturalistic driving can be assumed to be relatively high. The measurements are not executed in an obtrusive manner. However, the level of controllability is limited.

Presently, a large study is being conducted on the influence of in-car technology on efficiency and safety in driving behavior using a naturalistic driving observation approach (Schagen et al., 2011).

Remote sensing

With regard to remote sensing of traffic data several different methods can be distinguished. One often applied method is to record the information obtained from (double) loop detectors in the road at the vehicle level, which provide passing times (and therefore headways) and speeds at a specific location (i.e., Hoogendoorn, 2005, Bertini and Ahn, 2010). However, because of the fact that the vehicles are not followed over time, information is not provided about the dynamics in driving behavior.

Secondly, data can be remotely collected through a Global Positioning System (GPS). GPS can be used in order to record information on the speed and location of a vehicle over time. This systems does provide the dynamics in driving behavior for a particular vehicle, but does however not provide insight into interactions with other traffic (unless these are equipped with the instruments as well).

Vehicle trajectory data can also be collected by capturing video from a high viewpoint, which will provide insight into the behavior of drivers both longitudinally and laterally. This enables the analysis of headway choice as well as the influence of the distance from the lead vehicle on acceleration. A substantial advantage of this data collection method is that the information has both a spatial and a temporal dimension. Another advantage is that many drivers can be observed under similar conditions, although the extent in which this is possible is limited (e.g. changing traffic conditions, weather conditions etc.). An example is the data collection method developed by Hoogendoorn and Scheuder (2005).

Another example of remote sensing is the use of cameras alongside the road. The system proved to be able to classify and track vehicles over 100 meters using a single camera with high accuracy on different types of roads and in different weather conditions (Huis, Baan, & Loon, 2009). By combining multiple cameras individual vehicles can be tracked over more than one kilometer.

A drawback of these methods is however that in general only data for a relatively short roadway stretch can be collected (with a maximum around 500m). Another drawback is that conditions

cannot be adequately controlled. In other words, the controllability of this data collection method is relatively limited (see also Figure 3.1). Furthermore, presently this data collection method does not provide insight into the determinants of observed driving behavior, as it is not yet possible to receive information on personal characteristics of the drivers (e.g. gender, age, driving experience) and psychological constructs such as activation level and mental workload.

Driving simulators

Driving simulators are mock-ups of vehicles surrounded by screens on which simulated driving environments are displayed. Drivers control their vehicle through vehicle actuators and can therefore drive through the virtual environment.

Driving simulators possess a high degree of controllability. Through driving simulators driving performance can be assessed objectively and accurately in a standardized fashion (De Winter et al., 2006). In a driving simulator a high degree of control with regard to the driving scenarios, driving environment, participants etc. is possible. It is possible to present exactly the same conditions to all participants. This is not the case with remote sensing and naturalistic driving. In these data collection methods it is not possible to precisely control for confounding variables through controlling the test driving scenarios, driving environment etc.

A possible disadvantage is that driving simulators provide only a representation of reality and not reality itself. The high degree of control is accompanied by a reduction in validity. In this context, Rose et al. (1987) defined validity of driving simulators as the extent to which this data collection method serves its purpose.

In addition to the types of validity discussed in the previous subsection, Jamson (2000) made a distinction between behavioral and physical validity of driving simulators. The first refers to the ability of the driving simulator to induce the same behavioral response from drivers as in real life. The latter refers to the extent in which dynamics and the visual system of a driving simulator produces an experience which resembles real life.

Kaptein, Theeuwes, and Van Der Horst (1996) made distinctions between absolute, relative, internal and external validity. Absolute validity can be defined as the extent in which an effect during a certain task in the driving simulator can be compared to real life. For absolute validity to be present, the direction as well as the magnitude of the reaction has to be similar to real life reactions. Relative validity can be defined as the extent to which a comparable trend can be observed in the driving simulator as is the case in real life. For a driving simulator to possess relative validity, it is not required that the magnitude of the behavioral response is the same.

Several validation studies have been performed on the driving simulator used in the research reported in this thesis. In research conducted by Blaauw (1982) absolute and relative validity was evaluated in terms of system performance and driver behavior for inexperienced and experienced drivers. These participants had to perform lateral and longitudinal vehicle control both in the simulator and in an instrumented car on the road. Task demands for each control were varied with a free and forced accuracy instruction. Overall results showed good absolute and relative validity for longitudinal vehicle control, while lateral vehicle control offered good relative validity. Lateral control performance lacked absolute validity due to the drivers' di-

minished perception of lateral translations. Performance in the simulator was a more sensitive discriminator of driving experience than was performance in the instrumented car on the road.

Another study conducted with this fixed-base driving simulator evaluated the available visual information in order to determine which information is crucial in executing tasks by the driver (Kaptein, Van der Horst & Hoekstra, 1996). They performed two driving simulator experiments. The results were compared with real life data. When approaching a stationary vehicle, subjects were instructed to brake as late as possible, without causing a collision. The instruction was either to brake "hard" or to brake "normal". The first experiment showed that the timing of the start of the braking maneuver was not affected by field of view and scene complexity. Yet, the coordination of the ongoing braking maneuver was more realistic with increasing field of view. The results show that drivers took larger safety margins with higher approach speeds. In the second experiment in 50% of the trials the image was occluded immediately after the onset of the braking maneuver. Results showed that without visual information during the braking maneuver, drivers tended to exceed the intended stopping position more often. The results confirmed the relative validity of the driving simulator and stressed the importance of the presence of sufficient visual information.

Validation studies have also been conducted using the Daimler-Benz driving simulator located in Berlin. From an experiment reported in Riemersma et al. (1990) it followed that drivers in the driving simulator adjusted their speeds more in reaction to speed reducing measures than in real life. In this study it was also concluded that driving simulators possess relative validity.

Some experiments have been performed with the fixed-base Leeds Advanced Driving Simulator (LADS). Carsten et al. (1997) investigated speed and lateral position of vehicles under several traffic conditions. Mean speed when comparing behavior in the driving simulator with real life showed no significant difference. Lateral position however did show a difference, although the same trend could be observed as in real life. Therefore it was concluded that the driving simulator possessed relative validity.

Also recent research has confirmed the relative validity of driving simulators. For instance, Lee (2003) found that performance of a low cost driving simulator could explain more than two-thirds of the variance in 'on the road' assessments in elderly drivers.

Also recent research conducted by Yan et al. (2008) showed that driving simulators have relative validity. In their experiment differences between behavior in the driving simulator and real life at crossroads was investigated.

Furthermore, in a study reported in Reimer et al. (2006) self-reports were used in order to be able to compare behavior in a driving simulator with real life behavior. Significant relationships were found with regard to crashes, speeding, speed, overtaking and behavior at traffic signs. The researchers concluded that driving simulators are adequate instruments to measure driving behavior.

Finally in Bella (2008) a study was performed on the interactive fixed-base driving simulator of the Inter-University Research Center for Road Safety (CRISS). This study was conducted in order to verify whether driving simulators are a useful tool for speed research on two-lane rural roads. The statistical analyses established the relative validity and also revealed the absolute

validity in nine out of eleven measurement sites. Only in two non-demanding configurations speeds were significantly higher than those recorded in real life.

The aforementioned shows clearly that in general driving simulators possess relative validity. However, a validation study with regard to empirical longitudinal driving behavior under adverse conditions using the Advanced Driving Simulator has not yet been performed.

3.3.2 Mental workload

In Chapter 2 we defined mental workload as the extent to which a task imposes a demand on the limited mental resources of an individual. O'Donnell and Eggemeier (1986) distinguished between three measures of mental workload, namely:

- self-report measures;
- performance measures;
- physiological measures.

Self reports

Self reports are measures developed in order to measure workload in human-machine interactions. In self reports related to mental workload, participants provide a subjective indication of their effort expenditure. Several self-report measures are available, such as the Rating Scale Mental Effort (Zijlstra & Doorn, 1985), the Activation Scale (Bartenwerfer, 1969) and the NASA Task Load Index (Hart & Staveland, 1988).

The reliability of the Rating Scale Mental Effort (Zijlstra, 1993) across a range of laboratory and real life settings has been shown to be acceptable ($r = 0.88$ in laboratory and $r = 0.78$ in work settings). The scale has also been found to correlate strongly with validated psychophysiological indices of mental effort, for example, spectral variations in heart period variability (Zijlstra, 1993). The RSME consists of a vertical axis scale with a range of 0 to 150 mm, with nine descriptive indicators ranging from 3 ('absolutely no effort') to 114 ('extreme effort'). Participants are asked to mark a point on the scale which reflects the amount of mental effort invested in task performance (Figure 3.2).

On the Activation Scale (Bartenwerfer, 1969) subjects are also required to mark a line. The appearance of this scale is similar to the RSME (Zijlstra & Doorn, 1985). The activation scale also consists of a single axis with reference points. However, at the reference points statements of a different nature are given, like 'I'm reading a newspaper' and 'I am trying to cross a busy street'. Subjects are asked to mark the line with a cross at the position that equals their mental activation during task performance. The scale has a range from 0 to 270 and is scored by measuring the distance from the origin to the mark in millimeters.

The NASA TLX (Hart & Staveland, 1988) is a multi-dimensional rating procedure that derives an overall workload score based on a weighted average of ratings on six sub-scales. These sub-scales include Mental Demands, Physical Demands, Temporal Demands, Own Performance,

Rating Scale Mental Effort

Please indicate, by marking the vertical axis below, how much effort it took for you to complete the task you've just finished

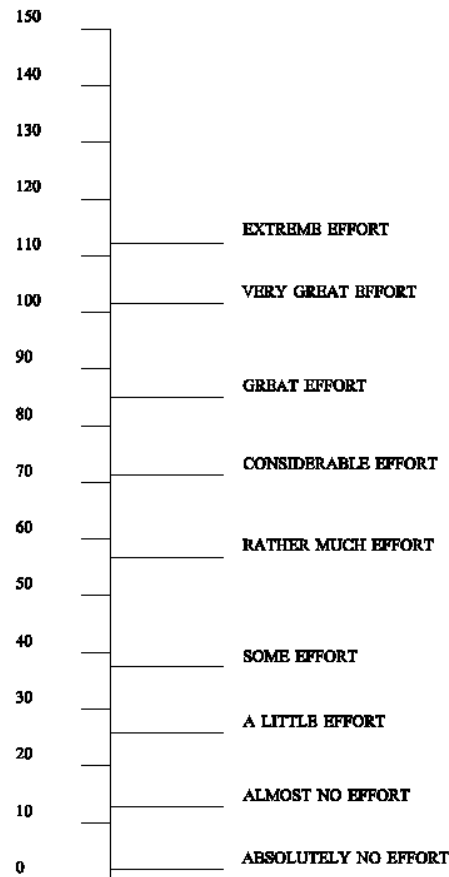


Figure 3.2: The Rating Scale Mental Effort (RSME) (Zijlstra, 1993).

Effort and Frustration. It can be used to assess workload in various human-machine environments such as aircraft cockpits, command, control, and communication workstations.

Muckler and Seven (1992) state that the strength of self-reports lies in their subjectivity. The awareness of increasing effort of the operator being used, even before any performance degradation occurs, should give self-report measures a special role to play (De Waard, 1996). Different dimensions of workload are integrated in self-report measures while at the same time individual differences are taken into account.

Self reports can be considered as instruments with a high degree of controllability. A drawback of self reports is however that these measures are only capable of revealing conscious processes. When drivers are not aware of an increase in mental workload, self reports can be assumed to be less sensitive.

Furthermore, although Muckler and Seven (1992) state that the strength of self reports lies in

their subjectivity as well as the fact that self reports possess a high degree of face validity, the lack of objectivity can pose a considerable bias problem. For example, respondents may avoid providing answers which they regard as too extreme (central tendency error) or may provide socially desirable answers.

Performance measures

A more objective measure of mental workload are performance measures. Here, a distinction can be made between:

- primary performance measures;
- secondary performance measures.

In performance measures the number of errors made, speed of performance or reaction times are often used (De Waard, 1996). According to O'Donnell and Eggemeier (1986) task performance is a measure of the overall effectiveness of man-machine interaction.

In the context of driving performance many possible performance measures are available. In Roskam et al. (2004) for example the following performance measures were distinguished:

- steering wheel reversal rate;
- lane keeping and lateral position;
- speed;
- standard deviation of speed;
- time headway;
- time to collision.

Also the performance on a secondary task can function as a measure of mental workload. A recently introduced measure is the Peripheral Detection Task (PDT). This secondary task is based on the assumption that visual attention reduces as mental workload increases (e.g. Van Winsum, 1999). In this secondary task a LED lights up randomly every 3 to 5 seconds. Participants are instructed to press a microswitch whenever they perceive this light. Mental workload is then determined through calculation of the reaction times and the percentage of missed signals of the participants.

Physiological measures

Mental workload can also be approximated through physiological measures. The main advantage is that contrary to self-reports, physiological indicators of mental workload can be measured during the execution of the driving task, thus revealing possible temporal changes in driver capability or task demands.

Information processing capabilities of individuals in the human cortex is supposed to be regulated by energetical mechanisms or resources (Heemstra, 1988; Kahneman, 1973; Waterink, 1997). During this mobilization different physiological systems are activated, depending on the type of activity an individual is engaged in.

One of the most frequently used measures of mental workload (i.e. energy mobilization) is the ElectroCardioGram. ECG is a test that measures the electrical activity of the heart. The time between successive R-waves, the Inter Beat Interval (IBI), as well as the variability in IBI are the most important measures.

Heart rate variability (HRV) can be computed in the time domain as well as in the frequency domain (Brookhuis & De Waard, 2001). In the time domain HRV is calculated by dividing the standard deviation of the Inter Beat Interval by the average Inter Beat Interval. IBI has been found to be sensitive to both driver alertness and effort expenditure, whereas the 0.10 Hz component is not sensitive to computational effort (De Waard, 1996).

Respiration is also an important mechanism that subserves homeostatic functioning (Waterink, 1997). Traditionally, respiratory analysis in psychophysiology has been largely confined to the classical breakdown of minute ventilation (MV) into tidal volume and respiration rate (RR). The relationship is captured in the following formula:

$$MV = VT * RR \quad (3.1)$$

This is justified by the fact that tidal volume and respiration rate are important determinants of alveolar ventilation. Compared to baseline conditions, mobilization of specific energetically resources is generally associated with an increase in respiration rate (Wientjes, Grossman, & Gaillard, 1998). In their research a baseline condition was applied after which participants were exposed to three conditions of a memory comparison task. It was shown that minute ventilation increased from the baseline to all of the conditions. Furthermore it was shown that respiration rate increased in all of the conditions. Task performance induced a minor degree of hyperventilation.

Finally facial ElectroMyoGraphical activity (EMG) has been shown to yield a valid approximation of mental effort. In an experiment reported in Waterink (1997) it was shown that EMG activity of the zygomatic major (smiling) and the corrugator supercillii (frowning) reflected the level of mental effort significantly.

In the previous subsections, the different indicators of mental workload were discussed separately. However, in order to obtain a valid approximation of mental workload, it is crucial to combine several measures (De Waard, 1996). It is therefore good practice to only conclude that there are changes in mental workload when more than one indicator points in this direction.

3.4 Experimental set-up

In the previous section we provided an overview of the available data collection methods for driving behavior and mental workload. In order to determine the influence of adverse conditions on longitudinal driving behavior as well as on mental workload (moderated by the personal characteristics age and driving experience) three separate driving simulator experiments were performed.

In order to determine this influence we chose a driving simulator, as a large degree of controllability is needed as adverse conditions are, by definition, exceptional. Furthermore, as was mentioned in the previous section, driving simulators may be assumed to possess relative validity and in some cases even absolute validity.

The conducted driving simulator experiments pertained to the influence of respectively emergency situations, adverse weather conditions (i.e. fog) and freeway incidents. In the remainder of this section we provide an introduction to the Advanced Driving Simulator owned by Delft University of Technology, Department Transport and Planning, the applied experimental designs, the developed driving environments, measures used to approximate longitudinal driving behavior and mental workload, a description of the participants in the three experiments and a presentation of the data analysis methods used.

3.4.1 The Advanced driving simulator

The driving simulator used in the three experiments consists of three screens which are, compared to each other, 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 (Figure 3.3). This central computer system consists of two personal computers (a controller personal computer with a Graphical User Interface and a Traffic personal computer) which are connected through a Local Area Network (LAN).

From the driver's seat the view of the driving environment consists of a projection of in total 210 degrees horizontally and 45 degrees vertically. The used software was developed by StSoftware (Van Wolffelaar & Van Winsum, 1992). The software consists of several modules, namely: StRoadDesign, StScenario, StControl, StTraffic and StRender.

The driving environments are designed with StRoadDesign. This tool generates a geometrically correlated graphical and logical database required for the traffic module and the graphical rendering module.

The actual test drives are generated with StScenario. StScenario makes use of a scripting language. This scenario controls the module StControl, which provides control over the simulation module StTraffic. StTraffic finally computes the dynamic traffic system based on intelligent agents based technology. During the test drives the graphics are rendered through StRender at a 60 fps frame rate.



Figure 3.3: Fixed base Driving Simulator.

3.4.2 Experimental designs

Emergency situations

In the driving simulator experiment pertaining to the influence of emergency situations on longitudinal driving behavior and mental workload, participants were randomly divided into two groups: a control group and an experimental group. In the experiment between subjects factors as well as within subject factors were distinguished, rendering up a complete multifactorial design.

Multi-factorial experimental designs are appropriate when more than one independent variable is studied. A complete factorial design is one in which all possible combinations of the selected values of each of the independent variable is used.

As a between subjects factor the factor Urgency was introduced. This between subjects factor consisted of the induction of a sense of urgency within the participants in the experimental group. In the control group no sense of urgency was induced.

This induction of a sense of urgency within the participants in the experimental group was achieved by communicating to these participants that they would receive a maximum reward of EUR 30,- under the condition that they would safely reach their destination on time. For every time unit the participants in the experimental group were late they would receive an equally smaller reward. In the control group it was communicated to the participants that they would receive a reward of EUR 20,- regardless whether they would reach their destination on time.

The use of monetary incentives has been proven to be very effective in inducing a sense of

urgency within participants. Monetary incentives have been used very often in for example the assessment of the effect of cabin location and passenger motivation during the evacuations of aircrafts (Muir, Marrison, & Evans, 1989; McLean, 1996).

As a within subject factor, the factor Time was implemented. To achieve this the test drive in the driving simulator was divided into three segments of equal duration. This was done in the experimental group as well as in the control group.

During the experiment longitudinal driving behavior as well as mental workload was measured in both groups and all conditions.

Adverse weather conditions

In the experiment pertaining to the influence of adverse weather conditions, all participants participated in the experimental condition as well as in the control condition, rendering up a complete within subject design. In the experimental condition an adverse weather condition (i.e. fog) was induced, while in the control condition normal driving conditions were applied. The order in which the participants were exposed to the conditions was varied between participants (counterbalanced across subjects).

Freeway incidents

All participants participated in two experimental conditions as well as in a control condition, rendering up a complete within subjects design. The two experimental conditions consisted of two versions of an incident in the other driving lane, while in the control condition no incident was present. All segments were counterbalanced across subjects. For each version of the incidents as well as the control condition longitudinal driving behavior was measured through three measurement periods, namely: before perception of the incident, during perception of the incident and after perception of the incident.

3.4.3 The driving environments

Emergency situations

For the purpose of this experiment, a driving environment was developed consisting of four segments. The first segment consisted of a short test drive through a suburban area to accustom participants to driving in a driving simulator and also to investigate whether the participants were prone to simulator sickness (Figure 3.4).

The other three segments were used in the experiment. These test trials took place on a virtual motorway with two lanes in the same direction. No speed limit was set. The length of the four segments combined was 18.9 km.

Between the three segments used in the experiment the level of urgency was varied in the experimental group. The variation in this level of urgency was achieved by exposing the participants to messages on the screen regarding the extent in which they still performed in accordance with the preset time limit.



Figure 3.4: Test drive suburban area.

In the first segment the participants received the message on-screen that they were still on time (Figure 3.5). In this message also the remaining reward (EUR 30,-) was communicated to the participants. In the ensuing this condition will be referred to as the 'On Time' condition.



Figure 3.5: Condition 'On Time'.

In the second segment the participants in the experimental group received the message that they were behind schedule. At the same time the remaining reward started to decrease (Figure 3.6). In the remainder this segment will be referred to as the 'Behind Schedule' condition.

Finally, in the third segment the participants in the experimental group received the message that time was running out. At the same time the remaining reward started to decrease even faster (Figure 3.7). In order to enforce the sense of urgency flooding of the environment was

simulated. In the ensuing this condition will be referred to as the 'Out of Time' condition.



Figure 3.6: Condition 'Behind Schedule'.



Figure 3.7: Condition 'Out of Time'.

In the control group the participants drove the same route as the participants in the experimental group. However, they did not receive the messages discussed earlier. Also, flooding was not simulated in the 'Out of Time' condition.

In both groups behavior of the other road users was equal. In both groups moderately congested traffic conditions were simulated as well as two stop-and-go traffic events.

The behavior of the lead vehicles before, between and after the two stop-and-go waves 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 condition, consisting of an increase in speed, acceleration and deceleration and an reduction in distance to the lead vehicle.

Adverse weather conditions

In the context of this experiment also use was made of the Advanced Driving Simulator. For the purpose of the experiment a driving environment was developed consisting of three segments. The first segment consisted of a short test driving through a suburban area to accustom the participants to driving in a driving simulator and to investigate whether a participant would suffer from simulator sickness (Figure 3.8).



Figure 3.8: Test drive (top) and experimental condition (bottom) in the driving simulator.

The other two segments were used in the experiment: an experimental and a control condition. In the experimental condition fog was generated (visibility around 150 m), while in the control condition normal visibility conditions were applied (Figure 3.8).

The test trials took place on a virtual 2 x 2 motorway. The speed limit was set to 100 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 distance to the lead vehicle.

Freeway incidents

In the context of this third driving simulator study again use was made of the Advanced Driving Simulator. For the purpose of this experiment a driving environment was developed consisting of four segments. The first segment consisted of a short test drive through a suburban area to accustom participants to driving in a driving simulator and also to investigate whether the participants would suffer from simulator sickness.

The other three segments were used in the experiment: two segments in which an incident in the other driving lane was generated and one segment in which no incident was generated, which was used as a control condition. The test trials took place on a virtual motorway with two lanes in the same as well as in the opposite direction. The speed limit on the motorway was set to 100 km/h. The length of the four segments combined was 10.8 km.

Between the two experimental conditions the severity of the generated incidents was varied. In experimental condition 1 an incident consisting of a vehicle crash was generated consisting of a crashed vehicle, a visible casualty and three police cars, while in experimental condition 2 the incident consisted of a vehicle crash with no visible casualties and only one police car (Figure 3.9).



Figure 3.9: Accidents in the driving simulator.

The behavior of other traffic was derived from a pilot study. This means that other vehicles showed actual adaptation effects, consisting of a decrease in speed, a decrease in acceleration as well as an increase in spacing.

3.4.4 Measures

Longitudinal driving behavior

In all three experiments, longitudinal driving behavior, represented by speed v , speed of the lead vehicle v_{i-1} , acceleration a , deceleration b and spacing s , were measured through registered behavior in the driving simulator at a sampling rate of 10 Hz. These indicators of longitudinal driving behavior were saved to a text file using StDataProc.

Mental workload

In the three experiments different measures of mental workload were used. In all experiments mental workload was approximated through the physiological indicators heart rate and heart rate variability.

Heart rate was measured through an ElectroCardioGram (ECG). Two bi-polar Ag/AgCl electrodes were placed on each side of the lower ribs of the participants. Also use was made of a reference electrode.

The ECG signal was amplified using a Nexus-4 (Nexus-10 in the experiment on the influence of freeway incidents), which was connected to the electrodes through a NX1-EXG2 snap cable. The ECG signal was digitally filtered using a Finite Impulse Response band pass filter of 0.5-100Hz in Biotrace+. With the use of Biotrace+, R-peaks were detected and saved to a text file.

In Biotrace+ time intervals between R-peaks were used to calculate heart rate. Heart rate variability was also measured through the ECG. A spectral analysis was performed using a frequency band of 0.07-0.14Hz as research has shown that the mid-frequency band is the most sensitive to changes in mental workload (Mulder, 1989). In Figure 3.10 an example is provided of HRV for one participant during the experiment with the emergency situation.

In the experiment regarding the influence of freeway incidents we additionally measured respiration rate and EMG activity of the zygomaticus major and the corrugator supercillii (see Figure 3.11)

Respiration rate was measured through the relative expansion of the thorax during inhalation and exhalation. This relative expansion was measured through an elastic band placed around the chest of the participants. This band was connected through a cable to the Nexus-10, which amplified the signal. Through a bluetooth connection, the signal was communicated to a laptop at a sampling rate of 32 samples per second. With the use of Biotrace+ time intervals between two peaks were used to calculate respiration rate.

In order to perform the EMG two pairs of bipolar Ag/AgCl electrodes (size 2 mm, contact area 4 mm and housing 11 mm in diameter) were placed on the zygomaticus major (smiling) and the corrugator supercillii (frowning) of the participants (Fridlund & Cacioppo, 1986).

These bipolar electrodes were placed 1 centimeter apart on the appropriate facial muscles. Also a reference electrode (ground) was placed. These electrodes were connected to a Nexus-10 through a NX1-EXG2 snap cable. The EMG signal, amplified through the Nexus-10 was sent to a laptop through a bluetooth connection at a sampling rate of 2048 samples per second.

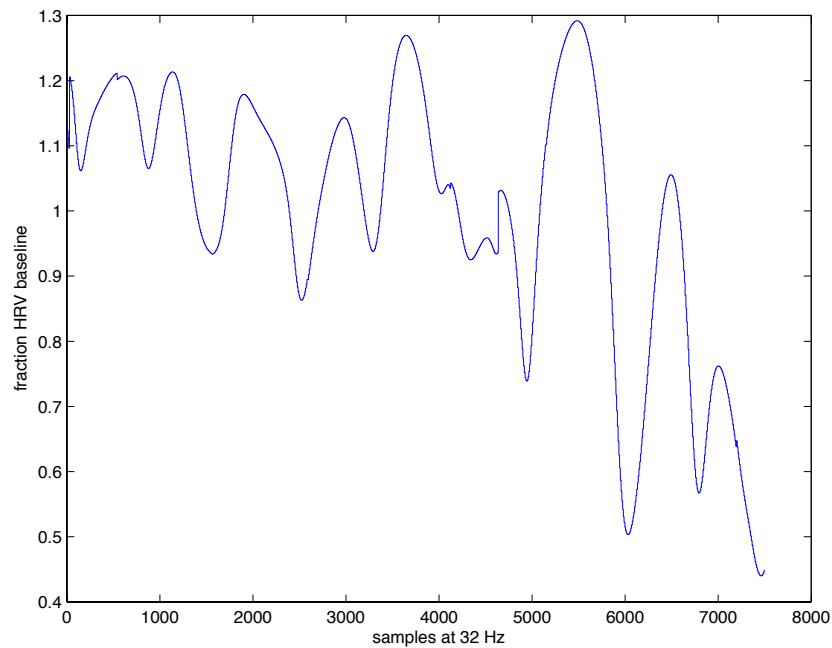


Figure 3.10: Example of HRV for one participant during the experiment with the emergency situation as a fraction of the baseline measurement.

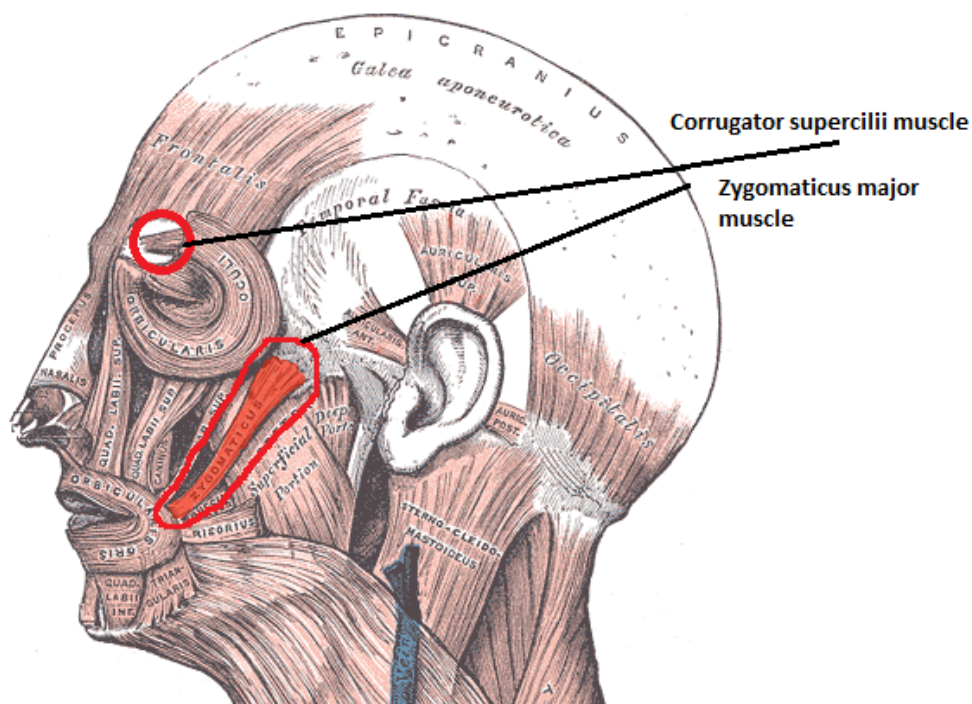


Figure 3.11: Position of the zygomaticus major (smiling) and the corrugator supercilii (frowning).

The signal was digitally filtered with a $-3dB$ high pass cut-off frequency at 20Hz and a $3dB$ low pass cut-off frequency at 520Hz (Waterink & Van Boxtel, 1994). For this purpose a digital Finite Impulse Response Band-pass filter (FIR), subtype Parks-McClellan was used in Bio-

trace+. Linear rectification was applied. The signal was smoothed using a low band-pass filter at 50Hz. Next, this signal was saved to a text file.

In the experiments pertaining to the influence of adverse weather conditions and freeway incidents we also measured subjective estimates of effort expenditure. Here the Rating Scale Mental Effort (RSME) was used (Zijlstra & Doorn, 1985). The RSME measures subjective ratings of perceived mental effort. The RSME is a one dimensional visual-analogue scale containing nine different verbal categories forming anchor points expressing different levels of mental effort. The scale ranges from 0 to 150. The RSME shows systematic relations with task difficulty and performance measures. In Table 3.1 the different data collection methods used in the experiments are summarized.

Table 3.1: Measures of mental workload used in the experiments.

	Subjective measures	Physiological measures
Emergency situations	None	Heart rate Heart rate variability (HRV)
Adverse weather	Rating Scale Mental Effort	Heart rate Heart Rate variability (HRV)
Incidents	Rating Scale Mental Effort	Heart rate Heart rate variability (HRV) Respiration rate EMG activity zygomaticus major EMG activity corrugator supercillii

3.4.5 Participants

The research population in the three experiments consisted of employees as well as students of Delft University of Technology. The optimal sample size was calculated through the following equation:

$$n \geq \frac{Z^2}{d^2} \sigma^2 \quad (3.2)$$

Table 3.2: Descriptives of participants in the experiments.

Conditions	<i>N</i>	Mean age (<i>SD</i>) (yrs)	Mean driving experience (yrs) (<i>SD</i>)
Emergency	38 (21 male / 17 female)	30.41 (5.30)	10.31 (6.41)
Weather	25 (13 male / 12 female)	32.65 (4.23)	8.44 (4.48)
Incidents	36 (17 male / 19 female)	34.92 (7.99)	10.94 (5.46)

In this equation, the variation in the phenomenon being measured is taken into account as well as the accuracy of the statement that is made along with the reliability of the statement. In Table 3.2 descriptive statistics with regard to the three research populations are presented.

3.4.6 Data analysis methods

In all three experiments we first calculated the descriptive statistics for speed v , acceleration a , deceleration b , positive and negative relative speed Δv and spacing s .

With regard to speed (v) we used the space mean speed. Space mean speed differs from time mean speed and does not comply with the fundamental relation of traffic flow.

Consider for example a motorway with two lanes. In the right lane vehicles travel at 50 km/h, while in the left lane they travel at 100 km/h. Suppose that all the vehicles that pass a detector loop on the right lane during 1 minute can be found on a road stretch of 1 kilometer. On the left lane, the length of this road stretch is 2 kilometers. When assessing time mean speed, faster cars are considered over a much longer road section than slower cars. However, when we calculate mean speed, the length of the road used is the same for fast and slow cars. Therefore the proportion of fast vehicles is overestimated when calculating time mean speed.

Spacing was collected in meters, measured from the front bumper of the follower to the rear bumper of the leader. For relative speed Δv a distinction was made between positive and negative values (Δv_{pos} and Δv_{neg}). Here, positive values represent closing relative speeds, while negative values of Δv represent opening relative speeds.

Descriptive statistics were also calculated for heart rate, heart rate variability (HRV), respiration rate and EMG activity of the zygomaticus major and corrugator supercilii. Before calculating the descriptive statistics, these physiological indicators of mental workload were transformed by expressing them as a fraction of a preceding baseline measurement.

Emergency situations

To analyze whether the observed effects in the descriptive statistics with regard to longitudinal driving behavior as well as the physiological indicators of mental workload were significant, a Multivariate Analysis of Variance (MANOVA) was performed. A MANOVA is a generalized form of univariate analysis of variance (ANOVA). Analogous to ANOVA, MANOVA is based on the product of the model variance matrix Σ_{model} and inverse of the error variance matrix Σ_{res}^{-1} or $A = \Sigma_{model} * \Sigma_{res}^{-1}$.

This analysis method was chosen as it allows for the determination of the effects of within as well as between subjects factors. Furthermore, this method allows for the determination of interaction effects (for example interactions between the level of urgency and time course).

In order to test for within and between subjects effects, longitudinal driving behavior (consisting of the measurements of speed v , acceleration a , deceleration b , relative speed Δv and spacing s) and the transformed values of the physiological indicators of mental workload were transformed into linear and quadratic trend contrast scores by means of computation of orthogonal polynomials. The analysis was applied to these contrast scores, which were chosen a priori for the control group as well as the experimental group with Time as a within subjects factor and Urgency as a between subjects factor.

Here Time consisted of the three conditions, respectively the 'On Time', 'Behind Schedule' and 'Out of Time' condition. The factor Urgency consisted of the two groups, respectively

the control group and the experimental group. In this regard, Mauchly's test of Sphericity was performed in order to test for homogeneity of variances. If this assumption was violated, degrees of freedom were corrected using the Greenhouse-Geisser estimates of sphericity.

In case of significant interactions of contrast scores with Urgency, testing of simple post-hoc contrast scores was performed. Due to the a priori character of the tests, they were performed with the conventional Type I error or 0.05 (Tabachnick & Fidell, 2001).

Also, Pillai's Trace was calculated for the within subjects factor Time as well as the effect of Urgency on time course, represented by the factor Time(3). Pillai's Trace is a summary based on the roots of the eigenvalues λ_p of the constructed matrix and provides an indication of the strength of the observed effect:

$$\lambda_{pillai} = \sum_{p=1} (1/(1 + \lambda_p)) \quad (3.3)$$

In order to test the influence of age and driving experience on mental workload Multiple Regression Analyses (MRA), method Enter, were performed with age and driving experience as the independent variables and HR and HRV as the dependent variables. These analyses were performed for the experimental group. Here also, a significance level of 0.05 was applied.

Adverse weather conditions

In order to examine the effect of the adverse weather condition on longitudinal driving behavior and mental workload, paired sample t-tests were performed with a significance level of 0.05. Paired sample t-tests compare two population means in the case of two samples that are correlated.

In order to test the influence of age and driving experience on mental workload Multiple Regression Analyses (MRA) were performed with age and driving experience as the independent variables and HR and HRV as the dependent variables. These analyses were performed for the experimental condition only. Here also, a significance level of .05 was applied

Freeway incidents

To analyze whether the observed effects in the descriptive statistics were significant for freeway incidents, a Multivariate Analysis of Variance for Repeated Measures was performed.

In order to test for within subjects effects empirical adaptation effects in longitudinal driving behavior (consisting of the measurements of speed v , acceleration a , deceleration b , relative speed Δv and spacing s) were transformed into linear and quadratic trend contrast scores by means of computation of orthogonal polynomials. The analysis was applied to these contrast scores, which were chosen a priori for the within subjects factor Condition and Time.

Here, the factor Condition consisted of the two experimental conditions, while the factor Time consisted of the measurement before, during and after perception of the incidents. In case of significant interactions of contrast scores with Condition (2), testing of simple post-hoc contrast

scores was performed. Due to the a priori character of the tests, they were performed with the conventional Type I error or 0.05 (Tabachnick & Fidell, 2001).

As was the case with the statistical analysis of emergency situations, Mauchly's test of Sphericity was performed in order to test for homogeneity of variances. Also, Pillai's Trace was calculated for the within subjects factors Condition and Time as well as the effect of Condition on time course, represented by the factor Time.

In order to analyze the influence of age and driving experience Multiple Regression Analyses were performed with age and driving experience as independent variables and amplitudes of the zygomaticus major, corrugator supercilii, respiration rate and heart rate as dependent variables. Here also, a significance level of 0.05 was used. These analyses were only performed for experimental condition 1.

3.5 Conclusions

In this chapter we presented an overview of available data collection methods for empirical longitudinal driving behavior as well as mental workload. In this section we distinguished for empirical longitudinal driving behavior between instrumented vehicles, remote sensing and driving simulators. We mentioned that these data collection methods vary in the level of validity as well as in their degree of controllability.

From the overview of available data collection methods we selected for empirical longitudinal driving behavior driving simulators. The main reason for this choice is the fact that adverse conditions have a low rate of occurring. Therefore a large degree of controllability is needed. The only data collection method which offers the needed degree of controllability are driving simulators. With regard to mental workload we chose a combination of several data collection methods, however with a strong focus on physiology.

In the ensuing of this chapter we presented the experimental set up of the three driving simulator experiments, aimed at simulating an emergency situation, adverse weather conditions and freeway incidents. In this context we discussed the experimental designs, the used data collection methods, the participants and the data analysis methods.

In the next chapter the results of the experiments with regard to the influence of adverse conditions on longitudinal driving behavior are discussed, followed by a presentation of the results of the influence of adverse conditions on mental workload in Chapter 5.

Chapter 4

Empirical Longitudinal Driving Behavior in Case of Adverse Conditions

4.1 Aim and structure of this chapter

The aim of this chapter is to present insight into the changes in empirical longitudinal driving behavior in case of emergency situations, adverse weather conditions and freeway incidents. Results of the analyses on the influence of these conditions on mental workload, moderated by personal characteristics are presented in the next chapter.

In Section 4.2 we start with a presentation of the statistical analyses of longitudinal driving behavior in case of emergency situations. In this section descriptive statistics as well as the results of the Multivariate Analysis of Variance are reported. We continue with a presentation of the results of the second driving simulator experiment, i.e., the influence of adverse weather conditions on longitudinal driving behavior in Section 4.3.

We conclude this chapter with a presentation of the results of the driving simulator study regarding the influence of freeway incidents on longitudinal driving behavior in Section 4.4 and conclusions in Section 4.5.

4.2 Emergency situations

In this section the results of the driving simulator experiment with regard to the influence of emergency situations on empirical longitudinal driving behavior are presented. We start with a presentation of the descriptive statistics.

Table 4.1 shows the mean values and the standard deviations (between parentheses) of speed v , acceleration a , deceleration b , spacing s and positive and negative relative speed Δv_{pos} and Δv_{neg} for the data collected in the emergency situation experiment. It does so for the control and for the experimental group, as well as for the different experimental conditions ('On time', 'Behind schedule' and 'Out of time').

From the table it can be observed that mean values of speed v in the control group differ substantially from mean values in the experimental group. Furthermore, in contrast with the

Table 4.1: Mean and standard deviation of speed (v), acceleration (a), deceleration (b), spacing (s), positive relative speed (Δv_{pos}) and negative relative speed (Δv_{neg}) for the control group and the experimental group per condition.

	speed (km/h)	acceleration (m/s^2)	deceleration (m/s^2)
<i>Control</i>			
On Time	86.38 (11.58)	0.41 (0.37)	-0.43 (0.90)
Behind Schedule	84.45 (4.87)	0.38 (0.54)	-0.63 (0.86)
Out of Time	83.05 (9.15)	0.35 (0.34)	-0.50 (0.66)
<i>Experimental</i>			
On Time	92.85 (17.81)	0.56 (0.98)	-0.74 (0.96)
Behind Schedule	110.45 (23.83)	0.59 (1.03)	-0.75 (1.01)
Out of Time	117.06 (19.60)	0.83 (1.36)	-0.97 (1.20)
	spacing (m)	pos. relspeed (km/h)	neg. relspeed (km/h)
<i>Control</i>			
On Time	45.53 (55.71)	3.11 (3.12)	-3.08 (3.13)
Behind Schedule	38.62 (67.00)	1.77 (2.01)	-3.21 (3.04)
Out of Time	39.01 (31.25)	0.97 (1.29)	-3.02 (2.97)
<i>Experimental</i>			
On Time	27.98 (43.91)	1.09 (1.59)	-2.80 (3.71)
Behind Schedule	24.74 (38.93)	0.63 (0.85)	-2.38 (3.34)
Out of Time	21.42 (31.93)	0.78 (1.65)	-2.13 (3.98)

control group, mean values of speed v differ substantially between the three conditions in the experimental group.

In the 'On Time' condition mean speed v is lower than in the 'Behind Schedule' condition, while mean speed v in the 'Out of Time condition' is larger than in the other two conditions. Furthermore, it can be observed from the table that in the experimental group standard deviations are substantially larger than in the control group.

A similar picture emerges for acceleration a and deceleration b . Overall, differences can be observed between the mean values of acceleration a and deceleration b in the control group and in the experimental group. The table shows that especially acceleration a is larger in the experimental group than in the control group. Mean values as well as standard deviations for the control group are quite similar between the three conditions. This is in contrast with the mean values and standard deviations in the experimental group, as here substantial differences in mean values and standard deviations of acceleration a can be observed.

From the table it can be also observed that when comparing the three conditions in the control group, the mean value of spacing s is larger in the 'On Time' condition compared to the 'Behind Schedule' condition and the 'Out of Time' condition. The difference in mean values between the 'Behind Schedule' and the 'Out of Time' condition is not substantial. Furthermore, it can be observed from the table that mean values of spacing s in the experimental group differ substantially from the control group. Also overall, standard deviations are smaller

in the experimental group.

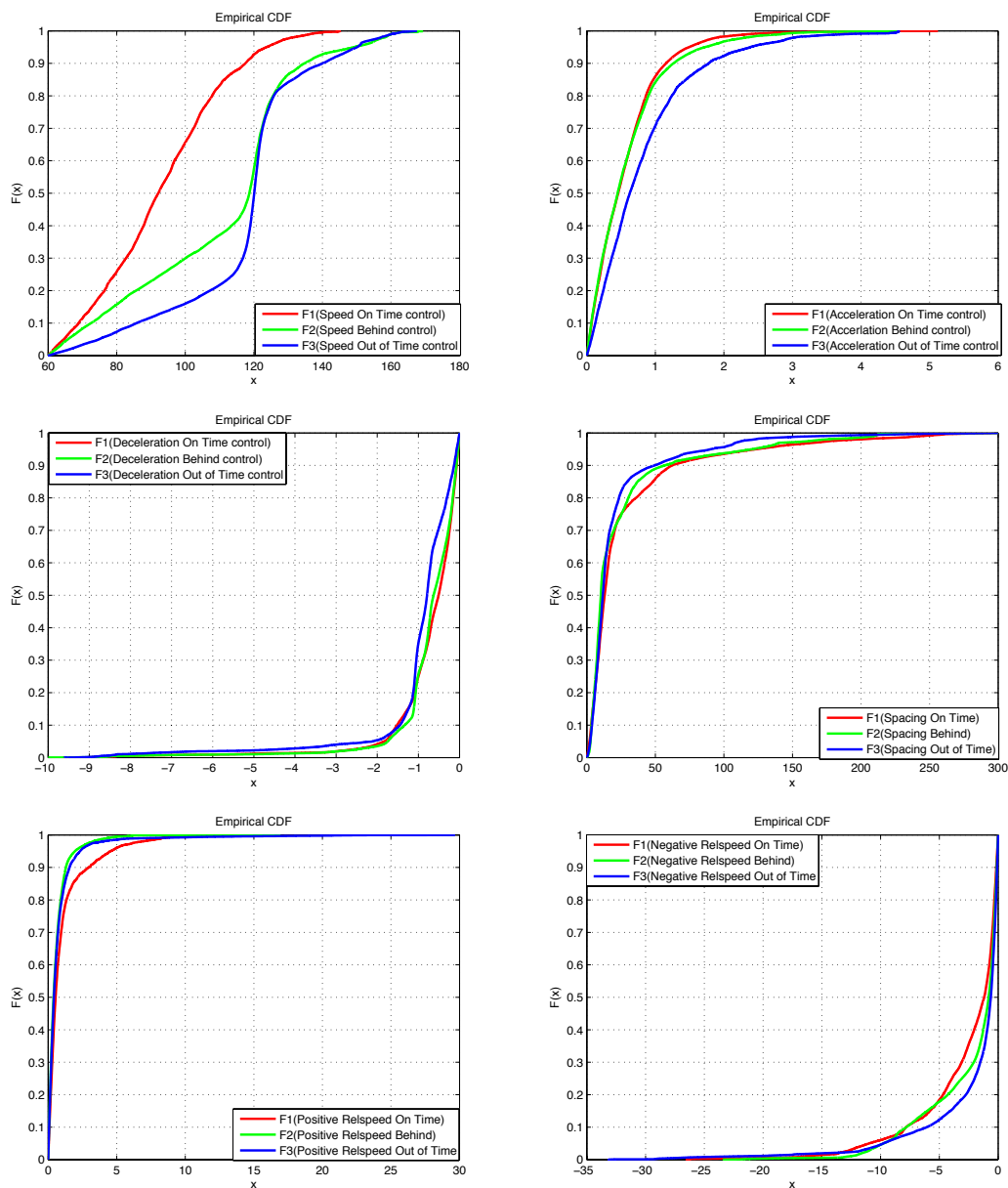


Figure 4.1: Empirical cumulative distribution functions of empirical adaptation effects in longitudinal driving behavior during the On Time, Behind Schedule and Out of Time condition in the experimental group.

For positive relative speed Δv_{pos} the table shows that mean values as well as standard deviations for the control group differ substantially between the three conditions. However, mean values of positive relative speed Δv_{pos} in the experimental group are smaller than in the control group, while standard deviations in the control group are larger than in the experimental group. Furthermore, it can be observed from the table that mean values as well as standard deviations of positive relative speed Δv_{pos} in the experimental group differ substantially between the three conditions. In the 'On Time' condition mean positive relative speed Δv_{pos} is substantially larger than in the 'Behind Schedule' and 'Out of Time' condition. The difference between the 'Behind Schedule' and the 'Out of Time' condition is less substantial.

Finally, it can be observed that mean values as well as standard deviations of negative relative speed Δv_{neg} for the control group do not substantially differ between the three conditions. It can however also be observed that on average mean values of negative relative speed Δv_{neg} in the experimental group are larger than in the control group. Furthermore on average standard deviations in the experimental group are larger. It can also be observed that mean values of negative relative speed Δv_{neg} differ substantially between the three conditions in the experimental group. When comparing these three conditions it becomes clear that mean negative relative speed Δv_{neg} is smaller in the 'On Time' condition compared to the 'Behind Schedule' condition. Furthermore the table shows that the mean value of negative relative speed Δv_{neg} in the 'Behind Schedule' condition is smaller than in the 'Out of Time' condition. In illustration, the cumulative distribution functions of speed v , acceleration a , deceleration b , spacing s , positive relative speed Δv_{pos} and negative relative speed Δv_{neg} are presented in Figure 4.1.

In summary, the descriptive statistics indicate substantial adaptation effects in empirical longitudinal driving behavior. In the experimental condition a substantial increase in speed v , acceleration a , deceleration b can be observed along with small distances to the lead vehicle s . Furthermore, the drivers seem to follow the lead vehicles more closely, as indicated by smaller positive and negative relative speeds Δv . From the descriptive statistics it can be concluded that in case of an emergency situation drivers seem to drive faster with stronger accelerations and decelerations as well as at smaller following distances.

The aforementioned is supported by the results of the MANOVA in Table 4.2. In the table F -values, the degrees of freedom (df), as well as the error and the p -value is displayed for speed v , acceleration a , deceleration b , spacing s , positive relative speed Δv_{pos} and negative relative speed Δv_{neg} .

Here, the F -value is defined as the between groups mean squares divided by the mean squares of error. The F -ratio is therefore the product of two ratios. The first ratio is the degrees of freedom for error divided by the between groups degrees of freedom. The second ratio is the between groups sum of squares divided by the sum of squares for error.

From Table 4.2, a significant effect of the between subjects factor Urgency can be observed for speed v , acceleration a , spacing s as well as positive relative speed Δv_{pos} and negative relative speed Δv_{neg} . As was mentioned in Chapter 3, this factor consists of the influence of no emergency (control) versus an emergency situation (experimental), irrespective of time course. This means that a significant difference (irrespective of time course) was present for speed v , acceleration a , spacing s as well as positive relative speed Δv_{pos} and negative relative speed Δv_{neg} .

Furthermore, the results show that overall time course, represented by the factor Time, being the On Time, Behind Schedule and Out of Time condition, has a significant effect on speed v , spacing s , positive relative speed Δv_{pos} and negative relative speed Δv_{neg} . This means that the three conditions, irrespective of the factor Urgency had a significant effect on these elements of longitudinal driving behavior. Also the influence of Urgency on time course was significant for speed v , spacing s , positive relative speed Δv_{pos} and negative relative speed Δv_{neg} . This means that time course in the experimental group is significantly different from time course in the control group.

Table 4.2: Results Multivariate Analysis of Variance for empirical adaptation effects in longitudinal driving behavior under emerging situations / evacuations.

Variable	Factor	Pillai's T	F	df	Error	p
Speed v	Urgency	-	39.53	1	38	0.00
	Time	0.29	8.30	2	76	0.00
	Urgency x Time	0.34	10.39	2	76	0.00
Acceleration a	Urgency	-	5.24	1	38	0.02
	Time	0.06	1.48	2	76	0.23
	Urgency x Time	0.07	1.74	2	76	0.18
Deceleration b	Urgency	-	1.63	1	38	0.24
	Time	0.05	0.99	2	76	0.37
	Urgency x Time	0.02	0.32	2	76	0.72
Spacing s	Urgency	-	34.94	1	38	0.00
	Time	0.33	9.41	2	76	0.00
	Urgency x Time	0.29	12.94	2	76	0.00
Positive relspeed Δv_{pos}	Urgency	-	17.80	1	38	0.00
	Time	0.22	6.19	2	76	0.00
	Urgency x Time	0.23	6.20	2	76	0.00
Negative relspeed Δv_{neg}	Urgency	-	9.02	1	38	0.00
	Time	0.16	4.12	2	76	0.00
	Urgency x Time	0.14	5.11	2	76	0.00

For acceleration a and deceleration b only the factor Urgency has a significant effect. This means that overall acceleration a and deceleration b different significantly between the two groups. However, overall time course nor Urgency on time course has a significant effect.

It can therefore be concluded that emergency situations can be assumed to lead to substantial and significant adaptation effects in longitudinal driving behavior. These effects are characterized by a substantial and significant increase in speed v and acceleration a , together with a significant reduction in spacing s and relative speed Δv .

4.3 Adverse weather conditions

In Table 4.3 the results of the driving simulator experiment intended to determine the influence of adverse weather conditions on empirical longitudinal driving behavior are presented. In the table the descriptive statistics are presented for the control condition (normal weather conditions) as well as the experimental condition (fog). Again, these descriptive statistics consist of the mean values in speed v , acceleration a , deceleration b , spacing s , as well as positive and negative relative speed (Δv_{pos} and Δv_{neg}). Standard deviations are displayed between parentheses.

From the descriptive statistics in Table 4.3 it follows that mean speed v , acceleration a and deceleration b decreased in the experimental condition compared to the control condition, while

Table 4.3: Mean values of empirical adaptation effects in longitudinal driving behavior for the control condition (normal weather conditions) and the experimental condition (fog). Standard deviations are between parentheses.

	Control	Experimental
Speed v (km/h)	75.33 (8.13)	63.01 (22.65)
Acceleration a (m/s ²)	0.44 (0.41)	0.32 (0.35)
Deceleration b (m/s ²)	-0.58 (0.75)	-0.38 (0.34)
Spacing s (m)	15.19 (6.54)	38.33 (38.13)
Positive relative speed Δv_{pos} (km/h)	0.85 (1.08)	1.20 (1.32)
Negative relative speed Δv_{neg} (km/h)	-0.75 (1.09)	-1.26 (1.37)

mean spacing s increased substantially. Also it follows from the table that positive relative speed Δv_{pos} and negative relative speed Δv_{neg} were larger and smaller respectively. This indicates that drivers followed the lead vehicle less actively in case of the adverse weather condition.

Standard deviations also differed substantially between the two conditions. This is especially the case for speed v and spacing s . For example, the standard deviation of speed v increase from 8.13 in the control condition to 22.65 in the experimental condition. This indicates that differences within as well as between drivers increased substantially in the experimental condition compared to the control condition.

The aforementioned is supported by the constructed cumulative distribution functions in Figure 4.2 as well as by the results of the paired samples t-tests. From these results it followed that speed v ($t(24) = 11.78, p < 0.05$), acceleration a ($t(24) = 2.79, p < 0.05$), and deceleration b ($t(24) = 2.88, p < 0.05$) differed significantly in the experimental condition from the control condition.

Furthermore it follows from the results that the difference in spacing s ($t(24) = 10.71, p < 0.05$) as well as positive relative speed Δv_{pos} ($t(24) = 2.45, p < 0.05$) and negative relative speed Δv_{neg} ($t(24) = 2.79, p < 0.05$) between the experimental condition and the control condition was significant.

It can therefore be concluded that substantial empirical adaptation effects in longitudinal driving behavior can be observed in case of this adverse weather condition. In the adverse weather condition speed v decreases while acceleration a and deceleration b also become smaller. Furthermore, a substantial increase in spacing s along with smaller values of positive relative speed Δv_{pos} and negative relative speed Δv_{neg} were observed. There are however substantial differences between drivers, as indicated by large standard deviations in the experimental condition. Especially with regard to speed v and spacing s large differences between drivers can be observed. This seems to indicate that some drivers adapt their driving behavior to the adverse weather condition, while other drivers do not.

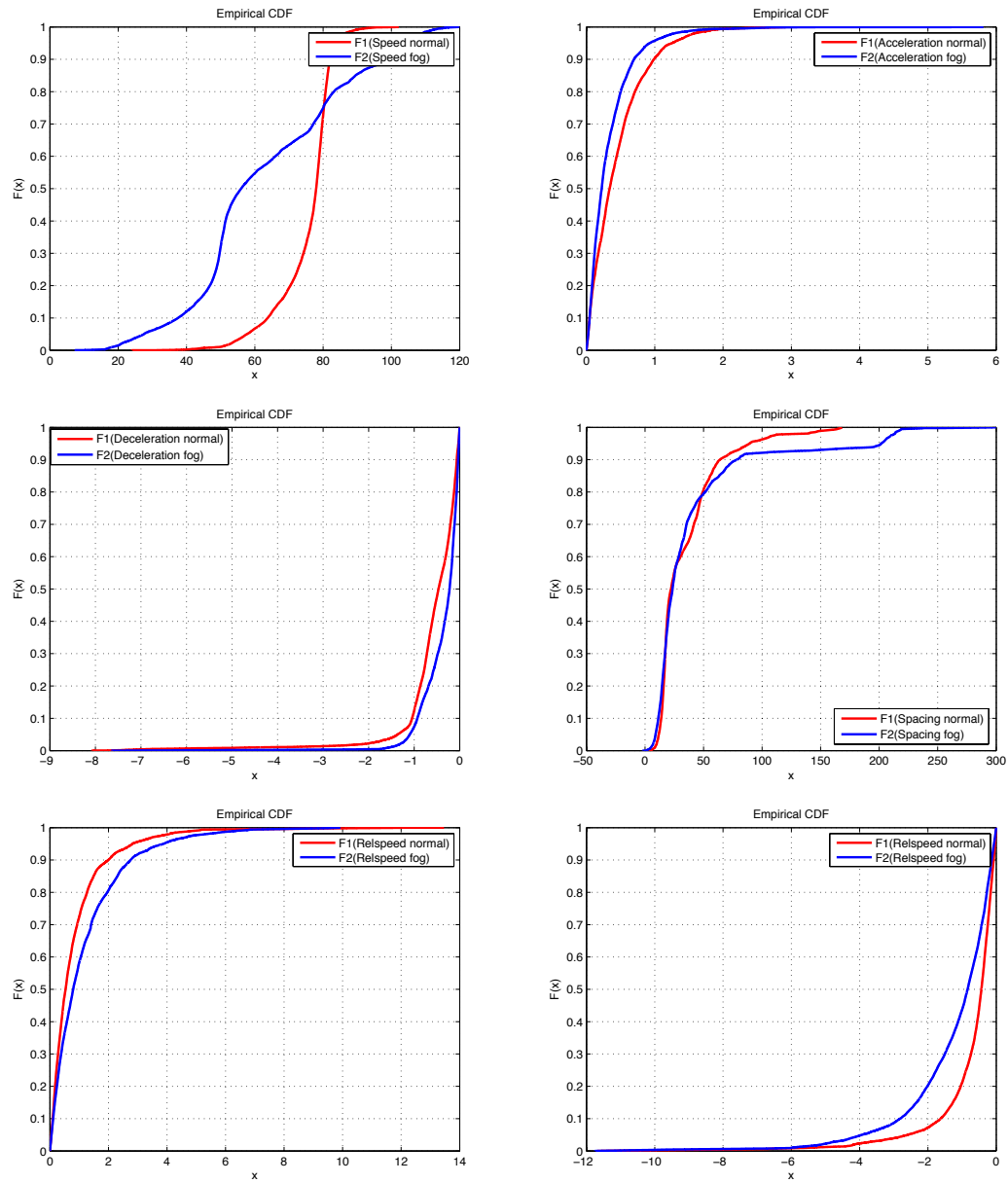


Figure 4.2: Empirical cumulative distribution functions in case of normal and adverse weather conditions.

4.4 Freeway incidents

Descriptive statistics with regard to the influence of freeway incidents on empirical longitudinal driving behavior are presented in Table 4.4. These descriptive statistics consist of the mean values in speed v , acceleration a , deceleration b , spacing s , as well as positive and negative relative speed (Δv_{pos} and Δv_{neg}) for the experimental conditions as well as the control condition ('before', 'during' and 'after' the incident in the other driving lane). As was mentioned in Chapter 3, the two experimental conditions consist of two car-accidents with a varying degree of severity. Standard deviations are displayed between parentheses.

From the table it can be observed that, in contrast with the control condition, mean values of speed v differ substantially between the three measurement periods in experimental condition 1 and 2. Before and after perception of the incidents mean speed v is higher than during perception of the incidents. Overall, standard deviations increased from before perception of the incidents to after perception of the incidents. For example the standard deviation in speed v increased from 12.70 before perception of the incident to 18.16 after perception of the incident in experimental condition 1.

With regard to the control condition it can be observed from Table 4.4 that mean values as well as standard deviations of acceleration a are quite similar. Furthermore it can be observed that in experimental condition 1 and 2 mean acceleration a decreased during perception of the incidents, after which it strongly increased after perception of the incidents.

For deceleration b a similar picture emerges as was the case with acceleration a . Here it can be observed from Table 4.4 that in the control condition no substantial differences are present between mean values of deceleration b . This is in contrast with experimental condition 1 and 2, in which it can be observed that mean deceleration b decreases substantially during perception of the incidents in the other driving lane. For example, deceleration b decreases from -0.19 before perception of the incident to -0.63 after perception of the incident in experimental condition 1. After the incidents were out of view deceleration b seems to increase again.

Spacing, denoted by s , also shows substantial adaptation effects during perception of incidents in the other driving lane. In the control condition no substantial differences can be observed between the three measurement periods. However, in experimental condition 1 and 2 a substantial increase in spacing s can be observed. For example, spacing s increases from 41.40 before perception of the incident to 57.61 during perception of the incident in the other driving lane. Standard deviations also increased substantially during perception of the incidents compared to before and after perception of the incidents.

As can be expected from these increases in spacing s , also an effect on relative speed Δv is present. In the control condition no substantial differences can be observed between the three measurement periods. Again, this is in contrast with experimental condition 1 and 2 in which positive relative speed Δv_{pos} and negative relative speed Δv_{neg} respectively increased and decreased during perception of the incidents in the other driving lane.

From the descriptive statistics presented in Table 4.4 it can therefore be concluded that substantial adaptation effects can be observed. As an illustration, cumulative distribution functions are

Table 4.4: Descriptive statistics of empirical adaptation effects in longitudinal driving behavior for the control group and the experimental group per condition.

	speed (km/h)	acceleration (m/s ²)	deceleration (m/s ²)
<i>Control condition</i>			
Before	73.44 (10.11)	1.45 (0.45)	-0.18 (0.41)
During	76.21 (11.98)	1.43 (0.54)	-0.23 (0.56)
After	74.37 (12.01)	1.38 (0.49)	-0.20 (0.38)
<i>Exp. cond 1</i>			
Before	72.39 (12.70)	1.47 (0.65)	-0.19 (0.45)
During	49.25 (18.00)	1.44 (0.30)	-0.63 (0.91)
After	61.64 (18.16)	1.65 (1.08)	-0.24 (0.39)
<i>Exp. cond. 2</i>			
Before	74.86 (8.20)	1.59 (0.99)	-0.23 (0.43)
During	47.20 (13.71)	1.37 (0.29)	-0.59 (0.68)
After	61.54 (15.59)	1.59 (0.57)	-0.26 (0.46)
	spacing (m)	pos. relspeed (km/h)	neg. relspeed (km/h)
<i>Control condition</i>			
Before	39.56 (29.88)	0.85 (0.45)	-0.76 (0.87)
During	43.22 (38.36)	0.96 (0.54)	-0.83 (0.45)
After	45.96 (28.63)	0.87 (0.49)	-0.79 (0.75)
<i>Exp. cond. 1</i>			
Before	41.40 (31.77)	0.96 (1.06)	-0.81 (0.97)
During	57.61 (58.28)	3.20 (3.06)	-2.42 (2.70)
After	32.62 (32.75)	1.64 (1.80)	-1.58 (2.11)
<i>Exp. cond. 2</i>			
Before	25.77 (16.02)	0.78 (1.10)	-0.72 (1.21)
During	35.21 (38.12)	2.08 (2.10)	-1.69 (1.62)
After	22.27 (14.58)	1.10 (0.86)	-1.34 (1.70)

presented for speed v , spacing s as well as positive relative speed Δv_{pos} and negative relative speed Δv_{neg} in experimental condition 1.

In order to establish whether these adaptation effects on longitudinal driving behavior are significant, a MANOVA for repeated measures was performed. The results of this analysis are presented in Table 4.5 and 4.6.

From Table 4.5 it can be observed that Time in the control condition does not have a significant influence on speed v , acceleration a , deceleration b , spacing s nor positive relative speed Δv_{pos} and negative relative speed Δv_{neg} . This is indicated by relative low values of F as well as large values of p . This is also supported by Pillai's Trace as values of λ_p are relatively low. This means that engaging in the control condition did not have a substantial effect on longitudinal driving behavior.

For the experimental conditions it follows from Table 4.6 that in general the factor Condition

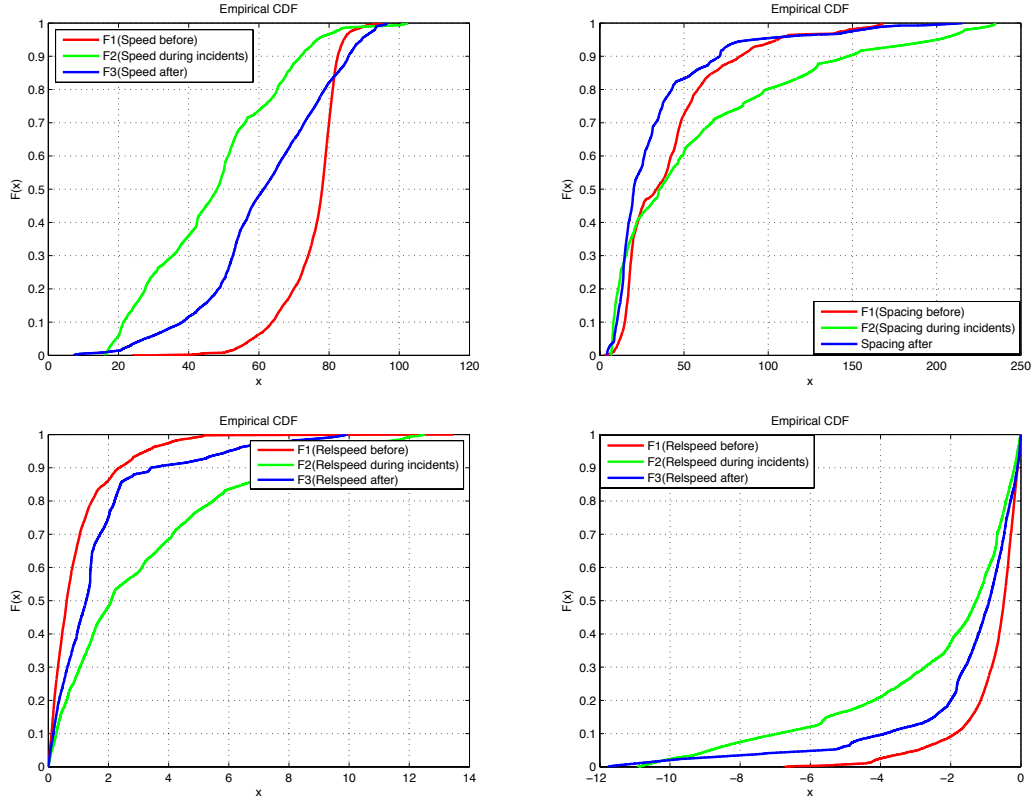


Figure 4.3: Cumulative distribution functions of v , s and Δv before, during and after perception of the incident in experimental condition 1.

Table 4.5: Results MANOVA for empirical adaptation effects in longitudinal driving behavior in case of freeway incidents for the control condition.

Variable	Pillai's Trace	F	df	Error df	p
Speed v	0.13	2.32	2	70	0.06
Acceleration a	0.06	1.54	2	70	0.36
Deceleration b	0.10	0.19	2	70	0.82
Spacing s	0.01	0.10	2	70	0.90
Positive relative speed Δv_{pos}	0.01	0.30	2	70	0.74
Negative relative speed Δv_{neg}	0.01	0.14	2	70	0.86

nor the interaction between Condition and Time has a significant effect on longitudinal driving behavior. Only a significant effect of Condition on spacing s can be observed. The factor Time however does have a significant effect on speed v , acceleration a , deceleration b , spacing s , positive relative speed Δv_{pos} and negative relative speed Δv_{neg} . This is indicated by relatively large values of F as well as smaller than 0.05 values of p . These findings are supported by Pillai's Trace as values of λ_p are relatively large. This means that overall time course has a significant effect on longitudinal driving behavior. However, no significant difference can be established between experimental condition 1 and 2.

From these results it can therefore be concluded that freeway incidents (i.e., incident in the

Table 4.6: Results Multivariate Analysis of Variance for empirical adaptation effects in longitudinal driving behavior freeway incidents.

Variable	Factor	Pillai's T	F	df	Error	p
Speed v	Condition	0.02	0.71	1	35	0.40
	Time	0.85	64.73	2	70	0.00
	Condition x Time	0.02	0.50	2	70	0.60
Acceleration a	Condition	0.00	0.00	1	35	0.98
	Time	0.22	6.59	1.56	54.80	0.00
	Condition x Time	0.00	0.02	1.57	55.07	0.90
Deceleration b	Condition	0.00	0.12	1	35	0.72
	Time	0.26	3.05	1.58	55.50	0.00
	Condition x Time	0.04	1.00	2	70	0.37
Spacing s	Condition	0.16	6.78	1	35	0.01
	Time	0.17	2.94	1.58	55.30	0.04
	Condition x Time	0.05	1.09	2	70	0.34
Pos. relspeed Δv_{pos}	Condition	0.06	2.35	1	35	0.13
	Time	0.38	13.54	1.50	52.67	0.00
	Urgency x Time	0.12	1.62	1.39	48.65	0.21
Neg. relspeed Δv_{neg}	Condition	0.05	1.82	1	35	0.18
	Time	0.19	5.10	2	70	0.01
	Condition x Time	0.05	0.59	1.68	58.81	0.52

other driving lane) have a substantial and significant effect on speed v , acceleration a , deceleration b , spacing s and relative speed Δv . Drivers seem to reduce their speed, while increasing their spacing. Furthermore it was shown that drivers reduce acceleration and deceleration. Finally, drivers follow the lead vehicle less closely, as indicated by larger values of relative speed.

4.5 Conclusions

In the previous sections the results with regard to empirical adaptation effects in longitudinal driving behavior in case of emergency situations, adverse weather conditions as well as freeway incidents were presented. In all the selected adverse conditions substantial adaptation effects in longitudinal driving behavior were observed.

From the results it followed that the adaptation effects of adverse weather conditions and freeway incidents are quite similar. Behavioral adaptation under these conditions is characterized by a substantial reduction in speed, acceleration and deceleration along with a substantial increase in spacing. Furthermore, it was concluded in the previous sections that drivers seem to follow the lead vehicle less actively in case of these adverse conditions. This was well-illustrated by the fact that positive and negative relative speed respectively increased and decreased substantially during the adverse conditions.

With regard to emergency situations a different picture emerged. In case of this adverse con-

dition, drivers adopt a higher speed along with stronger values of acceleration. Furthermore, it followed from the results that spacing decreased substantially. Also drivers seem to follow the lead vehicle more actively, which was well-illustrated by a reduction and an increase in respectively positive and negative relative speed.

However, when observing the reported results of empirical longitudinal driving behavior under adverse conditions, it can also be concluded that the degree of variability is quite substantial. In all three conditions standard deviations of speed, acceleration, deceleration, spacing and relative speeds were considerably large.

In Chapter 2 we introduced a theoretical framework relating adverse conditions to longitudinal driving behavior using the TCI model by Fuller (2005). In this framework it was proposed that adverse conditions lead to compensation effects as well as to performance effects.

In case of adverse weather conditions a compensatory reduction in speed can be observed along with an increase in spacing. This can also be assumed in case of freeway incidents. These conscious or deliberate reductions in speed are assumed to be executed in order to reduce the difficulty of the driving task. In other words: drivers reduce their speed in order to reduce task demands therefore aiming to resolve the imbalance between driver capability and task demands.

Under emergency situations also compensation effects in speed can be observed. Drivers show an increase in speed in order to reach their destination in time. Furthermore, they reduce distance to the lead vehicle to force other drivers to accelerate or move out of the way (Hamdar & Mahmassani, 2008). In other words: a large degree of tailgating could be observed.

Besides these compensation effects in speed and spacing, in the theoretical framework also less conscious effects are proposed. These performance effects are the result of a situation in which the compensation effects a driver applies are insufficient in order to resolve the imbalance between driver capabilities and task demands. These performance effects may for example consist of a reduction in the performance of the car-following subtask. These effects could be indicated by the amplitude of relative speed.

However, relative speed may not be a very good indicator of the adequacy of the performance of the car-following task, as it is largely dependent on spacing. In this context in Chapter 8 we turn to the determination of model performance of the Intelligent Driver Model (Treiber et al., 2000). Model performance can be assumed to be an adequate indicator of how well the car-following task is performed.

The observed adaptation effects in empirical longitudinal driving behavior in case of adverse conditions however do not inform us to what extent they are caused by an imbalance between driver capabilities and task demands leading to changes in mental workload. To this end, the next chapter reports the results of the influence of adverse conditions on mental workload.

Chapter 5

Mental workload and Driver Characteristics Under Adverse Conditions

5.1 Aim and structure of this chapter

In the theoretical framework introduced in Chapter 2, it was assumed that drivers strive for a balance between driver capabilities and task demands. Driver capabilities are influenced by personal characteristics of the driver (e.g., age and driving experience) as well as by activation level and distraction, while task demands are influenced by the difficulty of the driving task (e.g., visibility). When an imbalance between driver capabilities and task demands occurs, drivers are assumed to exert influence over the elements of the driving task over which they have direct control (compensation effects).

The results presented in Chapter 4 indeed are an indication for strong compensation effects in empirical longitudinal driving behavior. For example, during emergency situations an increase in speed can be observed as well as an increase in acceleration and deceleration along with a reduction in distance to the lead vehicle. During adverse weather conditions and freeway incidents a reduction in speed, acceleration and deceleration together with an increase in distance to the lead vehicle can be observed.

In the theoretical framework it was assumed that when these compensation effects are insufficient to resolve the imbalance between driver capability and task demands, mental workload will remain higher than normal and driving performance will deteriorate.

Following the theoretical framework it can therefore be assumed that adverse conditions lead to changes in mental workload, moderated by personal characteristics of drivers. However, as became clear from Chapter 2, no specific research on the influence of adverse conditions during driving tasks on mental workload, moderated by personal characteristics (i.e., age and driving experience) was found. To this end, the present chapter presents the results of the three driving simulator experiments on the influence of adverse conditions on mental workload (moderated by personal characteristics) as described in Chapter 3.

In Section 5.2 we start with a presentation of the results of the statistical analyses of the influence of emergency situations on mental workload. In this section descriptive statistics as well

as the results of the Multivariate Analysis of Variance pertaining to the indicators of mental workload are reported.

We continue with a presentation of the results pertaining to the influence of adverse weather conditions on mental workload in Section 5.3, followed by a presentation of the results regarding the influence of freeway incidents on mental workload in Section 5.4. This chapter is concluded with a Conclusion in Section 5.5.

5.2 Mental workload and driver characteristics in case of emergency situations

The theoretical framework in Chapter 2 assumes that emergency situations influence mental workload of the driver through activation level. A higher activation level is assumed to lead to an imbalance between driver capability and task demands, leading to an increase in mental workload. The personal characteristics age and driving experience of drivers are assumed to moderate the influence emergency situations have on mental workload, also through the influence on driver capability.

In order to empirically underpin the influence emergency situations have on mental workload (moderated by personal characteristics) in the next portion of this section we report the results of the driving simulator experiment described in Chapter 3. To this end in the next subsection we report the findings with regard to the influence of emergency situations on the physiological indicators of mental workload heart rate and heart rate variability (HRV).

5.2.1 Influences on physiological indicators of mental workload

In Table 5.1 the descriptive statistics of heart rate and HRV are displayed. In this table mean transformed values of heart rate as well as HRV are presented along with the standard deviations. In this context values of heart rate as well as HRV were transformed by expressing them as a fraction of a preceding baseline measurement. Heart rate and HRV were both synchronized with the duration of the within subject conditions.

In the table, transformed values are displayed per group (the experimental group and the control group) as well as per condition ('On Time', 'Behind Schedule' and 'Out of Time').

From Table 5.1 it can be observed that no substantial differences in heart rate are present between the experimental group and the control group. However, mean HRV is substantially lower in the experimental group. When comparing the three conditions per group it can be observed from the table that heart rate and also HRV do not substantially differ between the three conditions in the control group.

In contrast with heart rate, mean values of HRV differ substantially between the three conditions in the experimental group. In the 'On Time' condition mean HRV is higher than in the 'Behind Schedule' condition, while mean HRV in the 'Out of Time condition' is lower than in the other two conditions.

Table 5.1: Descriptive statistics of heart rate (HR) and heart rate variability (HRV) for the control group and the experimental group per condition. HR as well as HRV are expressed as a fraction of a preceding baseline measurement.

	Mean HR	SD HR	Mean HRV	SD HRV
On Time (contr)	1.16	0.32	1.00	0.25
Behind Schedule (contr)	1.15	0.30	0.99	0.29
Out of Time (contr)	1.11	0.22	0.99	0.26
On Time (exp)	1.13	0.30	0.96	0.31
Behind Schedule (exp)	1.14	0.23	0.88	0.40
Out of Time (exp)	1.12	0.36	0.79	0.45

When comparing the standard deviations for heart rate, it can be observed from the table that these differ substantially when comparing the three conditions in the control group. Also substantial differences in standard deviations can be observed when comparing the three conditions in the experimental group.

A similar picture emerges for HRV. Here also, large differences in standard deviations can be found when comparing the control group to the experimental group. Moreover, the standard deviations differ substantially when comparing the three conditions in the experimental group.

In Figure 5.1 the cumulative distribution functions for heart rate and HRV are depicted for the experimental group. From these functions it can be observed that there is no substantial difference in HR between the three conditions. Also, it can be observed from the figure that the cumulative distribution functions of HRV differ substantially. The function of HRV in the 'Out of Time' condition is substantially lower than the other two conditions. Also a substantial difference can be observed between the 'On Time' and the 'Behind Schedule' condition.

Table 5.2: Results Multivariate Analysis of Variance for physiological indicators of mental workload in case of emergency situations.

Variable	Factor	Pillai's Trace	<i>F</i>	<i>df</i>	Error <i>df</i>	<i>p</i>
HR	Urgency	-	1.53	1	38	0.22
	Time	0.02	0.47	2	76	0.62
	Urgency x Time	0.01	0.16	2	76	0.85
HRV	Urgency	-	7.79	1	38	0.00
	Time	0.09	1.65	2	76	0.09
	Urgency x Time	0.01	0.26	2	76	0.77

The aforementioned is partly supported by the results of the MANOVA in Table 5.2. In this table the result of Pillai's Trace as well as the F-ratio, degrees of freedom, the error degrees of freedom and the p-values are reported for heart rate as well as for HRV.

The table shows that neither for heart rate a main effect of Urgency nor the main effect of Time is significant ($p > 0.05$). Furthermore, no significant effect of Urgency on time course can be

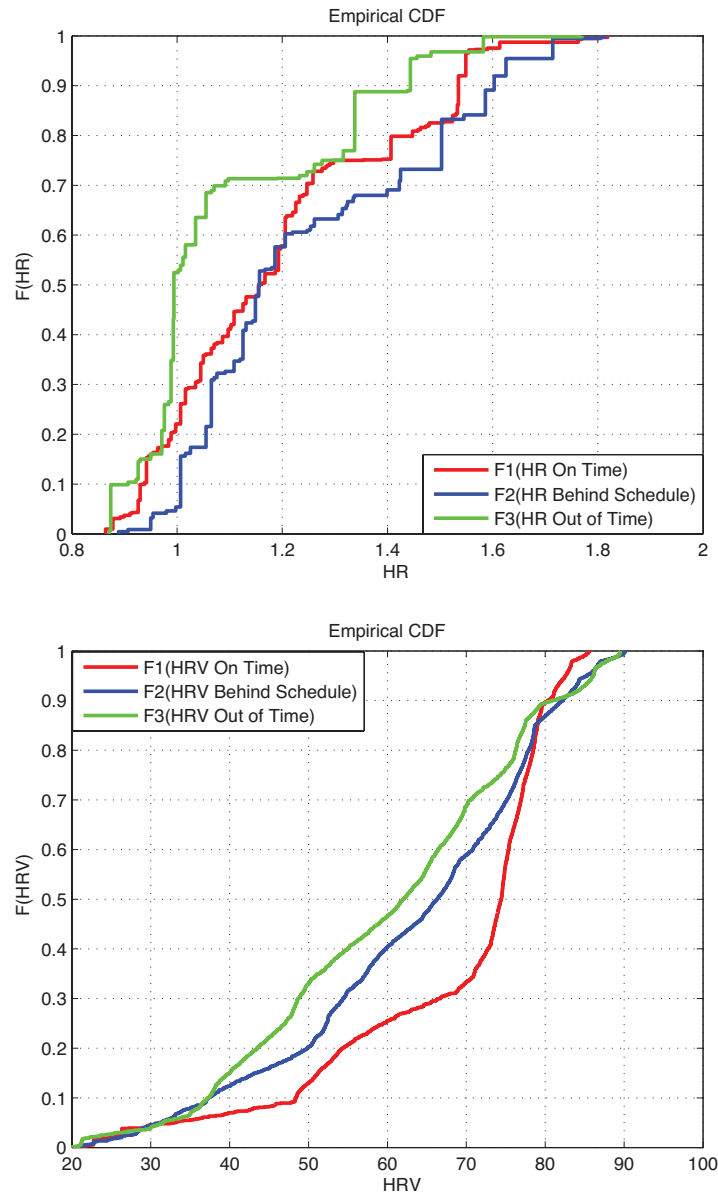


Figure 5.1: Cumulative distribution functions of HR (top) and HRV (bottom) during the On Time, Behind Schedule and Out of Time condition in the experimental group.

observed ($p > 0.05$). This is also supported by the results of Pillai's Trace as values of λ_p are relatively low.

For HRV it can be observed from Table 5.2 that there is a significant effect of Urgency ($F(1, 38) = 7.79, p < 0.05$). This means that HRV in the experimental group differs significantly from the control group. However, no significant effect of Time nor an effect of Urgency on time course can be observed ($p > 0.05$).

In this regard we additionally performed a MANOVA with the Factor Time as a within subject factor for the experimental group only. From this additional analysis it followed that there was a significant effect of Time on HRV, as $F(1, 18) = 8.27, p < 0.05$. These findings are also supported by Pillai's Trace, as $\lambda_p = 0.53$.

When observing the descriptive statistics as well the results of the MANOVA it can therefore be concluded that overall participants in the experimental group experienced a significantly lower HRV compared to the control group. The additional analysis showed clearly that time course has a significant influence on HRV.

Furthermore it was shown in this section that there was no significant difference in mean heart rate between the two groups. Also time course did not have a significant effect on heart rate.

In Chapter 3 we stated that mental workload can best be approximated using several measures. However, as became clear from the findings reported in this section, only an effect of emergency situations on one indicator of mental workload was established. Therefore these findings do not clearly support the assumptions made in the theoretical framework proposed in Chapter 2. In other words: although the reduction in HRV seems to suggest an increase in mental workload it is not clear whether emergency situations actually lead to changes in mental workload of the drivers due to the fact that this effect was not supported by other indicators.

5.2.2 Influence of driver characteristics

In the theoretical framework in Chapter 2 it was mentioned that the personal characteristics age and driving experience influence mental workload through driver capability. In order to analyze the effects of these variables several Multiple Regression Analyses were performed with age and driving experience as independent variables and heart rate and HRV as independent variables.

Table 5.3: Results Multiple Regression Analysis of HR and HRV in case of emergency situations.

Dependent	Conditions	Independent	<i>Beta</i>	R^2	<i>F</i>	<i>df</i>	Error	<i>p</i>
Heart rate	On Time	Age	-0.63	0.13	1.24	2	16	0.31
		Experience	0.28					
Heart rate	Behind Schedule	Age	-0.06	0.06	0.56	2	16	0.58
		Experience	-0.19					
Heart rate	Out of Time	Age	-0.72	0.09	0.87	2	16	0.43
		Experience	0.46					
HRV	On Time	Age	-0.07	0.84	43.10	2	16	0.00
		Experience	0.91					
HRV	Behind Schedule	Age	-0.09	0.31	3.60	2	16	0.05
		Experience	0.68					
HRV	Out of Time	Age	-0.17	0.43	6.05	2	16	0.01
		Experience	0.61					

In Table 5.3 the results of the MRA are reported. In this table *Beta* (being the coefficient) is displayed. Furthermore in the table R^2 (explained variance), the F-ratio, degrees of freedom, error degrees of freedom and the p-value are reported for the influence of age and driving experience on heart rate as well as on HRV.

From this table it can clearly be observed that personal characteristics had a substantial and significant influence on HRV ($p < 0.05$). The influence of age and driving experience on HR was not significant ($p > 0.05$).

From the table it also becomes clear that the explained variances (R^2) of these personal characteristics for HRV are quite substantial. Explained variances range from 0.84 in the 'On Time' condition to 0.31 in the 'Behind Schedule' condition.

The values of *Beta* indicate that there is a positive causal relationship between driving experience and HRV. When driving experience increases, HRV also increases. As a higher HRV is an indication for a lower mental workload, this result shows that more driving experience leads to less mental workload during an emergency situation as indicated by the HRV.

This is an indication in favor of the assumption that driving experience influences mental workload through driver capability. When drivers are more experienced, they experience less mental workload in case of driving under emergency situations.

With regard to the influence of age on HRV the relationships are less clear. Overall the values of *Beta* are quite small. For example, the value of *Beta* in the 'On Time' condition only amounted to -0.07. The value indicates that when age increases, HRV decreases. This can however be regarded as a small influence compared to driving experience.

5.3 Mental workload and driver characteristics in case of adverse weather conditions

In the theoretical framework in Chapter 2 it is assumed that adverse weather conditions influence mental workload of the driver through an increase in task demand. An increase in task demand is assumed to lead to an imbalance between driver capability and task demand, resulting in an increase in mental workload. Furthermore it was assumed that personal characteristics (i.e., age and driving experience) moderate the influence adverse weather conditions have on mental workload through the influence on driver capability. In order to test these assumptions the results of the driving simulator experiment on the influence of adverse weather conditions on mental workload are reported in this section.

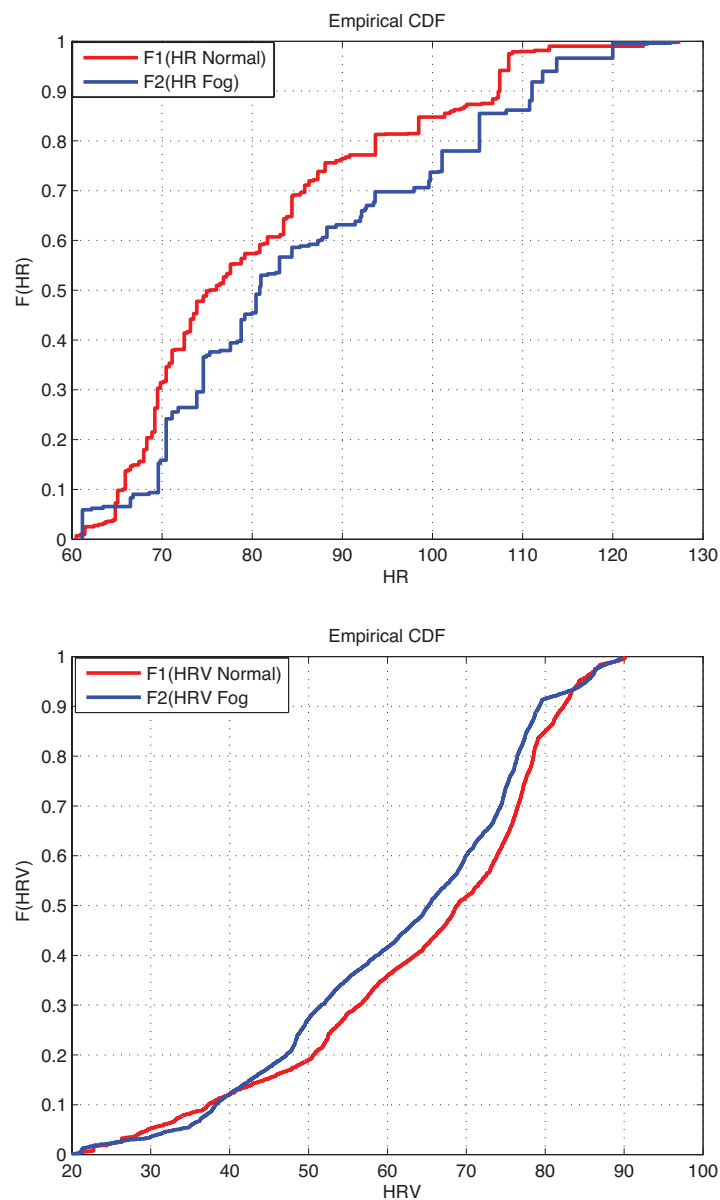
5.3.1 Influences on physiological indicators of mental workload

In Table 5.4 the descriptive statistics of the physiological indicators of mental workload are presented. The table shows the mean values of heart rate and HRV along with the standard deviations for the control condition (normal weather) as well as the experimental condition (adverse weather).

From the table it follows that mean heart rate increased from 1.15 ($SD = 0.21$) in the control condition to 1.22 ($SD = 0.23$) in the experimental condition. Furthermore from the results it follows that HRV decreased from 1.07 ($SD = 0.27$) in the control condition to 1.03 ($SD = 0.26$) in the experimental condition. These differences in heart rate and HRV between the experimental and the control condition are also well-illustrated by Figure 5.2. In this figure cumulative distribution functions are depicted for heart rate as well as for HRV.

Table 5.4: Descriptive statistics of transformed heart rate (HR) and HRV for the control condition (normal weather) and the experimental condition (fog).

	Mean HR	SD HR	Mean HRV	SD HRV
Normal weather (control cond.)	1.15	0.21	1.07	0.27
Adverse weather (experimental cond.)	1.22	0.32	1.03	0.26

**Figure 5.2: Cumulative distribution functions heart rate (top) and HRV (bottom) under normal driving conditions and adverse weather conditions (fog).**

The aforementioned differences are supported by the paired samples t-tests. Heart rate differences between the two conditions are significant as $t(24) = -2.13, p < 0.05$. For HRV the paired sample t-test showed that $t(24) = 2.08, p < 0.05$.

From the aforementioned it can be concluded that heart rate as well as HRV show significant changes due to the adverse weather condition. From the results it can be observed that heart rate increased significantly due to the adverse weather condition, while HRV decreased significantly. This is an indication for an increase in mental workload due to this adverse condition.

5.3.2 Influence on subjective estimates of effort

The results of the Rating Scale Mental Effort (Zijlstra & Doorn, 1985) show that in the control condition the mean score was 27.93 ($SD = 10.54$), while in the experimental condition this score amounted to 28.33 ($SD = 15.03$). From the paired sample t-tests it followed that differences between the two conditions were not significant ($p > 0.05$).

This means that subjectively measured mental workload, contrary to objectively measured mental workload, was not significantly influenced by the adverse weather condition.

5.3.3 Influence of driver characteristics

The theoretical framework in Chapter 2 also mentioned that personal characteristics (i.e., age and driving experience) influence mental workload in case of adverse weather conditions through driver capability. In order to analyze the effects of these variables Multiple Regression Analyses were performed with age and driving experience as independent variables and heart rate and HRV as independent variables.

From the Multiple Regression Analysis it follows that age and driving experience have a significant influence on HRV in case of the adverse weather condition ($p > 0.05$). The influence of age and driving experience on heart rate was not significant ($p > 0.05$). The significant causal relationship between age, driving experience and HRV was negative and positive respectively, indicating that an increase in age leads to a reduction in HRV, while an increase in driving experience leads to an increase in HRV.

5.4 Mental workload and driver characteristics in case of freeway incidents

In the theoretical framework in Chapter 2 it was assumed that freeway incidents may influence driver capability through distraction. Distraction is assumed to lead to an imbalance between driver capability and task demand, leading to an increase in mental workload. Furthermore it was assumed that the personal characteristics moderate the influence freeway incidents have on mental workload through the influence on driver capability as well. In order to test these assumptions the results of the driving simulator experiment on the influence of freeway incidents on mental workload are reported.

5.4.1 Influences on physiological indicators of mental workload

In Table 5.5 descriptive statistics are presented for transformed amplitudes of the zygomaticus major (smiling), corrugator supercillii (frowning), respiration rate, heart rate and HRV.

These descriptive statistics consist of the mean transformed values along with the standard deviations (between parentheses) for the different conditions. The table shows that the mean values in the control condition are quite similar. Also it can be observed from the table that standard deviations are relatively large.

Table 5.5: Mean transformed values and standard deviations (between brackets) of transformed amplitudes of the zygomaticus major, corrugator supercillii, respiration rate, heart rate and HRV for the various conditions.

	ZM	CS	RR	HR	HRV
Before (control)	0.95 (0.91)	0.98 (1.04)	0.89 (0.34)	1.05 (0.33)	0.98 (0.61)
During (control)	1.06 (0.89)	1.04 (1.22)	0.78 (0.25)	1.03 (0.27)	1.00 (0.73)
After (control)	0.86 (0.68)	1.03 (1.08)	0.88 (0.30)	1.06 (0.31)	0.99 (0.42)
Before (exp 1)	0.93 (0.73)	0.94 (0.96)	0.98 (0.42)	0.99 (0.14)	1.11 (0.63)
During (exp 1)	1.15 (0.91)	3.13 (2.75)	1.27 (0.64)	1.00 (0.17)	1.05 (0.74)
After (exp 1)	0.94 (0.75)	1.04 (1.04)	1.15 (0.58)	0.96 (0.13)	1.02 (1.21)
Before (exp 2)	1.03 (0.85)	0.95 (1.02)	1.03 (0.47)	0.93 (0.12)	1.01 (0.67)
During (exp 2)	1.14 (1.45)	2.83 (2.01)	1.36 (0.74)	0.95 (0.14)	0.97 (0.98)
After (exp 2)	1.15 (1.28)	1.02 (0.99)	1.22 (0.65)	1.01 (0.29)	0.83 (0.75)

It can also be observed from the table that the mean value of the amplitude of the zygomaticus major is substantially higher during perception of the incident in experimental condition 1 compared to before and after perception of the incident. Furthermore it can be observed from this table that this value is substantially higher after perception of the incident in experimental condition 2 compared to before and during perception of the incident. For mean transformed amplitudes of the corrugator supercillii and respiration rate a similar picture emerges as mean values were substantially higher during perception of the incidents in experimental condition 1 and 2 compared to the measurement periods before and after perception of the incidents.

For heart rate and HRV no substantial differences between the three measurement periods in experimental condition 1 and 2 can be observed. That a substantial difference in mean values between the three measurement periods for amplitudes of the zygomaticus major, corrugator supercillii as well as respiration rate is present, is supported by the constructed cumulative distribution functions in Figure 5.3.

These findings are also supported by the results of the MANOVA for repeated measures. The results are presented in Table 5.6 and 5.7. Again, in this table the results of Pillai's Trace are reported together with the F-ratio, the degrees of freedom, the error degrees of freedom and the p-value.

From Table 5.6 it can be observed that the effect of Time was not significant for transformed amplitudes of the zygomaticus major, corrugator supercillii, respiration rate, heart rate and HRV in the control condition. This means that engaging in the control condition did not have a significant influence on these physiological indicators of mental workload.

From Table 5.7 it can be observed that the factor Condition only has a significant effect on transformed amplitudes of the corrugator supercillii. The effect of Condition on amplitude

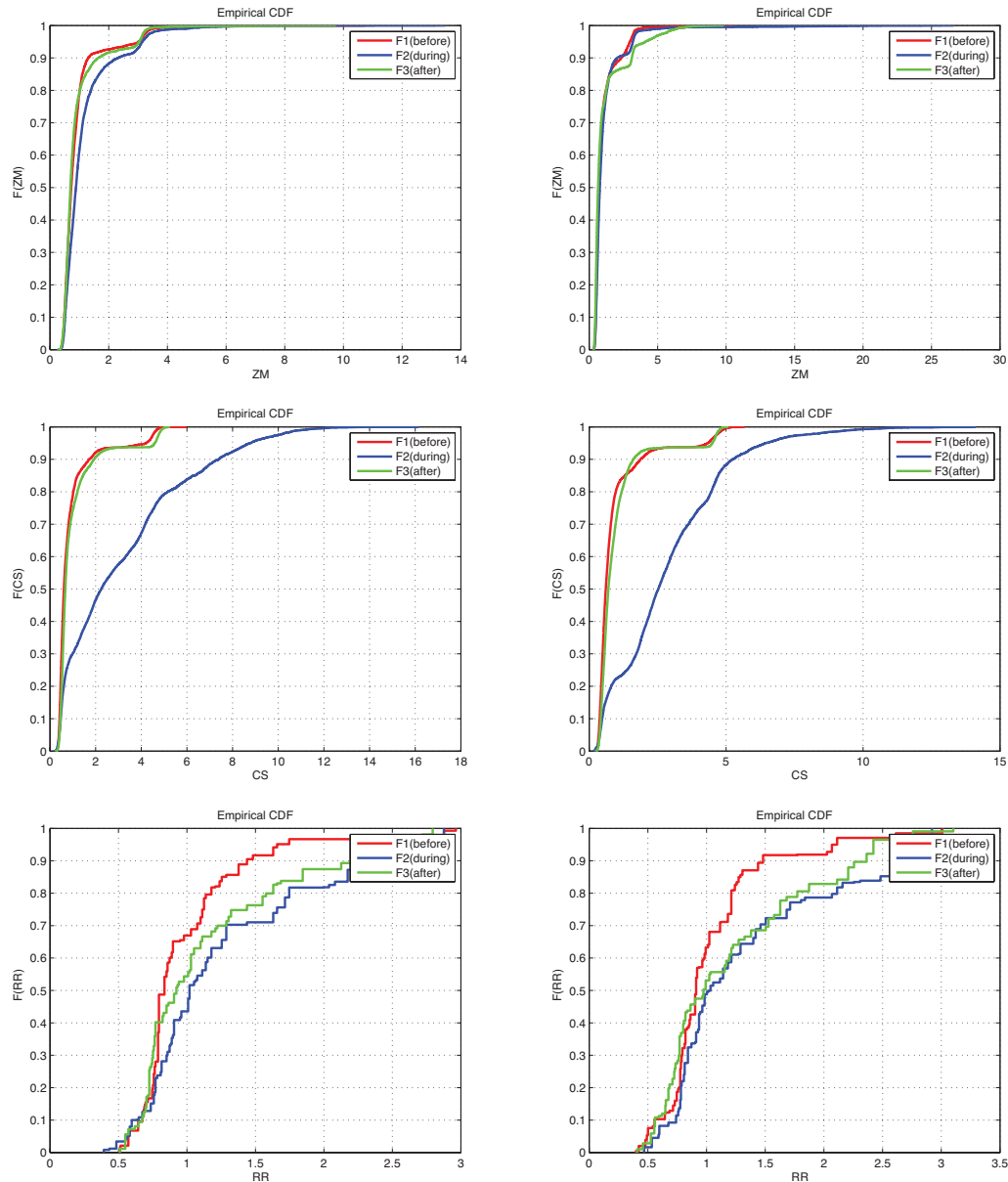


Figure 5.3: Cumulative distribution functions of transformed EMG amplitudes of the zygomaticus major (ZM), corrugator supercillii (CS) and respiration rate (RR) before, during and after perception of the incident in the control condition.

of the zygomaticus major, respiration rate, heart rate and HRV is not significant. This means that, regardless of time course, there is no significant difference between the two experimental conditions.

The factor Time has a significant effect on amplitude of the corrugator supercillii as well as respiration rate. This means that overall time course, irrespective of the experimental condition, has a significant effect on these physiological indicators of mental workload. For amplitude of the zygomaticus major, heart rate and HRV overall time course does not have a significant effect.

Finally, only for transformed amplitudes of the corrugator supercillii the interaction of Condi-

Table 5.6: Results MANOVA for EMG activity of the zygomaticus major (ZM), EMG activity of the corrugator supercillii (CS), respiration rate (RR), heart rate (HR) and heart rate variability (HRV) in case of freeway incidents for the control condition.

Variable	Pillai's Trace	<i>F</i>	<i>df</i>	Error <i>df</i>	<i>p</i>
ZM	0.13	0.75	3	105	0.18
CS	0.06	1.26	1.62	56.77	0.24
RR	0.10	2.38	2.12	74.28	0.13
HR	0.01	1.55	1.72	60.35	0.83
HRV	0.03	1.83	1.61	60.24	0.58

Table 5.7: Results MANOVA for EMG activity of the zygomaticus major (ZM), EMG activity of the corrugator supercillii (CS), respiration rate (RR), heart rate (HR) and heart rate variability (HRV) in case of freeway incidents for experimental condition 1 and 2.

Variable	Factor	Pillai's Trace	<i>F</i>	<i>df</i>	Error <i>df</i>	<i>p</i>
ZM	Condition	0.02	0.99	1	35	0.32
	Time	0.13	1.93	2	70	0.15
	Condition x Time	0.01	.24	2	70	0.78
CS	Condition	0.04	1.77	1	35	0.19
	Time	0.60	52.72	2	70	0.00
	Condition x Time	0.13	4.28	2	70	0.01
RR	Condition	0.00	0.10	1	35	0.75
	Time	0.09	22.72	2	70	0.00
	Condition x Time	0.01	0.07	2	70	0.92
HR	Condition	0.00	0.03	1	35	0.86
	Time	0.00	0.10	2	70	0.90
	Condition x Time	0.07	0.83	2	70	0.43
HRV	Condition	0.01	0.02	1	35	0.44
	Time	0.00	0.15	2	70	0.87
	Condition x Time	0.02	0.74	2	70	0.49

tion x Time has a significant effect. This means that for all other physiological indicators of mental workload no significant difference between the two experimental conditions could be observed.

It can therefore be concluded that freeway incidents lead to an increase in some physiological indicators of mental workload, as indicated by an increase in the amplitude of the corrugator supercillii as well as an increase in respiration rate. Overall, there is no significant difference between the two versions of the incident.

5.4.2 Influence on subjective estimates of effort

The results of the Rating Scale Mental Effort (Zijlstra & Doorn, 1985) show that in the control condition the mean score amounted to 28.91 ($SD = 12.22$). In experimental condition 1 the score was 29.30 ($SD = 15.40$), while in experimental condition 2 it amounted to 28.58 ($SD = 15.63$). From the Multivariate Analysis of Variance it follows that the factor Condition did not have a significant effect ($p > 0.05$). This means that the freeway incidents do not have a significant effect on subjective estimates of effort.

5.4.3 Influence of driver characteristics

In the previous sections the influence of freeway incidents on physiological indicators of mental workload as well as on subjective estimates of mental workload was analyzed. It was shown that freeway incidents lead to a significant increase in some of the physiological indicators of mental workload. In the theoretical framework in Chapter 2 it was however assumed that age and driving experience influence driver capability, thus having an influence on mental workload as well.

A Multiple Regression Analysis was performed with Age and Driving experience as independent variables and the physiological indicators of mental workload in experimental condition 1 as dependent variables. The results are presented in Table 5.8

From the Multiple Regression Analysis it follows that personal characteristics significantly predicted amplitudes of the zygomaticus major and corrugator supercillii. Explained variances were quite substantial, as indicated by the values of R^2 .

From the values of *Beta* it follows that an increase in age leads to a increase in the amplitude of these facial muscles before, during and after perception of an incident in the other driving lane. From the values of *Beta* it follows also that an increase in driving experience leads to a reduction in the amplitudes of the facial muscles before, during and after perception of an incident in the other driving lane.

Age and driving experience only significantly predicted respiration rate during perception of the incident in the other driving lane. It can be observed from Table 5.8 that an increase in age is accompanied by an increase in respiration rate during perception of an incident in the other driving lane. This was however not the case before and after perception of the incident, as these relationships were not significant. Personal characteristics did not significantly predict heart rate nor HRV in this experiment.

From the aforementioned it follows that personal characteristics (i.e., age and driving experience) have an influence on the physiological indicators EMG amplitudes of the zygomaticus major (smiling) and the corrugator supercillii (frowning) during before, during and after perception of a freeway incident. Only a significant causal relationship was found between these personal characteristics and respiration rate during perception of a freeway incident. The results showed that a higher age and less driving experience leads to a higher respiration rate.

Overall it can therefore be concluded that there is a strong indication that the personal characteristics age and driving experience have an influence on mental workload in the context of freeway incidents.

Table 5.8: Results Multiple Regression Analysis of the physiological indicators of mental workload amplitude of the zygomaticus major (ZM), corrugator supercillii (CS), respiration rate (RR), heart rate (RR) and heart rate variability (HRV) in case of a freeway incident.

Dependent	Conditions	Independent	<i>Beta</i>	R^2	<i>F</i>	<i>df</i>	Error	<i>p</i>
ZM	Before	Age	1.49	0.31	7.68	2	33	0.00
		Experience	-1.03					
ZM	During	Age	1.48	0.35	5.73	2	33	0.01
		Experience	-0.50					
ZM	After	Age	1.23	0.26	5.67	2	33	0.01
		Experience	-0.46					
CS	Before	Age	1.07	0.59	26.77	2	33	0.00
		Experience	-1.10					
CS	During	Age	1.42	0.61	83.61	2	33	0.00
		Experience	-0.60					
CS	After	Age	1.93	0.52	17.88	2	33	0.00
		Experience	-0.61					
RR	Before	Age	-0.70	0.13	2.64	2	33	0.08
		Experience	-1.05					
RR	During	Age	0.96	0.17	4.66	2	33	0.02
		Experience	-1.24					
RR	After	Age	-1.03	0.15	3.06	2	33	0.06
		Experience	1.96					
HR	Before	Age	-1.62	0.00	1.09	2	33	0.34
		Experience	0.71					
HR	During	Age	-0.36	0.04	0.83	2	33	0.44
		Experience	0.55					
HR	After	Age	-0.41	0.04	0.85	2	33	0.43
		Experience	0.59					
HRV	Before	Age	1.02	0.01	1.03	2	33	0.22
		Experience	-0.68					
HRV	During	Age	0.32	0.02	0.79	2	33	0.29
		Experience	-0.39					
HRV	After	Age	0.39	0.02	0.75	2	33	0.11
		Experience	-0.41					

5.5 Conclusion

In Chapter 2 a theoretical framework was introduced aiming to explain the effects adverse conditions have on empirical longitudinal driving behavior. It was proposed to divide adaptation effects in longitudinal driving behavior into compensation effects and performance effects. This theoretical framework based on the Task-Capability-Interface model by Fuller (2005) assumes that changes in mental workload occur through changes in the balance between driver capabilities and task demands.

In order to test this theoretical framework the results of three driving simulator experiments regarding the influence of adverse conditions on mental workload, moderated by driver characteristics were reported in this chapter. From the results it followed that emergency situations have a significant influence on heart rate variability (HRV). HRV was significantly lower in the experimental group with the emergency situation compared to the control group. Time course also had a significant influence, as in the experimental group the 'Out of Time' condition showed a lower mean HRV than in the 'On Time' and the 'Behind Schedule' condition. Mean HRV in the 'Behind Schedule' condition was lower than in the 'On Time' condition.

Heart rate however showed to not be affected by the emergency situation. No significant differences were found between the experimental group and the control group and no effect was found of time course on this physiological indicator of mental workload.

Adverse weather conditions did have a significant influence on heart rate as well as HRV. The adverse weather condition resulting in a reduction in visibility led to an increase in heart rate and a reduction in HRV. However, the adverse weather condition did not have a significant effect on subjective estimates of effort, measured through the RSME (Zijlstra & Doorn, 1985). This is probably due to the differing sensitivities of the used measures. In the rest of this section we will provide an in-depth explanation for these findings.

With regard to freeway incidents the results were less clear. Significant effects of perception of an incident in the adjacent driving lane were only established for mean amplitude of the corrugator supercilii (frowning) and respiration rate. No significant effects were found on heart rate and amplitudes of the zygomaticus major. As was the case with adverse weather conditions, no significant effects were found on subjective estimates of effort expenditure.

From these results it can be concluded that overall the adverse conditions emergency situations, adverse weather conditions and freeway incidents seem to have an influence on some of the physiological indicators of mental workload. As only an effect on one indicator of mental workload was found in case of emergency situations, no clear conclusions can be drawn. Although the significant reduction in HRV is a strong indication for increased effort, this is insufficient to empirically underpin the proposed theoretical framework proposed in Chapter 2.

With regard to adverse weather conditions and freeway incidents an influence on mental workload can be assumed. In both adverse conditions more than one indicator of mental workload changed substantially. For example, in case of freeway incidents both the amplitude of the corrugator supercilii (frowning) as well as respiration rate increased significantly. This can be regarded as an empirical underpinning of the proposed theoretical framework. Adverse

weather conditions and freeway incidents seem to lead to an increase in task demands and driver capability (through distraction) respectively.

The fact that with regard to some physiological measures no effect was found may be due to the different sensitivities of the physiological measures. It has indeed been shown that measures have different sensitivities even within the same region of mental workload. This is well illustrated in Figure 5.4 (borrowed from De Waard, 1996).

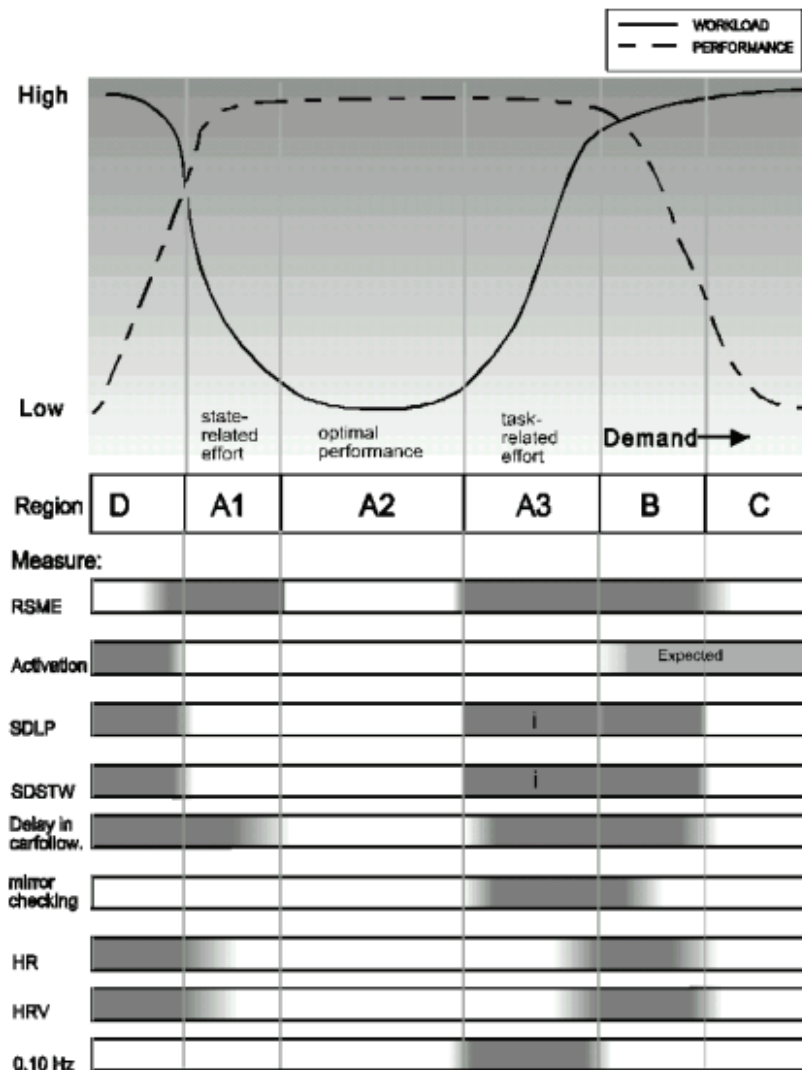


Figure 5.4: Workload in six regions and sensitivity of different measures (De Waard, 1996). The darker colors indicate a higher sensitivity of the measure.

From this figure it can clearly be observed that the sensitivity of a certain measure is dependent on workload in relation with task performance. According to the figure heart rate is most sensitive in regions where workload is very low or very high and the resulting task performance is low. The 0.10 Hz frequency band of HRV is most sensitive in the region where workload increases, but performance remains relatively high.

In our experiment with the emergency situation, workload may be assumed to be relatively high and increasing over time due to the increasing level of urgency. In Figure 5.4 this is represented by Region A3. From the figure it can be observed that in this region the 0.10 Hz

frequency band of HRV can be assumed to be a sensitive measure. Heart rate however is not a very sensitive measure in this region. Looking at the results reported in this chapter we indeed established an influence of the emergency situation on HRV, but not on heart rate.

In the experiment with the adverse weather condition, workload may be assumed to be relatively high, while performance deteriorates (also due to the reduced visibility). In Figure 5.4 this is represented by Region B. In this region heart rate as well as HRV are assumed to be sensitive measures. In our experiment we established an effect of the adverse weather condition on heart rate. We also established an effect on HRV. As we measured HRV through a frequency band of 0.07-0.14 Hz, it can be assumed that this measure is also sensitive in Region B. We indeed did establish an effect of adverse weather conditions on both heart rate and HRV.

During perception of a freeway incident (leading to driver distraction), it can be assumed that workload is quite high (due to the addition of a second task) and performance is deteriorated. In Figure 5.4 this is represented by Region C. Unfortunately for this region heart rate as well as HRV are not sensitive measures for establishing changes in mental workload.

In the experiment with the freeway incident, we observed that perception of an incident in the adjacent driving lane had a significant effect on EMG activity of the corrugator supercillii (frowning) as well as on respiration rate. The effect of perception of an incident in the other driving lane proved to be not significant for EMG activity of the zygomaticus major (smiling), heart rate and HRV. It might be that EMG activity is a relative sensitive measure for measuring workload in Region C depicted in Figure 5.4.

Besides the influence of adverse conditions on mental workload, we also analyzed the effect personal driver characteristics have on mental workload during the selected adverse conditions. We established that during emergency situations, adverse weather conditions and also freeway incidents the personal characteristics age and driving experience have a significant influence on some of the physiological indicators of mental workload. Overall it can be observed that an increase in age indicates an increase in mental workload, while an increase in driving experience leads to a reduction in mental workload.

Overall it can be concluded that the proposed theoretical framework in Chapter 2 is well supported. We showed that adverse weather conditions as well as freeway incidents led to significant changes in physiological indicators of mental workload. With regard to emergency situations, the results were less clear. This might be due to the fact that the character of this adverse condition is essentially different from adverse weather conditions and freeway incidents or by the fact that not all the used measures were as sensitive as needed. Furthermore we showed that there are strong indications for an influence of driver characteristics (i.e., age and driving experience) on mental workload during the selected adverse conditions. Overall a higher age and less driving experience seemed to lead to a higher mental workload during adverse conditions.

In the previous chapters we aimed at providing insight into the effects adverse conditions have on empirical longitudinal driving behavior as well as through which determinants these effects may be exerted. However, this does not provide us with insight into how longitudinal driving behavior under adverse conditions can best be modeled. This is the aim of the next part of this dissertation.

In the next chapter a state-of-the-art is provided on several often used car-following models. From this state-of-the-art it follows that little is known about which parameter value changes and model performance of continuous car-following models can be observed in case of adverse conditions. Furthermore, little is known to what extent psycho-spacing models provide an adequate description of longitudinal driving behavior under adverse conditions. To this end we estimated parameter values and determined model performance of several continuous car-following models as well as determined the positions of action points in the relative speed-spacing plane as well as acceleration at these action points in a psycho-spacing model.

To this end, Chapter 7 provides a description of the data analysis methods used in order to estimate parameter values in continuous car-following models and action points in psycho-spacing models, That chapter is followed by a presentation of the results of the estimation of parameter values and model performance in case of adverse conditions in Chapter 8.

In Chapter 9 the results are presented on the position of action points in the relative speed - spacing plane in case of adverse conditions as well as on acceleration at the action points in case of adverse conditions. Next in Chapter 10 we aim at modeling longitudinal driving behavior through a Bayesian network modeling approach.

Part II

Modeling of Longitudinal Driving Behavior Under Adverse Conditions

Chapter 6

Driving Behavior Modeling and Adverse Conditions: a State-of-the-art

6.1 Aim and structure of this chapter

In Chapter 4 we showed that emergency situations, adverse weather conditions and also free-way incidents lead to substantial adaptation effects in driving behavior, indicated by substantial changes in speed v , acceleration a , deceleration b and spacing s .

These adaptation effects in longitudinal driving behavior were explained through the proposed theoretical framework. From the results reported in Chapter 5 it followed that the framework was relatively well supported. We showed that adverse weather conditions as well as incidents in the other driving lane led to significant changes in physiological indicators of mental workload. With regard to emergency situations the results were less clear, although a significant effect of the emergency situation on Heart Rate Variability (HRV) was found. Furthermore we established that driver characteristics (i.e., age and driving experience) have an influence on some of the physiological indicators of mental workload during the selected adverse conditions.

However, this insight into the influence of the selected adverse conditions on empirical longitudinal driving behavior as well as the possible causes of the adaptation effects does not inform us how longitudinal driving behavior under adverse conditions can best be modeled. In the theoretical framework we assumed that adverse conditions lead to compensation as well as performance effects in longitudinal driving behavior. It is however not clear to what extent current mathematical models are adequate in describing these effects.

Insight into the extent to which compensation and performance effects in longitudinal driving behavior in case of adverse conditions are reflected in parameter values and model performance of mathematical models of longitudinal driving behavior is of high importance. Models of longitudinal driving behavior along with models of lateral driving behavior form the core of several microscopic simulation models, such as PARAMICS (Cova & Johnson, 2003), CORSIM (Williams et al., 2007), VISSIM (Han & Yuan, 2005) and INTEGRATION (Mitchell & Radwan, 2006).

Numerous mathematical microscopic models have been developed aiming to mimic car-following behavior under a wide range of conditions. Research has been performed pertaining to the influence of characteristics of vehicles, characteristics of the road, driver characteristics, external conditions and traffic regulations (Ossen & Hoogendoorn, 2007).

In the framework we assumed that compensation and performance effects are caused by an interaction between driver capabilities and task demands. As these may be assumed to vary considerably within and between drivers (due to external circumstances and personal characteristics) it can be assumed that a substantial degree of variability in parameter values can be observed.

This chapter aims to discuss the available literature on car-following models in connection with adverse conditions. To this end, first a general introduction into car-following models is provided in Section 6.2, followed by a presentation of several continuous mathematical models of car-following behavior in connection with adverse conditions in Section 6.3.

It is mentioned that continuous car-following models have a rather mechanistic character, as most models incorporate a finite reaction time as the only human element. In these models it is for example assumed that drivers react only to the direct lead vehicle and also react to all lead vehicle related stimuli, no matter how small. To adjust for the fact that only the behavior of the direct lead vehicle is incorporated in most of these models, multi-anticipative car-following models were developed. These models are also discussed in Section 6.3.

Although these models yield a more realistic representation of longitudinal driving behavior, they still do not account for other human elements, like thresholds in perception. To this end psycho-spacing models were developed. These types of models are discussed in Section 6.4. As we have seen in Chapter 4 longitudinal driving behavior in case of an adverse condition shows quite a large degree of variation. The extent to which current mathematical models of car-following are adequate in capturing this variability is briefly discussed in Section 6.5.

In Section 6.6 we present the available literature on car-following models in connection with adverse conditions. We show that, except for the adaptation of the Gipps model (Gipps, 1981) by Hamdar and Mahmassani (2008), no research is available on the modeling of longitudinal driving behavior under adverse conditions. In Section 6.7 we provide the conclusions following from this state-of-the-art.

6.2 An introduction to car-following models

Car-following can be regarded as a subtask of the longitudinal vehicle interaction task. This vehicle interaction subtask has received a lot of attention in the traffic flow community. Several 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 at the level of individual vehicles. They describe traffic flow through behavioral rules of individual vehicles. Therefore they are by definition built on driving behavior specifications (Boer, 1999). Research has been

performed as to the influence of characteristics of vehicles, characteristics of the road, driver characteristics, external conditions and traffic regulations.

According to Brackstone and McDonald (1999), in general three types of car-following models can be distinguished:

- stimulus-response models;
- safety distance models;
- psycho-spacing models.

In most of these models acceleration a at time t is dependent on speed of the vehicle v , reaction time τ , relative speed Δv and distance to the lead vehicle Δx .

$$a_i(t) = f_{cf}(v, \tau, \Delta v, \Delta x) \quad (6.1)$$

Each mathematical model of car-following has its own distinct control objective. For example, the model formulated by Gipps (1981) assumes that drivers want to reach a safe distance to the lead vehicle, while in the model formulated by Tampere (2004) it is assumed that drivers want to attain a desired distance to the lead vehicle and also want to synchronize their speed with the speed of the lead vehicle. Therefore the emphasis on the aforementioned determinants of car-following behavior differs substantially between models.

6.3 Continuous car-following models

6.3.1 Stimulus-response models

The GHR model (Gazis, Herman, & Rothery, 1963) is perhaps the most well-known stimulus-response model and dates from the late fifties and early sixties. The model is expressed in the following equation:

$$a(t) = cv^m(t) \frac{\Delta v(t - \tau)}{\Delta x^l(t - \tau)} \quad (6.2)$$

In Eq. 6.2 a is the acceleration of a vehicle implemented at time t and is proportional to the speed v , relative speed Δv and relative distance to the lead vehicle Δx assessed at an earlier time $t - \tau$. In this equation therefore τ represents the reaction time of the driver. Furthermore in this equation m , l and c are the parameters to be determined. As acceleration a is dependent on relative speed Δv and relative distance Δx , this model can be qualified as a stimulus-response model.

Around the same time the Helly model (Helly, 1959) was developed. In this model the driver of a following vehicle reacts to speed differences with the lead vehicle Δv as well as to differences between the actual distance to the lead vehicle Δx and the desired distance to the lead vehicle

s^* . These differences are moderated by the sensitivity parameters α and β . The model also incorporates reaction time of the driver τ . The model is expressed in the following equation:

$$a(t) = \alpha \Delta v(t - \tau) + \beta (\Delta x(t - \tau) - s^*) \quad (6.3)$$

Furthermore, in this model it is assumed that desired distance to the lead vehicle is linearly determined by speed represented by the parameter h_{min} . Furthermore, desired speed also depends on a minimal stopping distance when stationary s_0 . This is expressed in the following equation:

$$s^* = s_0 + h_{min}v \quad (6.4)$$

An alternative approach was taken by Treiber et al. (2000). Their Intelligent Driver Model (IDM) was developed as the models developed up to this point had unrealistically small acceleration and deceleration times (e.g., in case of Bando et al. (1995)) and because the more high fidelity models like the Wiedemann model (Leutzbach & Wiedemann, 1986) have too many parameters. Furthermore, Treiber et al. (2000) conjectured that most models do not adequately incorporate traffic flow phenomena, such as traffic instabilities and hysteresis.

Acceleration in the IDM (Treiber et al., 2000) is a continuous function incorporating different driving models for all speeds in freeway traffic as well as city traffic (Kesting, Treiber, & Helbing, 2010). Besides the following distance Δx and speed v the IDM (Treiber et al., 2000) also takes relative speed Δv into account.

The IDM acceleration is given by:

$$a = a_{max} \left[1 - \left(\frac{v}{v_0} \right)^\delta - \left(\frac{s^*(v, \Delta v)}{\Delta x} \right)^2 \right] \quad (6.5)$$

$$s^*(v, \Delta v) = s_0 + vT + \frac{v\Delta v}{2\sqrt{a_{max}b_{max}}} \quad (6.6)$$

The expression combines a free flow acceleration regime $a[1 - (v/v_0)^\delta]$ with a deceleration strategy $-a(s^*/\Delta x)^2$. The latter becomes relevant when the distance to the lead vehicle Δx is not significantly larger than the desired distance to the lead vehicle s^* .

The free flow acceleration is characterized by free speed v_0 , maximum acceleration a_{max} and the component δ . The component δ characterizes how acceleration decreases with speed.

The desired distance to the lead vehicle s^* is composed of a minimal stopping distance ('jam distance') s_0 , and a speed dependent distance vT . This corresponds to following the lead vehicle with a constant desired time headway T and a dynamic contribution which is only active in non-stationary traffic conditions. This implements an 'intelligent' driving behavior that, in normal situations, limits braking decelerations to the maximum deceleration b_{max} (Kesting et al., 2010).

In this context, the MIXIC model developed by Van Arem et al. (1997) can also be mentioned. As is the case with the model developed by Tampere et al. (2003), a distinction is made between free-driving and car-following behavior. The model can be regarded as an derivation of the Optimal Control Model formulated by Burnham et al. (1974).

The model is based on the assumption that drivers strive for a synchronization of their speed v_i with the speed of the lead vehicle v_{i-1} . Simultaneously they try to minimize the difference between the actual and the desired distance to the lead vehicle. Contrary to the Helly model (Helly, 1959), desired distance to the lead vehicle increases according to a quadratic function of speed (Hogema, 1995).

Furthermore, this model incorporates a perceptual threshold for relative speed Δv . This threshold was implemented based on a constant threshold for the detection of changes in the visual angle of a lead vehicle, preventing changes in acceleration due to relative speeds Δv at large headways. Finally, the model also incorporated multi-anticipation. Multi-anticipation in car-following will be discussed in Section 6.3.3.

In the previous sections a number of well-known types of stimulus-response car-following models were discussed. In the next section, an alternative approach is presented, namely safety-distance models.

6.3.2 Safety distance models

The original formulation of the safety distance approach dates back to Kometani and Sasaki (1959). The base relationship of this model does not describe a stimulus-response type function as proposed in for example the GHR model (Gazis et al., 1963) and the Helly model (Helly, 1959).

Safety distance models seek to specify a safe following distance through manipulation of the basic Newtonian equations of motion. When exceeding this safe distance a collision is assumed to be unavoidable. Based on this model, Gipps (1981) developed a safety distance model. In this model two different driving regimes (as was the case with the aforementioned MIXIC model by Van Arem et al. (1997)) can be distinguished:

- a free-flow mode in which the driver wants to attain a desired speed based on a given acceleration;
- a car following mode in which the speed of the driver-vehicle combination is governed by a safe speed allowing him / her to avoid rear-end collisions.

In this model (Gipps, 1981), the free flow regime is expressed by the following equation:

$$v(t + \tau) = v(t) + 2.5a_{max}\tau \left(1 - \frac{v(t)}{v_0}\right) \left(0.025 + \frac{v(t)}{v_0}\right)^{\frac{1}{2}} \quad (6.7)$$

Furthermore, the car-following regime is described by the following equation:

$$v(t + \tau) = b_{max}\tau + \sqrt{b_{max}^2\tau^2 - b_{max}[2[\Delta x(t) - L] - v(t)\tau - v_{lead}(t)^2/b_{max}]} \quad (6.8)$$

In these equations a_{max} is the maximum acceleration which a driver is willing to undertake, while b_{max} is the most severe braking a driver wishes to tolerate. Furthermore, L denotes the effective size of the vehicle, while v_0 denotes free speed. As was the case with some of the discussed stimulus response models, this model incorporates a reaction time τ . As was mentioned before, the model incorporates a free flow as well as a congested driving regime. The model assumed that a driver will always choose the minimum speed from these two regimes.

The aforementioned stimulus response models and the safety distance models in various ways have tried to describe acceleration or speed of a vehicle. These models have however some important drawbacks. These are:

- Only the behavior of the direct lead vehicle is incorporated in the models;
- The only human element is a finite reaction time, other human elements are rather mechanistic (e.g., influence of mental workload and perceptual narrowing);
- Drivers are assumed to react to small changes in relative speed even though headways are substantial;
- Drivers are assumed to perceive stimuli no matter how small;
- Situations are adequately evaluated and adequate responses are executed;
- The gas and brake pedals are operated in a precise manner. Errors made in operating the pedals are not taken into account;
- Drivers do not want to permanently be occupied with the car-following task.

In order to adjust for the drawback that only the behavior of the direct lead vehicle as a determinant of behavior of the following vehicle is incorporated in the discussed models multi-anticipative car-following models were developed. In general, these models describe acceleration of a following vehicle as a function of relative speed of the direct lead vehicle $\Delta v_{1,2}$ and relative speed to the second lead vehicle $\Delta v_{1,3}$. Some of these models also incorporate headways towards multiple lead vehicles as determinants of acceleration. An in-depth discussion of multi-anticipative car-following models is presented in the next subsection.

Another drawback that was mentioned was the fact that drivers are assumed to react to small changes in relative speed, even at larger headways. Besides in the previously mentioned MIXIC model (Arem, De Vos, & Vanderschuren, 1997) this was adjusted for in so-called psycho-spacing models (e.g., Leutzbach and Wiedemann (1986)). In psycho-spacing models longitudinal driving behavior is described on a relative speed - spacing $(\Delta v, s)$ plane incorporating perceptual thresholds. On crossing one of the perceptual thresholds a driver will change his or her behavior through a change in the sign of his acceleration. Psycho-spacing models are discussed extensively in Section 6.4.

6.3.3 Multi-anticipative car-following models

Several researchers have suggested that driving behavior cannot adequately be described by just considering the direct lead vehicle, as drivers also seem to anticipate traffic conditions further downstream (Hoogendoorn, Ossen & Schreuder, 2006).

The relatively simple model of Bexelius (1968) includes the behavior of lead vehicles further downstream. Bexelius (1968) extended in this sense the previously discussed GHR model (Gazis, Herman, & Potts, 1959) in order to incorporate multi-anticipation. This model assumes that drivers react to speed differences with lead vehicles. The model also incorporates reaction time of the driver τ . Furthermore, the model assumes that the speed differences with the leaders is moderated by a sensitivity parameter $\alpha_{1,i-j}$. This car-following model is expressed in the following equation:

$$a_i(t + \tau) = \sum_{j=1}^{m_i} \alpha_{i,i-j} \Delta v_{i-j,i}(t) \quad (6.9)$$

In order to incorporate anticipation to behavior of lead vehicles further downstream, Hoogendoorn et al. (2006) proposed the following transformation of the Helly model (Helly, 1959):

$$v_i(t) = \sum_{j=1}^{m_j} \alpha_j v_i^{(j)}(t - \tau) + \sum_{j=1}^{m_j} \beta_j (\Delta x_i^{(j)}(t - \tau - S_i^{(j)})) \quad (6.10)$$

Here also, desired distance to the lead vehicle is linearly dependent on speed:

$$S_i^{(j)} = s_0 + j h_{min} v_i \quad (6.11)$$

In this section multi-anticipative stimulus response car-following models were discussed. Multi-anticipative car-following models can be regarded as a substantial improvement compared to simple car-following models as they describe the actual car-following subtask more accurately. Hoogendoorn et al. (2006) showed that the extent to which this multi-anticipative behavior occurs is substantial. They observed that on average, the sensitivity with respect to stimuli coming from the second lead vehicle is half the sensitivity of the direct lead vehicle. For some driver-vehicle combinations, even higher sensitivities were found of the second lead vehicle compared to the direct lead vehicle.

Though these multi-anticipative car-following models describe the car-following subtask more realistically, they still do not account for the fact that drivers generally do not react to very small and very large differences in speed and spacing. To this end, psycho-spacing models are discussed in the next section.

6.4 A look at psycho-spacing models

As was discussed in the previous section, most continuous car-following models (e.g., safe-distance models, stimulus-response models and multi-anticipative car-following models) assume that drivers react to lead vehicle related stimuli, no matter how small. They therefore do

not incorporate thresholds in perception. This observation has led to the development of a new class of car-following models: psycho-spacing models.

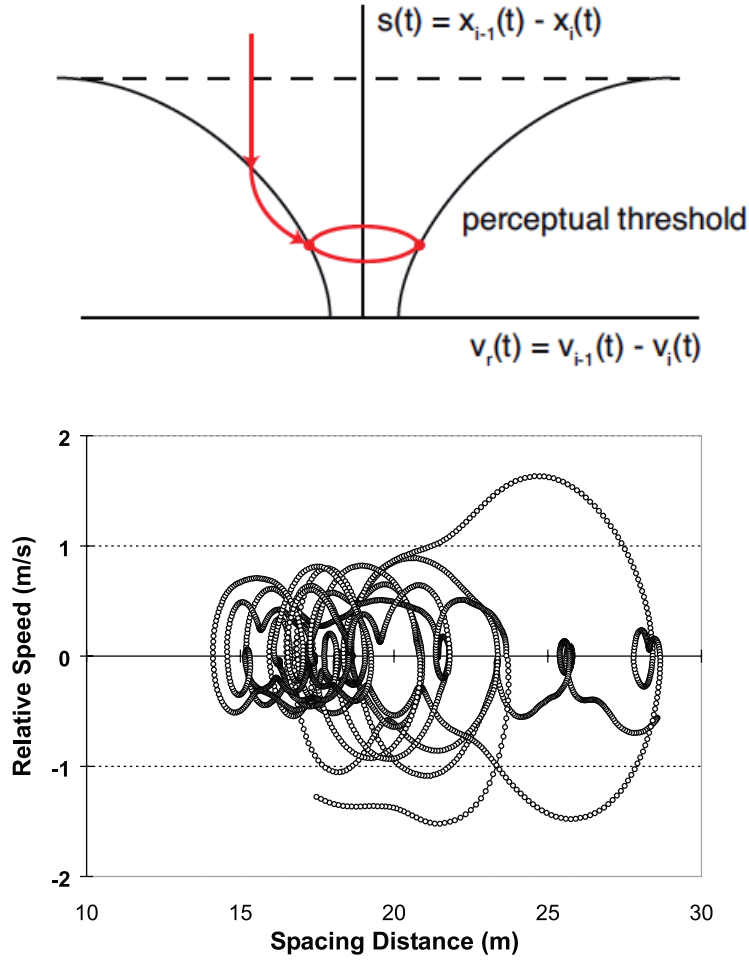


Figure 6.1: A basic psycho-spacing model (Leutzbach et al., (1986)) (top) and the typical 'close' following spirals (Brackstone et al., 2002) (bottom).

Michaels (1963) provided the basis for the first psycho-spacing model based on theories borrowed from perceptual psychology (cf. Leutzbach and Wiedemann (1986)). In these models, car-following behavior is described on a relative speed - spacing ($\Delta v, s$) plane.

In Figure 6.1 (top) it is assumed that the lead vehicle has a constant speed and that the follower catches up with a constant relative speed. As long as spacing is larger than the threshold, no response will occur. If the absolute value of Δv is smaller than a certain boundary value, there also is no response because the driver does not perceive Δv . The threshold value is not a constant, but depends on Δv .

In this context Brackstone et al. (2002) formulate four different perceptual thresholds, which they borrowed from Leutzbach and Wiedemann (1986). The first threshold is a threshold with regard to a minimum desired following distance ABX . This threshold is expressed as follows:

$$ABX(v) = AX + BX\sqrt{v} \quad (6.12)$$

In this equation AX denotes the minimum desired spacing when stationary (much like s_0 in the Intelligent Driver Model (Treiber et al., 2000) and the Helly model (Helly, 1959)). This includes the length of the vehicle. The parameter BX is the additional spacing required to account for speed. The next perceptual threshold is a threshold for a maximum desired following distance:

$$SDX(v) = AX + BX\sqrt{vEX} \quad (6.13)$$

This equation is similar to the one for minimum desired following distance with addition of the term EX . This parameter EX produces an increase of SDX over ABX of an additional 0.5-1.5 times the dynamic speed component (Brackstone et al., 2002).

A third perceptual threshold is a threshold for recognizing small negative (closing) relative speeds:

$$CLDV(DX) = \frac{-DX^2}{CX^2} \quad (6.14)$$

This equation corresponds to a threshold in the perception of the divergence of the visual angle according to the constant CX . Finally a similar threshold for small positive (opening) speeds is formulated, with the constant OP :

$$CLDV(DX) = \frac{DX^2}{OP^2} \quad (6.15)$$

If the vehicle crosses one of these thresholds, it will respond with a constant acceleration or deceleration, typically in the order of $0.2m/s^2$ (Montroll, 1959). In the remainder of this chapter this point in the $(\Delta v, s)$ plane is referred to as an 'action point'.

Leutzbach and Wiedemann (1986) have introduced the term 'penduling' with regard to the fact that spacing varies around a constant value, even if the lead vehicle has a constant speed. In this psycho-spacing model the size of acceleration $a(t)$ is arbitrary at first, whereas it is the main element in the continuous car-following models discussed in the previous sections.

This model can be regarded a a good step towards the incorporation of human elements thus producing more realistic longitudinal driving behavior (Treiber et al., 2000). However, as was the case with the continuous car-following models discussed in the previous section, longitudinal driving behavior may vary considerably within as well between drivers. In order to get more insight into the degree of variability in continuous car-following models as well as in psycho-spacing models, the next section discusses the available research on variability in these models.

6.5 Variability in continuous car-following models and psycho-spacing models

In the previous sections we discussed continuous car-following models (e.g., stimulus response models and safety distance models) as well as psycho-spacing models.

In Chapter 4 we showed that longitudinal driving behavior changes substantially due to the selected adverse conditions. Substantial adaptation effects in speed, acceleration, deceleration, distance to the lead vehicle and relative speeds were observed. Furthermore large differences within and between drivers were found.

In the present chapter we showed that continuous car-following models in general describe acceleration of a vehicle as a function of lead vehicle related stimuli in a more or less mechanistic manner. As human elements are not incorporated in these models it can be assumed that they do not adequately account for differences within and between drivers.

From research it indeed follows that the observed degree of variability is quite substantial. In for example Saffarian and Happee (n.d.) parameters of the Helly model (Helly, 1959) were estimated using driving simulator data from 20 participants. The applied model included linear feedback of relative speed, spacing and an acceleration feedforward term. The contribution of acceleration of the lead vehicle feedforward term was small and inconsistent. Substantial variations in parameter values between drivers were established even when the Helly model (Helly, 1959) was used without the feedforward term. Furthermore, the explained variance showed that the model only explained 44-60% of the variance in spacing, acceleration and speed.

Hoogendoorn et al. (2006) estimated the parameters of a multi-anticipative adaptation of the Helly model (Helly, 1959) using trajectory data collected with a helicopter. From the results it followed that some drivers apparently consider only the direct lead vehicle, while other drivers also consider the second and third lead vehicle. This suggests a considerable degree of variability in multi-anticipation as well.

In Hoogendoorn, Hoogendoorn et al. (2011) it was investigated whether the hysteresis phenomenon led to substantial changes in parameter values for the Helly model (Helly, 1959) as well as the Bexelius model (Bexelius, 1968). Traffic hysteresis refers to the observation that state transitions, i.e., changes from congestion to free-flow or vice versa are generally not on the fundamental diagram and follow different paths. This phenomenon is clearly observable from experimentally obtained flow-density plots. From the results it followed that substantial differences could be observed in parameter values between the deceleration phase and the acceleration phase. Furthermore, standard deviations were substantial, indicating a considerable degree of driver variability.

From the aforementioned brief overview of variability in continuous car-following models it can be concluded that the degree of variability due to differences within and between drivers is substantial. This might indeed be due to the fact that these models insufficiently incorporate human elements.

As was previously mentioned a good step toward the incorporation of human elements was made through the development of psycho-spacing models. However, these models also show a considerable degree of variability.

This was supported in Brackstone et al. (2002). In their research using empirical data from UK motorways they established that large variations could be observed in the position of action points on the $(\Delta v, s)$ plane. The aforementioned is also supported by Wagner (2005). He compared actual action points to the action points which would be expected in case of deterministic

perceptual thresholds. In this regard it was concluded in Hoogendoorn et al. (2011) that the assumption of deterministic perceptual thresholds incorporated in the original formulation of the model does not hold in reality.

Variability within as well as between drivers may be assumed to be caused by driver characteristics as well as external circumstances. An obvious example of external circumstances are adverse conditions. It can therefore be assumed that these conditions, in relationship with driver characteristics have a substantial influence on parameter values and model performance of continuous car-following models as well as of the position of action points in psycho-spacing models. To this end, the next section provides an overview of the available research on continuous car-following models as well as psycho-spacing models in connection with adverse conditions.

6.6 Car-following models and adverse conditions

As was previously mentioned, Tu et al. (2010) adjusted parameters in a simulation software package (i.e., PARAMICS) in order to account for aggressive or anxious driving during an emergency situation. In this context, they subscribed to the assumptions made by Hamdar and Mahmassani (2008).

Hamdar and Mahmassani (2008) took a step forward in the incorporation of adaptation effects in longitudinal driving behavior due to adverse conditions. They devised a model to capture longitudinal driving behavior under extreme conditions through modification of the safe-distance model by Gipps (1981). Hamdar and Mahmassani (2008) used this model as from their research it followed that this showed an acceptable degree of stability when relaxing its safety constraints.

Hamdar and Mahmassani (2008) state that with regard to acceleration under extreme conditions, drivers are more willing to apply higher acceleration rates than under normal driving conditions, which cause irregularities and possible instabilities in traffic flow patterns. The variable a_i was drawn from a truncated Gaussian shaped distribution to deal with unrealistically high and low volumes. With regard to maximum deceleration Hamdar and Mahmassani (2008) assume that the value of this parameter can increase in absolute value, as under extreme conditions drivers tend to have higher braking rates or an increased use of emergency braking. In their modification of the Gipps model (Gipps, 1981) they also altered the variable representing desired speed. In extreme conditions the true value of this parameter was drawn from a probabilistic mixture of two Gaussian distributions in which the means are respectively higher and lower than the suggested mean in the original formulation of the model.

However, this model only describes driving behavior under emergency situations (extreme conditions). Furthermore, this model does not incorporate human elements, like perceptual thresholds and therefore it might be less able to capture variability within and between drivers.

In the context of adverse weather conditions Asamer et al. (2011) calibrated parameters in a microscopic simulation software package (i.e., VISSIM) in case of snowy conditions. They changes single parameters (deceleration, acceleration, desired speed and 'clearance distance'), while the other parameters were kept constant. From their study three parameters remained for calibration, namely:

- acceleration;
- desired speed;
- 'clearance distance'.

From the simulation runs followed feasible regions of parameter values in order to achieve a saturation flow and start up delay as measured during driving conditions with snow.

Finally, in the context of freeway incidents it followed from Knoop et al. (2008) that reaction times increased from a normal reaction time of around 1.3s to 3.9s at the incident site. The normal indicators of longitudinal driving behavior were derived from literature. In addition, reaction times typically were centered around two values, namely 2 and 5 seconds. From a Kolmogorov-Smirnov test it followed that reaction times at the incident location differed significantly from reaction times under normal conditions.

It can therefore be concluded that research on adverse conditions in relation to mathematical modeling of longitudinal driving behavior is scarce. Some contributions were found in which parameters of microscopic simulation software packages (e.g., VISSIM, PARAMICS) were calibrated for emergency situations and adverse weather conditions. Also mention was made of the changes in reaction times as observed at freeway incidents (Knoop et al., 2008).

In Chapter 5 the results of the driving simulator experiment on the influence of adverse conditions on mental workload, moderated by age and driving experience were presented. From this chapter it became clear that mental workload can be assumed to play a substantial role in influencing longitudinal driving behavior under adverse conditions. One way in which these human elements may effect model performance of car-following models is through the influence of adverse conditions on performance effects. Performance of the car-following task may decrease resulting in a less adequate description of longitudinal driving behavior by continuous car-following models. In other words: car following may become to a lesser extent a determinant of longitudinal driving behavior, making continuous car-following models less adequate in describing longitudinal driving behavior under adverse conditions.

6.7 Conclusions

In this chapter an overview was provided with regard to continuous car-following models (stimulus-response, safe distance and multi-anticipative car-following models) as well as psycho-spacing models in connection with adverse conditions.

In this chapter we showed that most current continuous car-following models do not incorporate human elements and therefore describe longitudinal driving behavior in a mechanistic manner. Furthermore we showed that from previous research it follows that parameter values show a substantial degree of variability. When observing the results reported in Chapter 4 it can be assumed that especially in case of adverse conditions the degree of variability in longitudinal driving behavior is substantial.

It can be assumed that compensation effects and performance effects as proposed in the theoretical model in Chapter 2 are reflected in parameter values and model performance of continuous

car-following models. However, no research was found on the influence of adverse conditions on parameter value changes and model performance of continuous car-following models. Also we conjecture that substantial differences within and between drivers in parameter values can be observed as compensation effects come forth from the interaction between driver capabilities and task demands.

We hypothesize that psycho-spacing models provide a relatively adequate representation of car-following patterns under adverse conditions. However, the original formulation of the model incorporated deterministic perceptual thresholds. As adverse conditions are assumed to influence longitudinal driving behavior through an interaction between driver capabilities and task demands, it can be assumed that these deterministic perceptual thresholds do not hold in reality. For example, an increase in task demands due to heavy fog may lead to an imbalance between task demands and driver capabilities and therefore an increase in mental workload, resulting in compensation effects in longitudinal driving behavior. This effect may vary considerably within as well as between drivers.

In order to determine the effect adverse conditions have on parameter values and model performance in continuous car-following models we estimated parameters of the Intelligent Driver Model (Treiber et al., 2000) using the data derived from the three driving simulator experiments. We also estimated action points as well as acceleration and the 'jumps' in acceleration at action points in a psycho-spacing model.

In the next chapter the data analysis methods are described. The first method that is described was used to estimate parameter values and determine model performance in continuous car-following models. Furthermore in this chapter we will introduce a new data analysis technique used to determine the position of action points in psycho-spacing models as well as describe the data analysis method used to determine the influence of adverse conditions on acceleration and the 'jumps' in acceleration at the action points.

Chapter 7

Data Analysis Methods

7.1 Aim and structure of this chapter

In Chapter 4 we showed that the selected adverse conditions led to substantial changes in empirical longitudinal driving behavior. In order to gain more insight into the way in which adverse conditions influence longitudinal driving behavior, we proposed a new theoretical framework based on the Task-Capability-Interface model by Fuller (2005). In this framework, introduced in Chapter 2, a distinction was made between compensation and performance effects in longitudinal driving behavior due to adverse conditions.

It is however not clear to what extent these effects are adequately represented in mathematical models of driving behavior. In other words: to what extent are compensation and performance effects represented in parameter values and model performance of mathematical models of longitudinal driving behavior?

To this end, in Chapter 6 we discussed various car-following models in connection with adverse conditions. However, in this chapter we mentioned that most continuous car-following models have a rather mechanistic character, as most of these models to a very limited degree incorporate human elements. For example, the majority of these models incorporate a finite reaction time as the only human element. Also, continuous car-following models assume that drivers react to lead vehicle related stimuli (e.g., relative speed Δv), no matter how small. In order to adjust for this drawback, psycho-spacing models were developed. The basics of these models were also discussed in Chapter 6.

As compensation and performance effects are assumed to be caused by an interaction between task demands and driver capabilities, driving behavior in case of adverse conditions can be assumed to be quite variable. In Chapter 6 we therefore also discussed variability in continuous car-following models and psycho-spacing models. Several studies indicated that the degree of variability in continuous car-following models as well as in psycho-spacing models is considerable. It is however unclear to what extent adverse conditions influence the degree of variability in continuous car-following models and psycho-spacing models. In order to determine parameter value changes and model performance of continuous car-following models as well as determine the position of action points in psycho-spacing models, in this chapter two new data analysis techniques are proposed.

The first data analysis technique entails a calibration approach for joint estimation of parameters in continuous car-following models. This approach is presented in depth in Section 7.2.

The second data analysis technique entails a data filtering technique used to estimate action points in psycho-spacing models. This approach is discussed in Section 7.3. We also aim at determining acceleration as well as so-called 'jumps' in acceleration at the action points. The used method is also described in this section. The chapter concludes with a brief conclusion in Section 7.4.

7.2 Estimating parameter values and model performance in continuous car-following models

7.2.1 Estimation of continuous car-following models

Although car-following models are widely applied in microscopic simulation tools, parameter identification remains a difficult task. The main reason is that empirical longitudinal driving behavior is variable in time and space. Furthermore, parameter values are not directly observable from common (cross section) traffic data.

Several approaches to structured model calibration using macroscopic and in some case microscopic traffic data have been proposed, but still a good approach based on concepts of statistical theory is lacking. Model calibration consists of changing values of model input parameters in an attempt to match field conditions within some acceptable criteria. For the sake of illustration, let us consider two examples of automated approaches to model calibration.

Brockfeld et al. (2004) cross compared different microscopic traffic flow models using data from car-following experiments. To this end, they established car-following parameter sets minimizing Theil's U, which is an error term expressing the difference between prediction and observation. The error rates of the different models in comparison to the data varied between 9% and 24% and for validation between 12% and 30%. No single model appeared to be significantly better than the others (even the more complex ones). The authors argued that these errors could probably not be suppressed, irrespective of the model that is used, due to the different behavior of each driver, which is in line with the results presented in this dissertation.

Schultz and Rilett (2004) proposed a methodology to introduce and calibrate a parameter distribution using measures of mean and variance to generate input parameters for car-following sensitivity factors in microscopic simulation tools. The approach was applied using the COR-SIM model and calibrated through an automated genetic algorithm. An overview of the calibrated parameter values was reported by Brackstone and McDonald (1999).

7.2.2 A closer look at the proposed method

The approach presented in this chapter is a derivation of a statistical parameter estimation approach, enabling the statistical analysis of the model estimates and cross-comparison of models of differing model complexity. The approach allows using multiple trajectories simultaneously,

through which the estimation results are improved when the information in individual trajectories is limited. Also the approach allows for the inclusion of prior information on the parameter values to be estimated.

The approach allows for statistical analysis of the model estimates, including the standard error and the correlation of the parameter estimates. Also, we can easily test whether a specific model outperforms other models 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.

Let us assume that for each driver i we have an observed trajectory on a freeway, thus we have an observed position x_i at time instant t_k . Here $t_k = kh$ where h is the observation time step. As we have the positions x_i at time instants t_k , we can derive speed v_i . Note that when all drivers are observed, we can easily determine the different stimuli present in the different car-following models (spacing, relative speed etc.; see also Chapter 6).

The objective of the approach is to estimate the parameter vector $\vec{\theta}_i$ of the car-following model in question for driver i . This vector therefore describes the behavior of driver i using the data. To this end, we amended the Maximum-Likelihood procedure first proposed in Hoogendoorn and Ossen (2005) by enabling using prior information on the parameter distribution.

Let us briefly recall the approach first proposed in Hoogendoorn and Ossen (2005). Let the vector $\vec{y}_i(t_k)$ denote the observed state of vehicle i at time instants t_k . The difference between the observed state and the predicted state equals:

$$\vec{e}_i(t_k) = \vec{y}_i(t_k) - \vec{z}_i(t_k) \quad (7.1)$$

The driver state vector $\vec{z}_i(t_k)$ of driver i at time instants t_k is a function of the parameter vector $\vec{\theta}_i$ of the car-following model in question. Therefore the residuals $\vec{e}_i(t_k)$ of driver i at time instants t_k are also a function of $\vec{\theta}_i$:

$$\vec{e}_i(t_k) = \vec{e}_i(t_k | \vec{\theta}_i) \quad (7.2)$$

Let $p_K(\vec{e}_i(t_k), \dots, \vec{e}_i(t_k), \vec{e}_i(t_K))$ denote the joint probability density function of the residuals, in which K represents the number of observations. The Maximum Likelihood Estimate (MLE) is defined as follows:

$$\hat{\vec{\theta}} = \arg \max L(\vec{\theta}) \quad (7.3)$$

with the likelihood L defined by:

$$L(\vec{\theta}) = p_K(\vec{e}_i(t_k), \dots, \vec{e}_i(t_k), \vec{e}_i(t_K)) \quad (7.4)$$

If we assume that the residuals $\vec{e}_i(t_k)$ are serially independent - which obviously is not the case here - we would write the expression for the likelihood L as follows:

$$L(\vec{\theta}) = \prod_{k=1}^K p(\vec{e}_i(t_k)) \quad (7.5)$$

In this equation p denotes the probability density function of the residuals $\vec{e}_i(t_k)$ for driver i at time instants t_k . The issue of serial correlation will be discussed in the ensuing of this section. Furthermore, it is often easier to maximize the logarithm of the likelihood:

$$\tilde{L}(\vec{\theta}) = \ln L(\vec{\theta}) = \sum_{k=1}^K \ln p(\vec{e}_i(t_k)) \quad (7.6)$$

Now, let us furthermore assume that the residuals $\vec{e}_i$ follow the zero-mean multivariate normal distribution with covariance matrix Σ . From this it follows:

$$\ln p(\vec{e}) = \ln \left((2\pi)^{-N/2} \det(\Sigma)^{-1/2} \exp \left(-\frac{1}{2} \vec{e}^T \Sigma^{-1} \vec{e} \right) \right) \quad (7.7)$$

$$= -\frac{N}{2} \ln(2\pi) - \frac{1}{2} \ln(\det(\Sigma)) - \frac{1}{2} \vec{e}^T \Sigma^{-1} \vec{e} \quad (7.8)$$

where N is the number of elements in the state $\vec{\theta}$, thereby yielding:

$$\tilde{L}(\vec{\theta}, \Sigma) = -\frac{NK}{2} \ln(2\pi) - \frac{K}{2} \ln(\det(\Sigma)) - \sum_{k=1}^K \vec{e}_i^T(t_k | \vec{\theta}) \Sigma^{-1} \vec{e}_i(t_k | \vec{\theta}) \quad (7.9)$$

It can easily be shown that the ML estimate of the covariance matrix Σ equals:

$$\hat{\Sigma} = \hat{\Sigma}(\vec{\theta}) = \frac{1}{K} \sum_{k'=1}^K \vec{e}_i(t_{k'} | \vec{\theta}) \vec{e}_i^T(t_{k'} | \vec{\theta}) \quad (7.10)$$

which allows us to remove the dependency of Σ in Eq. 7.9. The ML estimate of the parameters $\vec{\theta}$ can now be determined by maximizing:

$$L^*(\vec{\theta}) = \tilde{L}(\vec{\theta}, \hat{\Sigma}(\vec{\theta})) \quad (7.11)$$

The main assumption that we have made in the aforementioned is the fact that the residuals are uncorrelated and that they follow the zero-mean multivariate normal distribution.

Serial correlation means that the consecutive error terms are not independent. This results in a reduction in the information richness of the data. Serial correlation occurs when the covariances of the consecutive error terms are larger than zero, i.e.:

$$\rho = \text{cov}(e_i(t_k), e_i(t_{k+1})) \quad (7.12)$$

To determine the extent in which serial correlation plays a role, we propose the following three step approach:

1. obtain the parameter estimates $\hat{\theta}$ by optimization of the log-likelihood (Eq. 7.11):
2. determine the residuals $e_i(t_k)$;
3. determine ρ directly.

One of the important applications of the MLE is that models of different complexity (i.e., with a different number of parameters) can be cross-compared, taken into account the fact that a simple model is generally preferred over a complex model. To this end, a so-called likelihood ratio test can be performed.

Suppose that we have two car following models and that the number of parameters of the models are equal to m_1 and m_2 respectively. The Likelihood Ratio test involves testing the statistic:

$$2(L_1^*(\hat{\theta}_1) - L_2^*(\hat{\theta}_2)) \quad (7.13)$$

which follows the χ^2 distribution with d degrees of freedom, where $d = m_1 - m_2$ denotes the number of parameters of the model. The likelihood-ratio test is passed with 95% confidence if:

$$2(L_1^*(\hat{\theta}_1) - L_2^*(\hat{\theta}_2)) > \chi^2(0.95, d) \quad (7.14)$$

meaning that model 1 outperforms model 2 significantly at 95% confidence.

In the aforementioned, we discussed how parameter estimates for a single trajectory could be established using a MLE technique. One way to deal with the reduced information richness of the data is to include prior information. In the ensuing of this section we therefore propose to use multiple trajectories.

Let us assume that we have a set of N trajectories for an equal number of drivers $i = 1, \dots, N$. 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, we can determine the likelihood $L^{(i)}(\vec{\theta}^{(i)})$ of observing this trajectory given that the car following is described by the set of parameters $\vec{\theta}^{(i)}$.

In combining the trajectories, we can easily determine the joint likelihood of observing the trajectories of drivers $i = 1, \dots, N$:

$$L_{mult}(\vec{\theta}^{(1)}, \dots, \vec{\theta}^{(N)}) = \prod_{i=1}^N L^{(i)}(\vec{\theta}^{(i)}) \quad (7.15)$$

Using this expression, we can also determine the likelihood that all drivers in the considered driver population can be described by the same parameter set $\bar{\theta}$:

$$L_{mult}(\bar{\theta}) = \prod_{i=1}^N L^{(i)}(\bar{\theta}) \quad (7.16)$$

The aforementioned therefore assumes that the behavior of all drivers is governed by the same parameter vector. If we assume that the parameters $\bar{\theta}$ are drawn from some random distribution with mean Θ and covariance matrix Σ , we know that:

$$E(\bar{\theta}) = \Theta \quad (7.17)$$

and

$$\text{var}(\bar{\theta}) = \frac{1}{\sqrt{N}} \Sigma \quad (7.18)$$

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

In this section we discussed the data analysis method used in order to estimate the parameter values and model performance of continuous car-following models under adverse conditions. As we conjectured in the previous chapter, these models do not incorporate human elements and can therefore be assumed to perform less adequately in describing longitudinal driving behavior under adverse conditions, which is then reason to suggest that psycho-spacing models are a more likely candidate. To this end the next section describes the data analysis method used in order to estimate action points in psycho-spacing models.

7.3 Estimation of action points and acceleration in psycho-spacing models

7.3.1 Determining action points

Recall that in psycho-spacing models longitudinal driving behavior is described on a relative speed - spacing $(\Delta v, s)$ plane and is governed by perceptual thresholds. If the vehicle crosses one of these thresholds, it will respond with a constant acceleration or deceleration, typically in the order of $0.2m/s^2$ (Montroll, 1959). In the remainder of this chapter this point in the $(\Delta v, s)$ plane is referred to as an action point.

In order to determine the positions of the action points in the $(\Delta v, s)$ plane, a new data analysis technique was used. This data analysis technique aims at identifying periods of constant (stationary) acceleration instead of filtering the data using often used filtering techniques (e.g., moving averages).

The basic assumption of the applied method is that a trajectory can be represented by non-equidistant periods in which acceleration is constant. This implies that speed $v(t)$ is a continuous piecewise linear function of time. Let t_j for $j = 0, \dots, M$ denote the time instants at which the acceleration changes (i.e., the action points). Given these time instants, we aim to find the points y_j describing the value of the piecewise linear function at the time instants t_j .

Let $\vec{t} = \{t_j\}$ and let $\vec{y} = \{y_i\}$ denote the vector of fixed time instants and the vector of function values respectively. Let $f(v | \vec{t}, \vec{y})$ denote the resulting piecewise linear function that can

be constructed using these vectors. Finding the optimal values for y_i can be mathematically described by:

$$\vec{y}_*(\vec{t}) = \arg \min \sum_{k=1}^n (f(t_k | \vec{t}, \vec{y}) - v^{obs}(t_k))^2 \quad (7.19)$$

where t_k denotes the time instants when the vehicle data are measured, and $v^{obs}(t_k)$ denotes the observed speed values. Note that $\vec{y}_* = \vec{y}_*(\vec{t})$ means that the optimal set of points y_j depends on the used time instants t_j . There are several approaches proposed in literature to numerically solve this minimization problem (see of example Imai and Iri (1987)).

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

$$\vec{t}_* = \arg \min \sum_{k=1}^n (f(t_k | \vec{t}, \vec{y}_*(\vec{t})) - v^{obs}(t_k))^2 \quad (7.20)$$

where $\vec{y}_*(\vec{t})$ is defined by Equation 7.19. The problem is solved using standard least-squares optimization approaches. This is done for different values of M , until the improvement in the error is less than some threshold value ϵ_0 .

In illustration, Figure 7.1 shows an example of how the proposed method approximates the observed noisy individual speed profiles using a piecewise linear function (implying constant acceleration between action points).

In this manner, action points are identified. Next, the distribution of action points is generated in a $(\Delta v, s)$ plane. Here, action points with small accelerations after an action point ($-0.01 > a(t) < 0.01$) are excluded from the analysis. Also, the distribution of action points in the $(\Delta v, s)$ plane is generated by excluding 'jumps' in acceleration that are smaller than 0.015. These exclusions of action points are applied in order to ensure that only 'reasonable' actions are included in the analysis. In order to determine whether the distributions of action points differ significantly between groups and conditions in the experiments, Kolmogorov-Smirnov tests were performed.

A Kolmogorov-Smirnov test is a non-parametric test for the equality of continuous probability distributions that can be used to compare a sample with a reference probability distribution. This test quantifies a distance between the empirical distribution function of the sample and the cumulative distribution function of the reference distribution.

Next, in order to get more insight into the degree of variability, we estimated the perceptual thresholds through finding the coefficients of the polynomials $p(x)$ in the third degree that fitted the action points $p(x(i))$ to $y(i)$ in a least squares sense:

$$p(x) = p_1x^3 + p_2x^2 + p_3x + p_4 \quad (7.21)$$

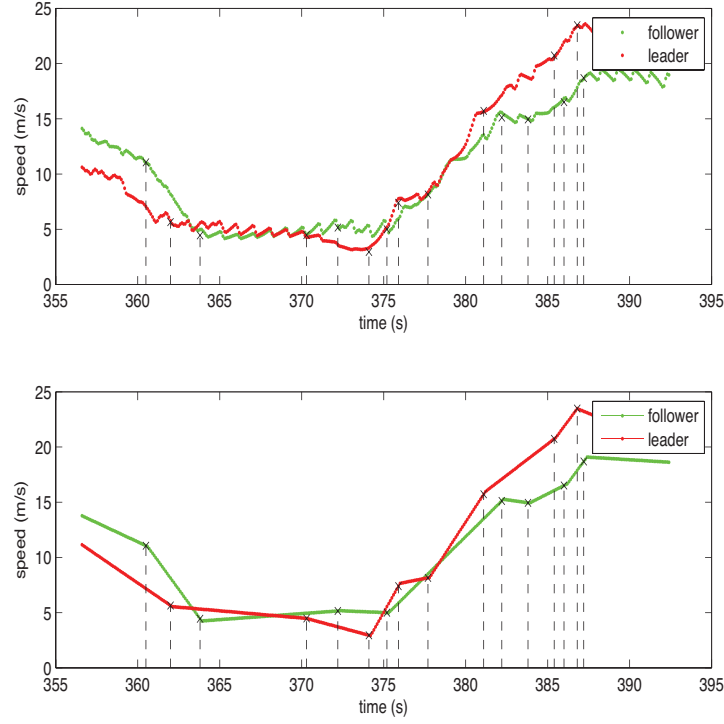


Figure 7.1: Example application of method for leader-follower pair from the Everdingen dataset (see also Hoogendoorn et al., 2007). The crosses indicate the action points.

This analysis was performed separately for acceleration reductions and acceleration increases. The goodness of fit, which in this chapter is regarded as an indication for the degree of within and between driver heterogeneity was determined through calculation of the Mean Squared Error (MSE) and the maximum absolute error (MAE).

7.3.2 Determining acceleration at action points

In order to determine the extent to which acceleration $a(t)$ at the action points is influenced by adverse conditions a Multivariate Regression Analysis is performed. In these analyses two models are fitted. These models were chosen as they showed the best possible fit to the data. Below these models will be referred to as Model 1 (Equation 7.22) and Model 2 (Equation 7.23):

$$a = b_1 \Delta v + b_2 s \quad (7.22)$$

and

$$a = b_1 \frac{\Delta v}{\sqrt{s}} + b_2 \Delta v \quad (7.23)$$

These relations assume that the acceleration $a(t)$ is a linear function of relative speed Δv , which implies that the larger Δv , the larger the chosen acceleration. Furthermore, the model shows that the magnitude of acceleration at the action points reduces for larger values of s . Note that

these relations do not describe whether a driver will accelerate or not. Instead, it describes the (average) acceleration the driver chooses to accelerate at a certain value of Δv and s .

Next, the estimated parameters as well as the errors for normal driving conditions and adverse conditions were compared between the conditions providing an indication of the influence of adverse conditions on acceleration as well as on driver variability.

Finally, the extent to which the adverse conditions influence 'jumps' in acceleration at the action points is compared between normal driving conditions and adverse conditions. The same steps were followed as in the aforementioned. However, here the following two models are fitted using the Multivariate Regression Analysis Method, which in the remainder of this chapter will be referred to as Model 3 (Equation 7.24) and Model 4 (Equation 7.25):

$$\Delta a = b_1 \Delta v + b_2 s \quad (7.24)$$

and

$$\Delta a = b_1 \frac{\Delta v}{\sqrt{s}} + b_2 \Delta v \quad (7.25)$$

7.4 Conclusions

In Chapter 6 we presented several continuous car-following models as well as psycho-spacing models. Furthermore, it followed from this state-of-the-art that research on the adequacy of current mathematical models of longitudinal driving behavior in relation to adverse conditions (i.e., emergency situations, adverse weather conditions and incidents) is not available. Therefore in the ensuing of this dissertation we estimated parameter values in continuous car-following models as well as estimated the position of action points in psycho-spacing models. This was performed as this provides us with insight into the extent in which compensation effects and performance effects due to an adverse condition are reflected in parameter values and model performance in continuous car-following models as well as to what extent these adaptation effects are reflected in the position of action points as well as acceleration at the action points in psycho-spacing models.

In this chapter we introduced two new data analysis techniques. The first technique was a data analysis method enabling the joint estimation of parameters in continuous car-following models. The second data analysis method makes it possible to estimate the position of action points in the $(\Delta v, s)$ plane in psycho-spacing models. In order to determine acceleration as well as the so-called 'jumps' in acceleration a Multivariate Regression Analysis method using four different models was proposed.

In the next chapter the results of the analysis of the parameter values and model performance in continuous car-following models is presented, followed by a presentation of the results of the estimation of the action points as well as the (jumps in) acceleration at the action points in Chapter 9.

Chapter 8

Continuous Car-following Models and Adverse Conditions

8.1 Aim and structure of this chapter

In Chapter 6 we presented an overview of continuous car-following models (stimulus-response, safe-distance and multi-anticipative car-following models). We showed that most current car-following models describe longitudinal driving behavior in a mechanistic manner and therefore insufficiently incorporate human elements.

We proposed in Chapter 2 that adverse conditions have an influence on longitudinal driving behavior through an imbalance between driver capabilities and task demands leading to a higher mental workload and consecutively to compensation effects and performance effects. However, with regard to the influence of adverse conditions on the adequacy of these models in describing these effects no research was found.

Furthermore, we conjectured that the degree of variability in parameter values is substantial, as it can be assumed that, for example, driver capability will differ substantially between drivers. However, no research on the influence of variability in car-following models in relation with adverse conditions was found.

In order to determine the extent in which continuous car-following models are adequate in describing longitudinal driving behavior under adverse conditions, in the present chapter we aimed at estimating parameters as well as determined model performance of an often used car-following model in case of adverse conditions, namely the Intelligent Driver Model (Treiber et al., 2000). To this end in Chapter 7 we introduced a calibration approach for joint estimation enabling a statistical analysis of parameter values and model performance of continuous car following models.

We start with a presentation of the results of the calibration approach of the Intelligent Driver Model using a dataset containing an emergency situation in Section 8.2. This dataset was obtained through the driving simulator experiment described in Chapter 3.

Next, in Section 8.3 we present the results of the estimation of the parameter values and model performance for the Intelligent Driver Model with regard to adverse weather conditions. In this

case parameters of this car-following models were also estimated using the driving simulator data described in Chapter 3.

Section 8.4 reports the results of the estimation of the parameter values and model performance for the Intelligent Driver Model using a dataset containing a freeway incident. As was the case with emergency situations as well as adverse weather conditions we used data from the driving simulator experiment.

In sum, in this chapter we estimate parameter values and determine model performance of the Intelligent Driver Model using the data of driving behavior in case of emergency situations, adverse weather conditions and freeway incidents obtained through the three driving simulator experiments described in Chapter 3.

Finally, in Section 8.5 we draw conclusions from the results of the application of the estimation approach to the datasets containing an emergency situation, adverse weather conditions and incidents in the other driving lane.

8.2 Parameter value changes and model performance under emergency situations

8.2.1 Parameter value changes in case of an emergency situation

This section discusses to what extent the Intelligent Driver Model (Treiber et al., 2000) is adequate in incorporating longitudinal driving behavior in case of emergency situations. In order to determine this, we estimated parameter values and model performance of the Intelligent Driver Model using the calibration approach for joint estimation discussed in Chapter 7. With regard to emergency situations use was made of the data obtained through the driving simulator experiment presented in Chapter 3.

In order to determine the influence of emergency situations on parameter values of the Intelligent Driver Model we compare parameter values of the control group (no emergency situation) to the parameter values of the experimental group (emergency situation) for this model. We estimated the parameter values of maximum acceleration a , maximum deceleration b , free speed v_0 and desired time headway T separately per driver and per longitudinal position and next calculated the mean values, minimum and maximum values as well as the standard deviations.

In Table 8.1 the mean values, standard deviations and ranges for the parameter values of the Intelligent Driver Model in case of an emergency situation are presented. This table shows the descriptive statistics of the parameter values for the control group (no emergency situation) as well as for the experimental group (emergency situation). In the next subsections we turn to a detailed discussion of the individual parameters of the Intelligent Driver Model in case of an emergency situation.

Maximum acceleration a

We start with discussing the effect emergency situations have on maximum acceleration a . Maximum acceleration a in the Intelligent Driver Model (Treiber et al., 2000) represents the

Table 8.1: Parameter values of the Intelligent Driver Model (Treiber et al., 2000) for the control group (no emergency situation) and the experimental group (emergency situation).

Parameter	Mean	Std	Min	Max
<i>Control group</i>				
Maximum acceleration a (m/s^2)	0.94	0.68	0.35	2.03
Maximum deceleration b (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 (s)	0.78	1.06	0.07	2.99
<i>Experimental group</i>				
Maximum acceleration a (m/s^2)	1.46	0.65	0.80	2.14
Maximum deceleration b (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 (s)	0.25	0.68	0.09	0.45

maximum acceleration a driver is willing to apply. As an illustration, Figure 8.1 shows the estimation results for the parameter maximum acceleration a obtained by fitting the Intelligent Driver Model to the observations of the driving simulator for the control group (no emergency situation) and the experimental group (emergency situation).

In the figure the bold blue line represents the estimates of the parameter values, while the thin blue lines represent the variation (expected value plus or minus the standard deviation). The dotted lines represent the start and end of the two stop-and-go waves. From the figure it can be observed that for both groups the parameter value of maximum acceleration a 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 maximum acceleration a . Furthermore, it can be observed that the variability between drivers is quite substantial, as indicated by the substantial standard deviations.

When comparing the two groups it can be observed from Table 8.1 as well as from Figure 8.1 that overall maximum acceleration a is larger in the experimental group than in the control group. The overall mean value of maximum acceleration a in the control group amounted to $0.94 m/s^2$, while in the experimental group the overall mean value amounted to $1.46 m/s^2$. When comparing the value of maximum acceleration a in the control group to values normally used in simulations (Kesting et al., 2010), it can be concluded that this value is quite similar. Overall the variation between drivers was smaller in the experimental group compared to the control group.

From an independent samples t-test it followed that the difference in maximum acceleration a between the control group and the experimental group is significant ($p < 0.05$). It can therefore be concluded that maximum acceleration a under emergency situations is significantly larger than under normal driving conditions.

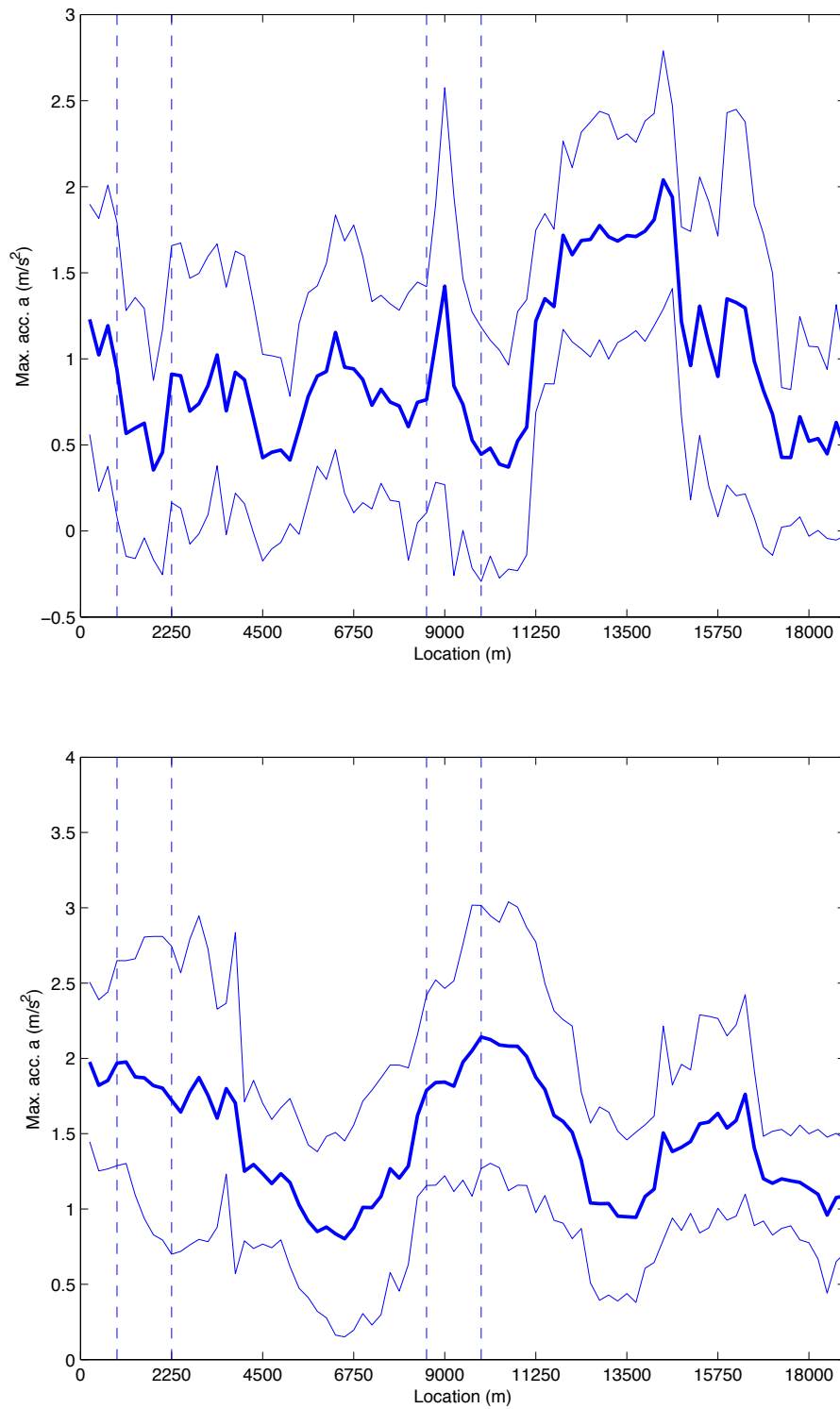


Figure 8.1: Parameter estimates of maximum acceleration a of the Intelligent Driver Model (Treiber et al., 2000) for the control group (top) and the experimental group (bottom) in case of an emergency situation. The bold blue line represents the estimates of the parameter values while the thin lines indicate the expected value plus or minus the standard deviation. The four dotted lines represent the start and end of the stop-and-go waves.

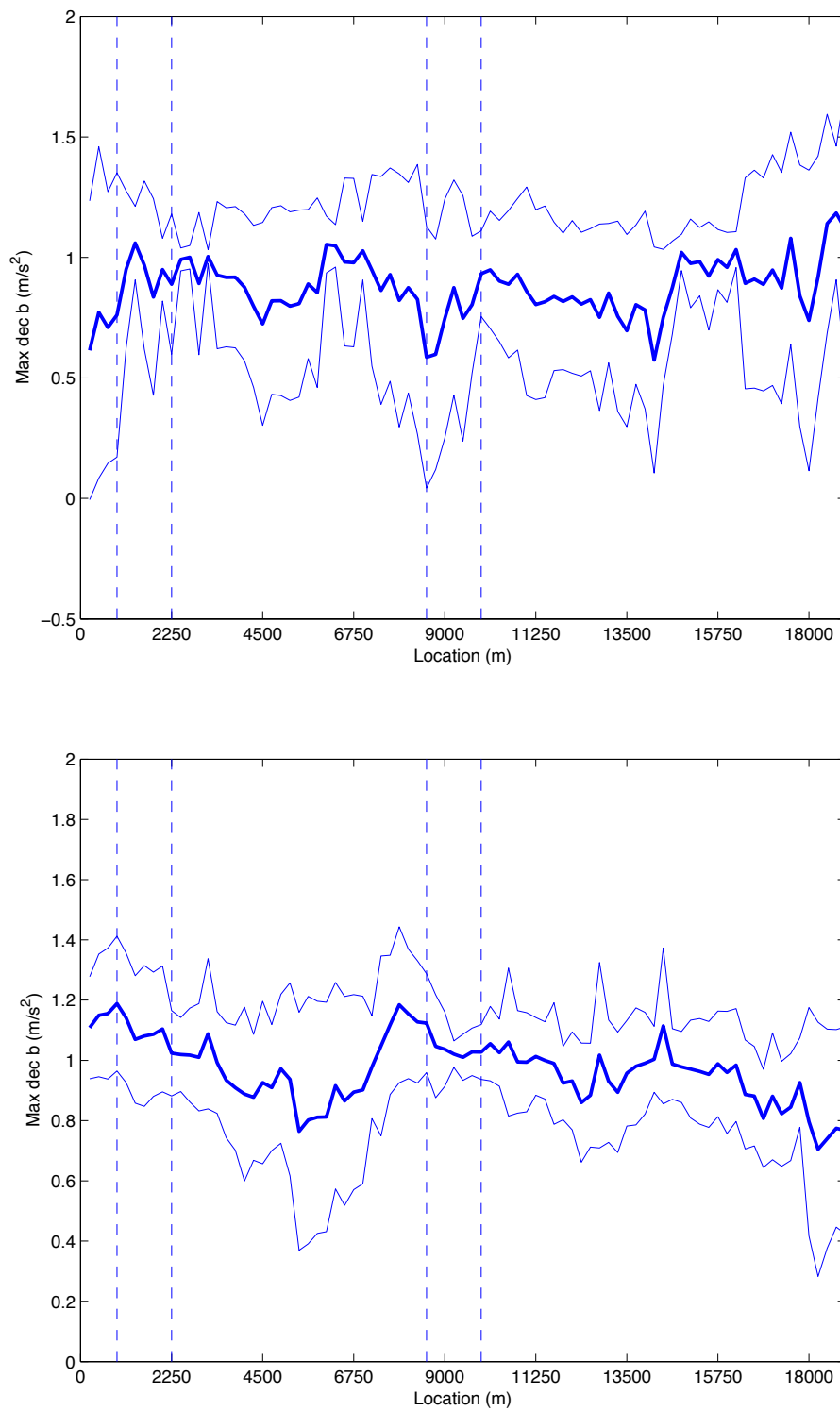


Figure 8.2: Parameter estimates of maximum deceleration b of the Intelligent Driver Model (Treiber et al., 2000) for the control group (top) and the experimental group (bottom) in case of an emergency situation. The bold blue line represents the estimates of the parameter values while the thin lines indicate the expected value plus or minus the standard deviation. The four dotted lines represent the start and end of the stop-and-go waves.

Maximum deceleration b

In Table 8.1 also descriptive statistics for maximum deceleration b are presented. Maximum deceleration b in the Intelligent Driver Model (Treiber et al., 2000) represents the maximum deceleration a driver is willing to apply. As an illustration, Figure 8.2 shows the estimation results for the parameters maximum deceleration b obtained by fitting the Intelligent Driver Model to the observations of the driving simulator for the control group (no emergency situation) and the experimental group (emergency situation). In the figure the bold blue line represents the estimates of the parameter values, while the thin blue lines represent the variation (expected value plus or minus the standard deviation). The dotted lines represent the start and end of the two stop-and-go waves.

From the figure it can be observed that for both groups the parameter value of maximum deceleration b fluctuates considerably over time. This is a strong indication for a substantial degree of variability within drivers. As was the case with maximum acceleration a , maximum deceleration b also shows substantial differences between drivers as indicated by the substantial standard deviations. In both groups the two stop-and-go waves do not seem to have a substantial influence on the mean parameter value of maximum deceleration b .

When comparing the two groups, it can be observed from Table 8.1 as well as from Figure 8.2 that overall maximum deceleration b is larger in the experimental group than in the control group. The overall mean value of maximum deceleration b in the control group amounted to 0.87 m/s^2 , while in the experimental group the overall mean value amounted to 0.97 m/s^2 . When comparing the value of maximum deceleration b in the control group to values normally used in simulations (Kesting et al., 2010), it can be concluded that this value is somewhat lower. Overall the variability between drivers was smaller in the experimental group compared to the control group.

From an independent samples t-test it followed that the difference in maximum deceleration b between the control group and the experimental group is significant ($p < 0.05$). It can therefore be concluded that maximum deceleration b under emergency situations is significantly larger than under normal driving conditions.

Free speed v_0

In Table 8.1 also descriptive statistics for free speed v_0 are presented. Again as an illustration, Figure 8.3 shows the estimation results for the parameter free speed v_0 obtained by fitting the Intelligent Driver Model (Treiber et al., 2000) to the observations of the driving simulator for the control group (no emergency situation) and the experimental group (emergency situation). In the figure the bold blue line represents the estimates of the parameter values, while the thin blue lines represent the variation (expected value plus or minus the standard deviation). The dotted lines represent the start and end of the two stop-and-go waves.

It can be observed that for both groups the parameter value of free speed v_0 remains fairly constant over time. Furthermore, it can be observed from Figure 8.3 that the standard deviation is relatively small, which is an indication of a small degree of variability between drivers with regard to this parameter of the Intelligent Driver Model. In both groups the two stop-and-go

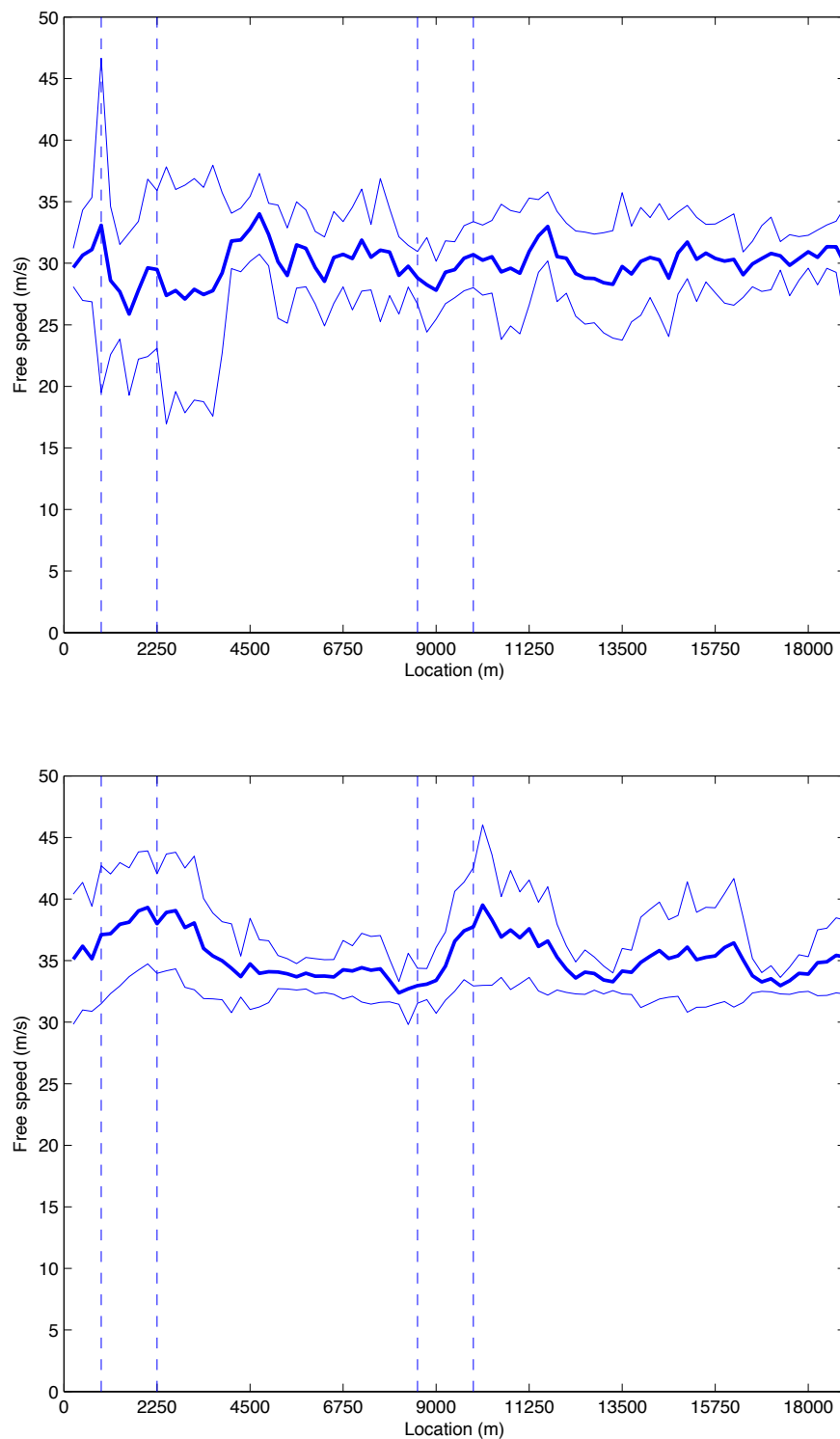


Figure 8.3: Parameter estimates of free speed v_0 of the Intelligent Driver Model (Treiber et al., 2000) for the control group (top) and the experimental group (bottom) in case of an emergency situation. The bold blue line represents the estimates of the parameter values while the thin lines indicate the expected value plus or minus the standard deviation. The four dotted lines represent the start and end of the stop-and-go waves.

waves do not seem to have a substantial influence on the mean parameter value of free speed v_0 .

When comparing the two groups it can be observed from Table 8.1 as well as from Figure 8.3 that overall free speed v_0 is larger in the experimental group than in the control group. The overall mean value of free speed v_0 in the control group amounted to 29.97 m/s, while in the experimental group the overall mean value amounted to 35.27 m/s. Again, overall the variability between drivers was smaller in the experimental group compared to the control group.

From an independent samples t-test it followed that the difference in free speed v_0 between the control group and the experimental group is significant ($p < 0.05$). It can therefore be concluded that free speed v_0 under emergency situations is significantly higher than under normal driving conditions.

Desired time headway T

Finally, in Table 8.1 also descriptive statistics for desired time headway T are presented. Desired time headway T in the Intelligent Driver Model (Treiber et al., 2000) represents the dynamic component of desired distance to the lead vehicle. This parameter determines the extent to which desired distance to the lead vehicle is dependent on the speed of the following vehicle.

Again as an illustration, Figure 8.4 shows the estimation results for the parameter desired time headway T obtained by fitting the Intelligent Driver Model to the observations of the driving simulator for the control group (no emergency situation) as well as the experimental group (emergency situation). In the figure the bold blue line represents the estimates of the parameter values, while the thin blue lines represent the variation (expected value plus or minus the standard deviation). The dotted lines represent the start and end of the two stop-and-go waves.

From the figure it can be observed that especially in the control group the parameter value of desired time headway T fluctuates considerably over time. This is a strong indication of a substantial degree of variability within drivers with regard to desired time headway in case of normal driving conditions. In the experimental group the fluctuations over time were considerably smaller.

Furthermore, it can be observed from Figure 8.4 that the variability between drivers is relatively large in both groups. In both groups the two stop-and-go waves do not seem to have a substantial influence on the mean parameter value of desired time headway T .

When comparing the two groups it can be observed from Table 8.1 as well as from Figure 8.4 that overall desired time headway T is substantially smaller in the experimental group than in the control group. The overall mean value of desired time headway T in the control group amounted to 0.78s, while in the experimental group the overall mean value amounted to 0.25s. Again, overall the variation between drivers was smaller in the experimental group compared to the control group.

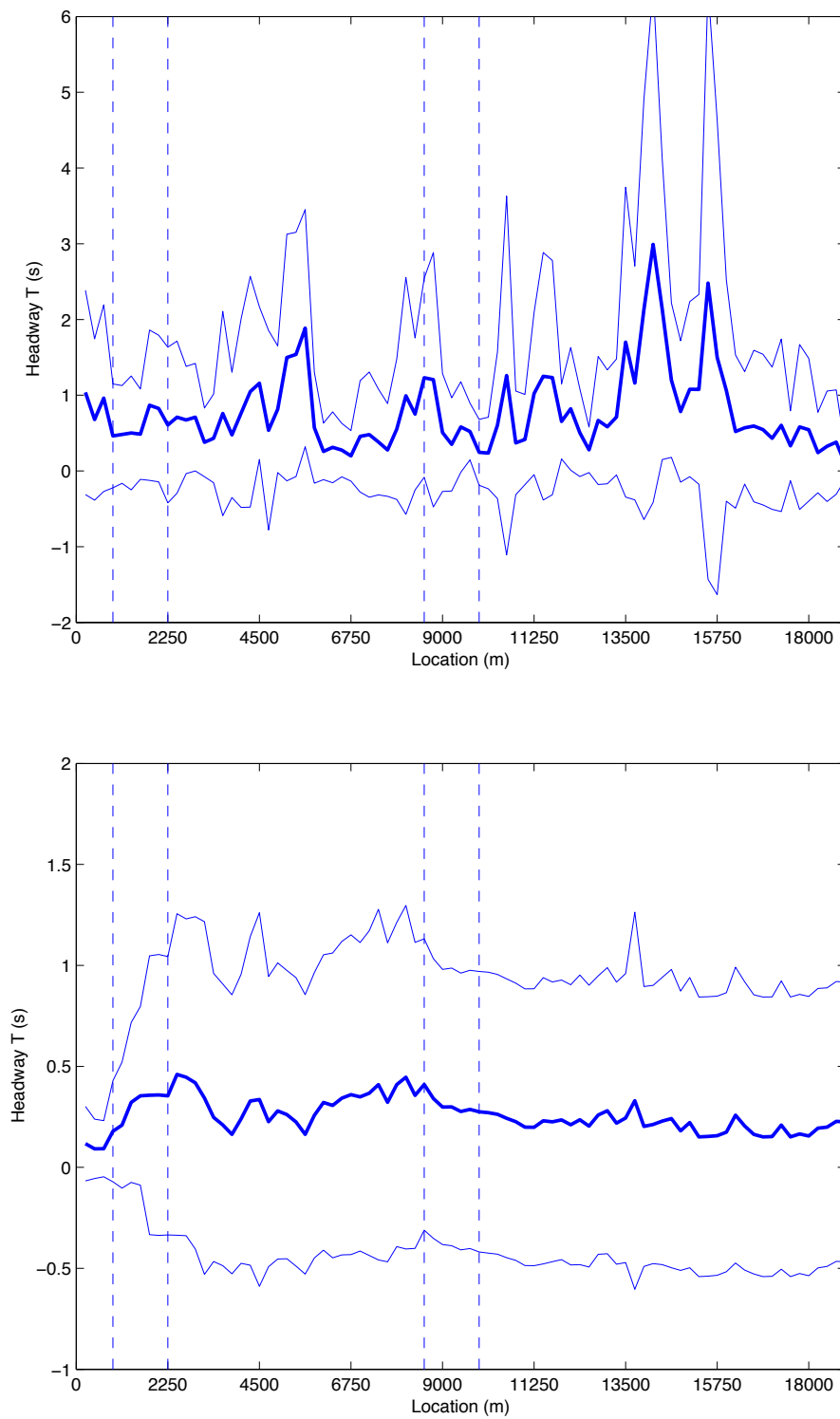


Figure 8.4: Parameter estimates of desired time headway T of the Intelligent Driver Model (Treiber et al., 2000) for the control group (top) and the experimental group (bottom) in case of an emergency situation. The bold blue line represents the estimates of the parameter values while the thin lines indicate the expected value plus or minus the standard deviation. The four dotted lines represent the start and end of the stop-and-go waves.

From an independent samples t-test it followed that the difference in desired time headway T between the control group and the experimental group is significant ($p < 0.05$). It can therefore be concluded that desired time headway T under emergency situations is significantly smaller than under normal driving conditions.

From this section it can be observed that emergency situations have a substantial influence on parameter values of the Intelligent Driver Model (Treiber et al., 2000). A substantial increase in maximum acceleration a and maximum deceleration b can be observed along with a substantial increase in free speed v_0 and a reduction in desired time headway T . When comparing variability between drivers, it can be observed that this is substantial and that the magnitude of the variability differs between normal driving conditions and driving in case of an emergency situation.

The observed effects in parameter values in the Intelligent Driver Model can be regarded as compensation effects as proposed in the theoretical framework in Chapter 2. Drivers seem to consciously increase their maximum acceleration and deceleration, reduce their desired time headway and increase their free speed.

However, in the proposed theoretical framework it was assumed that when these compensation effects are insufficient in order to resolve the imbalance between driver capability and task demands, an increase in mental workload will be the result with consequently performance effects in longitudinal driving behavior. It was stated that performance effects could for example result in a reduction in the performance of the car-following task.

If this is the case, it can be conjectured that model performance of car-following models will decrease, as car-following will to a lesser extent become a determinant of longitudinal driving behavior. To this end in the next section the results of the determination of model performance of the Intelligent Driver Model is reported.

8.2.2 Model performance in case of emergency situations

In order to gain insight into the performance of the Intelligent Driver Model (Treiber et al., 2000) the estimated model was compared to a null model (i.e., the model assuming zero acceleration). In other words: in the null model the parameter values were set to zero, allowing for a good comparison in model performance of the estimated model. Null models have been widely used in order to cross-compare model performance (see for example also Ossen and Hoogendoorn (2007) and Hoogendoorn and Daamen (2007)).

From Figure 8.5 it can be observed for the Intelligent Driver Model that in the control group as well as in the experimental group the estimated models (blue line) outperform the null model.

Furthermore, it can be observed from the figure that performance of the estimated model in the control group as well as in the experimental group increases during the segments in which a stop-and-go wave was present.

When comparing the log-likelihoods of the Intelligent Driver Model of the control group to the experimental group it can be observed that performance of the estimated model is quite similar. However, overall performance of the Intelligent Driver Model is somewhat lower in

the experimental group compared to the control group. From an independent samples t-test it followed that this difference is significant ($p < 0.05$).

This is a strong indication for the existence of performance effects in longitudinal driving behavior. According to the theoretical framework performance effects occur when compensation effects in driving behavior are insufficient to resolve an imbalance between driver capability and task demands. An example of a performance effect is that drivers are less able to adequately perform their car-following subtask, i.e., they follow their lead vehicle less adequately. When car-following becomes to a lesser extent a determinant of longitudinal driving behavior, model performance will decrease.

In summary, emergency situations lead to compensation effects, which are reflected in changes in the values of parameters of the Intelligent Driver Model. Furthermore, these conditions lead to a reduction in model performance of this often used car-following model. This is a strong indication for the existence of performance effects, as proposed by the theoretical framework.

8.3 Parameter value changes and model performance in case of adverse weather conditions

8.3.1 Parameter value changes in case of adverse weather conditions

This section discusses to what extent the Intelligent Driver Model (Treiber et al., 2000) is adequate in incorporating longitudinal driving behavior in case of adverse weather conditions (i.e., fog). In order to determine this, we again estimated parameter values and model performance for the Intelligent Driver Model using the calibration approach for joint estimation discussed in Chapter 7. With regard to adverse weather conditions use was made of the data obtained through the driving simulator experiment presented in Chapter 3.

In order to determine the influence of adverse weather conditions on parameter values of the Intelligent Driver Model we compare parameter of the control condition (normal driving conditions) to the parameter values of the experimental condition (fog). Again, this is achieved through the estimation of the parameter values of maximum acceleration a , maximum deceleration b , free speed v_0 and desired time headway T per individual driver and calculation of mean values, standard deviations, minimum as well as maximum values.

In Table 8.2 the mean values, standard deviations and ranges for the parameter values of the Intelligent Driver Model in case of adverse weather conditions are presented. This table shows the descriptive statistics for the control condition (normal driving conditions) and the experimental condition (fog).

In the next subsections we again provide a detailed discussion of the individual parameters of the Intelligent Driver Model (Treiber et al., 2000).

Maximum acceleration a

Again, we start with discussing the effect adverse weather conditions have on maximum acceleration a . As an illustration, Figure 8.6 shows the estimation results for the parameter maximum acceleration a obtained by fitting the Intelligent Driver Model (Treiber et al., 2000) to the

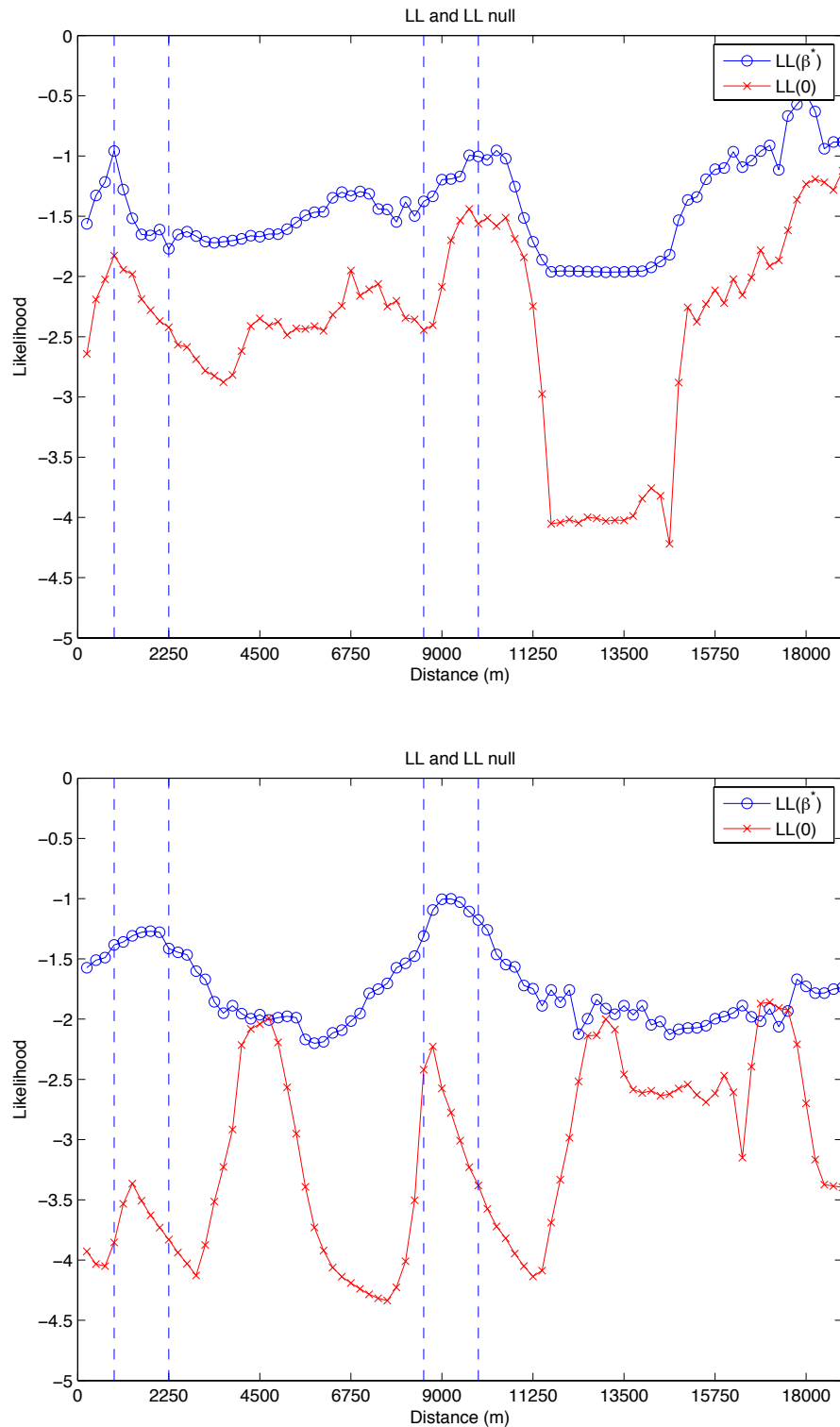


Figure 8.5: Performance of the model compared to the null model (zero acceleration) for the Intelligent Driver Model (Treiber et al., 2000) in case of an emergency situation. The blue line represents the log-likelihoods of the estimated model, while the red line represents the log-likelihoods of the null model. The dotted lines represent the location where the stop-and-go waves started and ended.

Table 8.2: Parameter values of the Intelligent Driver Model (Treiber et al., 2000) for the control condition (normal driving conditions) and the experimental condition (fog).

Parameter	Mean	Std	Min	Max
<i>Control condition</i>				
Maximum acceleration a (m/s^2)	1.20	0.28	0.81	1.43
Maximum deceleration b (m/s^2)	0.90	0.15	0.55	0.97
Free speed v_0 (m/s)	28.83	1.83	23.10	31.76
Desired time headway T (s)	1.18	0.19	0.46	1.74
<i>Experimental condition</i>				
Maximum acceleration a (m/s^2)	0.97	0.34	0.75	1.16
Maximum deceleration b (m/s^2)	0.63	0.40	0.52	0.70
Free speed v_0 (m/s)	33.46	3.70	31.44	34.80
Desired time headway T (s)	0.67	0.18	0.44	1.09

observations of the driving simulator for the control condition (normal driving conditions) and the experimental condition (fog).

In the figure the bold blue line represents the estimates of the parameter values, while the thin blue lines represent the variation (expected value plus or minus the standard deviation). The dotted line indicates the location where the adverse weather condition started.

From Figure 8.6 it can be observed that in the control condition as well as in the experimental condition the parameter value of maximum acceleration a fluctuates considerably over time. Again, this is a strong indication for a substantial degree of variability within drivers.

Furthermore, it can be observed that the variability between drivers with regard to maximum acceleration a in the control condition as well as in the experimental condition is relatively substantial, as indicated by the substantial standard deviations.

When comparing the two conditions it can be observed from Table 8.2 as well as from Figure 8.6 that overall maximum acceleration a is smaller in the experimental condition compared to the control condition. The overall mean value of maximum acceleration a in the control condition amounted to $1.20 m/s^2$, while in the experimental condition this value amounted to $0.97 m/s^2$. Overall the variability in the experimental condition was larger than in the control condition. This is an indication for the fact that variability between drivers was somewhat larger in the experimental condition than in the control condition.

From a paired samples t-test it followed that the difference between the control condition and the experimental condition was significant ($p < 0.05$). It can therefore be concluded that maximum acceleration a in case of adverse weather conditions is significantly smaller than under normal driving conditions.

Maximum deceleration b

We continue with discussing the effect adverse weather conditions have on maximum deceleration b . Figure 8.6 shows the estimation results for the parameter maximum deceleration b

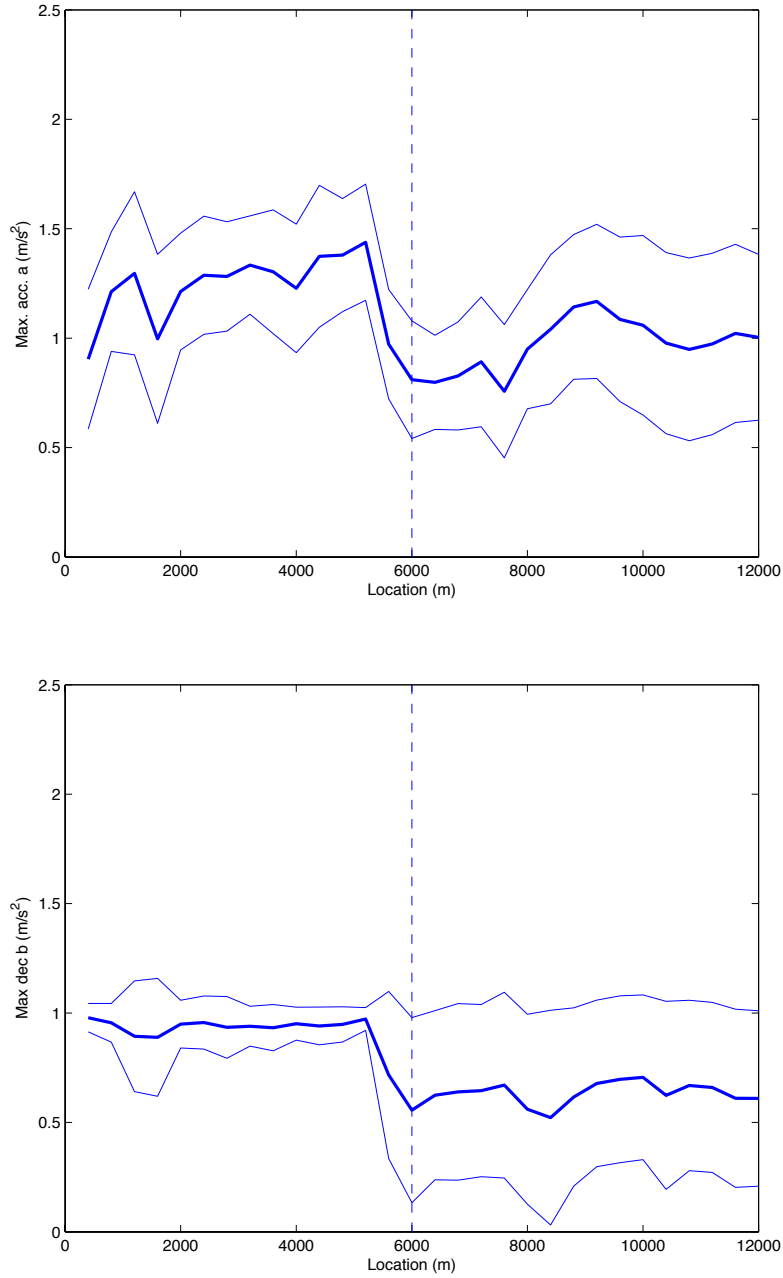


Figure 8.6: Parameter estimates of maximum acceleration a and maximum deceleration b for the Intelligent Driver Model (Treiber et al., 2000) in case of adverse weather (fog). The bold blue line represents the estimates of the parameter values while the thin lines indicate the expected value plus or minus the standard deviation. The vertical dotted line indicates the location where the adverse weather condition started. The area to the left of the dotted line represents the control condition, while the area to the right of the dotted line represents the adverse weather condition.

obtained by fitting the Intelligent Driver Model (Treiber et al., 2000) to the observations of the driving simulator for the control condition (normal driving conditions) and the experimental condition (fog). In the figure the bold blue line represents the estimates of the parameter values, while the thin blue lines represent the variation (expected value plus or minus the standard deviation). The dotted line represents the location where the adverse weather condition started.

It can be observed that in both conditions the parameter values of maximum deceleration fluctuate over time. This is to a larger extent the case in the experimental condition. This is a strong indication for a substantial degree of variability within drivers. As was the case with maximum acceleration a , maximum deceleration b shows substantial differences between drivers as indicated by the substantial standard deviations. This can especially be observed in the experimental condition.

When comparing the control condition to the experimental condition, it can be observed from Table 8.2 as well as from Figure 8.6 that overall maximum deceleration b is smaller in the experimental condition than in the control condition. The overall mean value of maximum deceleration b in the control condition amounted to 0.97 m/s^2 , while in the experimental condition it amounted to 0.63 m/s^2 . Overall the variability in the experimental condition was substantially larger than in the control condition. This means that the differences between drivers were substantially larger in case of the adverse weather condition.

From a paired samples t-test it followed that the differences between there control condition and the experimental condition was significant ($p < 0.05$). It can therefore be concluded that maximum deceleration b in case of an adverse weather condition is significantly smaller than under normal driving conditions.

Free speed v_0

We continue with discussing the effect adverse weather conditions have on free speed v_0 . Figure 8.7 shows the estimation results for the parameter free speed v_0 obtained by fitting the Intelligent Driver Model (Treiber et al., 2000) to the observations of the driving simulator for the control condition (normal driving conditions) and the experimental condition (fog). In the figure the bold blue line represents the estimates of the parameter values, while the thin blue lines represent the variation (expected value plus or minus the standard deviation). The dotted line represent the location where the adverse weather condition started.

It can be observed that in both conditions, the parameter values of free speed v_0 fluctuate over time. As was the case with maximum acceleration a and maximum deceleration b this is a strong indication for substantial degree of variability within drivers.

Furthermore, it can again be observed that the variability between drivers is substantial as well, as indicated by the substantial standard deviations. This can especially be observed in the experimental condition.

When comparing the two groups it can be observed from Table 8.2 as well as from Figure 8.7 that overall free speed v_0 is larger in the experimental condition than in the control condition. The overall mean value of free speed v_0 in the control condition amounted to 28.83 m/s , while in the experimental group the overall mean value amounted to 33.46 m/s . Overall, the

variability between drivers was smaller in the control condition compared to the experimental condition.

From a paired samples t-test it followed that the difference in free speed v_0 between the control condition and the experimental condition is significant ($p < 0.05$). It can therefore be concluded that free speed v_0 under adverse weather conditions is significantly larger than under normal driving conditions. From a behavioral point of view, this increase in free speed v_0 is not very insightful. Recall the results with regard to empirical longitudinal driving behavior in case of adverse weather conditions presented in Chapter 4. Here it was shown that speed v significantly decreased in case of an adverse weather condition. This contradicts the findings with regard to free speed v_0 presented in the present chapter. A possible explanation for the observed result is that it is due to the fact that model performance of the Intelligent Driver Model (Treiber et al., 2000) is not very sensitive to free speed v_0 . It may also be due to the estimation method used in this dissertation.

Desired time headway T

In Table 8.2 also descriptive statistics for desired time headway T are presented. Again as an illustration, Figure 8.7 shows the estimation results for the parameter desired time headway T obtained by fitting the Intelligent Driver Model (Treiber et al., 2000) to the observations of the driving simulator for the control condition (normal driving conditions) and the experimental condition (adverse weather condition). In the figure the bold blue line represents the estimates of the parameter values, while the thin blue lines represent the variation (expected value plus or minus the standard deviation). The dotted line represents the location where the adverse weather condition started.

It can be observed that the parameter value of desired time headway T fluctuates considerably over time. This is a strong indication for a substantial degree of variability within drivers with regard to desired time headway. Furthermore, it can be observed from Figure 8.9 that the variability between drivers is relatively small in both conditions, as indicated by the relatively small standard deviations.

When comparing the two conditions it can be observed from Table 8.2 as well as from Figure 8.7 that overall desired time headway T is substantially smaller in the experimental condition than in the control condition. The overall mean value of desired time headway T in the control condition amounted to 1.18s, while in the experimental condition the overall mean value amounted to 0.67s. Overall the variability between drivers was similar in both conditions.

From a paired samples t-test it followed that the difference in desired time headway T between the control condition and the experimental condition is significant ($p < 0.05$). It can therefore be concluded that desired time headway T under adverse weather conditions is significantly smaller than under normal driving conditions.

From a behavioral point of view the reduction in the parameter value desired time headway T is strange. However, desired distance to the lead vehicle consists not only of the speed dependent component T , but also of a minimum stopping distance s_0 . When calculating the descriptive statistics of this parameter it is shown that in the control condition the parameter value of s_0 amounts to 15.56 m ($SD = 16.18$), while in the experimental condition it amounts to 22.65

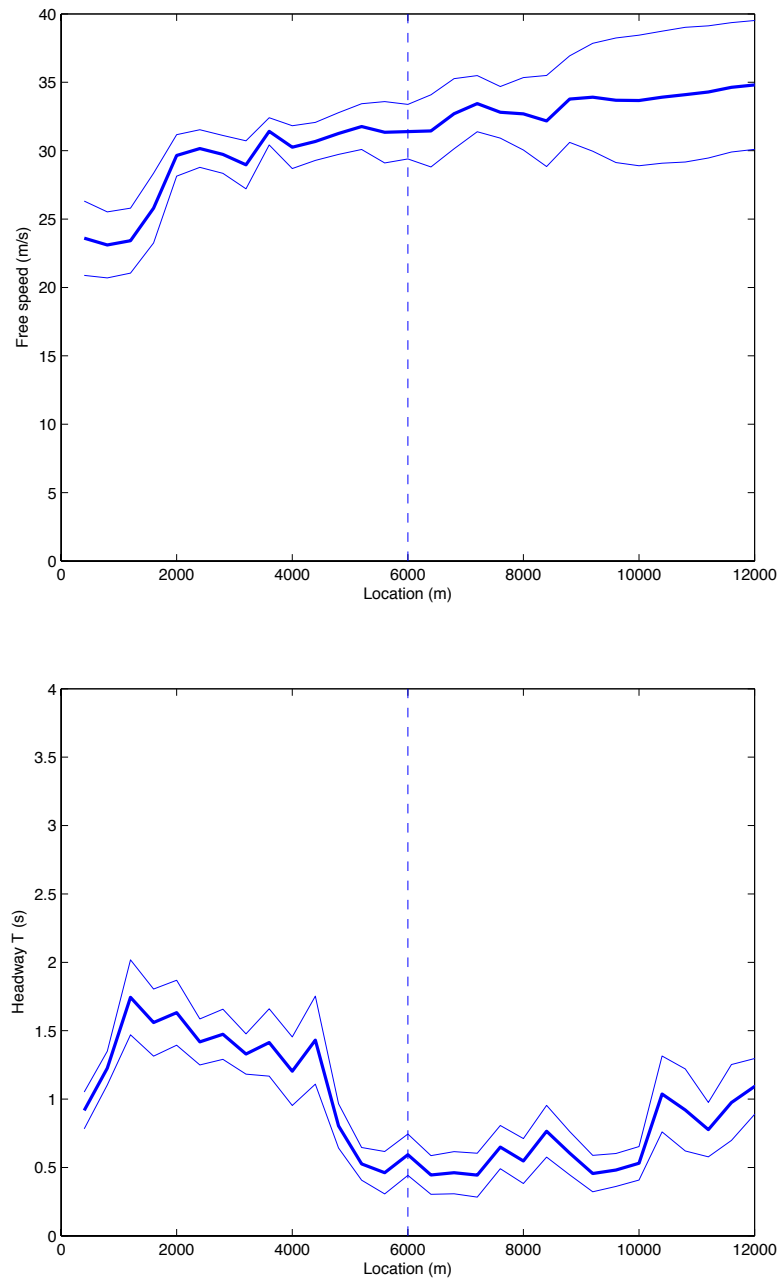


Figure 8.7: Parameter estimates of free speed v_0 and desired time headway T for the Intelligent Driver Model (Treiber et al., 2000) in case of adverse weather (fog). The bold blue line represents the estimates of the parameter values while the thin lines indicate the expected value plus or minus the standard deviation. The vertical dotted line indicates the location where the adverse weather condition started. The area to the left of the dotted line represents the control condition, while the area to the right of the dotted line represents the adverse weather condition.

m ($SD = 19.21$). From a paired samples t-test it followed that this difference is significant ($p < 0.05$). The reduction in desired time headway T is therefore compensated by an increase in minimum stopping distance s_0 .

From this section it can be observed that adverse weather conditions have a substantial influence on parameter values of the Intelligent Driver Model (Treiber et al., 2000). A substantial reduction in maximum acceleration a and maximum deceleration b can be observed. Furthermore, a reduction in desired time headway T accompanied by an increase in minimum stopping distance s_0 was observed.

The observed effects in parameter values in the Intelligent Driver Model (Treiber et al., 2000) can again be regarded as compensation effects as proposed in the theoretical framework in Chapter 2. For example, drivers seem to consciously reduce their maximum acceleration and deceleration.

However, in the proposed theoretical framework it was assumed that when these compensation effects are insufficient in order to resolve the imbalance between driver capability and task demands, an increase in mental workload will be the result with consequently performance effects in longitudinal driving behavior. It was stated that performance effects could for example be reflected in a reduction in the performance of the car-following task. If this is the case, it can be conjectured that model performance of car-following models will decrease, as car-following will to a lesser extent become a determinant of longitudinal driving behavior. To this end in the next section the results on the determination of model performance of the Intelligent Driver Model is reported.

8.3.2 Model performance in case of adverse weather conditions

In order to gain insight into the performance of the Intelligent Driver Model (Treiber et al., 2000) during adverse weather conditions, the estimated model was again compared to a null model. Recall that in the null model the parameter values of the Intelligent Driver Model were set to zero, allowing for a comparison of the performance of the estimated model.

In Figure 8.10 the log-likelihoods are displayed for the estimated model as well as the null model. From the figure it can be observed that the performance of the estimated model compared to the null model is quite similar. Furthermore, the estimated model outperforms the null model.

However, from the figure it can clearly be observed that model performance decreases after the start of the adverse weather condition. Also it can be observed that the difference between the estimated model and the null model increases after the start of the experimental condition.

It can be concluded that the Intelligent Driver Model performs less well during an adverse weather condition. From a paired samples t-test it followed that the difference in model performance between the control condition and the experimental condition was significant ($p < 0.05$).

This is a strong indication for the existence of performance effects in longitudinal driving behavior. It can be conjectured that car-following becomes to a lesser extent a determinant of longitudinal driving behavior in case of an emergency situation.

In summary, adverse weather conditions lead to compensation effects, which are reflected in changes in the values of parameters of the Intelligent Driver Model (Treiber et al., 2000). Furthermore, these conditions lead to a reduction in model performance of this often used car-following model. This is a strong indication for the existence of performance effects, as proposed by the theoretical framework.

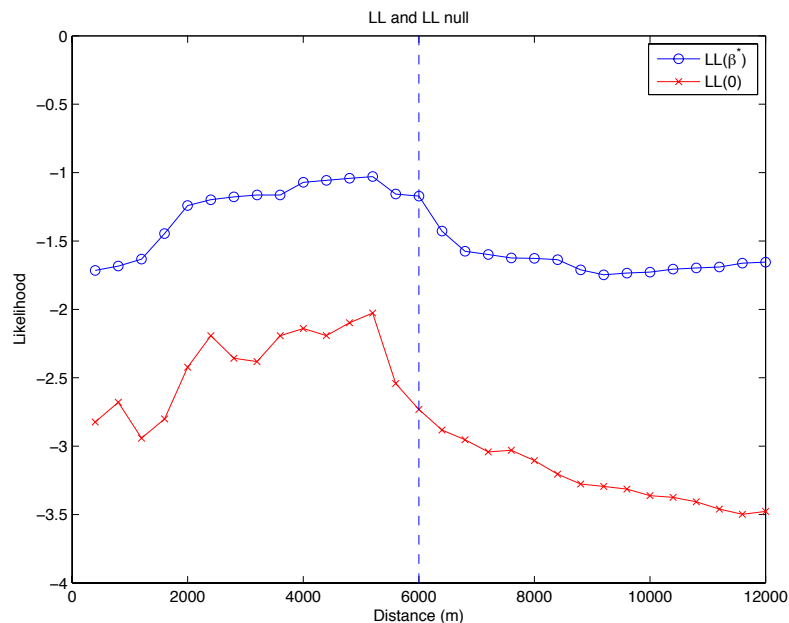


Figure 8.8: Performance of the model compared to the null model (zero acceleration) for the Intelligent Driver Model (Treiber et al., 2000) in case of an adverse weather condition. The dotted line indicates the location where the adverse weather condition started. The area to the left of the dotted line represents the control condition, while the area to the right of the dotted line represents the adverse weather condition.

8.4 Parameter value changes and model performance in case of freeway incidents

8.4.1 Parameter value changes in case of freeway incidents

This section discusses to what extent the Intelligent Driver Model (Treiber et al., 2000) is adequate in incorporating longitudinal driving behavior in case of a freeway incident. Again, in order to determine this, we estimated parameter values and model performance for the Intelligent Driver Model using the calibration approach for joint estimation discussed in Chapter 7. With regard to freeway incidents use was made of the data obtained through the driving simulator experiment presented in Chapter 3.

In order to determine the influence of freeway incidents on parameter values of the Intelligent Driver Model, we compare parameter values of the control condition (before perception of an incident in the other driving lane) to the experimental condition (during perception of an incident in the other driving lane). To this end we estimate the parameters maximum acceleration

a , maximum deceleration b , free speed v_0 and desired time headway T per individual driver and calculate mean values, standard deviations, minimum as well as maximum values.

In Table 8.3 the mean values, standard deviations and ranges for the parameter values of the Intelligent Driver Model in case of a freeway incident are presented. This table shows the descriptive statistics for the control condition as well as for the experimental condition.

Table 8.3: Parameter values of the Intelligent Driver Model (Treiber et al., 2000) for the control condition (normal driving conditions) and the experimental condition (incident in the other driving lane).

Parameter	Mean	Std	Min	Max
<i>Control condition</i>				
Maximum acceleration a (m/s^2)	0.84	0.32	0.65	1.25
Maximum deceleration b (m/s^2)	0.81	0.06	0.64	1.03
Free speed v_0 (m/s)	29.85	5.02	27.42	34.12
Desired time headway T (s)	0.41	0.22	0.48	0.74
<i>Experimental condition</i>				
Maximum acceleration a (m/s^2)	0.96	0.11	0.80	1.11
Maximum deceleration b (m/s^2)	0.71	0.09	0.59	0.70
Free speed v_0 (m/s)	34.34	2.34	34.88	34.98
Desired time headway T (s)	1.82	0.26	0.78	1.86

Maximum acceleration a

Again, we start with discussing the effect freeway incidents have on maximum acceleration a . As an illustration, Figure 8.9 shows the estimation results for the parameter maximum acceleration a obtained by fitting the Intelligent Driver Model (Treiber et al., 2000) to the observations of the driving simulator for the control condition (normal driving condition) and the experimental condition (freeway incident). In the figure the bold blue line represents the estimates of the parameter values, while the thin blue lines represent the variation (expected value plus or minus the standard deviation). The dotted lines represent the incident location.

It can be observed that maximum acceleration a shows a considerable large variation over time. Values of maximum acceleration a vary from $0.5m/s^2$ to around $1.5m/s^2$. The variability between drivers is also substantial. Furthermore, from the figure it can be observed that no substantial influence was present of the incident on maximum acceleration a .

When comparing the two conditions through the descriptive statistics presented in Table 8.3., it can be observed that maximum acceleration a on average is higher in the experimental condition than in the control condition. The overall mean value of maximum acceleration a in the control condition amounted to $0.84m/s^2$, while in the experimental condition it amounted to $0.96m/s^2$. Overall the variability was smaller in the experimental condition. However, from a paired samples t-test it followed that the difference in maximum acceleration a was not significant ($p > 0.05$). It can therefore be concluded that although maximum acceleration a was slightly higher in the experimental condition, freeway incidents do not seem to have a significant effect on this parameter of the Intelligent Driver Model (Treiber et al., 2000).

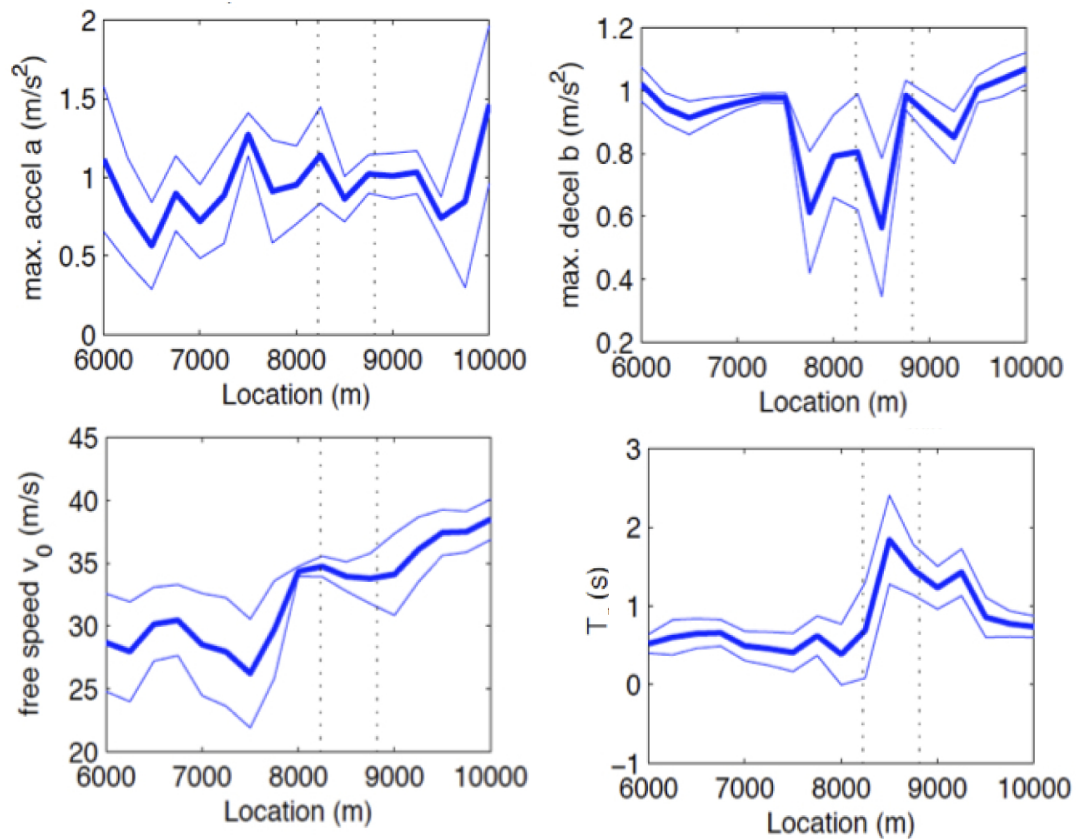


Figure 8.9: Parameter estimates of maximum acceleration a , maximum deceleration b , free speed v_0 and desired time headway T for the Intelligent Driver Model (Treiber et al., 2000) in case of a freeway incident. The bold blue line represents the estimates of the parameter values while the thin lines indicate the expected value plus or minus the standard deviation. The vertical dotted lines indicate the incident location.

Maximum deceleration b

Next we discuss the effect freeway incidents have on maximum deceleration b . As an illustration, Figure 8.9 shows the estimation results for the parameter maximum deceleration b obtained by fitting the Intelligent Driver Model (Treiber et al., 2000) to the observations of the driving simulator for the control condition (normal driving condition) and the experimental condition (freeway incident).

The figure shows that estimates of maximum deceleration b display substantial fluctuations. Overall values of maximum deceleration b vary from around $1m/s^2$ to around $0.7m/s^2$. In the vicinity of the incident site a substantial reduction in maximum deceleration b can be observed. The standard deviations are substantial, again indicating a substantial degree of variability between drivers.

When comparing the descriptive statistics presented in Table 8.3 for the parameter maximum acceleration b it can be observed that on average indeed a substantial reduction can be observed. The overall mean value of maximum deceleration b in the control condition amounted to $0.81m/s^2$ while in the experimental condition it amounted to $0.71m/s^2$. Overall, as indicated, the variability was larger in the experimental condition, compared to the control condition. From the paired samples t-test it followed that the difference between the two conditions with regard to maximum deceleration b was however not significant ($p > 0.05$). It can therefore be concluded that although maximum deceleration b decreased substantially in the experimental condition, perception of a freeway incident does not seem to have a significant influence on this parameter of the Intelligent Driver Model (Treiber et al., 2000).

Free speed v_0

Next we discuss the effect freeway incidents have on free speed v_0 . As an illustration, Figure 8.9 shows the estimation results for the parameter free speed v_0 obtained by fitting the Intelligent Driver Model (Treiber et al., 2000) to the observations of the driving simulator for the control condition (normal driving condition) and the experimental condition (freeway incident).

Again, the figure shows substantial fluctuations in the value of the parameter free speed v_0 . Overall values of this parameter range from around $26m/s$ to around $38m/s$. In the vicinity of the incident location a substantial increase in the value of free speed v_0 can be observed. The variability between drivers is substantial, but becomes smaller in the vicinity of the incident location.

When comparing the descriptive statistics presented in Table 8.3 for the parameter free speed v_0 it can be observed that on average a substantial increase in free speed v_0 can be observed. The overall mean value of free speed v_0 in the control condition amounted to $29.95m/s$ while in the experimental condition it amounted to $34.34m/s$. Overall, as indicated, the variability between drivers was smaller in the experimental condition compared to the control condition. From a paired samples t-test it followed that the difference in free speed v_0 was not significant.

Furthermore, it can be debated whether these values of v_0 are realistic. The result with regard to v_0 may be due to the fact that the performance of the Intelligent Driver Model (Treiber et al., 2000) is not very sensitive to v_0 , given that it is sufficiently high. This could also be observed with free speed v_0 in case of adverse weather conditions.

Desired time headway T

Finally, we discuss the effect freeway incidents have on desired time headway T . As an illustration, Figure 8.9 also shows the estimation results for the parameter desired time headway T obtained by fitting the Intelligent Driver Model (Treiber et al., 2000) to the observations of the driving simulator for the control condition (normal driving condition) and the experimental condition (freeway incident).

As was the case with the other parameters of the Intelligent Driver Model discussed in the aforementioned, the value of desired time headway seems to fluctuate considerably over time. Overall values seem to range from around 0.5s to a very high value of 2s. The variability between drivers is relatively small in the control condition as well as in the experimental condition.

When comparing the descriptive statistics presented in Table 8.3 for the parameter desired time headway T it can be observed that on average a substantial increase in desired time headway T is present in the vicinity of the incident location. This is an indication for a strong change in longitudinal driving behavior. In the control condition the mean value of desired time headway T amounted to 0.41s while in the experimental condition this value amounted to 1.82s. variability increased slightly in the experimental condition compared to the control condition. The paired samples t-test showed that the difference between the two conditions with regard to desired time headway T was significant ($p < 0.05$). It can therefore be concluded that desired time headway T is significantly larger during perception of a freeway incident.

From this section it can be observed that freeway incidents have a substantial influence on some of the parameter values of the Intelligent Driver Model. Although changes in maximum acceleration a and maximum deceleration b were not significant, a significant increase in desired time headway T was observed.

The observed effects in parameter values in the Intelligent Driver Model can again be regarded as compensation effects as proposed in the theoretical framework in Chapter 2. For example, drivers seem to consciously reduce their maximum acceleration and deceleration.

However, in the proposed theoretical framework it was assumed that when these compensation effects are insufficient in order to resolve the imbalance between driver capability and task demands, an increase in mental workload will be the result with consequently performance effects in longitudinal driving behavior. It was stated that performance effects could for example be reflected in a reduction in the performance of the car-following task. If this is the case, it can be conjectured that model performance of car-following models will decrease, as car-following will to a lesser extent become a determinant of longitudinal driving behavior. To this end in the next section the results on the determination of model performance of the Intelligent Driver Model (Treiber et al., 2000) is reported.

8.4.2 Model performance in case of freeway incidents

In order to gain insight into the performance of the Intelligent Driver Model (Treiber et al., 2000) in case of a freeway incident, the estimated model was compared to a null model. Recall that in the null model the parameter values of the model were set to zero.

In general from Figure 8.10 it can be observed that in the vicinity of the freeway incident, the difference between the null and the estimated models increases. This means that the estimated model performs substantially better at the incident site than the null models. However, it can also be observed that the log-likelihoods of the estimated models as well as the null models decrease at the incident site. This means that the models less adequately incorporate longitudinal driving behavior in case of incidents in the other driving lane.

This is a strong indication for the existence of performance effects in longitudinal driving behavior. It can be conjectured that car-following becomes to a lesser extent a determinant of longitudinal driving behavior in case of an emergency situation.

In summary, freeway incidents lead to compensation effects, which are reflected in changes in the values of parameters of the Intelligent Driver Model. Furthermore, these conditions lead to a reduction in model performance of this often used car-following model. This is a strong indication for the existence of performance effects, as proposed by the theoretical framework.

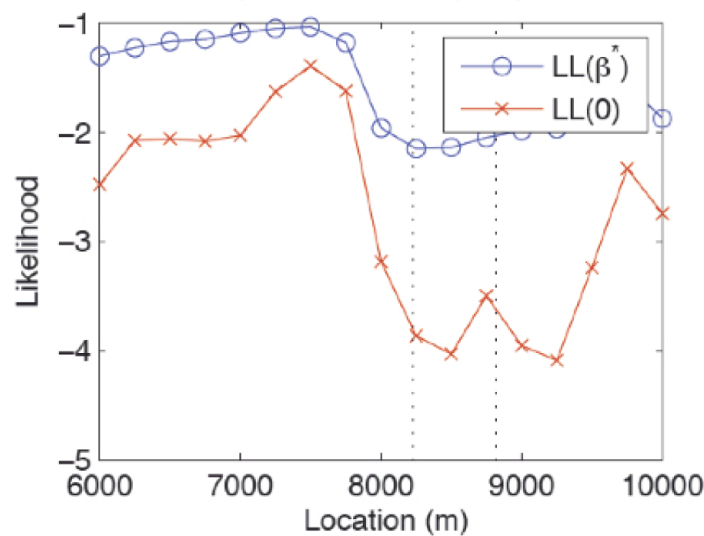


Figure 8.10: Performance of the model compared to the null model (zero acceleration) for the Intelligent Driver Model (Treiber et al., 2000).

8.5 Conclusions

In the theoretical framework in Chapter 2 we proposed that adverse conditions have an effect on mental workload, compensation and performance effects in longitudinal driving behavior. We conjectured that emergency situations lead for example to an increase in activation level, leading to an imbalance between driver capabilities and task demands. The driver will try to resolve this imbalance by consciously adjusting his driving behavior (compensation effects). When a driver is unable to resolve this imbalance, an increase in mental workload is assumed to be a consequence leading to performance effects. It can be assumed that compensation effects in longitudinal driving behavior due to an adverse condition are reflected in parameter values in mathematical models of car-following behavior, while performance effects may be reflected in a reduction in model performance. However, no research was found on the influence of

the selected adverse conditions on parameter values and model performance of continuous car-following models.

In order to determine parameter value changes of an often used car-following model, i.e., the Intelligent Driver Model (Treiber et al., 2000) in case of the selected adverse conditions, in Chapter 7 we introduced a calibration approach for joint estimation. In the present chapter we started with the estimation of the parameter values of the Intelligent Driver Model (Treiber et al., 2000) using a dataset containing an emergency situation. We concluded that emergency situations have a substantial and significant influence on all of the parameters of the Intelligent Driver Model (Treiber et al., 2000). In this context we showed that emergency situations lead to a significant increase in maximum acceleration a , maximum deceleration b and free speed v_0 . Furthermore we showed that emergency situations lead to a significant reduction in the value of the parameter desired time headway T .

We also showed that adverse weather conditions have a substantial and significant influence on parameter values of the Intelligent Driver Model. We showed that adverse weather conditions (i.e., fog) lead to a significant reduction in maximum acceleration a and maximum deceleration b . Strange enough free speed v_0 increased significantly in the adverse weather condition. It was argued that this might be due to the fact that model performance is not very sensitive to v_0 given that it is sufficiently high. Desired time headway T increased as well during the adverse weather condition. Although this might seem strange from a behavioral point of view, we showed that minimum stopping distance s_0 increased significantly. It can therefore be concluded that desired distance to the lead vehicle in case of an adverse weather condition becomes less dependent on speed, but to a larger extent on the minimum stopping distance.

Finally in the context of the influence of adverse conditions on parameter values of the Intelligent Driver Model we showed that freeway incidents have an influence on some of these parameter values. We showed that on average incidents in the other driving lane lead to an increase in maximum acceleration a as well as a reduction in maximum deceleration b . However, the differences between the control condition and the experimental condition proved to be non-significant. As was the case with adverse weather condition, free speed v_0 increased. Again we argued that this might be due to the fact that model performance is not very sensitive to v_0 given that it is sufficiently high. Most striking however was the substantial increase in desired time headway T . This increase proved to be significant.

In the context of the proposed theoretical framework of Chapter 2 these parameter value changes can be regarded as compensation effects. In other words: drivers consciously adapt their maximum acceleration and deceleration, free speed and change their desired time headway.

The framework also proposed that when compensation effects are insufficient to resolve the imbalance between driver capabilities and task demands, mental workload will increase with performance effects as a result. This was supported by the findings in Chapter 5, in which we showed that adverse conditions have a substantial influence on mental workload of drivers.

In this sense, we also showed that adverse conditions have an influence on model performance. We showed that emergency situations, adverse weather conditions as well as freeway incidents lead to a reduction in model performance of the Intelligent Driver Model. This is a strong

indication for the existence of performance effects in longitudinal driving behavior in case of an adverse condition. It can be conjectured that model performance declines due to the fact that car-following becomes to a lesser extent a determinant of longitudinal driving behavior.

As could be assumed from the theoretical framework a substantial degree of variability within as well as between drivers could be observed in the parameter values of the Intelligent Driver Model. Overall it can be observed that the variation between drivers in parameter values is quite substantial. The degree to which this is the case seems to be dependent on the external circumstances. In some cases the differences between drivers seemed to increase during an adverse condition, while in other cases it seemed to decrease. This supports the assumptions in the theoretical framework, as it can be assumed that the imbalance between driver capabilities and task demands will vary largely within and between drivers.

From the literature review of car-following models in Chapter 6 it followed that continuous car-following models, such as the intelligent Driver Model have a rather mechanistic character. In this regard in the next chapter we turn to the estimation of so-called action points in psycho-spacing models. These models describe longitudinal driving behavior on a relative speed - spacing $(\Delta v, s)$ plane governed by perceptual thresholds. In this chapter we will show that adverse conditions have a substantial influence on the position and shape of these perceptual thresholds, represented by the position of action points. Also we will show that the assumption of deterministic perceptual thresholds, assumed in the original formulation of these models, does not hold in reality.

Chapter 9

Psycho-spacing Modeling in Case of Adverse Conditions

9.1 Aim and structure of this chapter

The previous chapter discussed parameter value changes as well as model performance of the Intelligent Driver Model (Treiber et al., 2000) in case of the selected adverse conditions. It followed from the results that the adverse conditions lead to substantial parameter value changes in this often used car-following model. Furthermore, it could be observed that model performance decreased substantially when comparing normal driving conditions to adverse conditions. We argued that changes in parameter values are a strong indication of compensation effects while a reduction in model performance is a strong indication for the existence of performance effects due to adverse conditions.

In our literature review of car-following models in Chapter 6 it was conjectured that the character of most continuous car-following models is quite mechanistic as they to a very limited degree incorporate human elements like thresholds in perception. In the past, psycho-spacing models were developed to adjust for this mechanistic aspect of continuous car-following models.

Adverse conditions may be assumed to have a substantial influence on the shape of perceptual thresholds represented by the position of action points incorporated in these psycho-spacing models. This chapter therefore focuses on the description of longitudinal driving behavior under adverse conditions through psycho-spacing models. However, as was previously discussed, in the original formulation of psycho-spacing models perceptual thresholds are deterministic.

As adverse conditions can be assumed to have a different effect within and between drivers due to the interaction between task demands and driver capabilities, it may be assumed that these deterministic perceptual thresholds do not hold in reality (see also Chapter 6).

In this context, it can be assumed that conscious compensation effects in longitudinal driving behavior are reflected in the position of action points in the relative speed - spacing ($\Delta v, s$) plane. For example, it can be assumed that when a driver reduces his / her speed in order to

increase the distance to the lead vehicle, action points will be located at larger values of spacing s .

Furthermore, the original formulation of the model assumes that drivers, on crossing one of the perceptual thresholds, change their longitudinal driving behavior through a change in the sign of their acceleration. However, here also it can be assumed that acceleration is dependent on relative speed and spacing. The sensitivity of acceleration towards relative speed and spacing can be regarded as performance effects as proposed in the theoretical framework in Chapter 2. Therefore in this chapter the influence of adverse conditions on acceleration a at action points as well as on the difference between acceleration before and after an action point Δa is reported.

In this chapter the results of the data analysis with regard to the influence of adverse conditions on the positions of action points in psycho-spacing models is presented in Section 9.3. In this data analysis use was made of the data analysis method described in Chapter 7. This data analysis technique was applied to the data derived from the driving simulator experiments described in Chapter 3 and also to empirical trajectory data, which will be described in Section 9.2.

Also the results on the influence of adverse conditions on acceleration a as well as the 'jumps' in acceleration Δa (being the difference in acceleration before and after an action point) at the action points is discussed in the present chapter. These results will be presented in Section 9.4. The chapter concludes with a Discussion in Section 9.5.

9.2 Microscopic traffic data

In order to estimate action points in a psycho-spacing model using the data analysis technique described in Chapter 7, use was made of the data obtained through the driving simulator experiments. With regard to the determination of the position of action points in case of a freeway incident, we did however not use the driving simulator data, but instead chose to use empirical data collected with a helicopter. The reason for this was that the data collected with the driving simulator experiment yielded too few action points in order to draw reliable conclusions.

Therefore in order to determine the influence of freeway incidents on action points in a psycho-spacing model, two datasets were used. The first data set, which is regarded as a reference condition, consists of vehicle trajectory data collected through the data collection approach proposed by Hoogendoorn and Schreuder (2005). For this, an airborne observation platform (a helicopter) mounted with a high frequency camera and frame grabber was used.

Using image processing software, vehicles were detected and tracked from the images. This procedure yielded trajectory data covering 500 m of roadway stretch. The spatial resolution was less than 40 cm, while the temporal resolution was 0.1 s.

Vehicles driving in both directions were detected and tracked. However, only one direction is considered here (935 trajectories). The data were collected during the afternoon peak hour at the three-lane A15 motorway to the South of the Dutch city of Rotterdam. This period was characterized by stop-and-go traffic conditions. As an example, trajectories are presented in Figure 9.1.

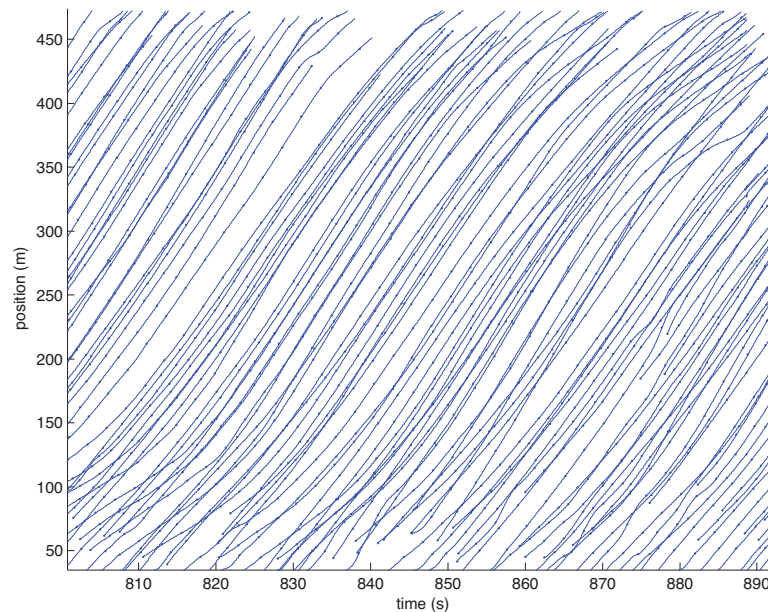


Figure 9.1: Vehicle trajectories (3 lanes) for data collected at the A15 site.

The second data set included an incident on the A1 near the Dutch city of Apeldoorn. Here also the data collection technique from Hoogendoorn and Schreuder (2005) was used.

Here, 199 vehicle trajectories were collected. At the incident a van rolled over at around 9.15 AM on 6 June 2007. The van ended in the median strip which consists of an unpaved area between the two carriageways of the motorway. Each carriageway consisted of two lanes. Congestion occurred in both directions with the head of both queues at the location of the incident (Figure 9.2).



Figure 9.2: The incident location near Apeldoorn (A1). The three white X's indicate where a lane blockage was present.

In this chapter only trajectories were considered for the westbound direction (from left to right in Figure 9.2) as the congestion in that direction was solely caused by rubbernecking.

9.3 Estimating the positions of action points

Recall that in psycho-spacing models longitudinal driving behavior is described on a relative speed - spacing ($\Delta v, s$) plane and controlled by perceptual thresholds. These perceptual thresholds in the ($\Delta v, s$) plane delineate an area in which the driver does not respond to any changes in his dynamic conditions. On crossing one of these thresholds, a driver is assumed to perceive that an unacceptable situation has occurred and will adjust his behavior through a change in the sign of his acceleration a . This point in the ($\Delta v, s$) plane is referred to as an 'action point'.

In order to determine the extent in which adverse conditions influence the positions of action points in the ($\Delta v, s$) plane in psycho-spacing models the data analysis approach described in Chapter 7 was applied to the driving simulator data derived from the experiments described in Chapter 3 as well as to the empirical trajectory data described in the previous section.

9.3.1 Emergency situations

In Figure 9.3 the results are presented of the estimation of the position of action points for the control group (no emergency situation) as well as the experimental group (emergency situation). Overall the figure shows that an overlap in acceleration reductions and accelerations is present. Though this might seem contradictory, this can be explained by the fact that, although a closing relative speed is present, drivers increase their acceleration. This may be caused by the fact that relative speed is not the only determinant of acceleration changes. However, a strong bias can be observed with regard to these overlapping regions when comparing the distributions for acceleration increases and acceleration reductions.

When comparing the distributions of action points of the control group (no emergency situation) and the experimental group (emergency situation) in Figure 9.3, it can be observed that in case of this adverse condition action points are much more concentrated at especially smaller values of spacing s than in the control group.

Secondly, it becomes clear from Figure 9.3 that, in contrast with the control group, in the experimental group drivers react to considerably smaller values of relative speed Δv . This may be due to the fact that drivers generally keep smaller values of spacing s in case of emergency situations.

In order to illustrate that drivers in case of emergency situations react to smaller speed differences with their lead vehicle at smaller spacing, Figure 9.4 shows the cumulative distribution functions of positive and negative relative speed Δv as well as spacing s .

From the figure it can clearly be observed that in general in case of emergency situations action points are located at smaller values of spacing s and also at smaller values of relative speed Δv . This is supported by the results of the Kolmogorov-Smirnov tests for relative speed Δv and spacing s , as $p < 0.05$.

In order to further quantify the influence emergency situations have on the position of action points in the psycho-spacing model, we aimed at finding the coefficients of the polynomials in the second degree that fitted the action points displayed in Figure 9.3 in a least squares sense. Here we fitted polynomials for acceleration increases and reductions for the control group as

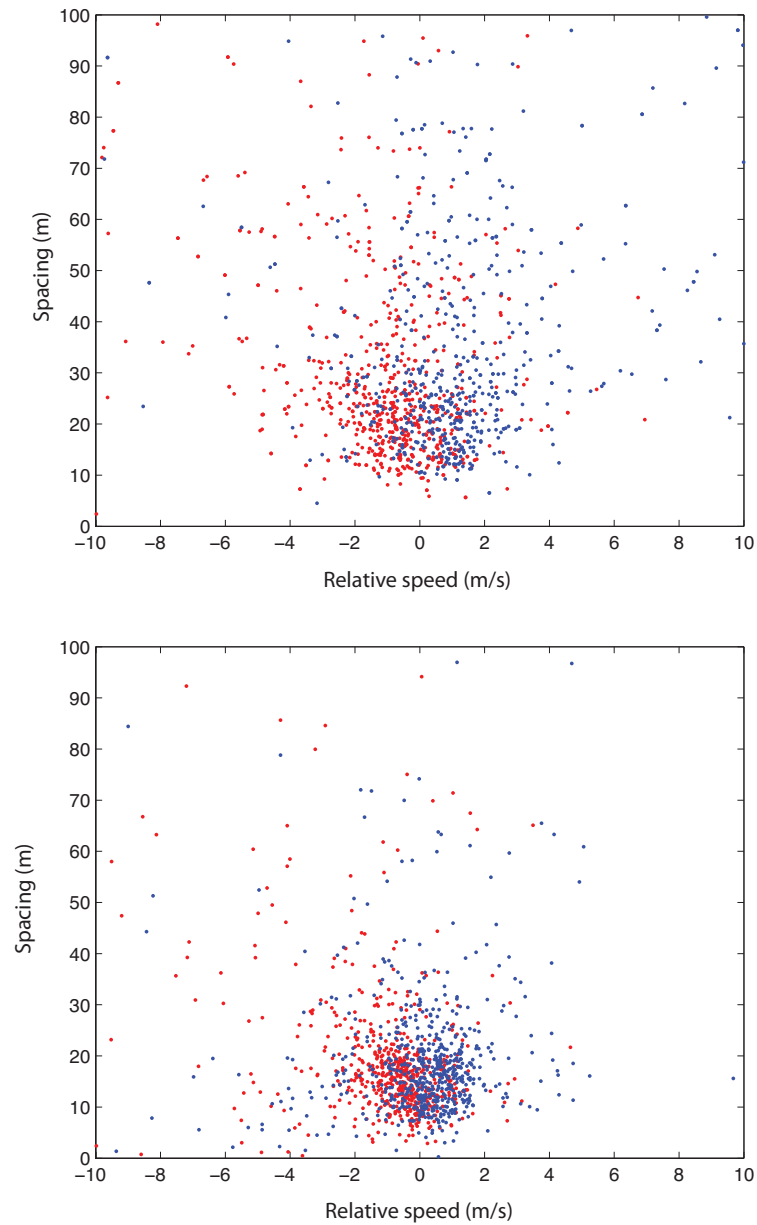


Figure 9.3: Distributions of action points for acceleration increases (blue) and acceleration reductions (red) in case of emergency situations. The top graph represents the control group (no emergency situation) while the bottom graph shows the action points for the experimental group (emergency situation).

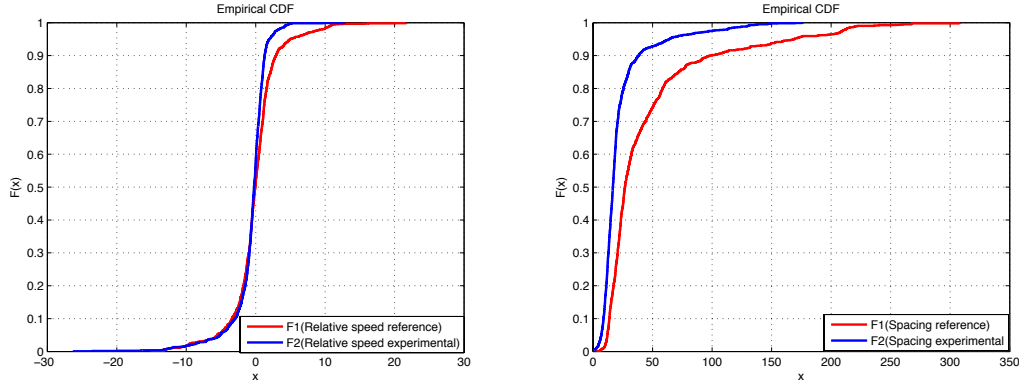


Figure 9.4: Cumulative distribution functions of Δv and s of action points for the reference data set and the experimental data set (emergency situation).

well as for the experimental group. The results are shown in Figure 9.5 and Table 9.1. In the table the coefficients p_n are displayed as well as the Mean Square Error (MSE) and the Mean Absolute Error (MAE).

Table 9.1: Results curve fitting for acceleration reductions and increases for the reference datasets and the datasets with the adverse conditions.

	p_1	p_2	p_3	MSE	MAE
<i>Emergency</i>					
Acc red ref	0.0002	-0.0464	0.5247	5.04	10.64
Acc inc ref	-0.0005	0.0739	-0.7439	5.76	10.76
Acc red evac	0.0007	-0.1053	1.5367	15.66	20.20
Acc inc evac	0.0000	0.0013	1.5141	12.32	17.66
<i>Adverse weather</i>					
Acc red ref	-0.0001	-0.0341	0.4497	6.58	13.64
Acc inc ref	-0.0008	0.0932	-0.9830	8.20	14.60
Acc red weather	0.0008	-0.1256	2.0576	19.21	19.94
Acc inc weather	0.0006	-0.0835	4.2843	11.09	15.44
<i>Incidents</i>					
Acc red ref	-0.0006	-0.0237	0.0880	3.24	7.02
Acc inc ref	0.0015	-0.0629	2.0845	3.72	7.76
Acc red weather	0.0079	-0.3376	3.6473	2.66	6.05
Acc inc weather	-0.0019	0.1360	-1.1870	2.57	6.77

From the figure as well as from the table it can be observed that the shape of the perceptual thresholds in the control group differs substantially from the shape of the perceptual thresholds in the experimental group. These graphs show that the perceptual thresholds for acceleration increases and reductions are much closer together in the group with the emergency situation than is the case in the control group. Furthermore it can be observed from these graphs that the perceptual thresholds for acceleration increases and acceleration reductions are asymmetric. This is especially the case in the dataset with the adverse condition.

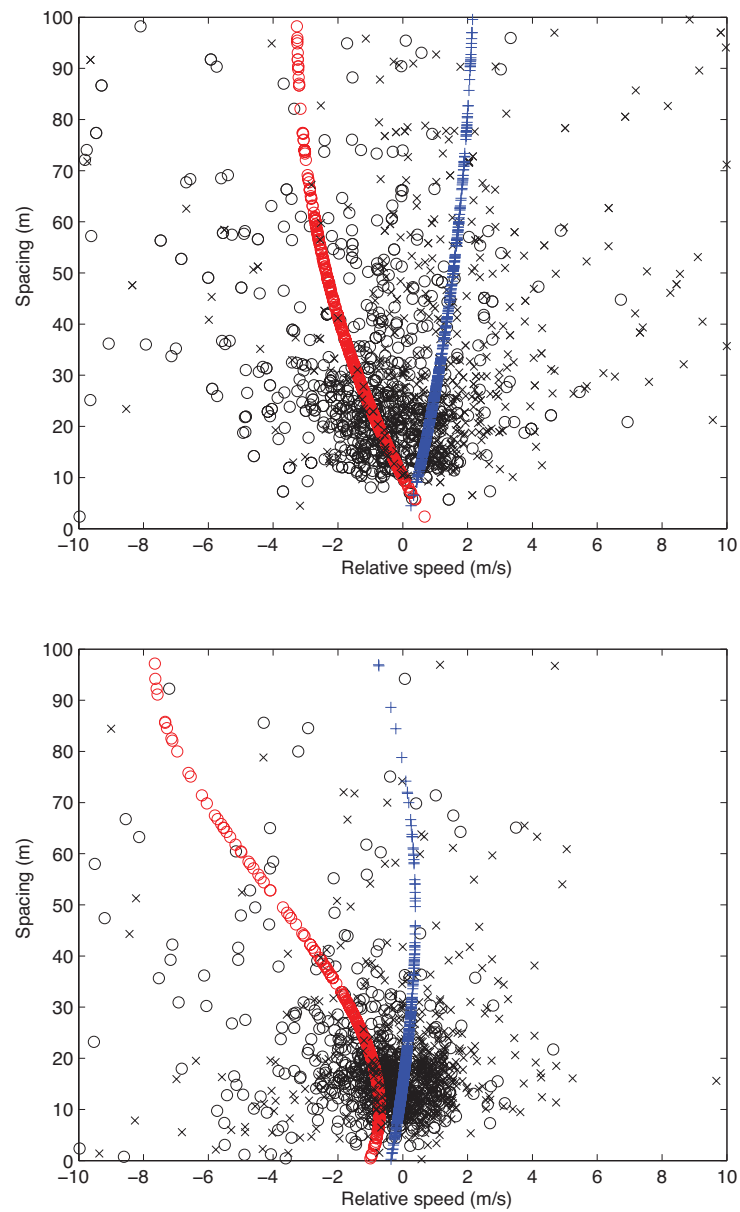


Figure 9.5: Curve fitting of action points for the reference dataset (top) as well as the dataset with the emergency situation (bottom).

From the aforementioned it can therefore be concluded that emergency situations have a substantial influence on perceptual thresholds represented by the position of action points in the relative speed - spacing ($\Delta v, s$) plane in psycho-spacing models.

9.3.2 Adverse weather conditions

As is the case with the distribution of action points in case of emergency situations, the distribution of action points in case of an adverse weather condition (i.e., fog) also shows considerable differences with normal driving conditions. This is clearly shown in Figure 9.6. When comparing the two distributions, it can clearly be observed that the action points are much more scattered in the experimental condition (adverse weather condition). Furthermore, the graphs show that in the condition with the adverse weather condition, drivers mostly seem to react to larger values of relative speed Δv (even at smaller values of spacing s).

This is to a lesser extent the case in the control condition in which drivers also seem to react to smaller values of relative speed Δv . The aforementioned may be due to the fact that in the condition with the adverse weather drivers are unable to perceive small speed differences with their lead vehicle, making corrections to larger values of relative speed Δv necessary. The Kolmogorov-Smirnov test showed that the two distributions of action points differed significantly with regard to relative speed Δv and spacing s as $p < 0.05$.

In order to further illustrate the differences between the condition with the adverse weather condition and the control condition, the cumulative distribution functions for relative speed Δv and spacing s are presented in Figure 9.7.

As was the case with emergency situations, we aimed at finding the coefficients of the polynomials in the second degree that fitted the action points displayed in Figure 9.6 in a least squares sense. This was done in order to gain insight into the shape of the perceptual thresholds incorporated in the psycho-spacing model. Again, we fitted polynomials for acceleration increases and reductions for the control condition as well as for the experimental condition (adverse weather). The results are shown in Figure 9.8 as well as in Table 9.1.

In contrast with the emergency situation, the thresholds in the dataset with the adverse weather condition are much further apart. This is also the case when comparing this experimental condition (adverse weather) with the control condition. This holds for smaller as well as larger values of spacing s .

From the aforementioned it can therefore be concluded that adverse weather conditions have a substantial influence on perceptual thresholds represented by the position of action points in the relative speed - spacing ($\Delta v, s$) plane in psycho-spacing models.

9.3.3 Freeway incidents

The extent to which the position of action points in the ($\Delta v, s$) plane is influenced by perception of an incident in the other driving lane is shown in Figure 9.9. Again, a substantial difference can be observed between the two distributions of action points. From the figure it can be observed that in the dataset with the freeway incident fewer action points are located at negative values of relative speed Δv compared to the reference dataset.

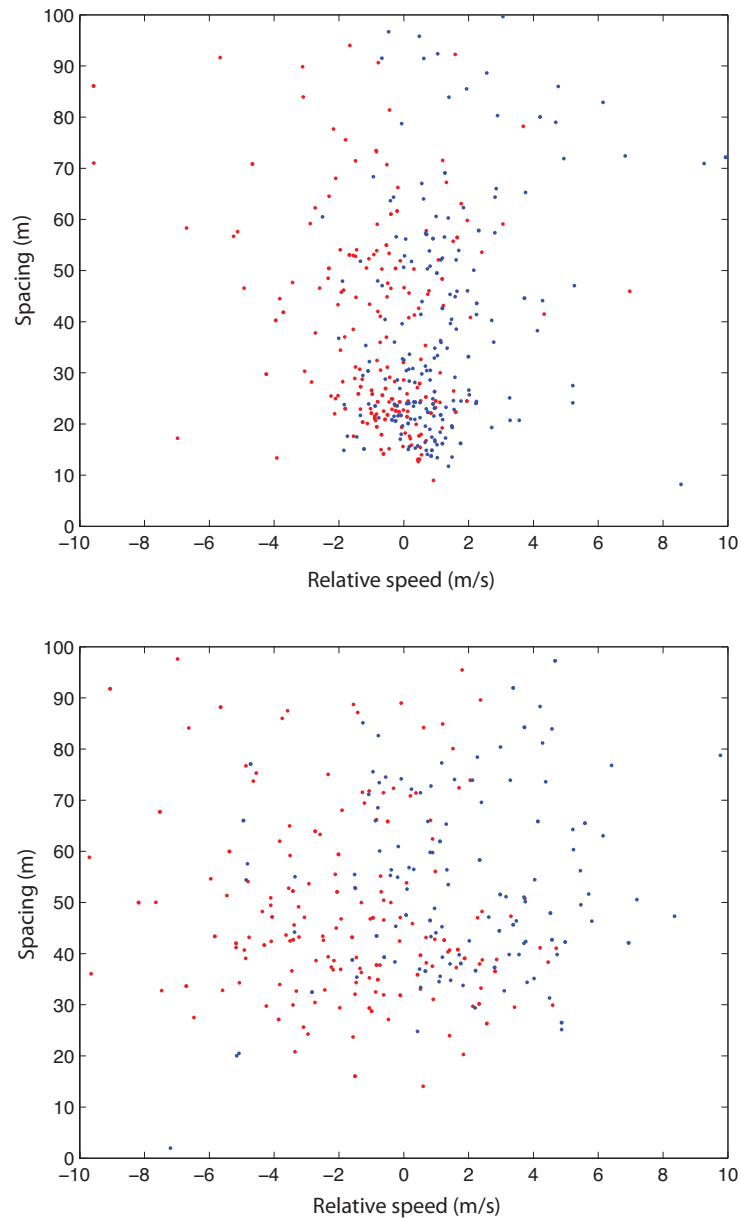


Figure 9.6: Distributions of action points for acceleration increases (blue) and acceleration reductions (red) in case of an adverse weather condition (i.e., fog). The top graph represents the control condition (normal driving conditions) while the bottom graph shows the action points for the experimental condition (adverse weather).

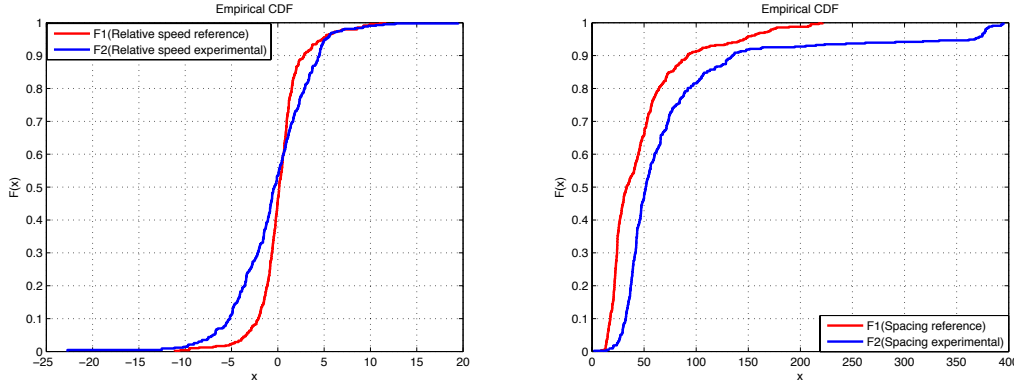


Figure 9.7: Cumulative distribution functions of Δv and s of action points for the reference data set and the experimental data set (adverse weather condition).

Furthermore it can be observed from the figure that for spacing s the action points in the reference dataset are more evenly distributed than in the dataset with the freeway incident. Also the graphs show that more action points in the dataset with the incident are located at smaller values of spacing s . This means that drivers at the incident site mostly reacted at smaller spacing. The fact that distributions of action points in the reference dataset and the dataset with the incident differed was supported by the results of the Kolmogorov-Smirnov test as $p < 0.05$. As an illustration, the cumulative distribution functions for relative speed Δv and spacing s are presented in Figure 9.10.

As was the case with emergency situations and adverse weather conditions here also we aimed at finding the coefficients of the polynomials in the second degree that fitted the action points displayed in Figure 9.9 in a least squares sense. This was done to gain insight into the shape of the perceptual thresholds incorporated in the psycho-spacing model. Again, we fitted polynomials for acceleration increases and reductions for the reference data set as well as for the experimental data set. The results are shown in Figure 9.11 and Table 9.1.

From the aforementioned it can therefore be concluded that freeway incidents have a substantial influence on perceptual thresholds represented by the position of action points in the relative speed - spacing $(\Delta v, s)$ plane in psycho-spacing models. In the theoretical framework proposed in Chapter 2 we assumed that adaptation effects in longitudinal driving behavior can be divided into compensation effects and performance effects. The change in the position of action points in the relative speed - spacing $(\Delta v, s)$ plane when comparing normal driving conditions to driving in case of an adverse condition can, in our view, be regarded as an indication for compensation effects in longitudinal driving behavior.

In the theoretical framework it was assumed that compensation effects and performance effects in longitudinal driving behavior come forth from an interaction between driver capabilities and task demands. It can therefore be assumed that the effect of adverse conditions will differ largely within as well as between drivers. When observing the position of the action points in the relative speed - spacing plane $(\Delta v, s)$ in relation to the fitted perceptual thresholds, it can indeed be observed that the degree of variability in these models is substantial. This is also well-illustrated by the MSE and MAE presented in Table 9.1. This leads to the conclusion that

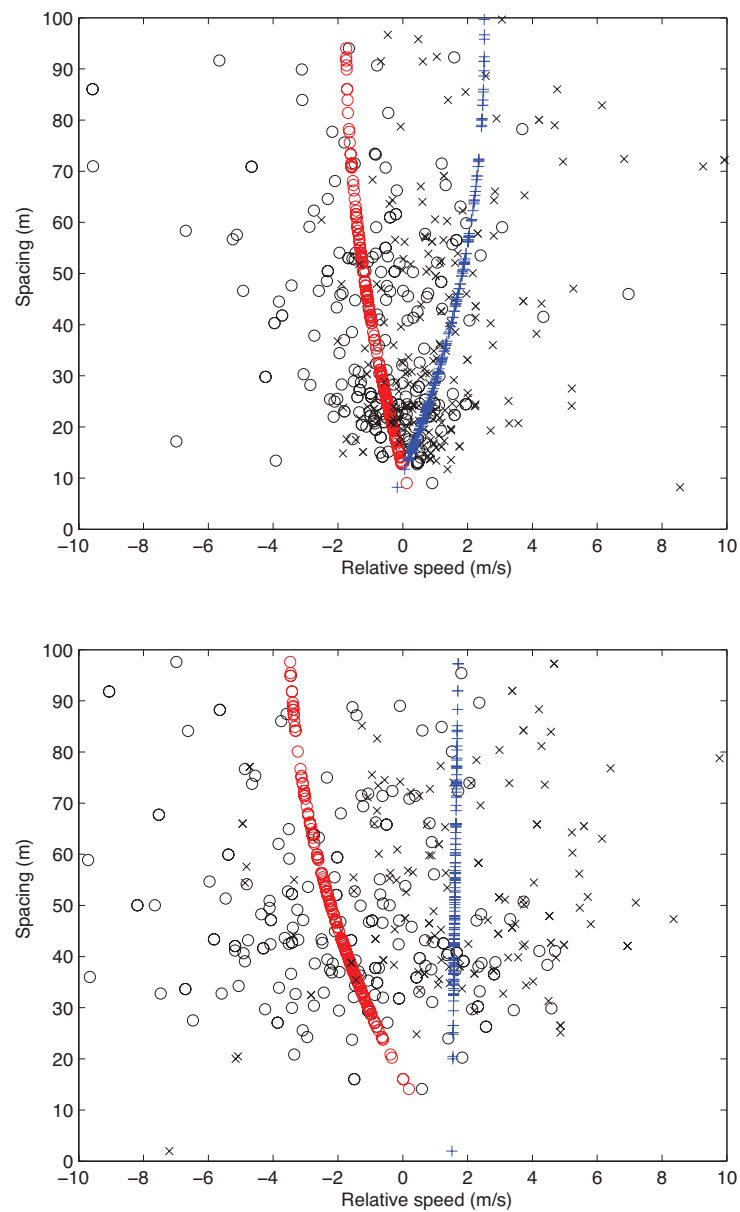


Figure 9.8: Curve fitting of action points for the reference dataset (top) as well as the dataset with the adverse weather condition (bottom).

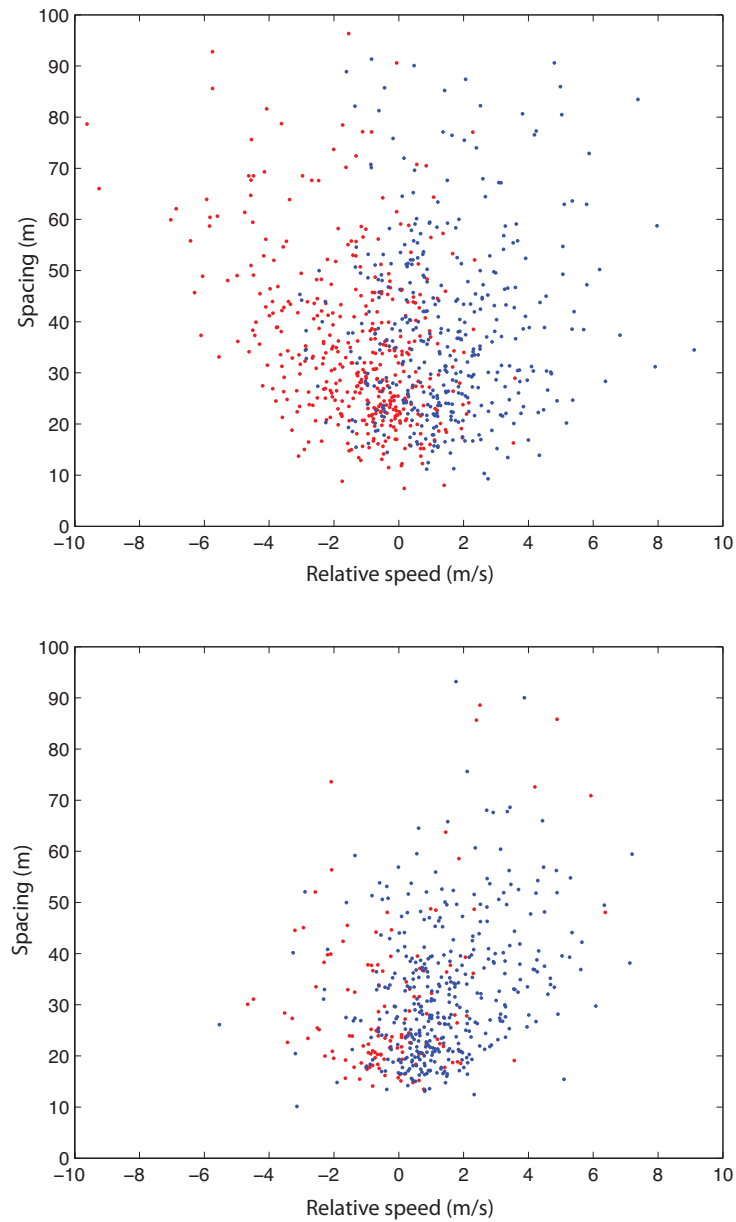


Figure 9.9: Distributions of action points for acceleration increases (blue) and acceleration reductions (red) in case of a freeway incident. The top graph represents the reference data set while the bottom graph shows the action points in case of an incident in the other driving lane.

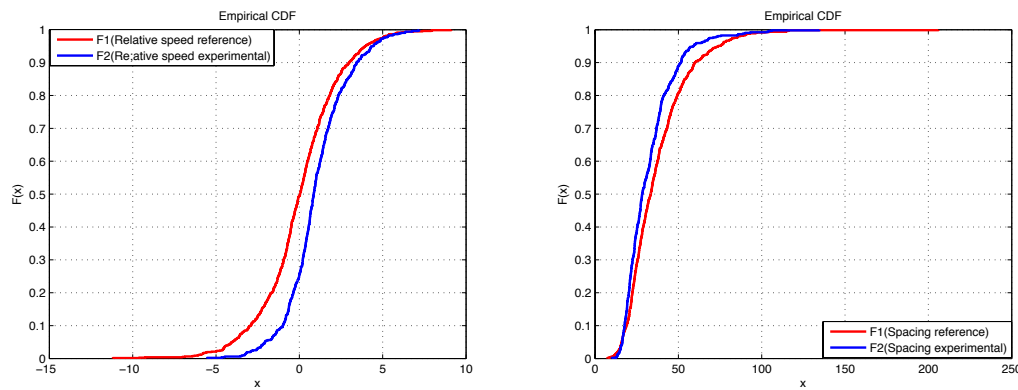


Figure 9.10: Cumulative distribution functions of Δv and s of action points for the reference data set and the experimental data set (incident in the other driving lane).

the assumption of deterministic perceptual thresholds incorporated in the original formulation of the model is not realistic.

The next section focuses on acceleration as well as the 'jumps' in acceleration (being the difference in acceleration before and after an action point) at the estimated action points. We assume that the sensitivity of acceleration towards relative speed Δv and spacing s at the action points is an indication for performance effects as proposed in the theoretical framework.

9.4 Acceleration at action points in case of adverse conditions

In the previous section we showed that adverse conditions lead to substantial changes in the position of action points. We conjectured that the differences in the position in the relative speed - spacing ($\Delta v, s$) plane of the action points is a strong indication of the presence of compensation effects in longitudinal driving behavior due to the selected adverse conditions. Furthermore, we concluded that the deterministic perceptual thresholds assumed in the original formulation of the model do not hold in reality due to the variable nature of the action points.

The changes in the position of action points in the relative speed - spacing ($\Delta v, s$) plane do not inform us to what extent acceleration and the jumps in acceleration change due to an adverse condition. The extent to which adverse conditions influence acceleration a at the action points as well as the difference between acceleration before and after an action point Δa ('jumps' in acceleration) was determined through a Multivariate Regression Analysis (MRA) using the four models presented in Chapter 7.

For convenience purposes these models are repeated here. Recall that Models 1 and 2 regard accelerations at the action points, while Model 3 and 4 regard the 'jumps' in acceleration (being the difference in acceleration before and after an action point).

$$a = b_1 \Delta v + b_2 s \quad (9.1)$$

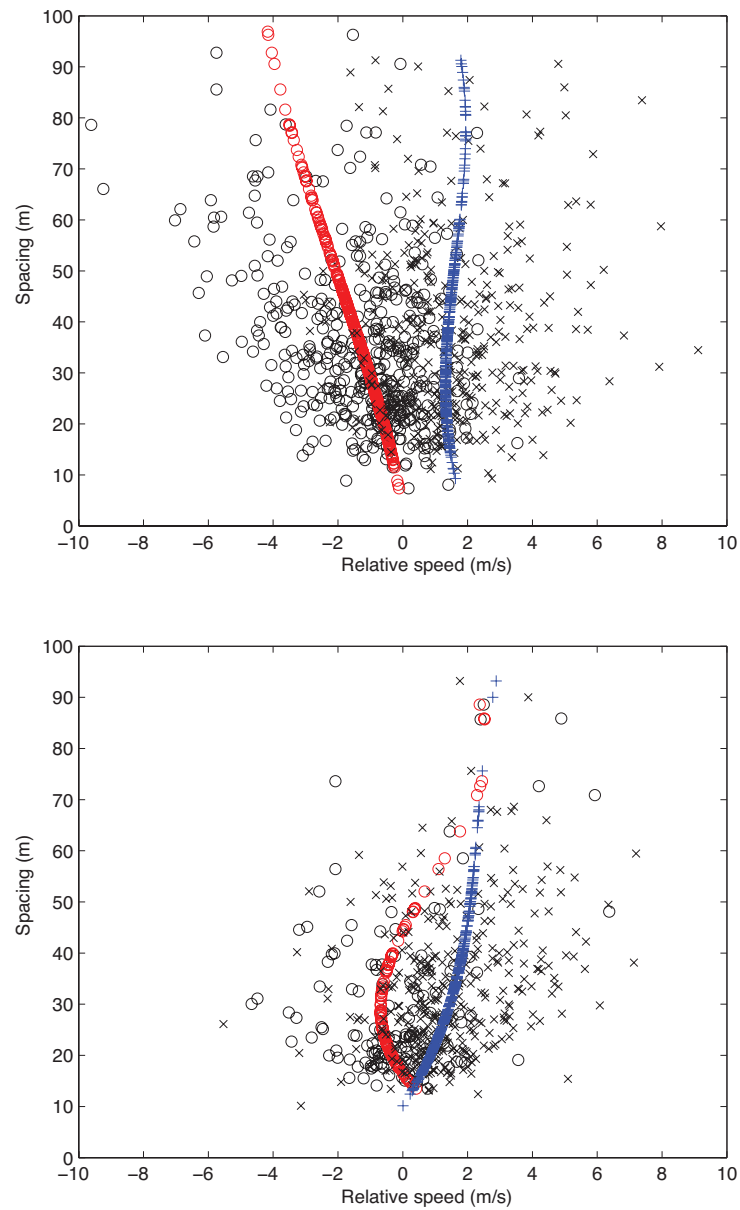


Figure 9.11: Curve fitting of action points for the reference dataset (top) as well as the dataset with the incident in the other driving lane (bottom).

$$a = b_1 \frac{\Delta v}{\sqrt{s}} + b_2 \Delta v \quad (9.2)$$

$$\Delta a = b_1 \Delta v + b_2 s \quad (9.3)$$

$$\Delta a = b_1 \frac{\Delta v}{\sqrt{s}} + b_2 \Delta v \quad (9.4)$$

In the context of the theoretical framework proposed in Chapter 2 we conjectured that the sensitivity of acceleration a and also the 'jumps' in acceleration toward relative speed Δv and spacing s , represented by the parameters b_1 and b_2 respectively, are indicators of the existence of performance effects in longitudinal driving behavior. When longitudinal driving behavior is to a lesser extent governed by car-following behavior, it can be assumed that the sensitivity of a following vehicle towards relative speed Δv and spacing s decreases compared to normal driving conditions.

9.4.1 Emergency situations

Table 9.2 shows the results of the MRA for the normal driving condition (control group) and the emergency situation (experimental group). Overall, it can be concluded that, in the group with the emergency situation as well as in the control group, drivers accelerate less strongly at larger values of s in response to speed differences with the lead vehicle Δv . Furthermore, it can be concluded from the table that the MSE of Model 2 is lower than the MSE of Model 1, making Model 2 the preferred model. As an example, Model 2 is shown in Figure 9.12.

Table 9.2: Results Multivariate Regression Analysis for the experimental group and the control group. The values of b_x refer to the parameter values incorporated in the models, while the error refers to the sum of the residuals. MSE refers to the Mean Squared Error.

	b_1	b_2	Error	MSE
<i>Reference dataset</i>				
Model 1	0.30	-0.01	489.80	0.11
Model 2	1.44	0.07	482.67	0.10
Model 3	0.26	-0.01	706.16	0.23
Model 4	2.86	-0.19	685.51	0.21
<i>Emergency situations</i>				
Model 1	0.13	-0.01	1099.30	0.59
Model 2	0.21	0.10	1071.70	0.56
Model 3	0.30	0.01	1567.60	1.21
Model 4	1.52	-0.03	1523.50	1.14

For Model 1 and 2 it can be observed that the value of b_1 is substantially lower in the group with the emergency situation compared to b_1 in the control group. The value of the sensitivity

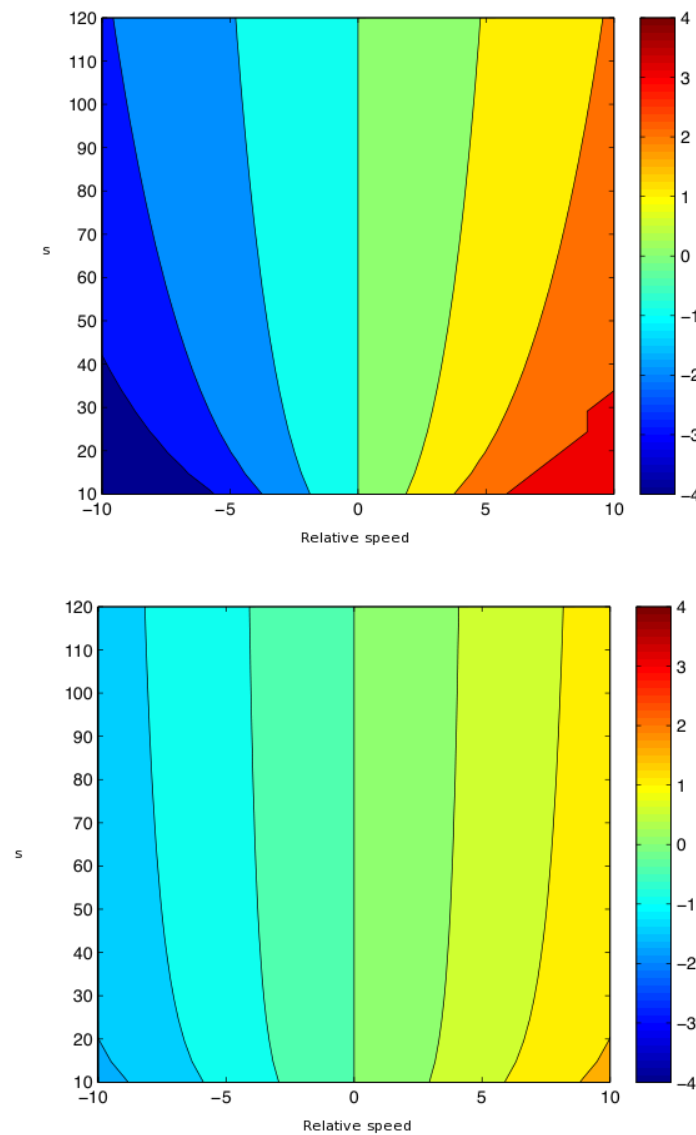


Figure 9.12: Results of Multivariate Regression analysis for Model 2 in case of emergency situations with regard to a for the control group (top) and the experimental group (bottom). On the horizontal axis relative speed is displayed, while on the vertical axis spacing is displayed. The color represents the accelerations.

parameter b_2 shows a slight increase. The aforementioned means that acceleration a is less sensitive to relative speed Δv in the group with the emergency situation compared to the control group.

Furthermore, it follows from the reported error and MSE in Table 9.2 that the error and MSE in the group with the emergency situation are substantially larger than in the control group. This means that the models less adequately describe acceleration in the group with the emergency situation than in the control group.

With regard to the 'jumps' in acceleration Δa (being the difference between acceleration before and after an action point), a similar picture emerges as was the case with acceleration a . This means that the sensitivity of the 'jumps' in acceleration Δa towards relative speed Δv and spacing s is lower in the group with the emergency situation than in the group with the normal driving conditions (Model 3 and 4 in Table 9.2). As was the case with Model 1 and 2, the MSE of Model 3 and 4 is substantially larger in the group with the emergency situation compared to the control group.

The result that acceleration a and the 'jumps' in acceleration Δa become less sensitive to relative speed Δv is a strong indication for the existence of performance effects in longitudinal driving behavior following an emergency situation. Drivers react less strongly to relative speed Δv . Furthermore, we showed that the models less adequately describe longitudinal driving behavior in case of an emergency situation, as indicated by the larger errors and MSE. This can be regarded as another indication of the existence of performance effects.

9.4.2 Adverse weather conditions

Table 9.3 shows the results of the MRA for the control condition (normal driving conditions) and the experimental condition (adverse weather condition). Overall, it can be observed that, in the condition with the adverse weather condition as well as in the control condition, drivers accelerate less strongly at larger values of s in response to speed differences with the lead vehicle. Furthermore, it can be observed from the table that the MSE of Model 2 is slightly lower than the MSE of Model 1, making Model 2 the preferred model. As an example, Model 2 is shown in Figure 9.13.

With regard to Model 1 and 2 it can be observed that the value of b_1 is substantially lower in the experimental condition compared to b_1 in the control condition. The aforementioned means that acceleration a is less sensitive to relative speed Δv in the data set with the adverse weather condition compared to the data set with normal driving conditions.

Furthermore, it follows from the reported error and MSE in Table 9.3 that the error and MSE in the condition with the adverse weather condition are substantially larger than in the control condition. This means that the models less adequately describe acceleration in the data set with the adverse weather condition than in the data set with normal driving condition.

With regard to the 'jumps' in acceleration Δa (being the difference between acceleration before and after an action point), again a similar picture emerges as was the case for acceleration a . This means that the sensitivity of the 'jumps' in acceleration Δa towards relative speed Δv and spacing s is lower in the condition with the adverse weather condition than in the condition

Table 9.3: Results Multivariate Regression Analysis for the control condition and the experimental condition (adverse weather condition). The values of b_x refer to the parameter values incorporated in the models, while the error refers to the sum of the residuals. MSE refers to the Mean Squared Error.

	b_1	b_2	Error	MSE
<i>Reference dataset</i>				
Model 1	0.20	0.01	215.49	0.19
Model 2	0.77	-0.09	215.28	0.19
Model 3	0.22	0.01	322.05	0.43
Model 4	0.78	-0.11	316.45	0.61
<i>Adverse weather</i>				
Model 1	0.10	-0.01	225.98	0.26
Model 2	0.37	0.05	223.02	0.26
Model 3	0.16	0.01	346.06	0.63
Model 4	0.66	0.07	341.66	0.61

with the normal driving conditions (Model 3 and 4 in Table 9.3). As was the case with Model 1 and 2 the MSE of Model 3 and 4 are substantially larger in the dataset with the adverse weather condition compared to the data set with normal driving condition.

The finding that acceleration a and the 'jumps' in acceleration Δa become less sensitive to relative speed Δv is again a strong indication for the existence of performance effects in longitudinal driving behavior following an adverse weather condition. Drivers react less strong to relative speed. Furthermore, we showed that the models less adequately describe longitudinal driving behavior in case of an adverse weather condition, as indicated by the larger errors and MSE. This can be regarded as another indication of the existence of performance effects.

9.4.3 Freeway incidents

Finally, we also investigated the influence of freeway incidents on acceleration $a(t)$ and the jumps in acceleration $\Delta a(t)$ using the empirical data earlier described in this chapter. In Table 9.4 the results of the Multivariate Regression Analysis of Model 1 and 2 are presented for the two datasets. In the table, the error as well as the Mean Square Error is also reported.

As an illustration Model 2 is depicted in Figure 9.14. Overall it can be concluded that in both datasets, drivers accelerate less strong at larger values of s in response to speed differences with the lead vehicle. Also, it can be observed that for both datasets the error of Model 2 is somewhat lower than the error of Model 1, again making Model 2 the preferred model.

From the results it can also clearly be observed that the parameter values of b_1 as well as b_2 are substantially lower in the dataset with the incident compared to the reference dataset. This means that drivers when perceiving an incident in the other driving lane become less sensitive to speed differences with the lead vehicle Δv .

Furthermore, it can be observed that, relatively speaking, in the dataset with the incident com-

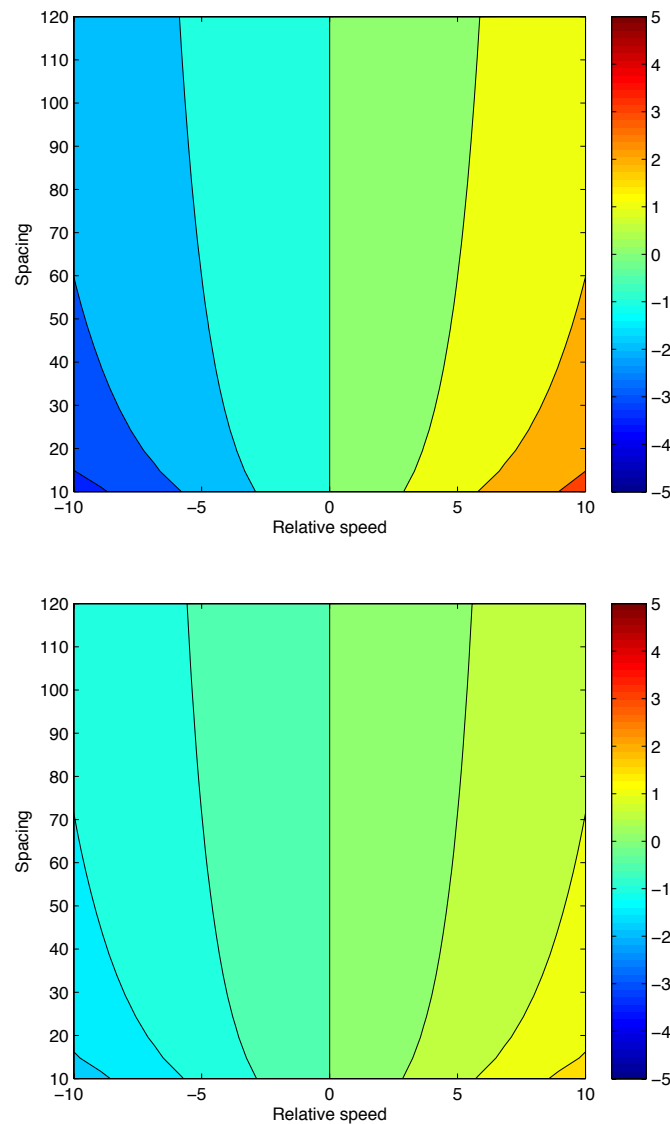


Figure 9.13: Results of Multivariate Regression analysis Model 2 with regard to a for the control condition (top) and the experimental condition (bottom). On the horizontal axis relative speed is displayed, while on the vertical axis spacing is displayed. The color represents the accelerations.

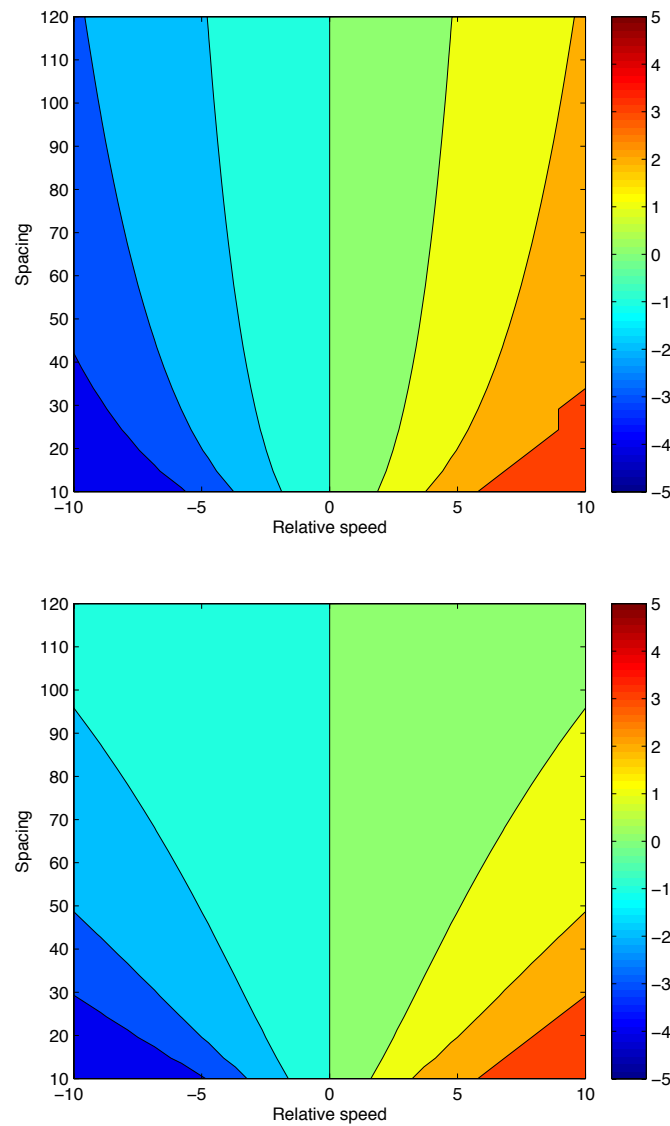


Figure 9.14: Results of Multivariate Regression analysis Model 2 in case of freeway incidents with regard to a for the reference dataset (top) and the dataset with the incident (bottom). On the horizontal axis relative speed is displayed, while on the vertical axis spacing is displayed. The color represents the accelerations.

Table 9.4: Results Multivariate Regression Analysis for the reference dataset (no incident) and the dataset with the incident. The values of b_x refer to the parameter values incorporated in the models. The error consists of the sum of the residuals. MSE refers to the Mean Squared Error.

	b_1	b_2	Error	MSE
<i>Reference dataset</i>				
Model 1	0.30	-0.00	489.72	0.36
Model 2	1.44	0.07	482.60	0.35
Model 3	0.26	-0.00	705.99	0.76
Model 4	2.86	-0.18	685.38	0.71
<i>Incident</i>				
Model 1	0.22	0.01	278.61	0.29
Model 2	1.12	-0.14	272.91	0.27
Model 3	0.38	-0.01	429.62	0.69
Model 4	4.59	-0.45	409.99	0.63

pared to the dataset without the incident, the MSE decreased slightly. This means that the model described longitudinal driving behavior slightly better in the data set with the incident than in the reference data set.

The extent to which 'jumps' in acceleration Δa are influenced by perception of an incident in the adjacent driving lane was also determined. Table 9.4 presents the results of the Multivariate Regression Analysis for Model 3 and 4 for the two datasets. Overall it can be observed from the table that parameter values of Model 3 and 4 are higher than those of Model 1 and 2. Furthermore it follows from the results that the MSE for Model 3 and 4 is much higher than for Model 1 and 2.

Also it follows from Table 9.4 that 'jumps' in acceleration at the action points are larger at smaller values than at larger values of spacing s . This can more strongly be observed in the dataset without the incident compared to the dataset with the incident. This means that the 'jumps' in acceleration were less sensitive to relative speed Δv in the data set without the freeway incident than in the data set with the freeway incident.

It can be concluded that freeway incidents lead to a reduction in the sensitivity of acceleration a towards relative speed. As was argued in this chapter, this can be regarded as an indication for the existence of performance effects in longitudinal driving behavior following this adverse condition.

9.5 Conclusions

In Chapter 8 we described changes in parameter values and model performance of the Intelligent Driver Model (Treiber et al., 2000) in case of adverse conditions. In this chapter we showed that adverse conditions have a substantial effect on parameter values of this often used car-following model. Furthermore we showed that model performance of the Intelligent Driver Model (Treiber et al., 2000) decreases substantially under these conditions.

It was argued that the parameter value changes represent compensation effects as proposed in the theoretical model of Chapter 2. Drivers consciously adapt their driving behavior to resolve an imbalance between driver capabilities and task demands. We also argued that the reduction in model performance of the IDM (Treiber et al., 2000) is an indication of the existence of performance effects in longitudinal driving behavior. It was proposed that these performance effects occur when compensation effects in longitudinal driving behavior are insufficient to resolve an imbalance between driver capabilities and task demands.

Furthermore, it was conjectured that most of these models have a mechanistic character as they insufficiently incorporate human elements. To this end Chapter 9 focused on the description of longitudinal driving behavior under adverse conditions using psycho-spacing models.

Using the data from two driving simulator experiments described in Chapter 3 as well as empirical trajectory data described in the present chapter, action points in the $(\Delta v, s)$ plane were estimated using a new data analysis technique described in Chapter 7.

From the results it followed that overall clear differences could be observed between the position of action points in the relative speed - spacing $(\Delta v, s)$ plane under normal driving conditions and in case of the selected adverse conditions. Firstly, in the case of an emergency situation action points are much more concentrated at smaller values of spacing s and drivers react to smaller speed differences with the lead vehicle Δv .

The picture that emerges from the position of action points in the case of adverse weather conditions is quite different. Under this condition drivers tend to keep larger values of spacing s . They also reacted predominantly to larger speed differences with the lead vehicle Δv , even at smaller values of spacing s .

In case of freeway incidents drivers mostly seem to react at smaller values of spacing s . Furthermore, it could be observed from the results that most action points regarded acceleration increases.

We argued that the difference in the position of action points are an indication for compensation effects as proposed in the theoretical framework of Chapter 2. Drivers consciously adapt their driving behavior resulting in a different position of action points when comparing adverse conditions to normal driving conditions. The aforementioned was well-illustrated by the curve fitting analysis reported in the present chapter, as the shape and location of the deterministic perceptual thresholds differed substantially between the different conditions. For example, thresholds in cases of emergency situations were much closer together at smaller values of spacing s than was the case under normal driving conditions.

Finally, acceleration as well as the so-called 'jumps' in acceleration at the estimated action points were analyzed using a Multivariate Regression Analysis. In general, the results showed that acceleration a as well as 'jumps' in acceleration Δa depend on relative speed Δv and spacing s . Overall it was shown that in case of adverse conditions the sensitivity of acceleration a and the 'jumps' in acceleration Δa towards relative speed Δv decreases in comparison with normal driving conditions. It was argued in the present chapter that this is a strong indication for performance effects due to an imbalance between driver capabilities and task demands following an adverse condition. This was also supported by the fact that the models used in

this chapter seemed to describe acceleration a as well as the 'jumps' in acceleration Δa less adequately in case of adverse conditions, as indicated by the larger MSE. This can be assumed to be an indication of the fact that in case of adverse conditions car-following is to a lesser extent a determinant of longitudinal driving behavior.

The aforementioned leads to the conclusion that in general car-following patterns closely resemble the ones predicted by psycho-spacing theory. However, in the original formulation of the model deterministic perceptual thresholds are assumed. When observing the results from the estimation of the action points in the relative speed - spacing ($\Delta v, s$) plane it can be conjectured that this assumption does not hold in reality. The position of action points seems to be largely dependent on external circumstances, such as adverse conditions. It was argued that this is the result of conscious compensation effects of drivers. Furthermore in the original formulation of the model it was assumed that on crossing one of these deterministic thresholds drivers change their behavior through a change in the sign of their acceleration. However, the results show that acceleration at the action points is dependent on relative speed Δv and spacing s . However, performance effects as proposed in the theoretical framework seem to play a substantial role. External circumstances (i.e., adverse conditions) largely determine the sensitivity of acceleration a and also the 'jumps' in acceleration Δa as well as the extent in which the models are adequate in describing acceleration a and the 'jumps' in acceleration Δa .

It is therefore recommended to develop a car-following model, based on the principles of psycho-spacing theory, which is data-driven. Furthermore, this model should include the variability due to compensation and performance effects as discussed in this chapter. This could for example be accomplished through the development of a car-following model based on a Bayesian network approach with parameter learning.

Chapter 10

A Stochastic Psycho-spacing Model through Bayes Net Modeling

10.1 Aim and structure of this chapter

In Chapter 4 it was shown that adverse conditions (i.e., emergency situations, adverse weather conditions and freeway incidents) have a substantial influence on adaptation effects in empirical longitudinal driving behavior. Furthermore, in Chapter 5 we showed that mental workload, moderated by age and driving experience, is substantially influenced by the selected adverse conditions. The findings in these chapters support the proposed theoretical framework discussed in Chapter 2.

Next in Chapter 6 we discussed continuous car-following models as well as psycho-spacing models in connection with adverse conditions. It was noted that research on the influence of adverse weather conditions on parameter value changes as well as model performance of continuous car-following models was not available. Furthermore it was not yet clear to what extent adverse conditions influence so-called action points as well as the position of action points in psycho-spacing models.

To this end parameter values as well as model performance of an often used car-following model, namely the Intelligent Driver Model (Treiber et al., 2000), in case of emergency situations, adverse weather conditions (i.e., fog) as well as freeway incidents were determined in Chapter 8. It was shown that the selected adverse conditions lead to substantial changes in parameter values as well to changes in model performance. We argued that the observed changes in parameter values in the Intelligent Driver Model can be regarded as compensation effects in longitudinal driving behavior following an adverse condition. Examples of these compensation effects in case of an emergency situation were an increase in maximum acceleration a and deceleration b along with a reduction in desired time headway T and an increase in free speed v_0 .

Next in Chapter 9, we estimated the position of action points as well as acceleration and the 'jumps' in acceleration at action points in psycho-spacing models. We showed that the selected adverse conditions lead to substantial changes in the position of action points in the relative

speed - spacing plane. Again we argued that the change in position of action points can be regarded as a consequence of compensation effects in longitudinal driving behavior following an adverse condition. Due to the stochastic nature of action points in psycho-spacing models we stated that the assumption of deterministic perceptual thresholds does not hold in reality.

Furthermore, we showed that acceleration as well as so-called 'jumps' in acceleration at action points are dependent on relative speed and to a lesser extent on spacing. However, the sensitivity of acceleration and the 'jumps' in acceleration towards relative speed showed to be largely dependent on external circumstances (i.e., adverse conditions). In case of adverse conditions, the sensitivity of acceleration and the 'jumps' in acceleration towards relative speed decreased substantially. Furthermore, it was shown that the used models describe acceleration and the 'jumps' in acceleration less adequately in case of adverse conditions. It was argued that the aforementioned reduced sensitivity and the reduction in the adequacy of the used models is a strong indication for the existence of performance effects proposed in our theoretical model. In other words: car-following seems to be to a lesser extent a determinant of longitudinal driving behavior in case of adverse conditions.

In this context, it was proposed to develop a stochastic car-following models able to capture the effects of adverse conditions on longitudinal driving behavior. It was suggested that this could be realized through a Bayesian network modeling approach with parameter learning. Therefore this chapter describes a new stochastic car-following model based on the principles of Bayesian network modeling and psycho-spacing theory.

Bayesian networks have already been used in simulation software packages in the past. For instance, in Miska and Van Zuylen (2004) a Bayesian network was used in order to describe car-following behavior and lane changing behavior. However, in the model proposed in this chapter Bayesian network modeling is coupled with psycho-spacing theory through parameter learning.

In the next section, a close look is provided into the Bayesian approach to probability and statistics. In Section 10.3 we describe how the Bayesian net, intended to predict action points in the relative speed spacing plane as well as acceleration reductions and increases at these action points, was set up.

In this section we start with setting up a simple Bayesian net with just six nodes aimed at predicting action points in the relative speed - spacing plane as well as acceleration at the action points. Also in this section the method used for parameter learning is described. The parameters in the conditional probability tables in the nodes were learned using empirical data, i.e., driving simulator data and trajectory data collected with a helicopter. Next in Section 10.4 an illustration of the workings of this model is provided using an example.

In Section 10.5 we extend the proposed simple stochastic model with adverse conditions. In this context we extended the Bayesian net with emergency situations, adverse weather conditions and freeway incidents and again learned parameters in the nodes using data from the driving simulator and trajectory data collected with a helicopter. Finally in Section 10.6 conclusions are presented.

10.2 Bayesian networks

Bayes Nets or Bayesian networks are graphical representations of probabilistic relationships among a set of variables (Pearl, 1988). Given a finite set $X = \{X_1, \dots, X_n\}$ of discrete random variables where each variable X_i takes values from a finite set, denoted by $Val(X_i)$.

A Bayes net is a directed acyclic graph G which encodes a joint probability distribution over X . The nodes of the net correspond to the variables $X_1, \dots, X_n$. The links of the graph correspond to the direct influence from one variable to the other. When a directed link is present from for example variable X_i to X_j , we call X_i the parent variable of X_j .

A variable X is conditionally independent of its non-descendants $Ndes(X)$ given the values of its parents $PA(X)$:

$$P(X | Pa(X), Ndes(X)) = P(X | Pa(X)) \quad (10.1)$$

Consider for example the Bayes net in Figure 10.1 (borrowed from Yap et al. (2008)). In this Bayes net six binary variables are incorporated, namely $X_1, \dots, X_6$. In this network the nodes are ordered such that all non-descendants of X_i are labelled with an index smaller than i (Yap et al., 2008).

The joint probability, denoted by $P(X_1 = x_1, X_2 = x_2, \dots, X_6 = x_6)$ can be factorized as:

$$P(x_1, x_2, \dots, x_6) = \prod_i P(x_i | x_1, \dots, x_{i-1}) \quad (10.2)$$

Exploitation of conditional independence (Eq. 10.1) leads to a reduction of the joint probability:

$$P(x_1, x_2, \dots, x_6) = \prod_i P(x_i | Pa(x_i)), Pa(x_i) \subseteq \{x_1, \dots, x_{i-1}\} \quad (10.3)$$

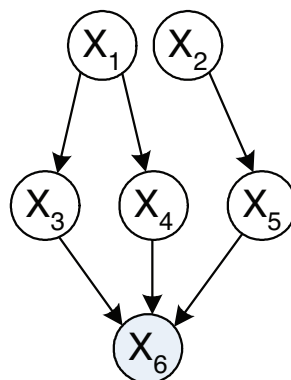


Figure 10.1: Example Bayesian network (borrowed from Yap et al. (2008)).

This allows a joint probability to be specified as a product of conditional probability tables (Yap et al., 2008). For each of the nodes a CPT (conditional probability table) displays the distribution of X for the possible values of $Pa(x)$ (Pearl, 1988).

In this section we briefly described the basics of Bayesian networks. The next section provides a presentation of the simple Bayesian network that was set up in order to predict action points and acceleration at action points based on psycho-spacing theory.

10.3 A simple Bayesian network for car-following

In setting up the Bayesian net, we started with designing a simple network through the connection of nodes regarding lead vehicle related stimuli, i.e., positive relative speed Δv_{pos} , negative relative speed Δv_{neg} and spacing s to action points Ap as well as to acceleration increases a_{inc} and acceleration reductions a_{red} at the action points. The constructed Bayesian net is depicted in Figure 10.2.

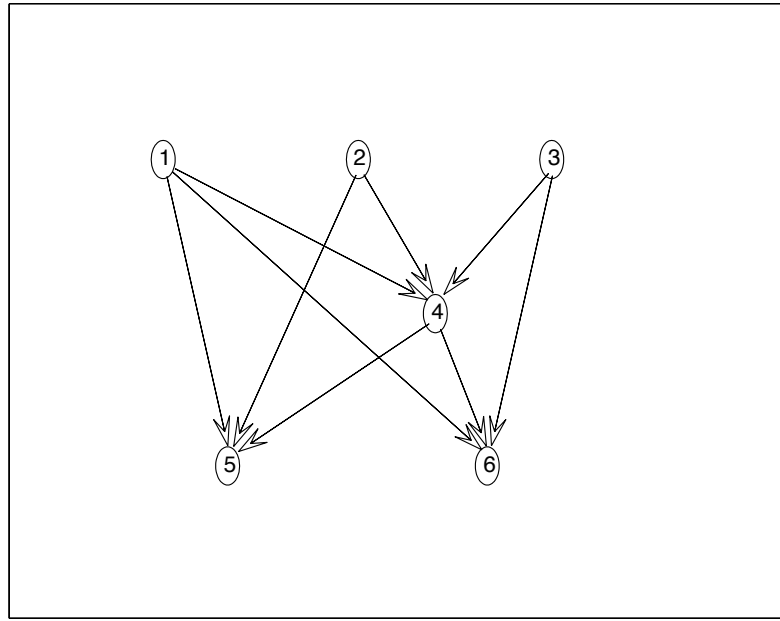


Figure 10.2: Designed Bayesian network. In this network the following nodes are incorporated: Spacing (1), Positive relative speed (2), Negative relative speed (3), Action point(4), Acceleration increases (5) and Acceleration reductions (6).

The net consists of six discrete nodes. The number of classes within the nodes for spacing s , positive relative speed Δv_{pos} and negative relative speed Δv_{neg} are based on the maximum values observed in the dataset discussed in the following. These classes represent therefore different classes of spacing and speed differences with the lead vehicle. The node representing action points consists of two classes (1=no action point, 2=action point). Finally, the nodes representing acceleration increases and reductions both consist of 6 discrete classes.

Next we constructed the CPT using random conditional probabilities and made inferences. These inferences were made based on a ground state, i.e., no evidence for a specific value of spacing s , positive relative speed Δv_{pos} or negative relative speed Δv_{neg} was fed to the network. As an example, joint probabilities $P(Ap \mid \Delta v_{pos}, \Delta v_{neg}, s)$ are plotted in Figure 10.3.

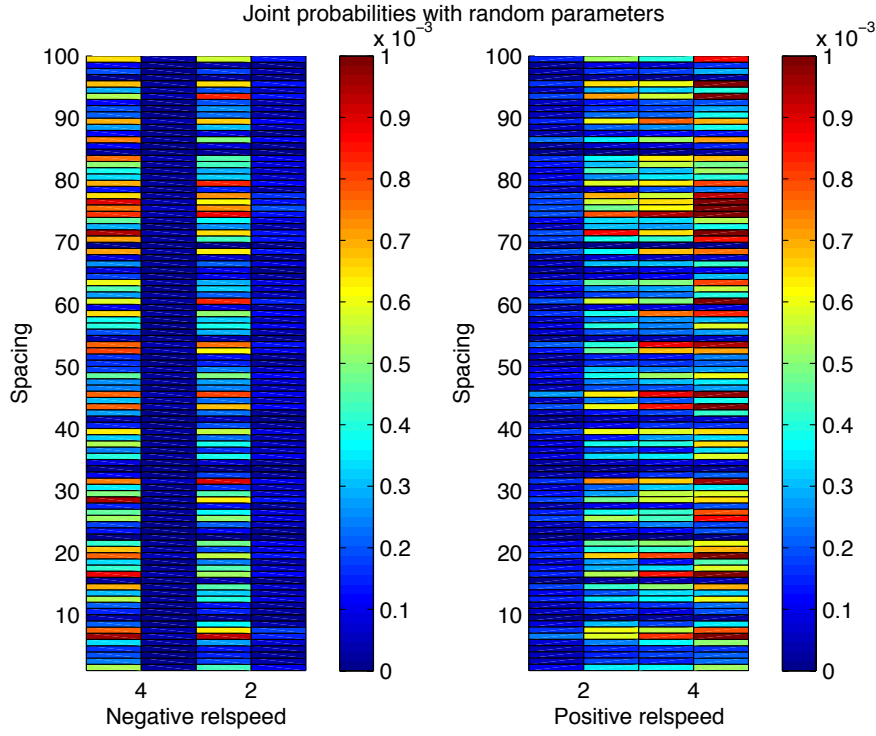


Figure 10.3: Joint probabilities $P(A_p \mid \Delta v_{pos}, \Delta v_{neg}, s)$ using random conditional probabilities.

In order to acquire a more realistic prediction of the position of action points in the relative speed - spacing $(\Delta v, s)$ plane as well as acceleration at these action points, we trained the network using empirical trajectory data.

The data set used in this contribution consists of vehicle trajectory data collected through the data collection approach proposed by Hoogendoorn and Schreuder (2005) (see also Chapter 9 for a more detailed description). Action points were estimated from the empirical trajectory data. To this end we used the data analysis technique proposed in Chapter 7. This resulted in the distribution of action points in the $(\Delta v, s)$ plane illustrated in Figure 10.4.

We continued by generating a tabula rasa through again filling the CPT's with random parameters. In this regard the initial parameters do not matter as we are able to find the globally optimal Maximum Likelihood Estimates (MLE) independent of where we start.

First we assumed that the examples in the data set are drawn independently from the underlying distribution. In other words: examples are conditionally independent given the parameters of the graphical model. Furthermore, in computing the parameter estimators in the discrete cases, we additionally assumed that all counts corresponding to the parameters in the Bayesian network are positive. In this regard the maximum likelihood estimators for the parameters are given by (Niculescu, Mitchell, & Rao, 2006):

$$\hat{\theta} = \frac{N_i}{k_i N} \quad (10.4)$$

The problem of maximizing the data-log-likelihood subject to the parameter sharing can be

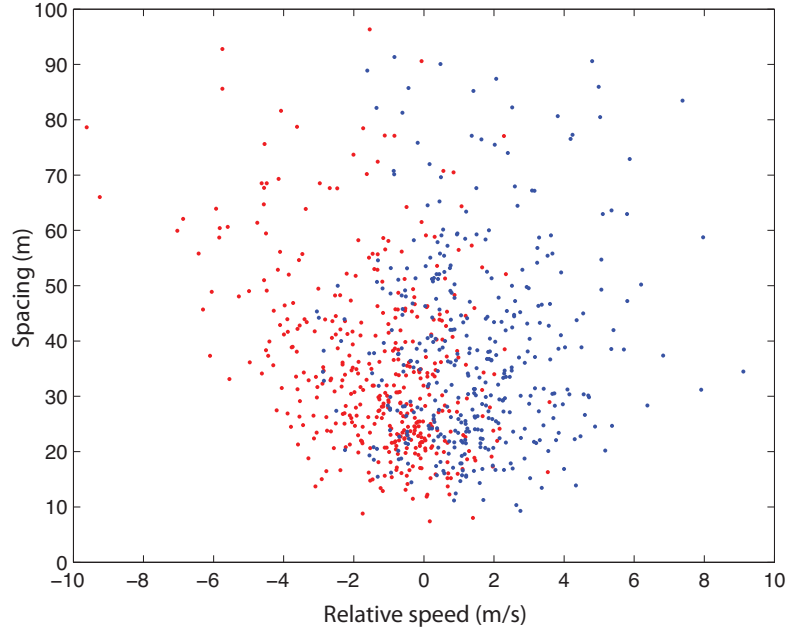


Figure 10.4: Estimated action points in the relative speed - spacing $(\Delta v, s)$ plane used for parameter learning.

broken down into subproblems, one for each probability distribution. One such subproblem can be restated as:

$$P = \operatorname{argmax}\{h(\theta) \mid g(\theta) = 0\} \quad (10.5)$$

where:

$$h(\theta) = \sum_i N_i \log \theta_i \quad (10.6)$$

and

$$g(\theta) = \left(\sum_i h_i \theta_i\right) - 1 = 0 \quad (10.7)$$

When all the counts are positive, it can be easily proven that P has a global maximum which is achieved in the interior of the region. In this case the solution of P can be found using Lagrangian multipliers. In this regard the Lagrangian multiplier λ is introduced. Let $LM(\theta, \lambda) = h(\theta) - \lambda g(\theta)$. Then the point which maximizes P is among the solutions of the system $\nabla LM(\theta, \lambda) = 0$.

Let $(\hat{\theta}, \lambda)$ be a solution for this system. We have $0 = \frac{\partial LM}{\partial \theta_i} = \frac{N_i}{\theta_i} - \lambda k_i$ for all i . Therefore $k_i \hat{\theta}_i = \frac{N_i}{\lambda}$. Summing up all the values of i , we get:

$$0 = \frac{\partial LM}{\partial \lambda} = \left(\sum_i k_i \hat{\theta}_i\right) - 1 = \left(\sum_i \frac{N_i}{\lambda}\right) - 1 = \frac{N}{\lambda} - 1 \quad (10.8)$$

From this last equation we compute the value of $\lambda = N$. This provides us with $\hat{\theta}_i = \frac{N}{k_i \cdot N}$. The fact that $\hat{\theta}$ is the set of maximum likelihood estimators follows as the objective function is concave.

10.4 Marginal and joint probabilities through parameter learning

After learning the parameters in the nodes using the method described in the previous section, we calculated the marginal probabilities for all the nodes in the Bayesian net. As an illustration, marginal probabilities for s , Δv_{pos} , Δv_{neg} , Ap , a_{inc} and a_{red} are displayed in Figure 10.5.

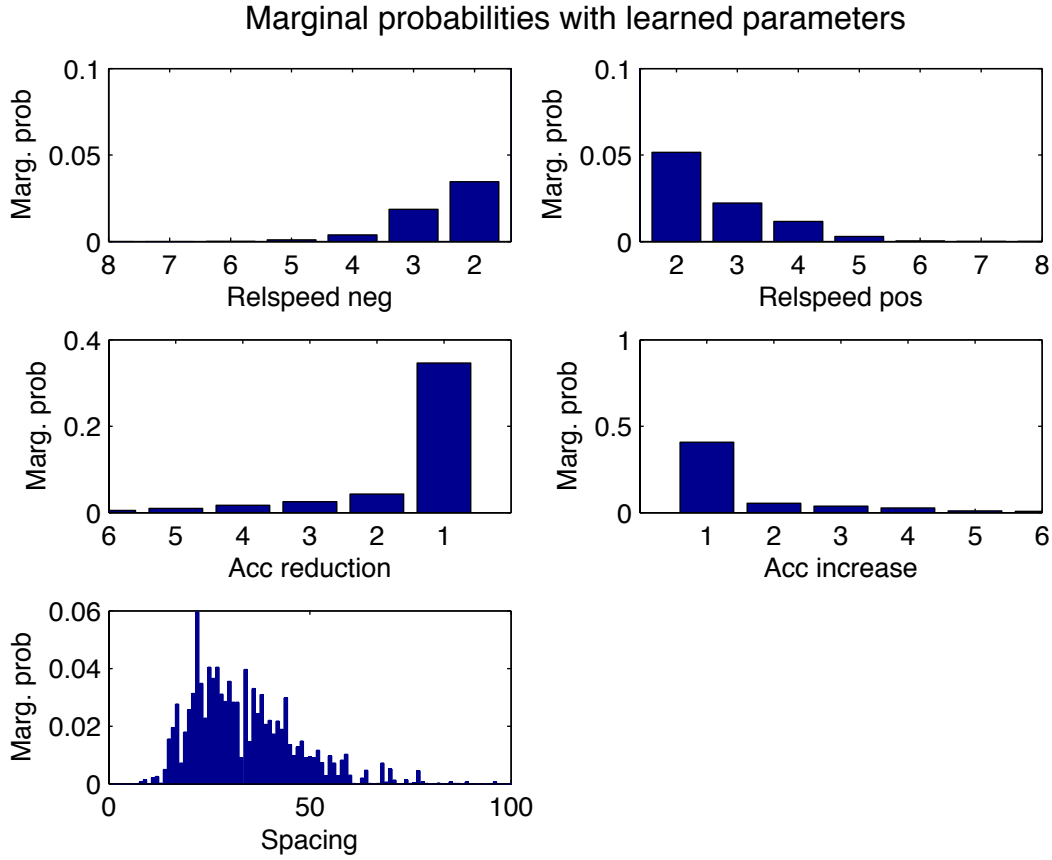


Figure 10.5: Marginal probabilities for Δv_{pos} , Δv_{neg} , a_{inc} , a_{red} and s .

After calculating the marginal probabilities we calculated the joint probabilities:

$$P(Ap \mid \Delta v_{pos}, \Delta v_{neg}, s) \quad (10.9)$$

using the learned parameters. This is the joint probability of an action point occurring given the probabilities of a certain value of s , Δv_{pos} and Δv_{neg} occurring. We also smoothed the joint probabilities twice using a 3-by-3 convolution kernel. The results are presented in Figure 10.6.

From the figure it can be observed that the highest joint probabilities of an action point occurring are located at smaller values of Δv_{pos} , Δv_{neg} and s . The joint probabilities at larger

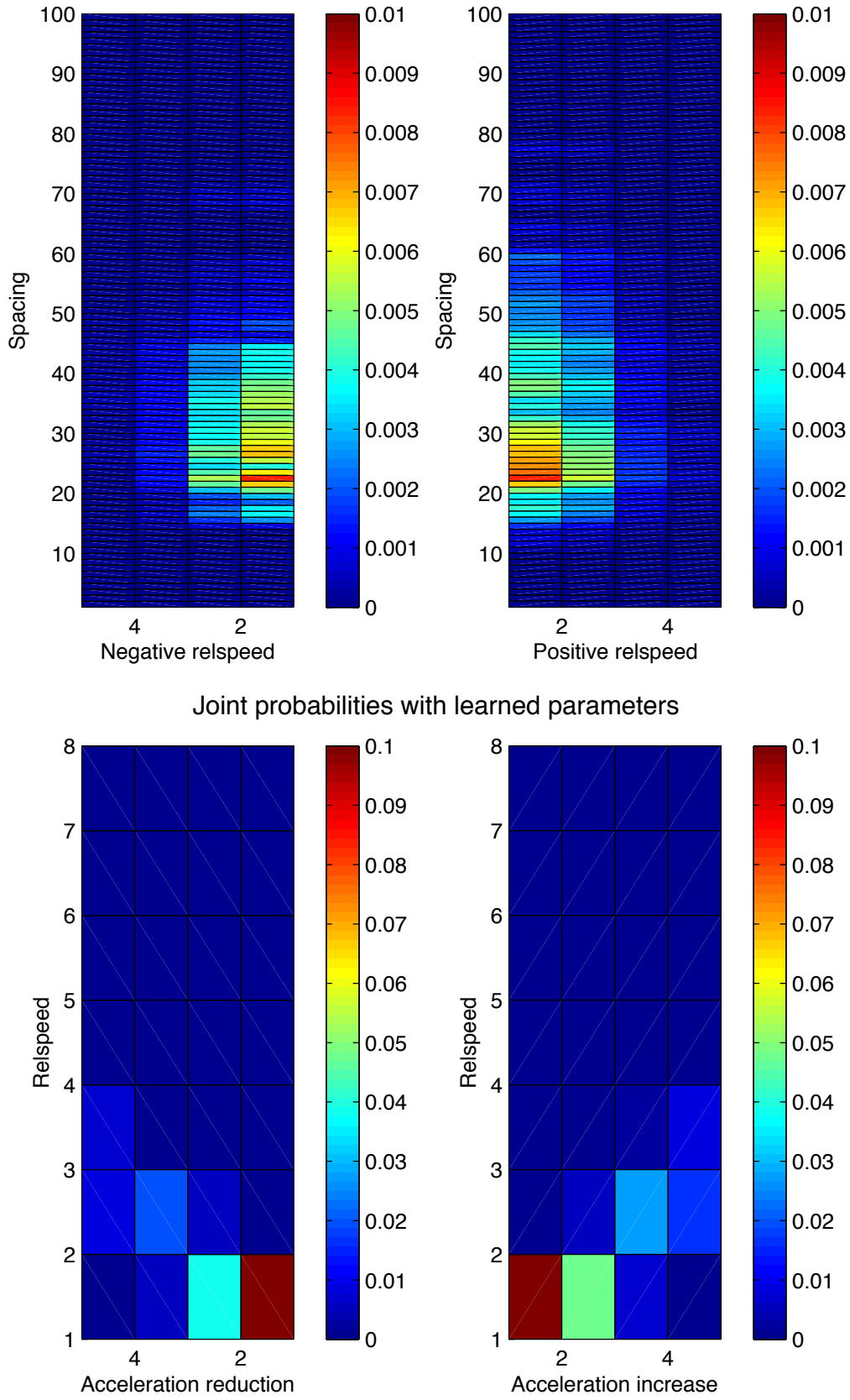


Figure 10.6: Smoothed joint probabilities $P(Ap \mid \Delta v_{pos}, \Delta v_{neg}, s)$ (top) as well as joint probabilities $P(a_{red} \mid \Delta v_{pos}, \Delta v_{neg}, s, Ap)$ and $P(a_{inc} \mid \Delta v_{pos}, \Delta v_{neg}, s, Ap)$ (bottom).

values of Δv and s are considerably lower. This means for example that the probability of a driver changing his acceleration is considerable higher at smaller distances from the lead vehicle. When comparing the distribution of joint probabilities to the position of the action points displayed in Figure 10.4 it can be observed that these are quite similar.

In Figure 10.6 also the joint probabilities for acceleration increases and reductions are displayed. In order to provide a more insightful figure, only joint probabilities are shown given the evidence that $s = 20$. From the figure it can be observed that the joint probabilities are the highest at smaller values of Δv and a . This means for example that the probability of larger accelerations at smaller speed differences with the lead vehicle is smaller than the probability of smaller accelerations at smaller speed differences with the lead vehicle.

10.5 Extending the Bayesian network with adverse conditions

Again, we started with setting up a network through the connection of nodes regarding lead vehicle related stimuli (i.e., positive relative speed Δv_{pos} , negative relative speed Δv_{neg} and spacing s) to action points Ap as well as to acceleration increases a_{inc} and acceleration reductions a_{red} at action points. However, here we extended the Bayesian net with adverse conditions. The constructed Bayesian net is depicted in Figure 10.7.

The net consists of nine discrete nodes. The number of classes within the nodes for spacing s , positive relative speed Δv_{pos} and negative relative speed Δv_{neg} are again based on the maximum values observed in the datasets discussed below. The node representing action points consists of two classes (1=no action point, 2=action point). The nodes representing acceleration increases and reductions both consist of six discrete classes. The added adverse conditions (i.e., emergency situations, adverse weather conditions and incidents) each consist of two discrete classes (1=no adverse condition, 2=adverse condition).

As was the case with the simple stochastic car-following models discussed in Section 10.3 we started with constructing the CPT using random conditional probabilities and making inferences. The inferences were made based on a ground state, i.e., no evidence was fed to the network for a specific adverse condition, value of spacing s , positive relative speed Δv_{pos} or negative relative speed Δv_{neg} .

Again, in order to acquire a more realistic prediction of the positions of action points as well as acceleration at the action points, we trained the network using empirical trajectory data. In this case the data used in this contribution consists of the vehicle trajectory data discussed in Section 10.3. However we also used the data derived from the driving simulator experiments described in Chapter 3 as well as the empirical trajectory data described in Chapter 9.

Action points were estimated from these datasets. To this end we again used the data analysis technique described in Chapter 7. This resulted in a distribution of action points in the $(\Delta v, s)$ plane. As an illustration these action points are depicted in Figure 10.8.

We continued with generating a tabula rasa through again filling the CPT with random parameters and learned the parameters using the approach discussed in Section 10.3. In order to show

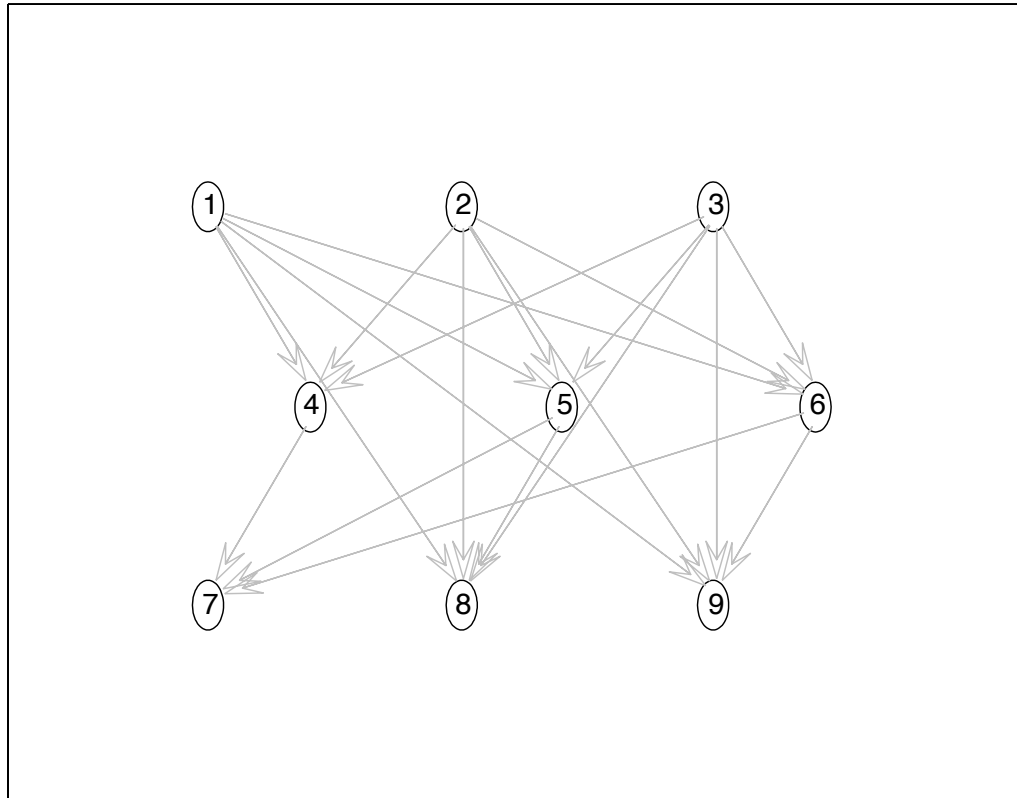


Figure 10.7: Designed extended Bayesian network. In this network the following nodes are incorporated: Emergency situations (1), Adverse weather conditions (2), Incidents (3), Spacing(4), Positive relative speed (5), Negative relative speed (6), Action point(7), Acceleration increases (8) and Acceleration reductions (9).

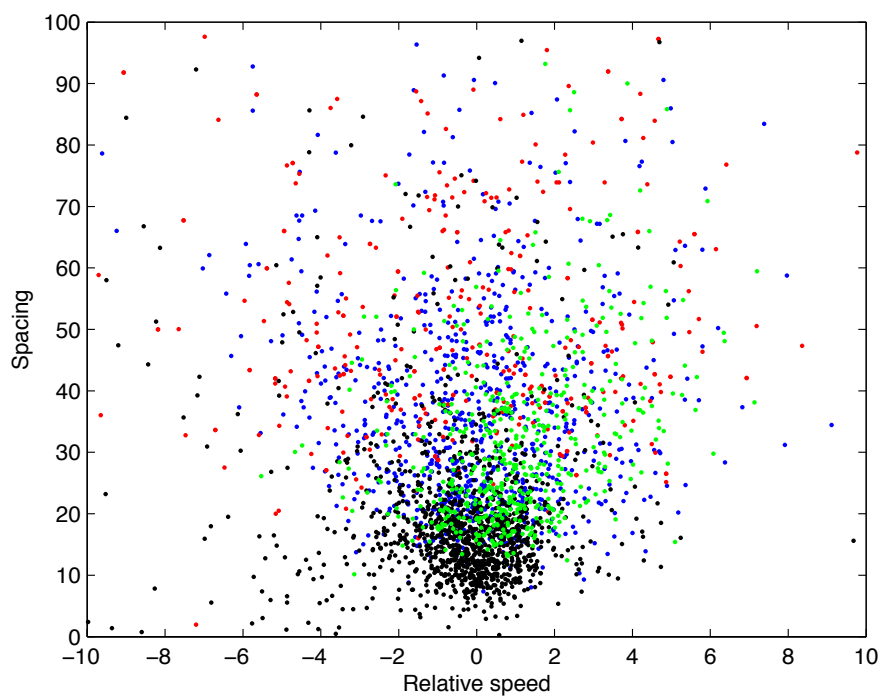


Figure 10.8: Distribution of action points in the $(\Delta v, s)$ plane. Action points under normal driving conditions are presented by blue points. The black, red and green points represent respectively the action points in case of emergency situations, adverse weather conditions and freeway incidents.

the workings of this extended Bayesian net we calculated the marginal and joint probabilities given the evidence of an emergency situation, adverse weather conditions and an incident respectively.

10.5.1 Evidence of an emergency situation

After learning the parameters in the nodes through the method described in Section 10.3 we calculated the marginal probabilities for all of the nodes in the Bayesian net given the evidence of an emergency situation (Emergency=2). As an illustration, marginal probabilities for spacing s , positive relative speed Δv_{pos} , negative relative speed Δv_{neg} , acceleration increases a_{inc} and acceleration reductions a_{red} are displayed in Figure 10.9.

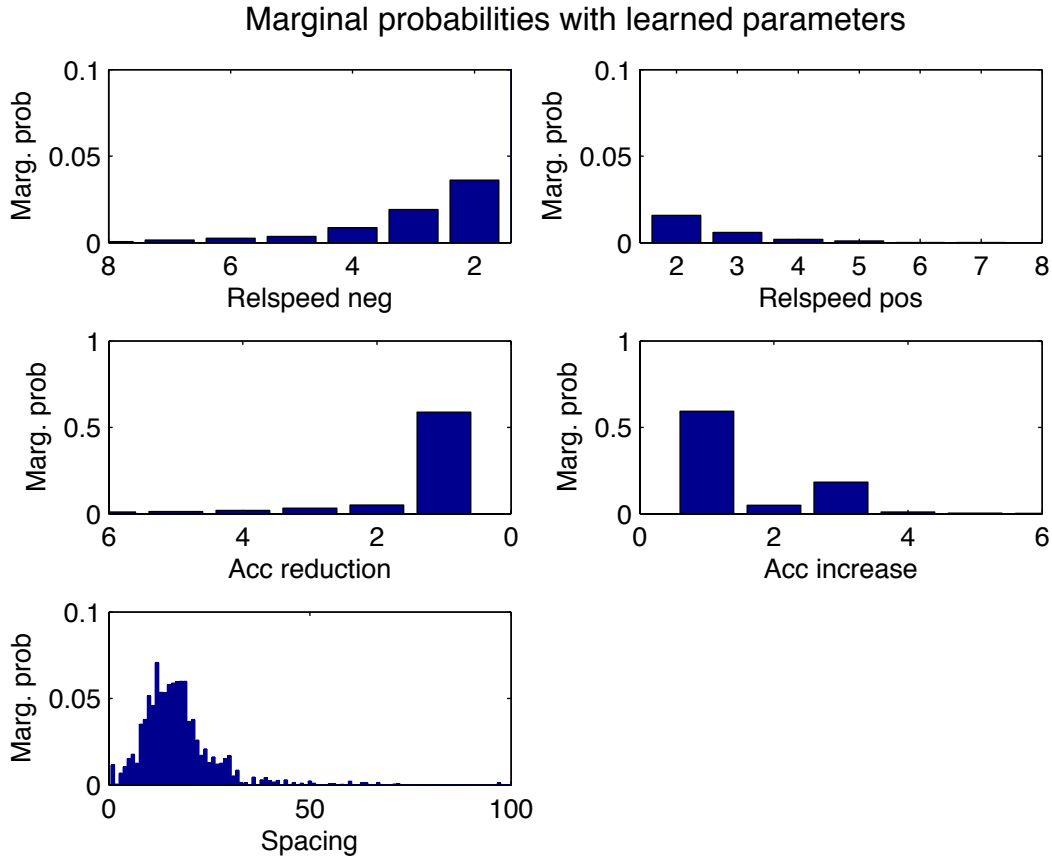


Figure 10.9: Marginal probabilities for Δv_{pos} , Δv_{neg} , a_{inc} , a_{red} and s given the evidence of an emergency situation.

After calculating the marginal probabilities we again calculated the joint probabilities

$$P(Ap \mid \Delta v_{pos}, \Delta v_{neg}, s) \quad (10.10)$$

using the learned parameters. This is the joint probability of an action point occurring given the probabilities of a certain value of spacing s , positive relative speed Δv_{pos} and negative relative speed Δv_{neg} occurring. Again, we also smoothed the joint probabilities twice using a 3-by-3 convolution kernel. The results are presented in Figure 10.10.

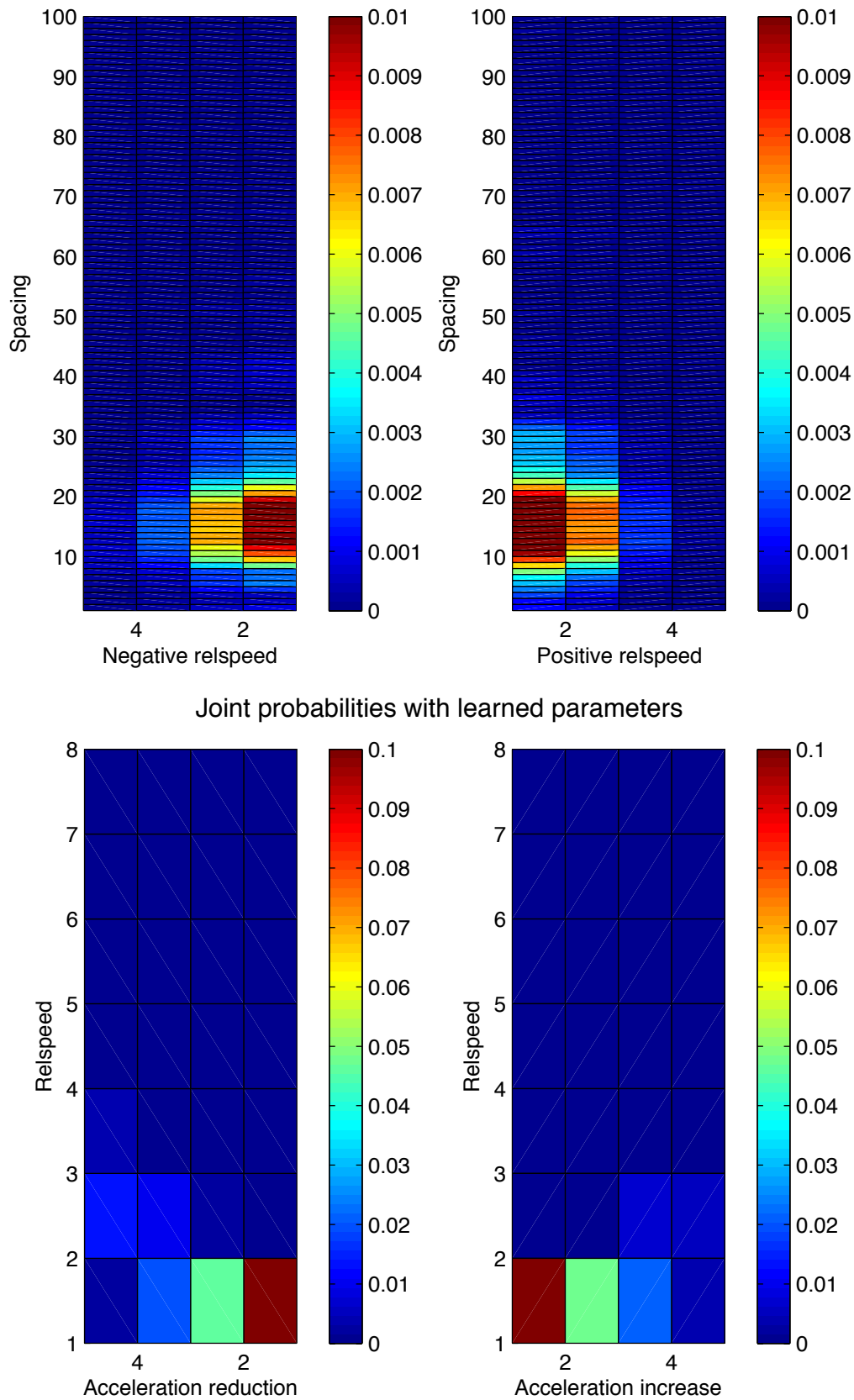


Figure 10.10: Smoothed joint probabilities $P(Ap \mid \Delta v_{pos}, \Delta v_{neg}, s)$ (top) and joint probabilities $P(a_{red} \mid \Delta v_{pos}, \Delta v_{neg}, s, Ap)$ and $P(a_{inc} \mid \Delta v_{pos}, \Delta v_{neg}, s, Ap)$ (bottom) given the evidence of an emergency situation.

From the figure it can be observed that the highest joint probabilities of an action point occurring are located at relatively small values of positive relative speed Δv_{pos} , negative relative speed Δv_{neg} and also spacing s . The joint probabilities at larger values of relative speed Δv and s are considerably smaller. When comparing the joint probabilities to the position of the action points in Figure 10.9 in case of an emergency situation it can be observed that they display a similar distribution.

Furthermore, when comparing the joint probabilities depicted in Figure 10.10 to the joint probabilities in Figure 10.6, it can be observed that these are remarkably different. From these figures it can be observed that in case of the emergency situation joint probabilities are much more concentrated at smaller values of relative speed Δv and spacing s . This is in accordance with the findings presented in Chapter 9.

In Figure 10.10 also the joint probabilities for acceleration increases and reductions are displayed. Again, in order to provide a more insightful figure, only joint probabilities are given the evidence that $s = 20$. From the figure it can be observed that the joint probabilities are the highest at smaller values of Δv and a .

This means for example that the probability of larger accelerations at smaller speed differences with the lead vehicle is smaller than the probability of smaller acceleration at smaller speed differences with the lead vehicle.

When comparing this figure to Figure 10.6 some small differences can be observed. With regard to small accelerations at smaller values of relative speed Δv both figures are quite similar. However, overall it can be observed that the joint probability of higher accelerations at smaller values of Δv (especially with Δv_{neg}) is somewhat higher than in the model without the emergency situation. This is in accordance with the findings in Chapter 4.

In this subsection we showed the workings of the model given the evidence of an emergency situation. In the next section we will illustrate the workings of the model given the evidence of an adverse weather condition.

10.5.2 Evidence of adverse weather conditions

After learning the parameters in the nodes as described in Section 10.3, we again calculated the marginal probabilities for all of the nodes in the Bayesian net given the evidence of an adverse weather condition (Weather=2). As an illustration, marginal probabilities for spacing s , positive relative speed Δv_{pos} , negative relative speed Δv_{neg} , acceleration increases a_{inc} and reductions a_{red} are displayed in Figure 10.11.

After calculating the marginal probabilities we again calculated the joint probabilities $P(Ap | \Delta v_{pos}, \Delta v_{neg}, s)$ using the learned parameters. This is the joint probability of an action point occurring given the probabilities of a certain value of spacing s , positive relative speed Δv_{pos} and negative relative speed Δv_{neg} occurring. Again, we also smoothed the joint probabilities twice using a 3-by-3 convolution kernel. The results are presented in Figure 10.12.

From the figure it can be observed that the highest joint probabilities of an action point occurring are located at relatively small values of positive relative speed Δv_{pos} . What is striking is

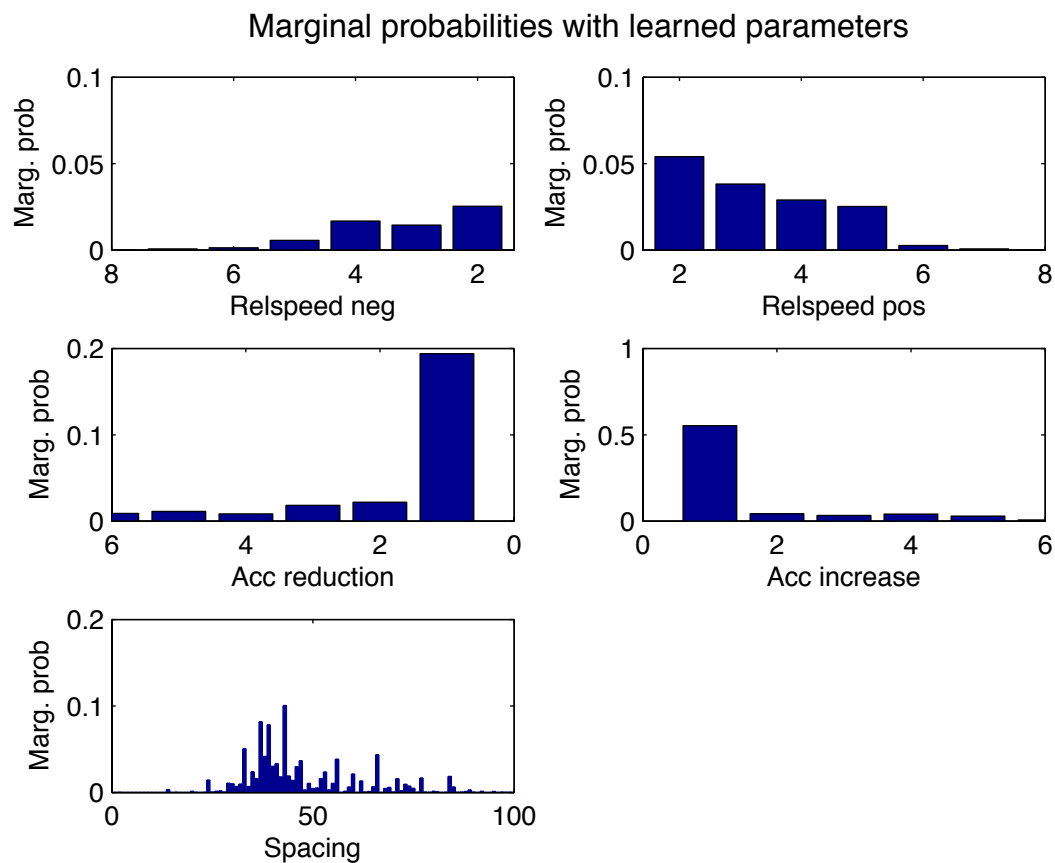


Figure 10.11: Marginal probabilities for Δv_{pos} , Δv_{neg} , a_{inc} , a_{red} and s given that Weather=2.

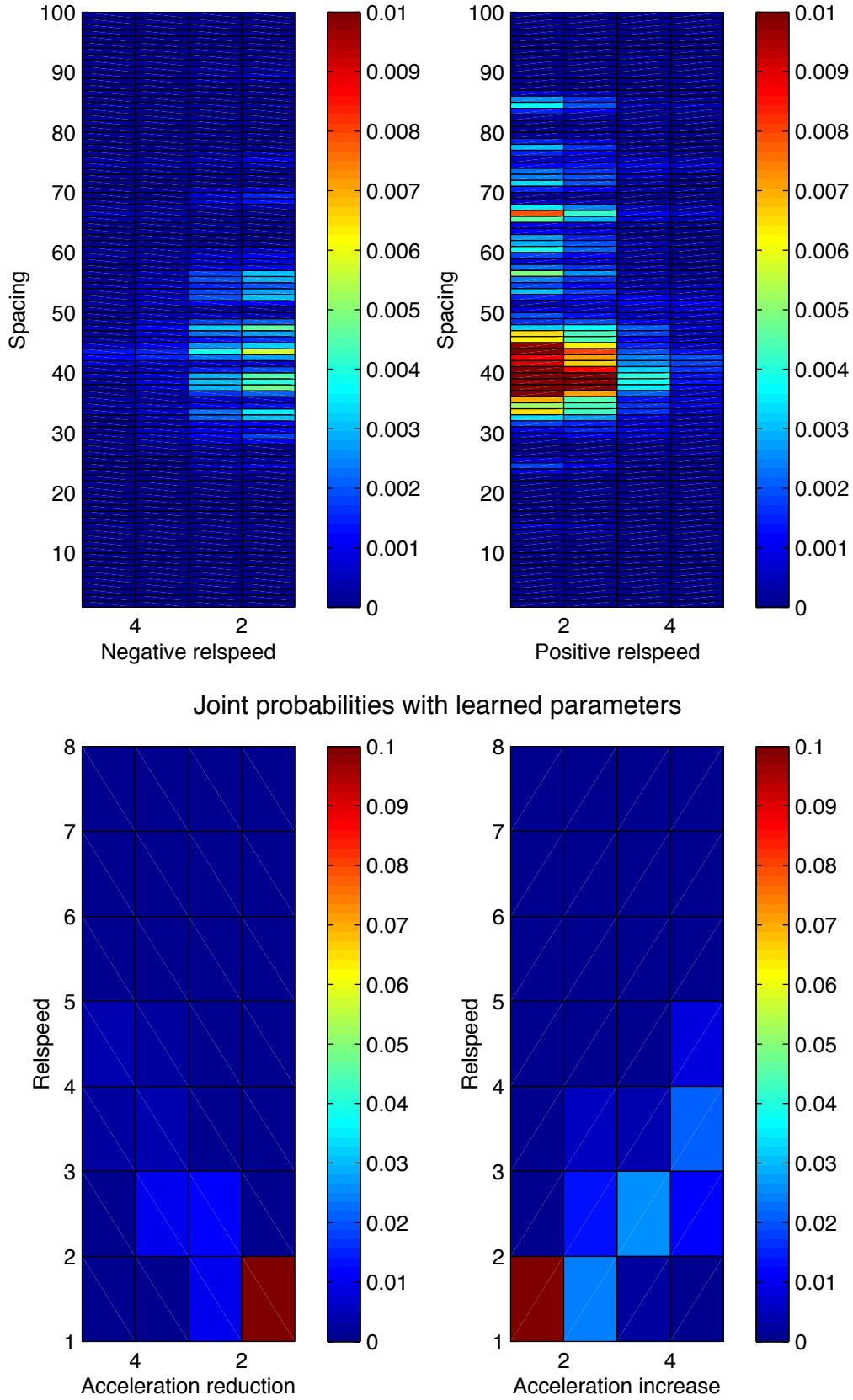


Figure 10.12: Smoothed joint probabilities $P(Ap \mid \Delta v_{pos}, \Delta v_{neg}, s)$ (top) and joint probabilities $P(a_{red} \mid \Delta v_{pos}, \Delta v_{neg}, s, Ap)$ and $P(a_{inc} \mid \Delta v_{pos}, \Delta v_{neg}, s, Ap)$ (bottom) given the evidence of an adverse weather condition.

that the higher joint probabilities can be observed at larger values of spacing s (around 40m). Probabilities at negative relative speeds Δv_{neg} are much lower, even at larger values of spacing s .

The joint probabilities at smaller and much larger values of s are considerably smaller. When comparing the joint probabilities to the position of the action points in Figure 10.8 in case of adverse weather conditions, it can be observed that they display a similar distribution.

Furthermore, when comparing the joint probabilities depicted in Figure 10.12 to the joint probabilities in Figure 10.6, it can be observed that these are remarkably different. From these figures it can be observed that in case of the emergency situation higher joint probabilities are much more concentrated at smaller values of relative speed Δv and spacing s , while higher joint probabilities in case of an adverse weather condition are much more concentrated at smaller positive relative speeds Δv_{pos} and larger values of spacing s . Furthermore it can be observed that in case of an adverse weather condition higher joint probabilities are much more scattered than in case of an emergency situation. This is in accordance with the findings presented in Chapter 9.

In Figure 10.12 also the joint probabilities for acceleration increases and reductions are displayed. Again, in order to provide a more insightful figure, only joint probabilities are given the evidence that $s = 20$. From the figure it can be observed that the joint probabilities are the highest at smaller values of Δv and a . When comparing the joint probabilities at acceleration increases a_{inc} and reductions a_{red} in case of adverse weather conditions to those in case of emergency situations it can be observed that the joint probabilities at larger values of a_{inc} and a_{red} in case of an adverse weather condition are considerably smaller than in case of an emergency situation.

In this subsection we showed the workings of the model given the evidence of an adverse weather condition. In the next section we will illustrate the workings of the model given the evidence of a freeway incident.

10.5.3 Evidence of a freeway incident

After learning the parameters in the nodes as described in Section 10.3 we again calculated the marginal probabilities for all of the nodes in the Bayesian net given the evidence of a freeway incident (Incident=2). As an illustration, marginal probabilities for spacing s , positive relative speed Δv_{pos} , negative relative speed Δv_{neg} , acceleration increases a_{inc} and reductions a_{red} are displayed in Figure 10.13.

After calculating the marginal probabilities we again calculated the joint probabilities $P(Ap | \Delta v_{pos}, \Delta v_{neg}, s)$ using the learned parameters. This is again the joint probability of an action point occurring given the probabilities of a certain value of spacing s , positive relative speed Δv_{pos} and negative relative speed Δv_{neg} occurring. Again, we also smoothed the joint probabilities twice using a 3-by-3 convolution kernel. The results are presented in Figure 10.14.

From the figure it can be observed that the highest joint probabilities of an action point occurring are located at relatively small values of negative relative speed Δv_{pos} . What is striking is that, compared to the joint probabilities in case of adverse weather conditions, the higher

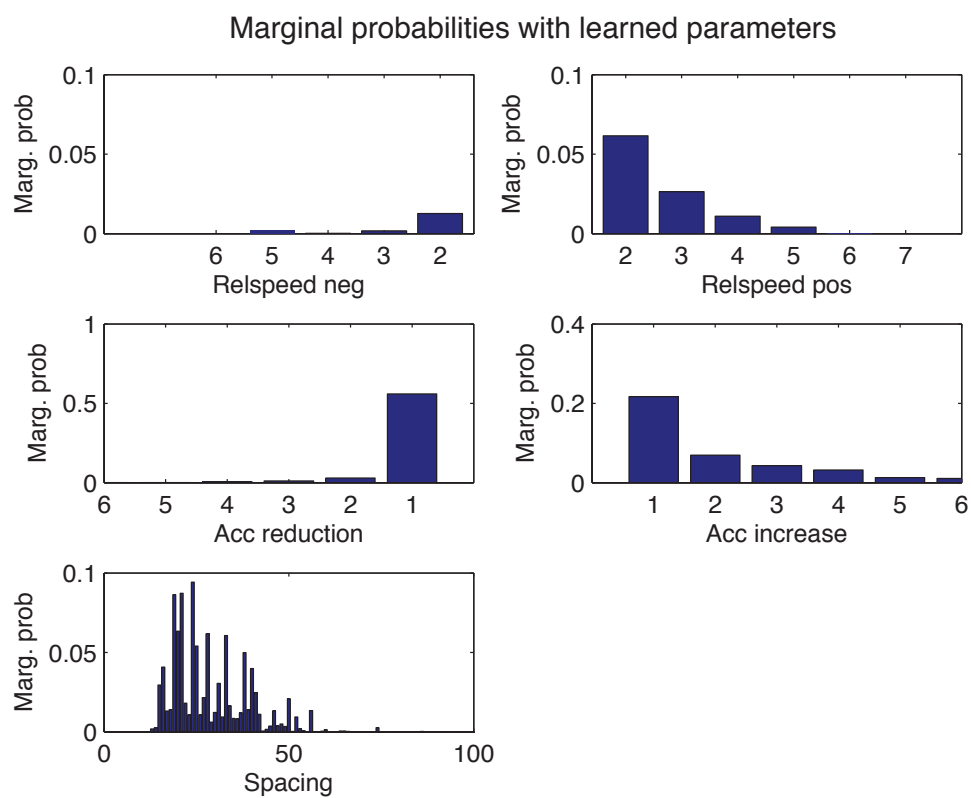


Figure 10.13: Marginal probabilities for Δv_{pos} , Δv_{neg} , a_{inc} , a_{red} and s given that Incident=2.

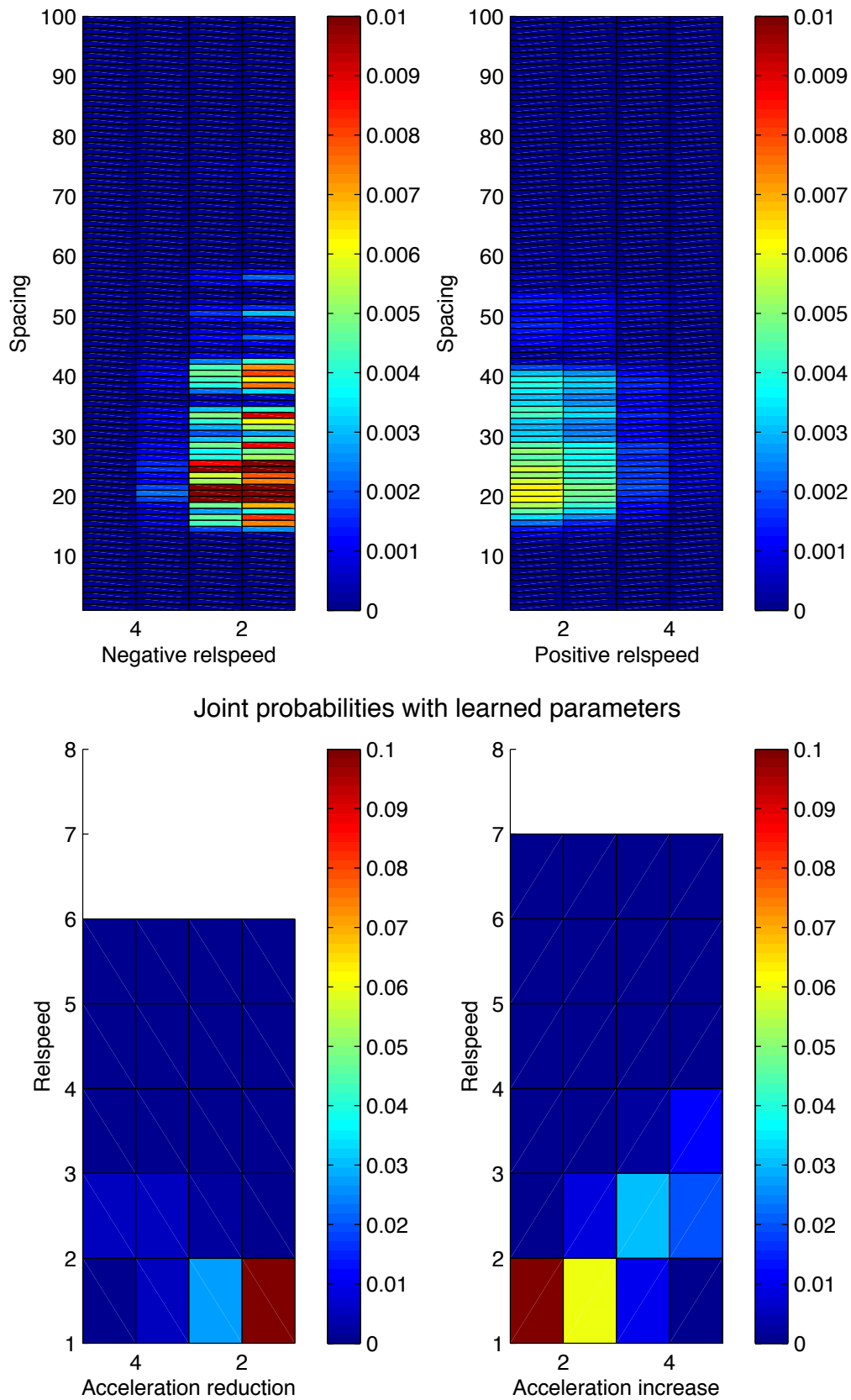


Figure 10.14: Smoothed joint probabilities $P(Ap \mid \Delta v_{pos}, \Delta v_{neg}, s)$ (top) and joint probabilities $P(a_{red} \mid \Delta v_{pos}, \Delta v_{neg}, s, Ap)$ and $P(a_{inc} \mid \Delta v_{pos}, \Delta v_{neg}, s, Ap)$ (bottom) given the evidence of a freeway incident.

joint probabilities can be observed at smaller values of spacing s (around 20m) and especially at negative relative speeds Δv_{neg} . Probabilities at positive relative speeds Δv_{pos} are somewhat lower. When comparing the joint probabilities with the joint probabilities given the evidence of an emergency situation again a larger scatter can be observed. This is accordance with the empirical action points discussed in Chapter 9.

In Figure 10.14 also the joint probabilities for acceleration increases and reductions are displayed. Again, in order to provide a more insightful figure, only joint probabilities are given the evidence that $s = 20$. From the figure it can be observed that the joint probabilities are the highest at smaller values of Δv and a . When comparing the joint probabilities at acceleration increases a_{inc} and reductions a_{red} in case of an incident in the adjacent driving lane to those in case of for example adverse weather conditions, it can be observed that the joint probabilities are quite similar. However, it can also be observed that the joint probability of larger acceleration increases a_{inc} at small speed differences with the lead vehicle is somewhat higher in case of an incident in the other driving lane compared to adverse weather conditions.

10.6 Conclusions

In Chapter 9 we showed that adverse conditions lead to substantial changes in the position of action points in the relative speed - spacing plane in action point models. It was argued that the difference in the shape and position of the perceptual thresholds, represented in the position of the action points in the relative speed - spacing ($\Delta v, s$) plane were indicators of compensation effects proposed in our theoretical model. The reduction in sensitivity of acceleration a as well as the 'jumps' in acceleration Δa and also the observation that the models less adequately describe these elements of longitudinal driving behavior was assumed to reflect performance effects. The aforementioned led to the conclusion that, although psycho-spacing models are relatively adequate in describing car-following patterns, the assumption of deterministic perceptual thresholds does not hold in reality.

In order to capture this stochasticity in driving behavior in this dissertation we took a first step in modeling car-following behavior under adverse conditions through a Bayesian network modeling approach based on psycho-spacing theory. We set up a Bayesian network with discrete nodes and connected the nodes through links, thus creating an acyclic graph. Parameters in the conditional probability tables in the nodes were learned through an Maximum Likelihood Estimation approach using data collected through the approach described in Chapter 7. Action points were estimated using a new data analysis technique also described in Chapter 7.

From the marginal as well as the joint probabilities displayed in the first working example in Section 10.4, it followed that the Bayesian network approach performs relatively well in predicting action points in the relative speed - spacing plane. The network also provided a reasonably adequate prediction of acceleration increases and reductions at the action points.

Next in Section 10.5 we extended the Bayesian network described in Section 10.3 with the adverse condition emergency situations, adverse weather conditions and freeway incidents. Again we learned parameters in the conditional probability tables in the nodes through the MLE approach, but in this case using the driving simulator data collected through the experiments described in Chapter 3 as well as the data collected through the approach described in

Chapter 9. Again action points were estimated using the data analysis technique described in Chapter 7. Here also it followed from the marginal as well as the joint probabilities that this Bayesian network modeling approach yields a relatively good representation of longitudinal driving behavior given the evidence of the various adverse conditions.

However, in order to acquire a more representative prediction of action points and acceleration at the action points in case of adverse conditions, more data is needed. Furthermore, the used Bayesian network was static and consisted of discrete nodes. In order to acquire a more realistic representation of the longitudinal driving task it is recommended to transform the current net into a dynamic continuous Bayesian network. This can for example be achieved through the approach proposed in Miska and Van Zuylen (2004). In their work a Bayesian network was transformed into a dynamic Bayesian network through the addition and removal of slices and accumulating evidence over time.

In the previous chapters we argued that human elements are assumed to play a substantial role in longitudinal driving behavior under adverse conditions. Therefore, it is recommended to extend the network with nodes representing human factors (e.g., age, driving experience, activation level, distraction etc.).

In this part of the dissertation we turned to modeling of longitudinal driving behavior in case of the selected adverse conditions. We showed the influence of emergency situations, adverse weather conditions as well as freeway incidents on parameter values and model performance of an often used continuous car-following model, i.e., the Intelligent Driver Model (Treiber et al., 2000) and also showed the influence of the selected adverse conditions on the position of action points as well as acceleration and the 'jumps' in acceleration at these action points in a psycho-spacing model. In the present chapter we made a first step towards a new stochastic car-following model using a Bayesian network modeling approach based on psycho-spacing theory.

In the final part of this research we present the conclusions and recommendations of this dissertation. In this final chapter, a summary of the main research aims as well as the approaches to achieve these aims is provided along with the main findings of this thesis. From these main findings conclusions are drawn with regard to the empirical and the modeling of longitudinal driving behavior in case of the selected adverse conditions. We continue in this chapter with a presentation of the practical implications, reflections on the performed research and some recommendations for future research.

Part III

Conclusions and Recommendations

Chapter 11

Conclusions and Recommendations

The aim of this final chapter is to reflect on the main conclusions of this dissertation. In Section 11.1 a summary is provided of the main research aims and the approaches to achieve these aims. This summary is followed by a discussion of the main research findings and the conclusions in respectively Section 11.2 and Section 11.3. Next we discuss several practical implications of the work reported in this dissertation, followed by a reflection on the presented research in respectively Section 11.4 and 11.5. Finally in Section 11.6 recommendations for future research are provided.

11.1 Summary of research aims and approaches

The ability of transport systems to deal with adverse conditions, defined as conditions following an unplanned event with a high impact and a low probability of occurring, has become increasingly important. Examples of adverse conditions are emergency situations following a man-made or naturally occurring disaster, adverse weather conditions and freeway incidents.

The impact of adverse conditions is complicated by its effect on traffic flow operations. Emergency situations, adverse weather conditions as well as freeway incidents have been shown to have, for example, a substantial impact on freeway capacity.

Several examples demonstrated how the dependence of society on transportation becomes apparent when problems arise. Therefore effective and innovative strategies are needed in order to limit the impact of adverse conditions, since both the infrastructure as well as the behavior are impacted considerably by these conditions.

However, since these adverse conditions have a low rate of occurring, hardly any knowledge is available about how to cope with them. In order to investigate whether strategies are effective, simulation studies must be performed. In microscopic simulation models mathematical models of driving behavior are used in order to approximate driving behavior. Therefore, in order to get a realistic prediction of traffic flow operations in relation with the efficacy of traffic management strategies, insight into adaptation effects in driving behavior under adverse conditions is essential.

In this thesis extensive empirical analyses of driving behavior under adverse conditions were presented. We also analyzed the determinants of driving behavior under these conditions, as

this might provide us with insight into which strategies might be most effective in order to optimize traffic flow operations under adverse conditions.

Furthermore, it was not yet clear to what extent current mathematical models of longitudinal driving behavior incorporated in microscopic simulation tools are adequate in approximating longitudinal driving behavior under adverse conditions. Therefore in this dissertation we also presented extensive analyses of the representation of adaptation effects in driving behavior under adverse conditions in several often used mathematical models of driving behavior.

This dissertation has focused on longitudinal driving behavior on freeways in case of emergency situations, adverse weather conditions and freeway incidents. These adverse conditions were selected as each was assumed to have a different effect on empirical longitudinal driving behavior as well as to have a different effect on the determinants of adaptation effects in empirical longitudinal driving behavior.

Another motivation for choosing emergency situations, adverse weather conditions and freeway incidents was that they might occur simultaneously. For example, it could easily be imagined that traffic accidents occur during an emergency situation. It can be also assumed that some emergency situations are accompanied by adverse weather conditions, leading to a reduction in visibility (e.g., bush fires, hurricanes etc.).

Furthermore, in this dissertation we focused on longitudinal driving behavior under adverse conditions. In other words: we focused on interactions between drivers moving in the same driving lane. This choice was motivated by the fact that dynamics in traffic flow on freeways are largely determined by interactions between vehicles in the same lane. For example, Ossen (2008) conjectured that longitudinal driving behavior of individual drivers determines to a large extent the equilibrium as well as the dynamic characteristics of traffic flow.

The main research objective of this dissertation was therefore: 'Establishing insight into longitudinal driving behavior in case of adverse conditions and developing mathematical models describing this behavior.'

11.1.1 Empirical adaptation effects in longitudinal driving behavior under adverse conditions

Although it may be assumed that adverse conditions have a substantial impact on longitudinal driving behavior of individuals drivers, little information was available about to what extent this behavior is actually influenced. The first main aim of this dissertation was therefore to determine the effects adverse conditions have on empirical longitudinal driving behavior. From the state-of-the-art presented in Chapter 2 it followed that research on the influence of emergency situations, adverse weather conditions and freeway incidents is scarce and sometimes even non-existent. For example, research performed on the influence of emergency situations in connection with longitudinal driving behavior is solely based on assumptions. Furthermore, research on the effect of adverse weather conditions and freeway incidents did not make use of a full experimental design making inferences with regard to observed adaptation effects difficult. Nevertheless, it was assumed that emergency situations, adverse weather conditions as well as freeway incidents have a significant and substantial effect on longitudinal driving behavior.

In order to determine the extent to which the aforementioned conditions have an effect on empirical longitudinal driving behavior, we performed three extensive driving simulator experiments. In these experiments use was made of the Advanced Driving Simulator owned by Delft University of Technology, Faculty Civil Engineering and Geosciences, Transport & Planning Department.

Emergency situations

In order to determine the influence of emergency situations on empirical longitudinal driving behavior a driving simulator experiment with a multi-factorial experimental design was performed. Such an experimental design is appropriate when more than one experimental variable is studied.

In the experiment between- as well as within-subjects factors were implemented. As a between-subjects factor the factor Urgency was introduced. This factor consisted of the induction of a sense of urgency within the participants of the experiment through communicating to participants in the experimental group that they would receive a monetary reward under the condition that they would reach their destination safely in time. To a control group it was communicated that they would receive a monetary reward regardless of whether they would reach their destination in time.

As a within subject factor the factor Time was implemented. To achieve this the test drive in the driving simulator was divided into three segments of equal duration in the control group as well as in the experimental group. In the experimental group the level of urgency was increased in these three segments through feedback on the screen.

For the purpose of this experiment, a driving environment was designed consisting of four segments. The first segment consisted of a short test drive in order to let participants get accustomed to driving in a driving simulator and to test whether the participants would suffer from simulator sickness. The other three segments were used in the experiment. The test trials were conducted on a virtual motorway with two lanes in the same direction. In the experimental group the level of urgency was increased by messages displayed on the screen ranging from 'On time' to 'You are running out of time'. These messages were accompanied by a counter of the remaining monetary reward.

In both the control group and the experimental group behavior of the other road users was similar. In both conditions moderately congested traffic conditions were simulated as well as two stop-and-go waves. Behavior of the other road users was derived from empirical longitudinal driving behavior of participants in a pilot study.

In the experiment longitudinal driving behavior was monitored through speed, acceleration, deceleration, spacing and speed of the lead vehicle at a sampling rate of 10Hz. This data were analyzed by first calculating the descriptive statistics for the aforementioned indicators of longitudinal driving behavior. Next, effects of the between as well as the within subject factors was analyzed through a Multivariate Analysis of Variance (MANOVA) with a significance level of 0.05.

Adverse weather conditions

In order to determine the influence of adverse weather conditions on empirical longitudinal driving behavior a within-subject driving simulator experiment was performed. This means that in this experiment all participants participated in a control condition as well as in an experimental condition. In the experimental condition, an adverse weather condition (fog) was induced, while in the control condition normal driving conditions were applied. In this experiment the order in which the participants were exposed to the conditions was varied to account for learning effects (counterbalancing across subjects).

For the purpose of this experiment another driving environment was designed. This driving environment consisted of three segments. Again, the first segment consisted of a short test drive to accustom participants to driving in a driving simulator and to test whether they would suffer from simulator sickness. The other two segments were used in the experiment: the control and the experimental condition. In the experimental condition fog was generated with a reduction in visibility to around 150 m.

The test trials took place on a virtual motorway with two lanes in the same direction. Again, the behavior of the other traffic was derived from actual longitudinal driving behavior of participants in a pilot study.

As was the case with measuring empirical longitudinal driving behavior under emergency situations, in this experiment longitudinal driving behavior was measured through registered speed, acceleration, deceleration, spacing and speed of the lead vehicle at 10Hz. These data were analyzed through calculation of the descriptive statistics and performance of paired samples t-tests with a significance level of 0.05.

Freeway incidents

In order to determine the influence of freeway incidents on empirical longitudinal driving behavior a driving simulator experiment with a repeated measures design was performed. In this experiment all participants participated in a control condition as well as in two experimental conditions. The two experimental conditions consisted of two versions of a car accident in the other driving lane, while in the control condition no accident was present. Again, the order of the segments was counterbalanced across subjects.

As was the case with the two previously described experiments a driving environment was developed for the purpose of this experiment. The driving environment consisted of four segments. Again the first segment consisted of a short test drive to accustom the participants to driving in a driving simulator and also to test for simulator sickness. The other three segments were used in the experiment: two segments in which a car accident in the other driving lane was generated and one without an accident. Between the two experimental conditions the severity of the accidents was varied.

The test trials were conducted on a virtual motorway with two lanes in the same direction. As was the case with the previously discussed experiments behavior of the other traffic was derived from a pilot study. As was the case with measuring empirical longitudinal driving behavior under emergency situations and adverse weather conditions, in this experiment longitudinal

driving behavior was measured through registered speed, acceleration, deceleration, spacing and speed of the lead vehicle at 10Hz. This data was analyzed through a MANOVA for repeated measures with Condition and Time as within subject factors. The factor Condition consisted of the longitudinal driving behavior in the two experimental conditions while Time consisted of longitudinal driving behavior before, during and after the incident location.

11.1.2 Determinants of longitudinal driving behavior under adverse conditions

In the previous subsection it was stated that adverse conditions were assumed to have a significant and substantial influence on empirical longitudinal driving behavior. However, this did not provide us with insight into which causes are responsible for the observed adaptation effects.

No research on determinants of adaptation effects in empirical longitudinal driving behavior under adverse conditions was found. However, in Chapter 2 some likely candidates were selected. One of these likely candidates is personal characteristics of drivers. Here, gender, age, driving experience, socio economic status and ethnicity were distinguished. We showed that from the available research it followed that gender, age, driving experience and ethnicity are assumed to have a substantial influence on empirical longitudinal driving behavior under adverse conditions.

It was also shown that dynamic psychological constructs can be assumed to have a substantial influence on empirical longitudinal driving behavior under adverse conditions. A large number of studies was reported showing the influence of mental workload on driving behavior in general. Emotions and panic were also discussed as possible determinants of adaptation effects in empirical longitudinal driving behavior under adverse conditions. It was stated that these constructs have considerable definition problems and that, overall, research was performed without making use of full experimental designs and objective measures. Furthermore, panic showed to be quite a rare phenomenon in case of adverse conditions.

The aforementioned selection of likely determinants of adaptation effects in empirical longitudinal driving behavior does however not provide us with insight into how these determinants actually influence longitudinal driving behavior under adverse conditions. To this end in Chapter 2 we proposed a new theoretical framework based on the Task-Capability-Interface model by Fuller (2005).

A theoretical framework

The theoretical framework aims to explain the relationship between emergency situations, adverse weather conditions and freeway incidents and empirical longitudinal driving behavior. It is assumed that these conditions have an influence on activation level, distraction or task demands, leading to an imbalance between task demands and driver capabilities. The driver will try to resolve this imbalance by exerting direct control over his driving behavior (compensation effects). When these actions are insufficient to resolve this imbalance, a driver will experience an increase in mental workload leading to a reduction in performance.

However, more insight was needed into the extent to which the theoretical framework provided an adequate explanation of adaptation effects in empirical longitudinal driving behavior under

adverse conditions. Therefore through the previously described three driving simulator experiments we determined the influence of the adverse conditions emergency situations, adverse weather conditions and freeway incidents on mental workload and determined the (moderating) influence of the personal characteristics age and driving experience on mental workload during these conditions.

Experiments on the influence of adverse conditions on mental workload

In the three experiments different measures of mental workload were used. However in all three experiments mental workload was monitored through the physiological measures heart rate and heart rate variability (HRV). Heart rate and HRV were both measured with an Electro-CardioGram (ECG).

In the experiments pertaining to the influence of adverse weather conditions and incidents in the other driving lane we also measured subjective estimates of effort expenditure. Here the Rating Scale Mental Effort (RSME) was used (Zijlstra & Doorn, 1985). The RSME measures subjective ratings of perceived mental effort. The RSME is a one dimensional visual-analogue scale containing nine different verbal categories forming anchor points expressing different levels of mental effort.

In the experiment regarding the influence of incidents in the other driving lane we additionally measured respiration rate and activity of two facial muscles, i.e., the zygomaticus major (smiling) and the corrugator supercilii (frowning). The latter measurements were performed through an ElectroMyoGraphy (EMG).

In all three experiments we started with calculating descriptive statistics for the physiological measures of mental workload as well as the subjective estimates of effort. Before calculating the descriptive statistics, physiological indicators of mental workload were transformed by expressing them as a fraction of a preceding baseline measurement. Analogous to the data analysis of empirical longitudinal driving behavior in case of an emergency situation, a MANOVA was performed in order to determine the effect of emergency situations on physiological indicators of mental workload. The influence of adverse weather conditions on physiological indicators of mental workload and subjective estimates of effort was determined through paired samples t-tests. As was the case with the influence of incidents on the freeway on empirical longitudinal driving behavior the influence of this adverse condition on physiological indicators of mental workload and subjective estimates of effort was determined through a MANOVA for repeated measures.

In order to test the influence of age and driving experience on mental workload Multiple Regression Analyses, were performed with age and driving experience as the independent variables and physiological indicators of mental workload as the dependent variables. Again, a significance level was of 0.05 was applied.

11.1.3 Mathematical modeling of longitudinal driving behavior under adverse conditions

The aforementioned research objectives aimed at establishing the empirical longitudinal driving behavior under adverse conditions, i.e., adaptation effects in empirical longitudinal driving

behavior and the determinants of these adaptation effects in empirical longitudinal driving behavior.

The next research objective was to determine the extent to which mathematical models of longitudinal driving behavior are adequate in incorporating adaptation effects in longitudinal driving behavior under adverse conditions. In Chapter 6 we provided an extensive overview with regard to continuous car-following models (stimulus-response, safe-distance and multi-anticipation) as well as psycho-spacing models in connection with adverse conditions. It is evident that most current continuous models of car-following behavior do not adequately incorporate human elements and therefore describe longitudinal driving behavior in a mechanistic manner. Furthermore, we showed that from previous research it follows that the degree of stochasticity in values of parameters incorporated in these models is substantial. From the results reported in Chapter 4 it can be observed that especially in relation with adverse conditions stochasticity is substantial, as large differences within and between drivers were reported.

In order to determine the effect adverse conditions have on parameter values and model performance in continuous car-following models we estimated the Intelligent Driver Model (Treiber et al., 2000) using the data derived from the three driving simulator experiments. To this end a new calibration approach for joint estimation was developed.

In Chapter 6 we hypothesized that psycho-spacing models provide a relative adequate representation of car-following patterns under adverse conditions. However, the original formulation of the model incorporates deterministic perceptual thresholds. We assumed that adverse conditions have a substantial influence on the position of action points in the relative speed - spacing plane through compensation effects proposed in the theoretical framework and that large differences between drivers can be observed. Furthermore, we assumed that acceleration at the action points as well as 'jumps' in acceleration (difference in acceleration before and after an action point) at the action points will also be influenced substantially by adverse conditions.

In order to determine the influence of emergency situations, adverse weather conditions and incidents on the freeway on the position of action points in psycho-spacing models a new data analysis technique was developed. In order to determine acceleration as well as 'jumps' in acceleration a Multivariate Regression Analysis (MRA) was performed using four different models.

Finally in the last chapter a first step was taken towards modeling longitudinal driving behavior under adverse conditions through a stochastic psycho-spacing model grounded on Bayesian network modeling. We started with setting up a simple Bayesian net with just six nodes aimed at predicting action points in the relative speed - spacing plane as well as acceleration at the action points. The parameters in the conditional probability tables in the nodes of the net were learned using empirical data, i.e., driving simulator data and trajectory data collected with a helicopter. Next we provided an illustration of the workings of this simple model using a brief example. We also extended the proposed stochastic model with adverse conditions and again illustrated the dynamics through providing evidence to the network of an emergency situation, an adverse weather conditions and a freeway incident.

11.2 Main findings

This section briefly summarizes the main findings presented in this thesis.

11.2.1 Empirical adaptation effects

This dissertation demonstrates that emergency situations, adverse weather conditions as well as freeway incidents have a substantial impact on empirical longitudinal driving behavior.

Emergency situations led to several significant adaptation effects in empirical longitudinal driving behavior. Speed was significantly higher in the experimental group (urgency) compared to the control group (no urgency). Furthermore it was shown that speed increased significantly over time with the level of urgency. Acceleration was also significantly higher in the experimental group compared to the control group. However, acceleration did not increase over time. Deceleration did not show to be significantly affected by the emergency situation, as no significant difference was found between the two groups and no effect of time course could be established. Spacing however was substantially smaller in the experimental group and even decreased over time as the level of urgency increased. Positive and negative relative speed were smaller in the experimental group compared to the control group. Driver heterogeneity was however substantial, as indicated by large standard deviations.

The picture that emerges with regard to adverse weather conditions was quite different. In case of fog drivers significantly reduce their speed along with a reduction in acceleration and deceleration. Most striking is however the substantial and significant increase in spacing in the adverse weather condition. This increase in spacing was accompanied by substantial increases in relative speeds. However, as was the case with empirical longitudinal driving behavior in case of an emergency situation, here also a substantially large degree of driver heterogeneity can be observed as indicated by the relatively large standard deviations.

Freeway incidents lead to similar adaptation effects as adverse weather conditions. Overall, perception of an incident in the other driving lane leads to a substantial reduction in speed along with a reduction in acceleration. Decelerations became stronger during perception of the incident in the other driving lane. These adaptation effects were accompanied by a substantial and significant increase in spacing along with larger positive and negative relative speeds. No significant differences were found between the two versions of the accident. As was the case with emergency situations and adverse weather conditions the degree of driver heterogeneity was quite substantial. Again, considerably large standard deviations in speed, acceleration, deceleration, spacing and relative speeds were established.

11.2.2 Determinants of longitudinal driving behavior under adverse conditions

From the results with regard to the influence of emergency situations on physiological indicators of mental workload, it followed that emergency situations have a significant influence on HRV. HRV was significantly lower in the experimental group with the emergency situation

compared to the control group. Time course also had a significant influence, as in the experimental group the Out of Time condition (condition with highest urgency level) showed a lower mean HRV than in the On Time (lowest urgency level) and the Behind Schedule condition. Mean HRV in the Behind Schedule condition was lower than in the On Time condition. Heart rate however showed to be not affected by the emergency situation. No significant differences were found between the experimental group and the control group and no effect was found of time course on this physiological indicator of mental workload.

Adverse weather conditions did have a significant influence on heart rate as well as HRV. The adverse weather condition resulting in a reduction in visibility led to an increase in heart rate and a reduction in HRV. However, the adverse weather condition did not have a significant effect on subjective estimates of effort, measured through the RSME (Zijlstra & Doorn, 1985). This leads to the conclusion that although objectively measured mental workload increased, the perception of mental workload by drivers was not significantly affected by this adverse condition.

With regard to the influence of freeway incidents on mental workload the results were less clear. Significant effects of perception of an incident in the other driving lane were only established for mean amplitude of the corrugator supercillii (frowning) and respiration rate. No significant effects were found on heart rate and amplitudes of the zygomaticus major. As was the case with adverse weather conditions, no significant effects were found on subjective estimates of effort expenditure. Furthermore, it followed from the MANOVA for repeated measures that overall no significant difference could be established between the two versions of the incident.

Besides the influence of adverse conditions on mental workload, we also analyzed the effect personal characteristics of drivers have on mental workload during adverse conditions. Through Multiple Regression Analyses we showed that the personal characteristics age and driving experience have a significant influence on physiological indicators of mental workload during adverse conditions. The physiological indicators indicate that a higher age as well as a less driving experience lead to a higher mental workload during adverse conditions.

11.2.3 Mathematical modeling of longitudinal driving behavior under adverse conditions

Continuous car-following models

In this dissertation it is shown that adverse conditions have a substantial impact on parameter value changes and model performance of an often used car-following model, namely the Intelligent Driver Model (Treiber et al., 2000).

We started with the estimation of the parameter values of the Intelligent Driver Model (Treiber et al., 2000) using a dataset containing an emergency situation. We concluded that emergency situations have a substantial and significant influence on all of the parameters of the Intelligent Driver Model. In this context we showed that emergency situations lead to a significant increase in maximum acceleration a , maximum deceleration b and free speed v_0 . Furthermore we showed that emergency situations lead to a significant reduction in the value of the parameter desired time headway T .

We showed that also adverse weather conditions have a substantial and significant influence on parameter values of the Intelligent Driver Model. We showed that adverse weather conditions (i.e., fog) lead to a significant reduction in maximum acceleration a and maximum deceleration b . Strangely enough free speed v_0 increased significantly in the adverse weather condition. It was argued that this might be due to the fact that model performance is not very sensitive to v_0 given that it is sufficiently high. Desired time headway T increased as well during the adverse weather condition. Although this might seem strange from a behavioral point of view, we showed that minimum stopping distance s_0 increased significantly. It can therefore be concluded that desired distance to the lead vehicle in case of an adverse weather condition becomes less dependent on speed, but to a larger extent on the minimum stopping distance.

Finally in the context of the influence of adverse conditions on parameter values of the Intelligent Driver Model we showed that freeway incidents have an influence on some of these parameter values. We showed that on average freeway incidents lead to an increase in maximum acceleration a as well as a reduction in maximum deceleration b . However, the differences between the control condition and the experimental condition proved to be non significant. As was the case with adverse weather condition, free speed v_0 increased. Again we argued that this might be due to the fact that model performance is not very sensitive to v_0 given that it is sufficiently high. Most striking however was the substantial increase in desired time headway T . This increase proved to be significant.

Besides an influence on parameter values, we also showed that adverse conditions have an influence on model performance. We showed that emergency situations, adverse weather conditions as well as incidents in the other driving lane lead to a reduction in model performance of the Intelligent Driver Model (Treiber et al., 2000).

Psycho-spacing models

Besides the findings that adverse conditions have a substantial influence on parameter values and model performance of continuous car-following models, we also showed that these conditions have a substantial impact on the position of action points and acceleration as well as the 'jumps' in acceleration at these action points in psycho-spacing models.

In case of an emergency situation action points are much more concentrated at smaller values of spacing s and drivers react to smaller speed differences with the lead vehicle Δv . The picture that emerges from the position of action points in case of adverse weather conditions was however quite different. Under this condition drivers tend to keep larger values of spacing s . They also reacted predominantly to larger speed differences with the lead vehicle Δv , even at smaller values of spacing s .

In case of freeway incidents, drivers mostly seem to react at smaller values of spacing s . Furthermore, it could be observed from the results that most action points regarded acceleration increases.

This was well-illustrated by the results of the curve fitting analysis, as the shape and location of the deterministic perceptual thresholds differed substantially between the different conditions. For example, thresholds in case of emergency situations were much closer together at smaller

values of spacing s than was the case under normal driving conditions. However, the results showed that the position of the action points was quite stochastic.

Finally, acceleration as well as the 'jumps' in acceleration at the estimated action points were analyzed using a Multivariate Regression Analysis. In general, the results showed that acceleration as well as the 'jumps' in acceleration depends on relative speed Δv and spacing s . Overall it was shown that in case of adverse conditions acceleration as well as the 'jumps' in acceleration were less sensitive to relative speed Δv and spacing s . Also, the models seemed to describe acceleration and the 'jumps' in acceleration less adequately, as indicated by substantially large errors and Mean Squared Errors.

Modeling adaptation effects through a Bayesian network modeling approach

In this dissertation we showed that adverse conditions lead to substantial changes in parameter values and model performance of continuous car-following models as well as in the position of action points in the relative speed - spacing plane in action point models. Furthermore it was shown that the position of action points in psycho-spacing models is dependent on and are substantially influenced by adverse conditions and is quite stochastic.

In order to capture stochasticity in driving behavior in this dissertation we took a first step in modeling car-following behavior under adverse conditions through a Bayesian network modeling approach based on psycho-spacing theory. We set up a Bayesian network with discrete nodes and connected the nodes through links, thus creating an acyclic graph. Parameters in the conditional probability tables in the nodes were learned through a Maximum Likelihood Estimation (MLE) approach using trajectory data collected with a helicopter. Action points were estimated using the new data analysis technique presented in this dissertation.

From the marginal as well as the joint probabilities displayed in the first working example, it followed that the Bayesian network approach performs relatively well in predicting action points in the relative speed - spacing plane. The network also provided a reasonably adequate prediction of acceleration increases and reductions at the action points.

Furthermore, we extended the Bayesian network with the adverse conditions emergency situations, adverse weather conditions and incidents in the other driving lane. Again we learned parameters in the conditional probability tables in the nodes through a MLE approach, but in this case using action points estimated using the driving simulator data collected through the experiments as well as the trajectory data collected with a helicopter. Here also it followed from the marginal as well as the joint probabilities that this Bayesian network modeling approach yields a relatively good representation of longitudinal driving behavior given the evidence of the various adverse conditions.

11.3 Conclusions

11.3.1 Empirical driving behavior under adverse conditions

In this dissertation empirical evidence was provided for substantial and significant adaptation effects in empirical longitudinal driving behavior in case of adverse conditions. We showed

that adaptation effects in empirical longitudinal driving behavior in case of adverse weather conditions and freeway incidents are quite similar. Both adverse conditions are characterized by a substantial reduction in speed, acceleration and deceleration along with a substantial increase in spacing.

Emergency situations following a man-made or naturally occurring disaster showed to have a substantially different effect on empirical longitudinal driving behavior. In case of this adverse condition, drivers adapted a higher speed with stronger values of acceleration.

In order to provide insight into why these adaptation effects in empirical longitudinal driving behavior are caused in Chapter 2 we introduced a new theoretical framework based on the TCI model by Fuller (2005). In this theoretical framework it was proposed that adverse conditions lead to compensation effects as well as to performance effects. Emergency situations presumably lead to an increase in activation level causing an increase in driver capability. This leads to an imbalance between task demands and driver capability. The driver will try to resolve this imbalance through a conscious increase in task demand by increasing speed and reducing spacing.

In case of adverse weather conditions task demands increase due to, for example, a reduction in visibility. Assuming that driver capability remains constant, an imbalance occurs between driver capability and task demands. As a result, drivers will try to reduce task demands by reducing speed and an increase in spacing.

Finally, it was assumed that freeway incidents lead to driver distraction. The theoretical framework proposed that this distraction leads to a reduction in driver capability. This reduction leads to an imbalance between task demands and driver capability. The driver will again try to resolve this imbalance through a reduction in speed and an increase in spacing.

The theoretical framework however also proposed that when the compensation effects are insufficient to resolve the imbalance between driver capability and task demands due to the adverse conditions mental workload will increase and possibly driving task performance will reduce.

In this dissertation it was therefore shown for the first time that the selected adverse conditions lead to changes in physiological indicators of mental workload during performance of a driving task. In this context, we showed that in case of emergency situations at least one physiological indicator of mental workload changed significantly. Although heart rate variability (HRV) decreased significantly, no significant changes were found for heart rate. These findings were assumed to be caused by the different sensitivity of the used measures. Although insufficient, the results provide an indication that mental workload will increase due to an emergency situation.

Adverse weather conditions had a significant effect on both measured physiological indicators (heart rate and HRV) providing a strong indication of an increase in mental workload due to the adverse weather condition. No significant effects on subjective estimates of effort were established.

Freeway incidents also led to a significant change in more than one of the physiological indicators of mental workload. Amplitude of the facial muscle corrugator supercillii (frowning)

as well as respiration rate indicated an increase in mental workload, while heart rate, HRV and amplitude of the facial muscle zygomaticus major (smiling) did not indicate a significant change in mental workload. No significant effects on subjective estimates of effort were established.

This leads to the conclusion that adverse conditions may be assumed to lead to an increase in mental workload. This supports our theoretical framework. Due to the adverse condition, drivers experience an imbalance between driver capabilities and task demands (e.g., through activation level, distraction or an increase in task demands) which they will try to resolve through compensation effects. When compensation effects are insufficient, an increase in mental workload will be the result.

The theoretical framework also proposed that driver capability is influenced by personal characteristics of drivers. In this context this dissertation showed that the personal characteristics age and driving experience have a significant influence on some of the physiological indicators of mental workload during the selected adverse conditions. It was shown that a higher age as well as less driving experience leads to a higher mental workload during these conditions.

With this in mind, we can carefully conclude that the findings with regard to the influence of adverse conditions empirically underpin the proposed theoretical framework.

11.3.2 Modeling of driving behavior under adverse conditions

As was mentioned before, insight into adaptation effects in empirical longitudinal driving behavior as well as into the determinants of these adaptation effects in driving behavior under adverse conditions does not inform us of the extent to which mathematical models of longitudinal driving behavior are adequate in incorporating longitudinal driving behavior under adverse conditions.

In this dissertation we demonstrated for the first time the effect of emergency situations, adverse weather conditions and freeway incidents on parameter values and model performance of an often used car-following model, i.e., the Intelligent Driver Model (Treiber et al., 2000).

With regard to the influence of emergency situations on parameter values of the Intelligent Driver Model, we showed that this condition has a substantial influence on parameter values. From a behavioral point of view the parameter value changes of this model are overall relatively insightful. The changes in parameter values can be regarded as compensation effects as proposed in the theoretical model. Drivers consciously adapt their maximum acceleration and deceleration, while desired time headway decreases.

However we also concluded that emergency situations lead to a reduction in model performance of the Intelligent Driver Model. This could be an indication that longitudinal driving behavior to a lesser extent is governed by car-following behavior. This assumption supports the notion of performance effects proposed in the theoretical framework.

With regard to the influence of adverse weather conditions on parameter values of the Intelligent Driver Model we also showed that substantial parameter value changes can be observed. For example, substantial and significant reductions in the parameter value of maximum acceleration a and maximum deceleration b were observed. From a behavioral point of view the

reported low value of T in the Intelligent Driver Model seemed strange, as from the results of the adaptation effect in empirical longitudinal driving behavior it followed that drivers actually increase their spacing (with large differences between drivers) during an adverse weather condition. This low value of T was however strongly compensated by a substantial increase in minimum stopping distance s_0 .

The parameter value changes of the Intelligent Driver Model are in case of an adverse weather condition, from a behavioral point of view, also relatively insightful. Compensation effects are reflected in, for example, a reduction in the value of maximum acceleration a and maximum deceleration b . Free speed v_0 was not very insightful from a behavioral point of view. It was argued that model performance is not very sensitive to free speed v_0 .

As was the case with emergency situations, adverse weather conditions led to a substantial reduction in model performance as well. Again, this supports the notion of performance effects, as proposed in the theoretical framework. As drivers are unable to restore the balance between driver capabilities and task demands through compensation effects, the adequacy of the driving task (i.e., car-following) will suffer.

As was the case with emergency situations and adverse weather conditions, freeway incidents also lead to parameter value changes in the Intelligent Driver Model. We showed that this adverse condition led to a non-significant increase in maximum acceleration a as well as a reduction in maximum deceleration b . Again free speed v_0 increased, which was argued to be due to the fact that model performance is not very sensitive to free speed. Most striking was the substantial increase in desired time headway T .

From a behavioral point of view the parameters are again relatively insightful. Especially the strong increase in desired time headway T is an indication of compensation effects in longitudinal driving behavior. This supports the notion proposed in the theoretical framework that incidents in the other driving lane lead to distraction, in turn leading to an imbalance between driver capabilities and task demands, which the driver will try to resolve (compensation effects).

As was the case with emergency situations and adverse weather conditions, freeway incidents lead to a reduction in model performance of the Intelligent Driver Model. As was argued in the aforementioned, this might be an indication for the presence of performance effects. Through the imbalance between driver capabilities and task demands, the car-following task suffers as a result.

Overall it can therefore be concluded that adverse conditions lead to substantial changes in parameter values as well as model performance in the Intelligent Driver Model. We hypothesize that the changes in parameter values reflections of compensation effects in longitudinal driving behavior as proposed in the theoretical framework. The reductions in model performance, as observed in all three adverse conditions, are an indication for the existence of performance effects. Car-following becomes to a lesser extent a determinant of longitudinal driving behavior.

From the literature review it follows that continuous car-following models insufficiently incorporate human elements, like thresholds in perception. In this context in this dissertation we presented the results of analyses with regard to the influence of adverse condition on the

position of action points as well as (jumps in) acceleration at action points in psycho-spacing models for the first time.

We showed that adverse conditions have a substantial influence on the position of action points in the relative speed - spacing ($\Delta v, s$) plane. For example, in case of an emergency situation action points were much more concentrated at smaller values of relative speed and spacing, while in case of adverse weather conditions action points were much more scattered.

It was argued that the change in the shape of the perceptual thresholds, represented by the position of action points in the relative speed - spacing plane are a result of compensation effects in longitudinal driving behavior following an adverse condition. We also concluded that acceleration as well as the 'jumps' in acceleration are substantially influenced by adverse conditions. Acceleration and the 'jumps' in acceleration become less sensitive to relative speed Δv and spacing s . Furthermore, the used models described acceleration a and the 'jumps' in acceleration Δa less adequately. We concluded that the aforementioned effects are the result of performance effects in longitudinal driving behavior following an adverse condition.

The aforementioned leads to the conclusion that in general car-following patterns closely resemble the ones predicted by psycho-spacing theory. However, in the original formulation of the model deterministic perceptual thresholds are assumed. When observing the results from the estimation of the action points in the relative speed - spacing ($\Delta v, s$) plane it was concluded that this assumption does not hold in reality. Furthermore in the original formulation of the model it was assumed that on crossing one of these deterministic thresholds drivers change their behavior through a change in the sign of their acceleration. However, the results show that acceleration at the action points is dependent on relative speed and spacing, with a strong influence of external circumstances (i.e., adverse conditions). The position of action points and acceleration at the action points therefore seem to have quite a stochastic nature.

To this end we made a first step towards the development of a stochastic psycho-spacing model using a Bayesian networking modeling approach. We proposed that this model yields a relatively good prediction of action points and acceleration at the action points in case of adverse conditions.

Finally, we can therefore conclude that adverse conditions have a substantial influence on empirical longitudinal driving behavior. These adaptation effects are relatively well explained through the proposed theoretical framework. This framework was empirically underpinned, as adverse conditions can be assumed to lead to an increase in mental workload, moderated by driver characteristics.

Continuous car-following models, represented by the Intelligent Driver Model showed substantial changes in parameter values and overall proved to be less adequate in describing and predicting longitudinal driving behavior under adverse conditions. This was hypothesized to be the result of compensation and respectively performance effects.

From a behavioral point of view psycho-spacing models are insightful. However, the assumption of deterministic perceptual thresholds proposed in the original formulation of the model does not hold in reality. In this regard a stochastic car-following model should be developed based on psycho-spacing theory. In this context we showed that a Bayesian network modeling approach provides a good solution.

11.4 Practical implications

Firstly, the findings in this dissertation with regard to adaptation effects in empirical longitudinal driving behavior under adverse conditions provide a solid empirical foundation for modeling longitudinal driving behavior in microscopic simulation tools. For example, recently a large number of evacuation studies have been performed in which these tools were used.

For example in Tu et al. (2010) the evacuation clearance time for the Dutch city of Almere was investigated. Evacuation clearance time is one of the key indicators of the efficacy of an evacuation plan. However, in evaluating this evacuation plan the city of Almere assumed normal driving behavior of the evacuees. In Tu et al. (2010) it was shown that driving behavior has a substantial impact on evacuation clearance time, making evaluations of evacuation plans using normal driving behavior less reliable.

Another example is the effect of contraflow on traffic flow operations in case of evacuations. In Knapper and Brookhuis (2010) this measure was used in a field operational test during the evacuation of the Euroborg Soccer Stadium in Groningen. In this study it was shown that this measure might have beneficial effects on traffic flow operations, as capacity gains between 50 and 80% were observed. However, in order to adequately quantify the effect this traffic management measure has on traffic flow operations, an accurate representation of driving behavior in mathematical models is crucial.

Our findings of adaptation effects in empirical longitudinal driving behavior under adverse conditions can therefore support microscopic simulation tools in becoming a more realistic means to perform evaluation studies on the effects of traffic management measures and adjustments of existing infrastructures in relation to adverse conditions. This is also the case for our findings with regard to parameter value changes and model performance of continuous car-following models under adverse conditions, as we showed that adverse conditions lead to substantial changes in parameter values and model performance of the Intelligent Driver Model (Treiber et al., 2000).

This is even to a larger extent the case for the findings with regard to the position of action points in the relative speed-spacing plane in psycho-spacing models. In numerous microscopic simulation tools, psycho-spacing models are used as a basis to describe and predict longitudinal driving behavior. We showed that the assumption of deterministic perceptual thresholds is unrealistic, as large differences exist within as well as between drivers. In order to get a more realistic prediction, microscopic simulation tools should account for the stochasticity in perceptual thresholds. In this context we took a first step towards a stochastic psycho-spacing model using a Bayesian network modeling approach.

The aforementioned is important as the effects of adverse conditions reported in this dissertation may be assumed to have a substantial impact on traffic flow operations. For example, in Hoogendoorn et al. (2010) it was shown that the effects in longitudinal driving behavior due to fog had a substantial effect on free-flow capacity. Here, the estimation of the influence of the adaptation effects in driving behavior on free-flow capacity was carried out by setting up a micro-simulation model (S-Paramics). Through the use of loop detectors information on speed and flow was collected. The data was analyzed using the Product Limit Method of Brilon

(Brilon, Geistefeldt, & Regler, 2005). The results show that the observed changes in driving behavior led to a capacity reduction of 37% in case of fog.

Secondly the findings on adaptation effects in empirical longitudinal driving behavior as well as the findings on the determinants of adaptation effects in empirical longitudinal driving behavior under adverse conditions possibly provides valuable information for developers of road-side and in-car support systems. Longitudinal driving behavior differs between drivers and also strongly depends on the conditions, presumably caused by differences in task demands and driver capability, provides the aforementioned developers with indications on how to best tailor information provision and automated assistance to drivers.

Furthermore, the methodological outcomes with regard to calibration of parameters of continuous car-following models as well as the data analysis technique used for the estimation of action points in psycho-spacing models are useful to everyone involved in studies based on microscopic trajectory observations.

11.5 Reflections

In this section we briefly reflect on the work presented in this thesis.

In order to perform our analyses on adaptation effects in empirical longitudinal driving behavior, use was made of a driving simulator. Using this data collection method we were able to collect longitudinal driving behavior data providing us with the opportunity to perform statistical analyses on adaptation effects in empirical longitudinal driving behavior. In using this data collection method however some validity issues exist.

As we showed in Chapter 3 driving simulators may be assumed to possess relative validity. This means that the direction of behavioral responses in reaction to a stimulus may be assumed to be similar as in real life. However, the magnitude of the observed response may actually differ from real life. The observed adaptation effects in empirical longitudinal driving behavior may therefore be assumed to differ with regard to their magnitude compared to real life behavior.

A more fundamental reflection is that we only investigated the influence of adverse conditions on empirical longitudinal driving behavior. Recently it has become clear from research that lateral driving behavior (merging, lane changing, overtaking) also has a substantial influence on traffic flow operations in general (Kesting, Treiber, & Helbing, 2007). It can therefore be assumed that this vehicle interaction subtask has a substantial influence on traffic flow operations in case of adverse conditions as well.

Another fundamental reflection is that this dissertation was limited to the adverse conditions emergency situations, adverse weather conditions (i.e., fog) and freeway incidents. In this context we did not differentiate between emergency situations following different man-made or naturally occurring disasters. It could be that different disasters lead to different behavioral responses during the emergency situation. Furthermore, we only looked at fog as a representative of adverse weather conditions. It is likely that a reduction in visibility due to heavy rain or a reduction in traction due to black ice leads to different adaptation effects in empirical longitudinal driving behavior than fog.

Another limitation of this dissertation is that only longitudinal driving behavior on freeways was investigated. We did not investigate longitudinal driving behavior during adverse conditions on urban roads and secondary roads.

In this dissertation we also presented extensive research on the influence of adverse conditions on mental workload, moderated by the driver characteristics. In order to measure mental workload we used heart rate, heart rate variability, respiration rate and amplitudes of facial muscles. Although we showed that adverse conditions lead to significant changes in some of these physiological indicators of mental workload, not every indicator showed an effect. It was proposed that this might be due to the difference in sensitivity of the used measures, which sensitivity is assumed to be dependent on workload and task performance. Furthermore, with regard to the influence of personal characteristics on mental workload during adverse conditions we only analyzed age and driving experience. From the state-of-the art in Chapter 2 it followed however that gender and ethnicity may also be assumed to have a substantial effect.

Besides adaptation effects in empirical longitudinal driving behavior and the determinants of these adaptation effects we also investigated the influence of these conditions on parameter values and model performance in continuous car-following models as well as on the position of action points in psycho-spacing models.

Analogous to the reflections on adaptation effect in longitudinal driving behavior under adverse conditions, we only studied the effect of adverse conditions on car-following models. Mathematical models of lane changing behavior were not considered in this thesis.

Furthermore, this dissertation was limited in the number of continuous car-following models that were considered. For example, the influence of adverse conditions on performance of safe distance models, multi anticipative car-following models and cellular automata models was not considered in this thesis. Also the number of stimulus-response models that was considered was limited.

We showed that psycho-spacing models provide a relatively adequate description of the car-following subtask during adverse conditions. However we also showed that the assumption of deterministic perceptual thresholds in the original formulation of these models does not hold in reality. In this regard we took a first step in the development of a stochastic psycho-spacing model using a Bayesian network modeling approach. However, the developed model was discrete and static. In order to obtain more realistic predictions a continuous and dynamic model should be explored.

11.6 Recommendations for future research

In this final section we discuss future research directions following from the research presented in this dissertation. More specifically, we describe how our research on empirical and the modeling of longitudinal driving behavior needs to be expanded.

In the previous section it was stated that due to the fact that a driving simulator was used in order to determine the influence of adverse conditions, some validity issues exist. The extent to which validity issues exist is not yet clear. It is therefore recommended to perform an exten-

sive validation study using empirical data. The empirical data could for example be collected through an instrumented vehicle (or through a naturalistic driving observation approach).

Another reflection that was mentioned was that this dissertation was limited in the number of adverse conditions that were considered. It is therefore recommended to expand this line of research with other adverse conditions, such as emergency situations following different types of disasters and different adverse weather conditions, such as heavy rain, snow and black ice. Another expansion is that driving behavior on urban roads as well as secondary roads should be considered.

In the previous section it was also mentioned that only longitudinal driving behavior was considered. Lateral driving behavior was not studied in the context of this dissertation. It is therefore recommended to perform research on the influence of adverse conditions on empirical lateral driving behavior. This research should be performed for an expanded number of adverse conditions applied to performance of the driving task on freeways as well as on urban roads and secondary roads.

In this dissertation mental workload was measured through some selected physiological indicators as well as through the Rating Scale Mental Effort (Zijlstra & Doorn, 1985). Presumably due to the different sensitivities of the measures some indicators did not show a significant effect. It is therefore recommended to perform additional research in which the sensitivity of the chosen measures is sufficient for the adverse condition in question. Again, this research should be performed for an expanded number of adverse conditions applied to performance of the driving task on freeways as well as on urban roads and secondary roads.

Furthermore, we did not establish the influence of freeway incidents on visual distraction. This could for example be achieved through the use of eye scanning software. It is therefore recommended to perform future research on the influence of perception of an incident on the freeway on distraction using eye scanning.

In the previous section mention was made of the fact that only car-following models were considered in this dissertation. It is therefore recommended to expand this line of research with the influence of adverse conditions on mathematical models of lateral driving behavior. Furthermore we recommend future research in which more car-following models are incorporated, such as safe distance models, multi-anticipative car-following models and cellular automata models. This research should also be performed for an expanded number of adverse conditions applied to performance of the driving task on freeways as well as on urban roads and secondary roads.

Finally in the previous section we mentioned that the proposed stochastic psycho-spacing models is a discrete and static model. We therefore recommend conversion of this model to a continuous dynamic model. Furthermore, we recommend expansion of the Bayesian network with human factors, such as mental workload and situational awareness.

References

- Agarwal, M., Maze, T. H., & Souleyrette, R. (2006). The weather and its impact on urban free-way traffic operations. In *Proceedings of the 85th annual meeting of the transportation research board*. Washington DC.
- Allen, R. W., & Reimer, B. (2006). New approaches to simulation and the older operator. *Advances in Transportation Studies*, 9–20.
- Anastasi, A., & Urbina, S. (1997). *Psychological tests*. Upper Saddle River, NJ: Prentice Hall.
- Anund, A., & Kircher, K. (2009). *Advantages and disadvantages of different methods to evaluate sleepiness warning systems*. Sweden: VTI The Swedish National Road and Transport Research Institute.
- Arem, B., van, De Vos, A. P., & Vanderschuren, M. J. W. A. (1997). *The microscopic traffic simulation model mixic 1.3* (Tech. Rep.). TNO.
- Arem, B., van, Vlist, M. J. M. van der, & Smulders, S. A. (1993). Application of an on-line procedure for estimating capacity under prevailing roadway and traffic conditions. In *Vehicle navigation and information systems conference, 1993., proceedings of the ieee-ieee* (pp. 169–173).
- Asamer, J., Zuylen, H. van, & Heilmann, B. (2011). *Calibrating vissim to adverse weather conditions*. Proceedings of the 2nd Conference on Models and Technologies for Intelligent Transport Systems, Leuven.
- Baddeley, A. (1996). Exploring the central executive. *The Quarterly Journal of Experimental Psychology Section A*, 49(1), 5–28.
- Bando, M., Hasebe, K., Nakanishi, K., Nakayama, A., Shibata, A., & Sugiyama, Y. (1995). Phenomenological study of dynamical model of traffic flow. *Journal de Physique I*, 5(11), 1389–1399.
- Bartenwerfer, H. (1969). Einige praktische konsequenzen aus der aktivierungstheorie. *Zeitschrift für experimentelle und angewandte Psychologie*, 16, 195–222.
- Barton, A. H. (1969). *Communities in disaster: A sociological analysis of collective stress situations* (Vol. 352). Doubleday Garden City, New York.
- Bella, F. (2008). Driving simulator for speed research on two-lane rural roads. *Accident Analysis & Prevention*, 40(3), 1078–1087.
- Bertini, R., & Ahn, S. (2010). *Characteristics of transitions in freeway traffic* (Tech. Rep.). Oregon Transportation Research and Education Consortium.
- Bexelius, S. (1968). An extended model for car-following. *Transportation Research*, 2(1), 13–21.
- Blaauw, G. J. (1982). Driving experience and task demands in simulator and instrumented car:

- A validation study. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, 24(4), 473–486.
- Blake, S. J., Galea, E. R., Westeng, H., & Dixon, A. J. P. (2004). An analysis of human behaviour during the wtc disaster of 11 september 2001 based on published survivor accounts. In *Proceedings of the 3rd international symposium on human behaviour in fire* (Vol. 1, p. 3).
- Boer, E. R. (1999). Car following from the driver's perspective. *Transportation Research Part F: Traffic Psychology and Behaviour*, 2(4), 201–206.
- Brackstone, M., & McDonald, M. (1999). Car-following: a historical review. *Transportation Research Part F: Traffic Psychology and Behaviour*, 2(4), 181–196.
- Brackstone, M., Sultan, B., & McDonald, M. (2002). Motorway driver behaviour: studies on car following. *Transportation Research Part F: Traffic Psychology and Behaviour*, 5(1), 31–46.
- Brlon, W., Geistefeldt, J., & Regler, M. (2005). Reliability of freeway traffic flow: a stochastic concept of capacity. In *Proceedings of the 16th international symposium on transportation and traffic theory* (pp. 125–144).
- Brockfeld, E., Kuhne, R. D., & Wagner, P. (2004). Calibration and validation of microscopic traffic flow models. *Transportation Research Record: Journal of the Transportation Research Board*, 1876(1), 62–70.
- Brodsky, W. (2001). The effects of music tempo on simulated driving performance and vehicular control. *Transportation Research Part F: Traffic Psychology and Behaviour*, 4(4), 219–241.
- Brookhuis, K. A., & De Waard, D. (2001). Assessment of drivers' workload: Performance and subjective and physiological indexes. *Stress, workload, and fatigue*, 321–333.
- Brookhuis, K. A., Vries, G. de, & Waard, D. de. (1991). The effects of mobile telephoning on driving performance. *Accident Analysis and Prevention*, 23(4), 309–316.
- Broughton, K. L. M., Switzer, F., & Scott, D. (2007). Car following decisions under three visibility conditions and two speeds tested with a driving simulator. *Accident Analysis and Prevention*, 39(1), 106–116.
- Brown, I. D. (1982). Exposure and experience are a confounded nuisance in research on driver behaviour. *Accident Analysis and Prevention*, 14(5), 345–352.
- Bulte, B. (1985). *Comportement par visibilité réduite* (Tech. Rep.). Rapport CETE Nord Picardie.
- Burnham, G., Seo, J., & Bekey, G. (1974). Identification of human driver models in car following. *Automatic Control, IEEE Transactions on*, 19(6), 911–915.
- Cahour, B. (2008). Discomfort, affects and coping strategies in driving activity. In *Proceedings of the 15th european conference on cognitive ergonomics: the ergonomics of cool interaction* (p. 1-7).
- Cannon, W. B. (1915). *Bodily changes in pain, hunger, fear, and rage*. D. Appleton and Co.
- Caro, S., Cavallo, V., Marendaz, C., Boer, E., & Vienne, F. (2009). Can headway reduction in fog be explained by impaired perception of relative motion? *Human Factors: The Journal of the Human Factors and Ergonomics Society*, 51(3), 378.
- Carsten, O. M. J., Groeger, J. A., Blana, E., & Jamson, A. H. (1997). Driver performance in the epsrc driving simulator: A validation study (report no. gr/k56162). *Leeds: University*

- of Leeds.
- Chung, E., Ohtani, O., Warita, H., Kuwahara, M., & Morita, H. (2006). Does weather affect highway capacity. In *Proceedings of the 5th international symposium on highway capacity and quality of service*. Yakoma, Japan.
- Cova, T. J., & Johnson, J. P. (2003). A network flow model for lane-based evacuation routing. *Transportation research part A: Policy and Practice*, 37(7), 579-604.
- Crundall, D., Underwood, G., & Chapman, P. (1999). Driving experience and the functional field of view. *Perception*, 28, 1075-1088.
- Damasio, A. R., Everitt, B. J., & Bishop, D. (1996). The somatic marker hypothesis and the possible functions of the prefrontal cortex. *Philosophical transactions: Biological sciences*, 351(1346), 1413-1420.
- Deci, E. L., & Ryan, R. M. (1985). *Intrinsic motivation and self-determination in human behavior*. Springer.
- De Winter, J., Wieringa, P., Kuipers, J., Mulder, M., Van Paassen, M., & Dankelman, J. (2006). Driver assessment during self and forced-paced simulation-based training. In *Proceedings of the driving simulation conference europe* (pp. 157-166).
- Dingus, T. A., Klauer, S. G., Neale, V. L., Petersen, A., Lee, S. E., Sudweeks, J. D., et al. (2006). *The 100-car naturalistic driving study, phase ii-results of the 100-car field experiment* (Tech. Rep.).
- Donald, I., & Canter, D. (1990). Behavioural aspects of the king's cross disaster. *Fires and human behaviour. Second edition*. David Fulton Publishers Ltd, London, 15-30.
- Eisenberg, D., & Warner, K. E. (2005). Effects of snowfalls on motor vehicle collisions, injuries, and fatalities. *American journal of public health*, 95(1), 120.
- Endsley, M. R. (2000). Theoretical underpinnings of situation awareness: A critical review. *Situation awareness analysis and measurement*, 3-32.
- Freund, B., Colgrove, L. A. A., Petrakos, D., & McLeod, R. (2008). In my car the brake is on the right: Pedal errors among older drivers. *Accident Analysis and Prevention*, 40(1), 403-409.
- Fridlund, A. J., & Cacioppo, J. T. (1986). Guidelines for human electromyographic research. *Psychophysiology*, 23(5), 567-589.
- Fuller, R. (2005). Towards a general theory of driver behaviour. *Accident Analysis and Prevention*, 37(3), 461-472.
- Gazis, D. C., Herman, R., & Potts, R. B. (1959). Car-following theory of steady-state traffic flow. *Operations Research*, 499-505.
- Gazis, D. C., Herman, R., & Rothery, R. W. (1963). Analytical methods in transportation: Mathematical car-following theory of traffic flow. *Journal of the Engineering Mechanics Division, ASCE Proc. Paper*, 3724(89), 29-46.
- Gipps, P. G. (1981). A behavioural car-following model for computer simulation. *Transportation Research Part B: Methodological*, 15(2), 105-111.
- Glass, A. (1959). Psychosocial aspects of disaster. *JAMA*, 171(2), 222-227.
- Gleser, G. C., Green, B. L., & Winget, C. (1981). *Prolonged psychosocial effects of disaster: A study of buffalo creek*. Academic Press New York.
- Grier, R., Wickens, C., Kaber, D., Strayer, D., Boehm-Davis, D., Trafton, J., et al. (2008). The red-line of workload: Theory, research, and design. In *Human factors and ergonomics*

- society annual meeting proceedings* (Vol. 52, pp. 1204–1208).
- Hale, A. R., Stoop, J., & Hommels, J. (1990). Human error models as predictors of accident scenarios for designers in road transport systems. *Ergonomics*, 33(10-11), 1377–1387.
- Hamdar, S. H., & Mahmassani, H. S. (2008). From existing accident-free car-following models to colliding vehicles: Exploration and assessment. *Transportation Research Record: Journal of the Transportation Research Board*, 2088(-1), 45–56.
- Han, L. D., & Yuan, F. (2005). Evacuation modeling and operations using dynamic traffic assignment and most desirable destination approaches. In *Proceedings of the 84th annual meeting of the transportation research board*. Washington DC.
- Hart, S. G., & Staveland, L. E. (1988). Development of nasa-tlx (task load index): Results of empirical and theoretical research. *Human mental workload*, 1, 139–183.
- Heemstra, M. L. (1988). *Efficiency of human information processing: A model of cognitive energetics*. Heemstra.
- Helly, W. (1959). Simulation of bottlenecks in single lane traffic flow. In *Proceedings of the symposium on theory of the traffic flow*. Elsevier.
- Hoedemaker, M. (1999). *Driving with intelligent vehicles*. Delft University Press, Delft.
- Hogema, J. H. (1995). Individual car-following behaviour on motorways; a simulator study. In *Proceedings of the annual meeting of the transportation research board 1995*. Washington DC.
- Hogema, J. H. (1996). *Effects of rain on daily traffic volume and on driving behaviour*. TNO-TM.
- Hollands, J. G., & Wickens, C. D. (1999). *Engineering psychology and human performance*. Prentice Hall.
- Hoogendoorn, R. G., Hoogendoorn, S. P., Brookhuis, K. A., & Daamen, W. (2011). Anticipation and hysteresis: Parameter value changes and model performance in simple and multi-anticipative car-following models. In *Proceedings of the annual meeting of the transportation research board 2011*. Washington DC.
- Hoogendoorn, R. G., Tamminga, G., Hoogendoorn, S. P., & Daamen, W. (2010). Longitudinal driving behavior under adverse weather conditions: adaptation effects, model performance and freeway capacity in case of fog. In *Intelligent transportation systems (itsc), 2010 13th international ieee conference on* (pp. 450–455).
- Hoogendoorn, R. G., Waterink, W., Hoogendoorn, S. P., Brookhuis, K. A., & Daamen, W. (2011). Longitudinal driving behavior in case of incidents in the other driving lane: The influence of emotions. *Transportation Research Part F: Traffic Psychology and Behaviour*, Under review.
- Hoogendoorn, S., & Daamen, W. (2007). Microscopic calibration and validation of pedestrian models: cross-comparison of models using experimental data. *Traffic and Granular Flow 2005*, 329–340.
- Hoogendoorn, S. P. (2005). Unified approach to estimating free speed distributions. *Transportation Research Part B: Methodological*, 39(8), 709–727.
- Hoogendoorn, S. P., Hoogendoorn, R. G., & Daamen, W. (2011). Wiedemann revisited: A new trajectory filtering technique and its implications for car-following modeling. In *Proceedings of the annual meeting of the transportation research board 2011*. Washington DC.

- Hoogendoorn, S. P., Knoop, V. L., Pel, A., Huibregtse, O., Hoogendoorn, R. G., & Landman, R. (2009). Verkeersmanagement bij exceptionele omstandigheden. *NM Magazine*.
- Hoogendoorn, S. P., & Ossen, S. (2005). Parameter estimation and analysis of car-following models. In *Transportation and traffic theory. flow, dynamics and human interaction. 16th international symposium on transportation and traffic theory*.
- Hoogendoorn, S. P., Ossen, S., & Schreuder, M. (2006). Empirics of multianticipative car-following behavior. *Transportation Research Record: Journal of the Transportation Research Board*, 1965(-1), 112–120.
- Hoogendoorn, S. P., & Schreuder, M. (2005). Tracing congestion dynamics with remote sensing: Towards a robust method for microscopic traffic data collection. In *Transportation research board annual meeting*. Washington DC.
- Horrey, W. J., Lesch, M. F., & Garabet, A. (2009). Dissociation between driving performance and drivers' subjective estimates of performance and workload in dual-task conditions. *Journal of Safety Research*, 40(1), 7–12.
- Huis, J. R. van, Baan, J., & Loon, A. van. (2009). Traffic monitoring using video-based vehicle tracking. In *Proceedings of the 16th its world congress and exhibition on intelligent transport systems and services*.
- Ibrahim, A. T., & Hall, F. L. (1994). Effect of adverse weather conditions on speed-flow-occupancy relationships. *Transportation Research Record: Journal of the Transportation Research Board*, 1457, 184–191.
- Imai, H., & Iri, M. (1987). An optimal algorithm for approximating a piecewise linear function. *Journal of Information Processing*, 9(3), 159–162.
- Jamson, H. (2000). Driving simulation validity: issues of field of view and resolution. In *Proceedings of the driving simulation conference* (pp. 57–64).
- Janis, M. (1952). Air war and emotional stress: Psychological studies of bombing and civilian defense. *JAMA*, 148(17), 1543.
- Janssen, W. H., Wierda, M., & Horst, A. R. A. Van der. (1992). *Automatisering van de rijtaak en gebruikersgedrag: een inventarisatie en research agenda (automation of driving and user behaviour)*. Report TNO-IZF.
- Johnson, N. R. (1988). Fire in a crowded theater: a descriptive investigation of the emergence of panic. *International Journal of Mass Emergencies and Disasters*, 6(1), 7–26.
- Jones, E. R., Goolsby, M. E., & Brewer, K. A. (1970). The environmental influence of rain on freeway capacity. *Highway Research Record*, 321, 74–82.
- Kahneman, D. (1973). *Attention and effort*. Prentice-Hall Inc.
- Kaptein, N. A., Horst, A. R. A. Van der, & Hoekstra, W. (1996). Visual information in a driving simulator: A study on braking behavior and time-to-collision. *TNO Human Factors Research Institute, Soesterberg, the Netherlands*.
- Kaptein, N. A., Theeuwes, J., & Van Der Horst, A. R. A. (1996). Driving simulator validity: Some considerations. *Transportation Research Record: Journal of the Transportation Research Board*, 1550(-1), 30–36.
- Kass, S. J., Cole, K. S., & Stanny, C. J. (2007). Effects of distraction and experience on situation awareness and simulated driving. *Transportation Research Part F: Traffic Psychology and Behaviour*, 10(4), 321–329.
- Keating, J. P. (1982). The myth of panic. *Fire Journal*, 76(3), 57–61.

- Kesting, A., Treiber, M., & Helbing, D. (2007). General lane-changing model mobil for car-following models. *Transportation Research Record: Journal of the Transportation Research Board*, 1999(-1), 86–94.
- Kesting, A., Treiber, M., & Helbing, D. (2010). Enhanced intelligent driver model to access the impact of driving strategies on traffic capacity. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, 368(1928), 4585–4605.
- Knapper, A., & Brookhuis, K. (2010). Field research concerning contra-flow as a measure for massive evacuation. *Procedia Engineering*, 3, 77–86.
- Knee, C. R., Neighbors, C., & Vietor, N. A. (2001). Self-determination theory as a framework for understanding road rage1. *Journal of Applied Social Psychology*, 31(5), 889–904.
- Knoop, V. L., Hoogendoorn, S. P., & Van Zuylen, H. J. (2008). Capacity reduction at incidents: empirical data collected from a helicopter. *Transportation Research Record: Journal of the Transportation Research Board*, 2071(-1), 19–25.
- Kometani, E., & Sasaki, T. (1959). Dynamic behavior of traffic with a nonlinear spacing-speed relationship'. *Theory of Traffic Flow*, 105–119.
- Koppa, R. J. (1998). *Human factors - update of report 165* (Tech. Rep.). Traffic Flow Theory.
- LaBerge, D. (1995). *Attentional processing: The brain's art of mindfulness*. Harvard University Press.
- Leach, J. (1994). *Survival psychology*. Macmillan.
- Lee, H. (2003). The validity of driving simulator to measure on-road driving performance of older drivers. *Transport Engineering in Australia*, 8, 89–100.
- Leutzbach, W., & Wiedemann, R. (1986). Development and applications of traffic simulation models at the karlsruhe institut für verkehrswesen. *Traffic engineering & control*, 27(5), 270–278.
- Litman, T. (2006). Lessons from katrina and rita: What major disasters can teach transportation planners. *Journal of Transportation Engineering*, 132, 11.
- Makishita, H., & Matsunaga, K. (2008). Differences of drivers' reaction times according to age and mental workload. *Accident Analysis and Prevention*, 40(2), 567–575.
- Martin, P., Perrin, J., Hansen, B., & Quintana, I. (2000). Inclement weather signal timings. *UTL Research Report MPC01–120*, UTL, University of Utah, Salt Lake City.
- Matthews, G., Dorn, L., Hoyes, T. W., Davies, D. R., Glendon, A. I., & Taylor, R. G. (1998). Driver stress and performance on a driving simulator. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, 40(1), 136–149.
- Matthews, G., Sparkes, T. J., & Bygrave, H. M. (1996). Attentional overload, stress, and simulate driving performance. *Human Performance*, 9(1), 77–101.
- McLean, G. A. (1996). *Aircraft evacuations onto escape slides and platforms i: Effects of passenger motivation*. (Tech. Rep.). DTIC Document.
- Mesken, J., Hagenzieker, M. P., Rothengatter, T., & Waard, D. de. (2007). Frequency, determinants, and consequences of different drivers' emotions: An on-the-road study using self-reports,(observed) behaviour, and physiology. *Transportation Research Part F: Traffic Psychology and Behaviour*, 10(6), 458–475.
- Michaels, R. M. (1963). Perceptual factors in car following. In *Proceedings of the 2nd international symposium on the theory of road traffic flow (london, england)*, oecd.
- Michon, J. A. (1985). A critical view of driver behavior models: What do we know, what

- should we do. *Human behavior and traffic safety*, 485–520.
- Minderhoud, M. M. (1999). *Supported driving: impacts on motorway traffic flow*. Delft University Press, Delft.
- Miska, M., & Zuylen, M. O. S. A. van. (2004). Microscopic online simulator. In *Cd-rom proceedings of the its world conference*.
- Mitchell, T. M., & Radwan, E. (2006). Heuristic prioritization of emergency evacuation staging to reduce clearance time. In *Proceedings of the 85th annual meeting of the transportation research board*. Washington DC.
- Montroll, E. W. (1959). Acceleration and clustering tendency of vehicular traffic. In *Proceeding symposium on theory of traffic flow* (pp. 147–157).
- Moray, N. (1988). Mental workload since 1979. *International reviews of ergonomics: current trends in human factors research and practice*, 123.
- Muckler, F. A., & Seven, S. A. (1992). Selecting performance measures:” objective” versus” subjective” measurement. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, 34(4), 441–455.
- Muir, H., Marrison, C., & Evans, A. (1989). *Aircraft evacuations: the effect of passenger motivation and cabin configuration adjacent to the exit* (Tech. Rep.). Civil Aviation Authority, UK.
- Mulder, L. J. M. (1989). Cardiovascular reactivity and mental workload. *International Journal of Psychophysiology*, 7(2-4), 321–322.
- Neighbors, C., Vietor, N. A., & Knee, C. R. (2002). A motivational model of driving anger and aggression. *Personality and Social Psychology Bulletin*, 28(3), 324.
- Niculescu, R. S., Mitchell, T. M., & Rao, R. B. (2006). Bayesian network learning with parameter constraints. *The Journal of Machine Learning Research*, 7, 1357–1383.
- O'Donnell, R. D., & Eggemeier, F. T. (1986). *Workload assessment methodology*. John Wiley & Sons.
- Ossen, S. (2008). *Theory and empirics of longitudinal driving behavior*. Delft University Press, Delft.
- Ossen, S., & Hoogendoorn, S. P. (2007). *Calibrating car-following models using microscopic trajectory data* (Tech. Rep.). Internal Report, Delft University of Technology, T&P 2006.010.
- Parkinson, B. (2001). Anger on and off the road. *British Journal of Psychology*, 92(3), 507–526.
- Pearl, J. (1988). *Probabilistic reasoning in intelligent systems: networks of plausible inference*. Morgan Kaufmann.
- Pel, A., Bliemer, M., & Hoogendoorn, S. P. (2011). A review on travel behavior modeling in dynamic simulation models for evacuations. *Transportation*, 6, 50-62.
- Pisano, P., & Goodwin, L. (2002). Surface transportation weather applications. *FHWA Office of Transportation Operations in cooperation with Mitretek Systems, Inc.*
- Porter, B. E., & England, K. J. (2000). Predicting red-light running behavior:: A traffic safety study in three urban settings. *Journal of Safety Research*, 31(1), 1–8.
- Powell, J., & Rayner, J. (1952). Progress notes: Disaster investigation july 1, 1951–june 30, 1952. *Edgewood, Mary-land: Army Chemical Center, Chemical Corps Medical Laboratories*.

- Rasmussen, J., Duncan, K., & Leplat, J. (1987). *New technology and human error*. John Wiley and Sons.
- Reimer, B., D'Ambrosio, L. A., Coughlin, J. F., Kafrissen, M. E., & Biederman, J. (2006). Using self-reported data to assess the validity of driving simulation data. *Behavior research methods*, 38(2), 314.
- Riemersma, J. B. J., Van Der Horst, A. R. A., Hoekstra, W., & Alink, G. M. M. (1990). The validity of a driving simulator in evaluating speed-reducing measures. *Traffic engineering and control*, 31(7), 416–420.
- Rimmo, P. A., & Hakamies-Blomqvist, L. (2002). Older drivers' aberrant driving behaviour, impaired activity, and health as reasons for self-imposed driving limitations. *Transportation Research Part F: Traffic Psychology and Behaviour*, 5(1), 47–62.
- Rose, A., Evans, R., & Wheaton, G. (1987). Methodological approaches for simulator evaluations. *Transfer of Learning*. Ed. Stephen M. Cormier and Joseph D. Hagman. San Diego: Harcourt.
- Rosenbloom, T., & Wolf, Y. (2002). Sensation seeking and detection of risky road signals: a developmental perspective. *Accident Analysis and Prevention*, 34(5), 569–580.
- Roskam, A. J., Brookhuis, K. A., De Waard, D., Carsten, O. M. J., Read, L., Jamson, J., S. Ostlund, et al. (2004). *Development of experimental protocol* (Tech. Rep.). EU Projecty Haste (GRD1/2000/25361 S12.319626) Deliverable 1.
- Rumar, K. (1990). The basic driver error: late detection. *Ergonomics*, 33(10), 1281–1290.
- Rundmo, T. (2002). Associations between affect and risk perception. *Journal of Risk Research*, 5, 119–135.
- Saberi, M., & Bertini, R. (2010). Empirical analysis of the effects of rain on measured freeway traffic parameters. In *Transportation research board 89th annual meeting*.
- Saffarian, M., & Happee, R. (n.d.). Supporting drivers in car following: A step towards cooperative driving. In *Intelligent vehicles symposium (iv), 2011 ieee* (pp. 939–944).
- Sagberg, F., & Bjørnskau, T. (2006). Hazard perception and driving experience among novice drivers. *Accident Analysis and Prevention*, 38(2), 407–414.
- Sayer, J. R., Devonshire, J. M., & Flanagan, C. A. (2007). Naturalistic driving performance during secondary tasks. In *Proceedings of the fourth international driving symposium on human factors in driver assessment, training and vehicle design*.
- Schaap, T. W., Horst, A. R. A. van der, & Van Arem, B. (2008). Influence of unexpected events on driving behaviour at different hierarchical levels: a driving simulator experiment. In *Proceedings of european conference on human centred design for intelligent transport systems* (p. 131).
- Schagen, I. van, Welsh, R., Backer-Grondahl, A., Hoedemaeker, M., Lotan, T., Morris, A., et al. (2011). *Towards a large scale european naturalistic driving study: final report of prologue*. (Tech. Rep.).
- Schultz, G. G., & Rilett, L. R. (2004). Analysis of distribution and calibration of car-following sensitivity parameters in microscopic traffic simulation models. *Transportation Research Record: Journal of the Transportation Research Board*, 1876(1), 41–51.
- Sheridan, T. B. (2004). Driver distraction from a control theory perspective. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, 46(4), 587–599.
- Silber, B. Y., Papafotiou, K., Croft, R. J., Ogden, E., Swann, P., & Stough, C. (2005). The

- effects of dexamphetamine on simulated driving performance. *Psychopharmacology*, 179(3), 536–543.
- Sime, J. D. (1983). Affiliative behaviour during escape to building exits. *Journal of environmental psychology*, 3(1), 21–41.
- Snowden, R. J., Stimpson, N., & Ruddle, R. A. (1998). Speed perception fogs up as visibility drops. *Nature*, 392, 450.
- Stanton, N. A., & Young, M. S. (2001). Developing a psychological model of the driver. i. In *Behavioural research in road safety: eleventh seminar proceedings* (pp. 131–136).
- Stephens, A. N., & Groeger, J. A. (2006). Do emotional appraisals of traffic situations influence driver behaviour? In *Behavioural research in road safety 2006: Sixteenth seminar* (p. 49).
- Stutts, J., Feaganes, J., Reinfurt, D., Rodgman, E., Hamlett, C., Gish, K., et al. (2005). Driver's exposure to distractions in their natural driving environment. *Accident Analysis and Prevention*, 37(6), 1093–1101.
- Sullman, M. J. M., Gras, M. E., Cunill, M., Planes, M., & Font-Mayolas, S. (2007). Driving anger in Spain. *Personality and Individual Differences*, 42(4), 701–713.
- Summala, H., & Naatanen, R. (1974). Perception of highway traffic signs and motivation. *Journal of Safety Research*.
- Sumner, R., Baguley, C., & Burton, J. (1977). Driving in fog on the m4. *Transportation and Road Research Laboratory, UK*.
- Tabachnick, B. G., & Fidell, L. S. (2001). Using multivariate statistics 4th ed. *Needham, MA: Allyn & Bacon*.
- Tampere, C. (2004). *Human kinetic multiclass traffic flow theory and modeling*. TRAIL Thesis Series.
- Tampere, C., Arem, B. van, & Hoogendoorn, S. P. (2003). Gas-kinetic traffic flow modeling including continuous driver behavior models. In *Proceedings of the annual meeting of the transportation research board 2003*. Washington DC.
- Taylor, R. G. (1964). Personality traits and discrepant achievement: A review. *Journal of Counseling Psychology*, 11(1), 76–82.
- Thordarson, S., & Olafsson, B. (2008). Weather induced road accidents, winter maintenance and user information. *Transport Research Arena Europe, Ljubljana*.
- Tornros, J., & Bolling, A. K. (2006). Mobile phone use: Effects of conversation on mental workload and driving speed in rural and urban environments. *Transportation Research Part F: Traffic Psychology and Behaviour*, 9(4), 298–306.
- Treiber, M., Hennecke, A., & Helbing, D. (2000). Congested traffic states in empirical observations and microscopic simulations. *Physical Review E*, 62(2), 1805–1824.
- Tu, H., Tamminga, G., & Drolenga, H. (2010). The impacts of driving behaviors on traffic safety in case of evacuation. In *Proceedings of the 12th wcr. , Lisbon Portugal*.
- Tversky, A., & Kahneman, D. (1974). Judgment under uncertainty: Heuristics and biases. *Science*, 185(4157), 1124.
- Tyhurst, J. S. (1951). Individual reactions to community disaster. *American Journal of Psychiatry*, 107(764–769), 265.
- Ulleberg, P. (2002). *Influencing subgroups of young drivers and their passengers. motivational influences of personality traits on risk-taking attitudes and driving behaviour*. Fakultet

- for samfunnsvitenskap og teknologiledelse.
- Underwood, G. (2007). Visual attention and the transition from novice to advanced driver. *Ergonomics*, 50(8), 1235–1249.
- Urbina, E., & Wolshon, B. (2003). National review of hurricane evacuation plans and policies: a comparison and contrast of state practices. *Transportation Research Part A: Policy and Practice*, 37(3), 257–275.
- Vaa, T. (2001). Cognition and emotion in driver behaviour models: Some critical viewpoints. In *Road user characteristics with emphasis on life-styles, quality of life and safety*. Caserta, Italy.
- Waard, D., de. (1996). *The measurement of drivers' mental workload*. Groningen University, Traffic Research Center.
- Wagner, P. (2005). Empirical description of car-following. In *Proceeding of tgf 2005*.
- Waterink, W. (1997). *Facial muscle activity as an index of energy mobilization during processing of information: An emg study*. Unpublished doctoral dissertation, Katholieke Universiteit Brabant.
- Waterink, W., & Van Boxtel, A. (1994). Facial and jaw-elevator emg activity in relation to changes in performance level during a sustained information processing task. *Biological psychology*, 37(3), 183–198.
- Whissell, R. W., & Bigelow, B. J. (2003). The speeding attitude scale and the role of sensation seeking in profiling young drivers at risk. *Risk Analysis*, 23(4), 811–820.
- White, M. E., & Jeffery, D. J. (1989). Some aspects of motorway traffic behaviour in fog.
- Wickens, C. D. (2002). Multiple resources and performance prediction. *Theoretical Issues in Ergonomics Science*, 3(2), 159–177.
- Wientjes, C. J. E., Grossman, P., & Gaillard, A. W. K. (1998). Influence of drive and timing mechanisms on breathing pattern and ventilation during mental task performance. *Biological psychology*, 49(1-2), 53–70.
- Wilde, G. J. S. (1982). The theory of risk homeostasis: implications for safety and health. *Risk analysis*, 2(4), 209–225.
- Williams, B. M., Tagliaferri, A. P., Meinhold, S. S., Hummer, J. E., Roupail, N. M., et al. (2007). Simulation and analysis of freeway lane reversal for coastal hurricane evacuation. *Journal of urban planning and development*, 133, 61.
- Winsum, W., van. (1999). The human element in car following models. *Transportation Research Part F: Traffic Psychology and Behaviour*, 2(4), 207–211.
- Winsum, W., van, Martens, M., & Herland, L. (1999). *The effects of speech versus tactile driver support messages on workload driver behaviour and user acceptance: Tno-report, tm-99-c043*. TNO Human Factors Research Institute.
- Wolffelaar, P. C., van, & Winsum, W. van. (1992). A new driving simulator including an interactive intelligent traffic environment. In *Vehicle navigation and information systems, 1992. vnis., the 3rd international conference on* (pp. 499–506).
- Yagil, D. (1998). Gender and age-related differences in attitudes toward traffic laws and traffic violations. *Transportation Research Part F: traffic psychology and behaviour*, 1(2), 123–135.
- Yan, X., Abdel-Aty, M., Radwan, E., Wang, X., & Chilakapati, P. (2008). Validating a driving simulator using surrogate safety measures. *Accident Analysis and Prevention*, 40(1),

-
- 274–288.
- Yap, G. E., Tan, A. H., & Pang, H. H. (2008). Explaining inferences in bayesian networks. *Applied Intelligence*, 29(3), 263–278.
- Zijlstra, F. R. H. (1993). Efficiency in work behaviour: A design approach for modern tools(ph. d. thesis).
- Zijlstra, F. R. H., & Doorn, L. (1985). *The construction of a scale to measure subjective effort*. Delft University Press, Delft.

About the author

Raymond G. Hoogendoorn was born in 1969 in Rotterdam. After many different career switches, in 2006 he started a study in Psychology at the Open University in the Netherlands. Within 3 years he obtained his bachelor degree as well as his master degree (with honor). In the context of his Master's thesis he performed research on the influence of emotions on driving behavior in relation with the Somatic Marker Hypothesis (Damasio et al., 1996).

Since 2009, Raymond has been affiliated with the Transport & Planning Department of the Faculty of Civil Engineering and Geosciences of Delft University of Technology. He conducted his Ph.D. research on the empirics and modeling of longitudinal driving behavior in case of adverse conditions within the research program Traffic and Travel Behavior in Case of Exceptional Events sponsored by the Dutch Foundation of Scientific Research MaGW - NWO.

Besides his Ph.D. research, Raymond has been involved in many commercial projects. For example, Raymond conducted a behavioral study on the influence of dynamic maximum speed limits on perception, mental workload and compliance. Furthermore he performed a driving simulator study regarding the efficacy of traffic management measures at a tunnel near the Dutch city of Utrecht.

Raymond has also been involved in several teaching activities. He organized, for instance, a TRAIL course on theories and methods in transportation, supervised several MSc students and gave lectures to MSc students on car-following modeling and statistics.

Finally, Raymond was a member of the TRAIL Ph.D. Council.

List of publications and conference proceedings by the author

Journal papers:

- Hoogendoorn, R.G., Hoogendoorn, S.P., Van Arem, B., Brookhuis, K.A., & Daamen, W. (2012) Connecting the Task-Capability-Interface Model to Parameter Value Changes and Model Performance of the Intelligent Driver Model in case of Adverse Conditions. *Transportation Science* (submitted)
- Hoogendoorn, R.G., Hoogendoorn, S.P. & Brookhuis, K.A. (2012). Driving Behavior in case of Emergency Situations: A Psycho-Spacing Modeling Approach. *Transportation Research Records: Journal of the Transportation Research Board* (accepted for publication).
- Hoogendoorn R.G., Harms, I.M., Hoogendoorn, S.P. & Brookhuis, K.A. (2012). Dynamic Maximum Speed Limits: Perception, Mental Workload and Compliance. *Transportation Research Records: Journal of the Transportation Research Board* (accepted for publication).
- Hoogendoorn, S.P., Hoogendoorn, R.G., Wang, M. & Daamen, W. (2012). Driver, Driver Support, and Cooperative Systems Modeling by Dynamic Optimal Control. *Transportation Research Records: Journal of the Transportation Research Board* (accepted for publication).
- Hoogendoorn, S.P., Hoogendoorn, R.G. & Daamen, W. (2011). Wiedemann Revisited: A New Trajectory Filtering Technique and its Implications for Car-following Modeling. *Transportation Research Records: Journal of the Transportation Research Board*, Issue 2260, 10 February 2012, pages 152-162
- Hoogendoorn, R.G., Hoogendoorn, S.P., Brookhuis, K.A. & Daamen, W. (2011). Adaptation Effects in Longitudinal Driving Behavior, Mental workload and Psycho-spacing Models in Fog. *Transportation Research Record: Journal of the Transportation Research Board*, Issue 2249, 1 December 2011, Pages 20-28
- Hoogendoorn, R.G., Hoogendoorn, S.P., Brookhuis, K.A. & Daamen, W. (2011). Longitudinal Driving Behavior under Adverse Conditions: A Close Look at Psycho-spacing Models. (2011). *Procedia - Social and Behavioral Sciences* Volume 20, pp 536-546
- Hoogendoorn, R.G., Hoogendoorn, S.P., Brookhuis, K.A. & Daamen, W. (2011). Psycho-spacing Models and Adverse Conditions: A Close Look at Incidents. *2011 International*

Conference on Networking, Sensing and Control, ICNSC 2011, Article number 5874915, Pages 329-334

Hoogendoorn, R.G., Hoogendoorn, S.P., Brookhuis, K.A. & Daamen, W. (2010). Psychological Elements in Car-following Models: Mental Workload in case of Incidents in the Other Driving Lane. *Procedia Engineering* Volume 3, Pages 87-99

Hoogendoorn, R.G., Hoogendoorn, S.P., Tamminga, G. & Daamen, W. (2010). Longitudinal Driving Behavior under Adverse Weather Conditions: Adaptation effects, Model Performance and Freeway Capacity in case of fog. *IEEE Conference on Intelligent Transportation Systems, Proceedings, ITSC 2010*, Article number 5625046, Pages 450-455

Hoogendoorn, S.P. & Hoogendoorn, R.G. (2010). Generic Calibration Framework for Joint estimation of Car-following Models by using Microscopic Data. *Transportation Research Record: Journal of the Transportation Research Board*, Issue 2188, 1 December 2010, Pages 37-45

Hoogendoorn, R.G., Hoogendoorn, S.P., Brookhuis, K.A. & Daamen, W. (2010). Mental Workload, Longitudinal Driving Behavior, and Adequacy of Car-following Models for Incidents in Other Driving Lane. *Transportation Research Record: Journal of the Transportation Research Board*, Issue 2188, 1 December 2010, Pages 64-73.

Hoogendoorn, S.P. & Hoogendoorn, R.G. (2010). Calibration of Microscopic Traffic-flow Models using Multiple Data Sources. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences* Volume 368, Issue 1928, 13 October 2010, Pages 4497-4517

Conference proceedings:

Hoogendoorn, R.G., Breukink, H.J., & Van Arem, B. (2012) A Context Aware Intelligent Speed Adaptation System: A Field Operational Test. *IEEE ITSC* (submitted);

Hoogendoorn, R.G., Hoogendoorn, S.P., Van Arem, B., & Brookhuis, K.A. (2012) Longitudinal Driving Behavior in case of Emergency Situations: An Empirically Underpinned Theoretical Framework. *ISTTT 2012* (abstract accepted for presentation)

Wang, M., Hoogendoorn, S.P., Daamen, W., Hoogendoorn, R.G. & Van Arem, B. (2012) Driver Support and Cooperative Systems Control Design. *American Control Conference 2012* (accepted for presentation)

Hoogendoorn, R.G., Hoogendoorn, S.P. & Brookhuis, K.A. (2011). Towards a Stochastic Psycho spacing Model. *Proceedings of the Annual Meeting of the Transportation Research Board 2012*.

Hoogendoorn, R.G., Hoogendoorn, S.P. & Brookhuis, K.A. (2011). Empirical Adaptation Effects and Modeling of Longitudinal Driving Behavior in case of Emergency Situations. *Proceedings of Traffic and Granular Flow 2011, Moscow*.

Hoogendoorn, S.P., & Hoogendoorn, R.G. (2011). Driving Theory and Modeling by Stochastic Optimal Control. *Proceedings of the Annual Meeting of the Transportation Research Board 2011, Washington DC*.

Hoogendoorn, R.G., Hoogendoorn, S.P., Brookhuis, K.A. & Daamen, W. (2011). Anticipation during Hysteresis: Parameter Value Changes and Model Performance. Proceedings of the Annual Meeting of the Transportation Research Board 2011, Washington DC.

Hoogendoorn, R.G., Hoogendoorn, S.P., Brookhuis, K.A. & Daamen, W. (2010). Simple and Multi-anticipative Car-following Models: Model Performance and Parameter Value Effects in case of Fog. Proceedings of the TFT Summer Meeting, Annecy, France.

Hoogendoorn, R.G., Hoogendoorn, S.P., Brookhuis, K.A. & Daamen, W. (2010). Longitudinal Driving Behavior under Adverse Weather Conditions. Proceedings of the 2010 TRAIL Conference.

Hoogendoorn, R.G., Hoogendoorn, S.P., Brookhuis, K.A. & Daamen, W. (2009). State-of-the-art Theory and Modeling Longitudinal Driving Behavior under Adverse Conditions. Proceedings of the 1st Conference on Evacuation Modeling and Planning, The Netherlands

Other publications:

Hoogendoorn, R.G., Brookhuis, K.A. & Hoogendoorn, S.P. (2011). De Factor Mens in Verkeersmanagement. NM Magazine.

Hoogendoorn, S.P., Knoop, V.L., Pel, A.J. , Huibregtse, O., Hoogendoorn, R.G. & Landman, R. (2009) Verkeersmanagement bij Exceptionele Omstandigheden. NM Magazine.

Summary

Although it may be assumed that a variety of adverse conditions has a substantial impact on longitudinal driving behavior of individual drivers, little information is available on to what extent this behavior is actually influenced. The first main aim of this dissertation is therefore to determine the effects that specific adverse conditions have on empirical longitudinal driving behavior.

From the state-of-the-art study it follows that research on the influence of emergency situations, adverse weather conditions and incidents on the freeway is scarce and sometimes even non-existent. Nevertheless, we assumed that emergency situations, adverse weather conditions as well as freeway incidents have a significant and substantial effect on longitudinal driving behavior.

In order to determine the extent to which the aforementioned conditions have an effect on empirical longitudinal driving behavior, we performed three driving simulator experiments. In these experiments use was made of the Advanced Driving Simulator owned by Delft University of Technology, Faculty Civil Engineering and Geosciences, Transport & Planning Department.

In order to determine the influence of emergency situations on empirical longitudinal driving behavior a driving simulator experiment with a multi-factorial experimental design was performed. In the experiment a sense of urgency within the participants was induced through a monetary reward. In order to vary the sense of urgency, the test drive was divided into three segments which were accompanied by messages on the screen with an increasing urgency (e.g. 'You are running out of time'). We analyzed within as well as between subject effects through a Multivariate Analysis of Variance (MANOVA) with a significance level of 0.05.

Emergency situations led to several significant adaptation effects in empirical longitudinal driving behavior. Speed was significantly higher in the experimental group (urgency) compared to the control group (no urgency). Furthermore we showed that speed increased significantly over time as the level of urgency also increased. Acceleration was significantly higher in the experimental group compared to the control group. However, acceleration did not increase over time. Deceleration did not show to be significantly affected by the emergency situation, as no significant difference was found between the two groups and no effect of time course could be established. Spacing however was substantially smaller in the experimental group and even decreased over time as the level of urgency increased. The standard deviations were however considerably large.

In order to determine the influence of adverse weather conditions on empirical longitudinal driving behavior another driving simulator experiment was performed with a repeated measures

design. In the experimental condition, an adverse weather condition (i.e. fog) was induced, while in the control condition normal driving conditions were applied. The data was analyzed through performance of paired sample t-tests with a significance level of 0.05.

The picture that emerges with regard to adverse weather conditions is quite different from emergency situations. In case of fog drivers significantly reduce their speed along with a reduction in acceleration and deceleration. Most striking however is the substantial and significant increase in spacing in the adverse weather condition. This increase in spacing was accompanied by substantial increases in relative speeds. However, as was the case with empirical longitudinal driving behavior in case of an emergency situation, here also a substantially large degree of driver heterogeneity can be observed as indicated by the relatively large standard deviations.

In order to determine the influence of freeway incidents on empirical longitudinal driving behavior a third driving simulator experiment with a repeated measures design was performed. In this experiment all participants participated in a control condition as well as in two experimental conditions. The two experimental conditions consisted of two versions of a vehicle crash in the other driving lane, while in the control condition no crash was present. Between the two experimental conditions the severity of the crashes was varied. The data were analyzed through a MANOVA for repeated measures with a significance level of 0.05.

Freeway incidents led to similar adaptation effects as adverse weather conditions. Overall, perception of an incident leads to a substantial reduction in speed along with a reduction in acceleration. Decelerations became stronger during perception of the freeway incident. These adaptation effects were accompanied by a substantial and significant increase in spacing along with larger positive and negative relative speeds. No significant differences were found between the two versions of the crash. Again, substantial standard deviations could be observed.

Adverse conditions therefore show to have a substantial effect on empirical longitudinal driving behavior. This does however not provide us with insight into which causes are responsible for the observed adaptation effects. The second research objective is therefore to determine which determinants of adaptation effects in empirical longitudinal driving behavior under adverse conditions can be identified.

From the literature review on determinants of adaptation effects in empirical longitudinal driving behavior under adverse conditions it follows that no similar research was found. However personal characteristics of drivers may be assumed to have an influence on longitudinal driving behavior in case of adverse conditions. Here we distinguish gender, age, driving experience, socio-economic status and ethnicity. We show that from the available research it follows that gender, age, driving experience and ethnicity are assumed to have substantial influences on empirical longitudinal driving behavior under adverse conditions.

We also show that more dynamic psychological constructs can be assumed to have substantial influences on empirical longitudinal driving behavior under adverse conditions. A large number of studies are reported showing the influence of mental workload on driving behavior in general. Emotions and panic are also discussed as possible determinants of adaptation effects in empirical longitudinal driving behavior under adverse conditions. It is stated that these constructs have considerable definition problems and that, overall, research was performed without

making use of full experimental designs and objective measurement measures. Furthermore, panic shows to be quite a rare phenomenon in case of adverse conditions.

The aforementioned selection of likely determinants of adaptation effects in empirical longitudinal driving behavior does however not provide us with insight into how these determinants actually influence longitudinal driving behavior under adverse conditions. To this end we propose a new theoretical framework based on the Task-Capability-Interface model by Fuller (2005).

This theoretical framework aims at explaining the relationship between emergency situations, adverse weather conditions and freeway incidents and empirical longitudinal driving behavior. It is assumed that these conditions have influence activation level, distraction or task demands, leading to an imbalance between task demands and driver capabilities. The driver will try to resolve this imbalance by exerting direct control over his driving behavior (compensation effects). When these actions are insufficient to resolve this imbalance, a driver will experience an increase in mental workload leading to a reduction in performance.

More insight is however needed into the extent to which this theoretical framework provides an adequate explanation of adaptation effects in empirical longitudinal driving behavior under adverse conditions. Therefore through the previously described three driving simulator experiments we determined the influence of the adverse conditions emergency situations, adverse weather conditions and freeway incidents on mental workload and determined the (moderating) influence of the personal characteristics age and driving experience on mental workload during these conditions.

In the three experiments different measures of mental workload were used. However in all three experiments mental workload was approximated through the physiological measures heart rate and heart rate variability (HRV). In the experiments pertaining to the influence of adverse weather conditions and freeway incidents we also measured subjective estimates of effort expenditure. Here, the Rating Scale Mental Effort (RSME) was used (Zijlstra & Doorn, 1985).

In the experiment regarding the influence of freeway incidents we additionally measured respiration rate and activity of two facial muscles, namely the zygomaticus major (smiling) and the corrugator supercilii (frowning). In order to analyze the effects of adverse conditions on mental workload we used MANOVA's and paired samples t-tests. The moderating influence of personal characteristics was analyzed through Multiple Regression Analyses. In all statistical analyses a significance level of 0.05 was applied.

From the results with regard to the influence of emergency situations on mental workload, it follows that emergency situations have a significant influence on HRV. HRV is significantly lower in the experimental group with the emergency situation compared to the control group. Time course also has a significant influence, as significant differences between the conditions are reported. Heart rate however shows no effect of the emergency situation nor of the factor time.

Adverse weather conditions have a significant influence on heart rate as well as HRV. The adverse weather condition leads to an increase in heart rate and a reduction in HRV. However, the adverse weather condition does not have a significant effect on subjective estimates of effort, measured through the RSME (Zijlstra & Doorn, 1985).

With regard to freeway incidents the results are less clear. Significant effects of freeway incidents are only established for amplitudes of the corrugator supercillii (frowning) and respiration rate. No significant effects are found on heart rate and amplitudes of the zygomaticus major (smiling). Again, no significant effects are reported on subjective estimates of effort expenditure. Furthermore, it follows from the MANOVA that overall no significant difference can be established between two versions of the incident.

Furthermore, through statistical analyses we show that the personal characteristics age and driving experience have significant influences on physiological indicators of mental workload during adverse conditions. The physiological indicators show that a higher age as well as a less driving experience lead to a higher mental workload during adverse conditions. The aforementioned supports the theoretical framework proposed in this dissertation.

The research objectives so far aimed at establishing the empirics of longitudinal driving behavior under adverse conditions, i.e. adaptation effects in empirical longitudinal driving behavior and the determinants of these adaptation effects in empirical longitudinal driving behavior. In this context the third research objective is to determine the extent to which current mathematical models of longitudinal driving behavior are adequate in incorporating adaptation effects in longitudinal driving behavior due to an adverse condition.

An extensive overview of continuous car-following models (stimulus-response, safe-distance and multi-anticipation) as well as psycho-spacing models in connection with adverse conditions is provided. It appears that most current continuous models of car-following behavior describe longitudinal driving behavior in a mechanistic manner. Furthermore, we show that from previous research it follows that the degree of stochasticity in values of parameters incorporated in these models is substantial. However, no research on the influence of adverse condition on parameter value changes and model performance was found.

In order to determine the effect adverse conditions have on parameter values and model performance in continuous car-following models, we estimated the Intelligent Driver Model (IDM) (Treiber et al., 2000) using the data derived from the three driving simulator experiments. To this end a new calibration approach for joint estimation was developed.

We conclude that emergency situations have a substantial and significant influence on all of the parameters of the IDM. In this context we show that emergency situations lead to significant increases in maximum acceleration a , maximum deceleration b and free speed v_0 . Furthermore we show that emergency situations lead to a significant reduction in the value of the parameter desired time headway T .

We also show that adverse weather conditions have a substantial and significant influence on parameter values of the IDM. We show that adverse weather conditions (i.e. fog) lead to a significant reduction in maximum acceleration a and maximum deceleration b . Strangely enough free speed v_0 increases significantly in the adverse weather condition. It is argued that this might be due to the fact that model performance is not very sensitive to v_0 given that it is sufficiently high. Desired time headway T however decreases during the adverse weather condition. Although this might seem strange from a behavioral point of view, we show that minimum stopping distance s_0 increased significantly.

Finally in the context of the influence of adverse conditions on parameter values of the IDM we show that freeway incidents also have an influence on parameter values. We show that on average freeway incidents lead to an increase in maximum acceleration a as well as a reduction in maximum deceleration b . However, the differences between the control condition and the experimental condition proved to be non-significant. Furthermore, on average free speed v_0 is higher. Again we argue that this might be due to the fact that model performance is not very sensitive to v_0 given that it is sufficiently high. Most striking however is the substantial increase in desired time headway T . This increase is significant.

It is therefore concluded that adverse conditions have a substantial influence on parameter values of the IDM. We argue that these changes in parameter values reflect compensation effects as proposed in the theoretical framework.

Besides an influence on parameter values, we also show that adverse conditions have an influence on model performance. We show that emergency situations, adverse weather conditions as well as freeway incidents lead to a reduction in model performance of the IDM. We argue that this reflects performance effects, as proposed in the theoretical framework. In case of an adverse condition car-following becomes to a lesser extent a determinant of longitudinal driving behavior.

From the literature overview of car-following models it follows that most continuous car-following models have a rather mechanistic character. In order to adjust for this psycho-spacing models were developed in the past. However, it is not clear to what extent adverse conditions influence the position of action points as well as acceleration and the 'jumps' in acceleration (difference in acceleration before and after an action point) in these models.

In order to determine the influence of emergency situations, adverse weather conditions and incidents on the freeway on the position of action points in psycho-spacing models a new data analysis technique was developed. In order to determine acceleration as well as 'jumps' in acceleration a Multivariate Regression Analysis is performed using four different models.

We show that adverse conditions lead to substantial changes in the position of action points in the relative speed - spacing plane. For example, we show that action points in the psycho-spacing model are much more concentrated at smaller values of spacing and relative speed in case of an emergency situation than under normal driving conditions. We also showed that that adverse conditions substantially influence acceleration and the jumps in acceleration at the action points.

We argue that the change in the shape and location of the perceptual thresholds incorporated in these models (represented by the position of the action points) reflect compensation effects in longitudinal driving behavior following an adverse condition. The effects with regard to acceleration and the 'jumps' in acceleration at the action points were argued to be reflections of performance effects in longitudinal driving behavior. The latter also holds for the fact that we establish that acceleration is to a lesser extent described by the used models in the Multivariate Regression Analysis. Considering the findings in this thesis we conclude that the assumption of deterministic perceptual thresholds proposed in the original formulation of the model does not hold in reality.

To this end we propose to develop a stochastic car-following model able to capture the effects of adverse conditions on longitudinal driving behavior. It is argued that this could be realized through a Bayesian network modeling approach with parameter learning. In this dissertation we show that this approach yields a relatively good representation of action points and acceleration at action points.

In sum, in this dissertation insight is provided into adaptation effects in empirical longitudinal driving behavior in case of a selection of adverse conditions, the determinants of these adaptation effects as well as are indications provided on how to best model these adaptation effects. Insight into adaptation effects in empirical longitudinal driving behavior in case of these adverse conditions had important implications for network managers, for example. Measures aimed at reducing the impact of the selected adverse conditions are evaluated through simulation studies. However, in order to acquire a reliable prediction of the efficacy of these measures it is crucial that driving behavior is incorporated in these simulation models in a realistic manner.

Samenvatting

Hoewel er kan worden aangenomen dat exceptionele condities een substantiële impact hebben op longitudinaal rijgedrag van individuele bestuurders, is slechts weinig informatie beschikbaar over de mate waarin deze gebeurtenissen rijgedrag werkelijk beïnvloeden. Het eerste doel van deze dissertatie is dan ook om de effecten van een aantal exceptionele condities op empirisch longitudinaal rijgedrag vast te stellen. Uit het state-of-the-art onderzoek blijkt dat onderzoek over de invloed van noodsituaties, slecht weer condities en incidenten op de snelweg schaars is en soms zelfs niet beschikbaar is. Echter, wordt aangenomen dat noodsituaties, slecht weer condities en incidenten op de snelweg een substantiële invloed hebben op longitudinaal rijgedrag.

Om de invloed van de voornoemde condities op longitudinaal rijgedrag te kunnen vaststellen hebben we drie rijimulator studies uitgevoerd. In deze rijimulator experimenten is gebruik gemaakt van de rijimulator van de Technische Universiteit Delft, Faculteit Civiele Techniek en Geowetenschappen, Afdeling Transport & Planning.

Om de invloed van noodsituaties op empirisch longitudinaal rijgedrag te kunnen vaststellen, is een rijimulator experiment met een multi-factorieel design uitgevoerd. In het experiment is een noodsituatie gesimuleerd door een gevoel van urgentie binnen de participanten te induceren middels een geldelijke beloning. Om het gevoel van urgentie te variëren, was de testrit verdeeld in drie segmenten van gelijke duur, waarbij berichten op het scherm werden getoond met een toenemende mate van urgentie (bijvoorbeeld: "You are running out of time"). Binnen- als ook tussenpersoonsfactoren zijn geanalyseerd door een Multivariate Analysis of Variance (MANOVA) met een significantie niveau van .05.

Noodsituaties leiden tot verschillende significante adaptatie effecten in empirisch longitudinaal rijgedrag. Snelheid is significant hoger in de experimentele groep (urgentie) vergeleken met de controle groep (geen urgentie). Verder wordt aangetoond dat snelheid significant over tijd toeneemt naarmate het urgentie niveau toeneemt. Acceleratie is ook significant hoger in de experimentele groep in vergelijking met de controlegroep. Echter, acceleratie neemt niet significant toe of af over tijd.

Deceleratie ondervindt geen significant effect van de noodsituatie, aangezien geen significant verschil tussen de twee groepen kon worden vastgesteld noch een effect van tijd op deceleratie. Afstand tot de voorligger vertoont wel een significant effect van de noodsituatie. Volgafstand is significant kleiner in de experimentele groep en vertoont een significant effect van de factor tijd. Met betrekking tot empirisch longitudinaal rijgedrag in het geval van een noodsituatie blijken echter verschillen tussen bestuurders substantieel, zoals aangegeven door de substantiële standaarddeviaties.

Om de invloed van slecht weer condities op empirisch longitudinaal rijgedrag te kunnen vaststellen is eveneens een rij simulator experiment uitgevoerd, echter in dit geval met een repeated measures design. In de experimentele conditie is een slecht weer conditie (dichte mist) geïnduceerd, terwijl in de controleconditie sprake was van normale weersomstandigheden. De data zijn geanalyseerd door gepaarde t-tests met een significantie niveau van .05.

Het beeld dat voortkomt uit de analyses van dit laatste rij simulator experiment is substantieel verschillend van het beeld bij de noodsituaties. In het geval van slecht weer condities reduceren bestuurders significant hun snelheid tezamen met een afname in acceleratie en deceleratie. Het meest opvallend is de substantiële toename in volgafstand in de slecht weer conditie vergeleken met normale condities. Deze toename in volgafstand gaat gepaard met een toename in relatieve snelheid. Echter, zoals ook het geval is bij empirisch rijgedrag in noodsituaties bleken de verschillen binnen en tussen bestuurders substantieel, zoals aangegeven door de grote standaarddeviaties.

Om de invloed van incidenten op de snelweg op empirisch longitudinaal rijgedrag te kunnen vaststellen is een derde rij simulator experiment uitgevoerd. In dit experiment is eveneens gebruik gemaakt van een repeated measures design. In dit experiment participeerden de participanten in een controle conditie als ook in twee experimentele condities. De twee experimentele condities bestonden uit twee versies van een auto ongeluk op de andere rijstrook. Tussen deze twee versies is de ernst van de ongelukken gevarieerd. De data zijn geanalyseerd door een MANOVA met een significantieniveau van .05.

Incidenten op de snelweg leiden tot vergelijkbare adaptatie effecten in longitudinaal rijgedrag als slecht weer condities. Perceptie van een incident op de andere rijstrook leidt tot een reductie in snelheid als ook een reductie in acceleratie. Deceleratie wordt echter sterker tijdens perceptie van een incident op de andere rijstrook. Deze adaptatie effecten gaan vergezeld van een substantiële toename in volgafstand alsmede grotere relatieve snelheden. Geen significant verschil kon worden gevonden tussen de twee versies van het incident.

Geconcludeerd kan derhalve worden dat exceptionele condities een substantiële invloed hebben op empirisch longitudinaal rijgedrag. Dit verschaft ons echter geen inzicht in welke determinanten verantwoordelijk zijn voor de geobserveerde adaptatie effecten in empirisch longitudinaal rijgedrag. Het tweede onderzoeksdoel is daarom het vaststellen welke determinanten van adaptatie effecten in longitudinaal rijgedrag in het geval van exceptionele condities kunnen worden geïdentificeerd.

Echter is geen onderzoek aangaande determinanten van longitudinaal rijgedrag in het geval van vergelijkbare exceptionele condities bekend. Een mogelijke kandidaat is echter de persoonlijke karakteristiek van bestuurders. Hier onderscheiden we geslacht, leeftijd, rijervaring, sociaal-economische status en etniciteit. We tonen aan dat uit de beschikbare literatuur aangenomen kan worden dat geslacht, leeftijd, rijervaring en etniciteit van invloed zijn op longitudinaal rijgedrag in het geval van exceptionele condities.

Ook tonen we aan dat meer dynamische psychologische constructen aangenomen kunnen worden een substantiële invloed te hebben op empirisch longitudinaal rijgedrag in het geval van exceptionele condities. In deze dissertatie vermelden we een groot aantal studies over de invloed van mentale taakbelasting op rijgedrag in het algemeen. Emoties en paniek worden

ook besproken als mogelijke determinanten van adaptatie effecten in longitudinaal rijgedrag in het geval van exceptionele condities. We stellen dat deze constructen te maken hebben met aanzienlijke definitie problemen en dat, in zijn algemeenheid, uitgevoerd onderzoek geen gebruik maakt van experimentele designs en objectieve meetinstrumenten. Verder blijkt paniek een zeldzaam verschijnsel te zijn in het geval van exceptionele condities.

De voorgaande selectie van mogelijke kandidaten van determinanten van empirisch longitudinaal rijgedrag in het geval van exceptionele condities verschaft echter geen inzicht in de wijze waarop deze determinanten empirisch longitudinaal rijgedrag in het geval van een exceptionele gebeurtenis beïnvloeden. Daarom introduceren we een nieuw theoretisch raamwerk gebaseerd op het Task-Capability-Interface model van Fuller (2005).

Dit theoretisch raamwerk doelt op het verklaren van de relatie tussen noodsituaties, slecht weer condities en incidenten op de snelweg en empirisch longitudinaal rijgedrag. Aangenomen wordt dat deze condities een invloed hebben op activatie niveau, afleiding en taakeisen, welke leiden tot een disbalans tussen taakeisen en de capaciteiten van de bestuurder. De bestuurder zal proberen deze disbalans op te heffen door controle uit te oefenen over zijn rijgedrag (compensatie effecten). Wanneer deze acties onvoldoende zijn om de disbalans op te heffen, zal de bestuurder een toename in zijn mentale taakbelasting ervaren met performance effecten als gevolg.

Meer inzicht is echter nodig in de mate waarin dit theoretisch raamwerk een adequate verklaring vormt voor adaptatie effecten in longitudinaal rijgedrag in het geval van een exceptionele conditie. Om deze reden hebben we de invloed van exceptionele condities op mentale taakbelasting van bestuurders onderzocht door de hiervoor besproken rijsimulator experimenten. Bovendien hebben we de modererende invloed van persoonlijke karakteristieken van bestuurders (hier: leeftijd en rijervaring) op mentale taakbelasting gedurende exceptionele condities onderzocht.

In de drie experimenten zijn verschillende indicatoren van mentale taakbelasting gebruikt. In alle drie de experimenten is hartslag en hartslagvariabiliteit (HRV) gebruikt als fysiologische indicator van mentale taakbelasting. In het experiment aangaande de invloed van slecht weer condities op mentale taakbelasting en incidenten op de snelweg is mentale taakbelasting ook gemeten door subjectieve schattingen van de geleverde inspanning. Hier is de Rating Scale Mental Effort (RSME) (Zijlstra & Doorn, 1985) gebruikt.

In het experiment aangaande de invloed van incidenten op de snelweg op mentale taakbelasting is aanvullend respiratie en de activiteit van twee gezichtsspieren, namelijk de zygomaticus major (glimlachen) en de corrugator supercillii (fronzen), gemeten. Om de invloed van de exceptionele condities op mentale taakbelasting te analyseren is gebruik gemaakt van MANOVA's en gepaarde t-tests. De modererende invloed van persoonlijke karakteristieken is geanalyseerd door Multiple Regressie Analyses. In de statistische analyses is een significantie niveau gehanteerd van .05.

Uit de resultaten met betrekking tot de invloed van noodsituaties op mentale taakbelasting volgt dat deze situaties een significante invloed hebben op HRV. HRV is significant lager in de experimentele groep met de noodsituatie vergeleken met de controlegroep. De factor tijd

heeft eveneens een effect, daar significante verschillen tussen de drie condities zijn gevonden. Hartslag vertoont echter geen significant effect van de noodsituatie noch de factor tijd.

Slecht weer condities hebben een significant effect op zowel hartslag als HRV. Slecht weer condities leiden tot een hogere hartslag en een lagere HRV. Echter, de slecht weer condities hebben geen significant effect op subjectieve schattingen van de geleverde inspanning, gemeten middels de RSME (Zijlstra & Doorn, 1985).

Met betrekking tot de invloed van incidenten op de snelweg zijn de resultaten minder eenduidig. Significante effecten van perceptie van een incident op de andere rij-strook konden alleen worden vastgesteld voor amplitudes van de corrugator supercillii (fronzen) en respiratie. Wederom werden geen significante effecten gevonden voor de subjectieve schatting van de geleverde inspanning (RSME). Verder volgt uit de MANOVA dat geen significant verschil kon worden waargenomen tussen de twee versies van het incident.

Aan de hand van statistische analyses tonen we aan dat de persoonlijke karakteristieken leeftijd en rijervaring een significante invloed hebben op de fysiologische indicatoren van mentale taakbelasting gedurende een exceptionele conditie. De fysiologische indicatoren geven aan dat een hogere leeftijd als ook minder rijervaring leiden tot een hogere mentale taakbelasting tijdens een exceptionele conditie. Dit ondersteunt het theoretisch raamwerk zoals voorgesteld in deze dissertatie.

De hiervoor genoemde doelstelling van deze dissertatie was gericht op het vaststellen van de empirie van longitudinaal rijgedrag in het geval van een exceptionele conditie, te weten adaptatie effecten in empirische longitudinaal rijgedrag en de determinanten van deze adaptatie effecten. In die context is de derde doelstelling van deze dissertatie om vast te stellen in welke mate huidige mathematische modellen van longitudinaal rijgedrag adequaat zijn in het beschrijven van longitudinaal rijgedrag in het geval van een exceptionele conditie.

In deze dissertatie wordt in dit kader een uitgebreid overzicht verschaft van continue car-following modellen (stimulus-response, safe-distance en multi-anticipatie) als ook van psycho-spacing modellen in relatie tot exceptionele condities. Uit het state-of-the-art onderzoek komt naar voren dat de meeste huidige continue car-following modellen longitudinaal rijgedrag op een mechanische manier beschrijven. Verder tonen we aan dat uit onderzoek naar voren komt dat de parameters in deze modellen een relatief stochastisch karakter hebben. Echter, geen onderzoek aangaande de invloed van exceptionele condities op parameterwaarden en performance van de modellen kon worden gevonden.

Om vast te kunnen stellen wat de invloed is van exceptionele condities op parameterwaarden en performance van car-following modellen, hebben we de parameterwaarden geschat van het Intelligent Driver Model (IDM) (Treiber et al., 2000), waarbij gebruik is gemaakt van de data van de drie rij simulator experimenten. In dit kader is een nieuwe schattingstechniek ontwikkeld.

Hieruit concluderen we dat noodsituaties een substantiële en significante invloed hebben op parameterwaarden van het IDM. We tonen aan dat gemiddeld noodsituaties leiden tot een toename in maximum acceleratie a , maximum deceleratie b en vrije snelheid v_0 . Verder tonen we aan dat de gewenste volgtijd T substantieel afneemt.

Eveneens tonen we aan dat slecht weer condities een substantiële invloed hebben op parameterwaarden van het IDM. We tonen aan dat slecht weer condities leiden tot een significante

reductie in de waarde van de parameters maximum acceleratie a en deceleratie b . Vreemd genoeg leidde deze exceptionele gebeurtenis tot een hogere waarde van vrije snelheid v_0 . Dit wordt mogelijk veroorzaakt doordat model performance niet erg sensitief is voor v_0 , gegeven dat de waarde vrij hoog is. Gewenste volgtijd T nam echter af tijdens de slecht weer conditie. Terwijl dit vanuit het oogpunt van gedrag vreemd lijkt, tonen we aan dat de minimale volgafstand bij stilstand s_0 substantieel toeneemt tijdens deze exceptionele gebeurtenis.

Tot slot tonen we in dit kader aan dat parameterwaarden van het IDM aanzienlijk veranderen in het geval van een incident op de snelweg. We tonen aan dat gemiddeld incidenten op de andere rijstrook leiden tot een toename in de waarde van de parameter maximum acceleratie a alsmede een afname in de maximale deceleratie b . De verschillen met normale condities is echter niet significant. Verder blijkt gemiddeld vrije snelheid v_0 hoger. Ook hier kan worden gesteld dat dit wordt veroorzaakt door het gegeven dat model performance niet erg sensitief is voor vrije snelheid v_0 . Meest opvallend is echter de substantiële toename in gewenste volgtijd T . Deze toename is significant.

Geconcludeerd kan dan ook worden dat exceptionele condities een substantiële invloed hebben op parameterwaarden van het IDM. In deze dissertatie beargumenteren we dat deze effecten kunnen worden beschouwd als compensatie effecten in rijgedrag, zoals voorgesteld in het theoretisch raamwerk.

Naast een invloed van exceptionele condities op parameterwaarden van het IDM tonen we ook aan dat deze condities een substantiële invloed hebben op model performance. We tonen aan dat noodsituaties, slecht weer condities en incidenten op de snelweg leiden tot een aanzienlijke afname in model performance van het IDM. We beargumenteren in deze dissertatie dat deze reductie in model performance een gevolg is van performance effecten, zoals verondersteld in het theoretisch raamwerk, daar car-following in mindere mate een determinant wordt van longitudinaal rijgedrag tijdens exceptionele condities.

Daar uit de literatuurreview naar voren kwam dat het merendeel van de continue car-following modellen een mechanisch karakter heeft, is eveneens onderzocht wat de invloed is van exceptionele condities op de positie van actiepunten en op acceleratie als ook op de 'sprongen' in acceleratie op de actiepunten in een psycho-spacing model.

Om de invloed van exceptionele condities op de positie van actiepunten in een psycho-spacing model te kunnen bepalen, is een nieuwe data-analysetechniek ontwikkeld. De invloed van deze condities op acceleratie en de 'sprongen' in acceleratie is bepaald door een Multivariate Regressie Analyse (MRA) met behulp van vier verschillende modellen.

We tonen aan dat exceptionele condities leiden tot substantiële veranderingen in de positie van actiepunten in het relatieve snelheid - volgafstand vlak. We tonen bijvoorbeeld aan dat in het geval van noodsituaties actiepunten veel meer geconcentreerd zijn op kleine waarden van volgafstand en relatieve snelheid vergeleken met normale condities. Bovendien tonen we aan dat acceleratie en de 'sprongen' in acceleratie op de actiepunten een substantiële invloed ondervinden van de exceptionele condities.

We beargumenteren in deze dissertatie dat de verandering in de positie en vorm van de perceptuele grenzen, gerepresenteerd door de positie van de actiepunten, duiden op compensatie

effecten in longitudinaal rijgedrag als gevolg van een exceptionele conditie. De effecten met betrekking tot acceleratie en de 'sprongen' in acceleratie worden beschouwd als indicaties voor performance effecten. Dit geldt eveneens voor het gegeven dat we vaststellen dat acceleratie minder adequaat wordt beschreven voor de modellen gebruikt in de Multivariate Regressie Analyse. Het voorgaande in beschouwing genomen concluderen we dat de assumptie van deterministische perceptuele grenzen in de originele formulering van het model niet realistisch is.

Om deze reden stellen we voor een stochastisch car-following model te ontwikkelen dat in staat is de effecten van exceptionele condities op longitudinaal rijgedrag te beschrijven. We beargumenteren dat dit kan worden gerealiseerd door een Bayesiaanse netwerk benadering en het leren van parameters. In deze dissertatie tonen we aan dat deze benadering een redelijk goede representatie verschaft van actiepunten en acceleratie op de actiepunten.

Samenvattend verschaft deze dissertatie inzicht in adaptatie effecten in empirisch longitudinaal rijgedrag in het geval van een aantal exceptionele condities, de determinanten van deze adaptatie effecten en worden indicaties verschaft met betrekking tot op welke wijze deze adaptatie effecten het beste kunnen worden gemodelleerd. Inzicht in adaptatie effecten in empirisch longitudinaal rijgedrag in het geval van deze exceptionele condities heeft belangrijke implicaties voor bijvoorbeeld netwerkbeheerders. Maatregelen ter vermindering van de impact van de in deze dissertatie bestudeerde exceptionele condities worden in de praktijk geëvalueerd door simulatie studies. Om echter een betrouwbare voorspelling te verkrijgen van de effectiviteit van een voorgestelde maatregel is het noodzakelijk dat rijgedrag op een realistische manier is geïncorporeerd in deze simulatiemodellen.

TRAIL Thesis Series

The following list contains the most recent dissertations in the TRAIL Thesis Series. For a complete overview of more than 100 titles see the TRAIL website: www.rsTRAIL.nl. The TRAIL Thesis Series is a series of the Netherlands TRAIL Research School on transport, infrastructure and logistics.

Hoogendoorn, R.G., *Empirical Research and Modeling of Longitudinal Driving Behavior under Adverse Conditions*, T2012/3, July 2012, TRAIL Thesis Series, the Netherlands

Carmona Benitez, R., *The Design of a Large Scale Airline Network*, T2012/2, June 2012, TRAIL Thesis Series, the Netherlands

Schaap, T.W., *Driving Behaviour in Unexpected Situations: a study into the effects of drivers compensation behaviour to safety-critical situations and the effects of mental workload, event urgency and task prioritization*, T2012/1, February 2012, TRAIL Thesis Series, the Netherlands

Muizelaar, T.J., *Non-recurrent Traffic Situations and Traffic Information: determining preferences and effects on route choice*, T2011/16, December 2011, TRAIL Thesis Series, the Netherlands

Cantarelli, C.C., *Cost Overruns in Large-Scale Transportation Infrastructure Projects: a theoretical and empirical exploration for the Netherlands and Worldwide*, T2011/15, November 2011, TRAIL Thesis Series, the Netherlands

Vlies, A.V. van der, *Rail Transport Risks and Urban Planning: solving deadlock situations between urban planning and rail transport of hazardous materials in the Netherlands*, T2011/14, October 2011, TRAIL Thesis Series, the Netherlands

Pas, J.W.G.M. van der, *Clearing the Road for ISA Implementation? Applying adaptive policymaking for the implementation of intelligent speed adaptation*, T2011/13, October 2011, TRAIL Thesis Series, the Netherlands

Zegeye, S.K., *Model-Based Traffic Control for Sustainable Mobility*, T2011/12, October 2011, TRAIL Thesis Series, the Netherlands

Mhr, T., *Vehicle Routing under Uncertainty*, T2011/11, September 2011, TRAIL Thesis Series, the Netherlands

Pel, A.J., *Transportation Modelling for Large-scale Evacuations*, T2011/10, July 2011, TRAIL Thesis Series, the Netherlands

Zheng, F., *Modelling Urban Travel Times*, T2011/9, July 2011, TRAIL Thesis Series, the Netherlands

Vlassenroot, S.H.M., *The Acceptability of In-vehicle Intelligent Speed Assistance (ISA) Systems: from trial support to public support*, T2011/8, June 2011, TRAIL Thesis Series, the Netherlands

Kroesen, M., *Human Response to Aircraft Noise*, T2011/7, June 2011, TRAIL Thesis Series, the Netherlands

Nielsen, L.K., *Rolling Stock Rescheduling in Passenger Railways: applications in short-term planning and in disruption management*, T2011/6, May 2011, TRAIL Thesis Series, the Netherlands

Qing, O., *New Approach to Fusion of Heterogeneous Traffic Data*, T2011/5, May 2011, TRAIL Thesis Series, the Netherlands

Walta, L., *Getting ADAS on the Road: actors interactions in Advanced Driver Assistance Systems deployment*, T2011/4, April 2011, TRAIL Thesis Series, the Netherlands

Lin, S., *Efficient Model Predictive Control for Large-Scale Urban Traffic Networks*, T2011/3, April 2011, TRAIL Thesis Series, the Netherlands

Oort, N. van, *Service Reliability and Urban Public Transport Design*, T2011/2, April 2011, TRAIL Thesis Series, the Netherlands

Mahmod, M.K.M., *Using Co-Operative Vehicle-Infrastructure Systems to Reduce Traffic Emissions and Improve Air Quality at Signalized Urban Intersections*, T2011/1, March 2011, TRAIL Thesis Series, the Netherlands

Corman, F., *Real-Time Railway Traffic Management: dispatching in complex, large and busy railway networks*, T2010/14, December 2010, TRAIL Thesis Series, the Netherlands

Kwakkel, J., *The Treatment of Uncertainty in Airport Strategic Planning*, T2010/13, December 2010, TRAIL Thesis Series, the Netherlands

Pang, Y., *Intelligent Belt Conveyor Monitoring and Control*, T2010/12, December 2010, TRAIL Thesis Series, the Netherlands

Kim, N.S., *Intermodal Freight Transport on the Right Track? Environmental and economic performances and their trade-off*, T2010/11, December 2010, TRAIL Thesis Series, the Netherlands

Snelder, M., *Designing Robust Road Networks: a general design method applied to the Netherlands*, T2010/10, December 2010, TRAIL Thesis Series, the Netherlands

Hinsbergen, C.P.IJ. van, *Bayesian Data Assimilation for Improved Modeling of Road Traffic*, T2010/9, November 2010, TRAIL Thesis Series, the Netherlands

Zuurbier, F.S., *Intelligent Route Guidance*, T2010/8, November 2010, TRAIL Thesis Series, the Netherlands

Larco Martinelli, J.A., *Incorporating Worker-Specific Factors in Operations Management Models*, T2010/7, November 2010, TRAIL Thesis Series, the Netherlands

Ham, J.C. van, *Zeehavenontwikkeling in Nederland: naar een beter beleidsvormingsproces*, T2010/6, August 2010, TRAIL Thesis Series, the Netherlands