Odd André Hjelkrem

Heavy Vehicle Following Behavior

The Effect of Vehicle Properties, Road Characteristics and Environmental Factors on Vehicular Interactions

Odd André Hjelkrem

Doctoral Thesis

NTNU
Norwegian University of
Science and Technology
Faculty of Engineering
Science and Technology
Department of Civil and Transport Engineering

◉ NTNU
Norwegian University of
Science and Technology

◉ NTNU

◉ NTNU
Norwegian University of
Science and Technology

Odd André Hjelkrem

Heavy Vehicle Following Behavior

The Effect of Vehicle Properties, Road Characteristics and Environmental Factors on Vehicular Interactions

◩ NTNU
Norwegian University of
Science and Technology

Abstract

This thesis describes a series of studies made in the field of modelling heavy vehicle behavior. The main goal of the thesis was to investigate how car-following behavior of heavy vehicles differs from that of cars, how external factors affect this behavior, and how to incorporate this knowledge into traditional car-following models.

In a discipline where heavy vehicles have been neglected in favor of cars, an increased effort in research is needed to properly include heterogeneous traffic streams. However, any introduced complexity in the models should not increase the calibration demands. A large share of practitioners today spend too little time and effort on calibration, and increased calibration demands might increase this share.

The main focus of the thesis is describing heavy vehicle behavior. Through three research papers and one paper describing a data set, several aspects of heavy vehicle following behavior are investigated.

Previous work have shown that vehicle type of both leader and follower are important. Findings in the first paper indicate that only the follower vehicle type matters. A relationship between vehicle weight and time gap was found. It is also shown that both the threshold value for car-following behavior, and the desired time gap is different for cars and heavy vehicles.

The behavior of vehicles differ from location to location, depending on properties of the road and surroundings. It is shown that whether a heavy vehicle is in a rural or urban environment in combination with either congested or free flow, will affect the behavior. For cars, the most important factor was the number of lanes.

Weather also affects driver behavior. By measuring the speed and time gap in different weather and road surface situations, it is apparent that a snow covered road will reduce the speed and increase the time gap for both heavy vehicles and cars. Precipitation has a large effect on the following behavior of cars, but does not seem to have an impact on the behavior of heavy vehicles.

These empirical studies required several data sets about vehicle behavior to be collected. The data used in the first paper was collected from a Weigh-In-Motion detector, and included variables such as time gap, speed, vehicle weight, vehicle length, axle weight, and number of axles. About 670 000 time gaps were collected from a rural two-lane road for the study. The data set used in the second paper consisted of about 21 million observations from 16 detectors at different places in Norway. They were carefully selected for studying the impact of road

characteristics. For the third paper, about 70 000 joint observations from a Weigh-In-Motion detector and a weather station were collected.

In the last research paper, Gipps' car-following model was modified to have one common parameter set for all vehicle types, instead of one parameter set for each vehicle type. This was done by introducing a new parameter γ, a double exponential function of the gross vehicle weight. It was incorporated into Gipps' model by multiplying it with the deceleration parameters of the leader and follower vehicle. The results showed that the measured time gap distributions had a slightly better fit to measured data in the field, despite less parameters to calibrate.

Preface

This thesis is submitted to the Norwegian University of Science and Technology (NTNU) for partial fulfilment of the requirements for the degree of philosophiae doctor.

This doctoral work has been performed at the Department of Civil Engineering and Transport, NTNU, Trondheim, with Eirin Olaussen Ryeng as main supervisor and Tomas Levin as co-supervisor.

The PhD project was initially funded by NTNU through the research project GOFER, which was co-financed by the SMARTRANS-programme of the Research Council of Norway and a consortium of public road authorities, municipalities, transport operators and technology developers. After the GOFER-project reached its end, the PhD project received funding from NTNU and the National Public Roads Administration (NPRA).

One of the tasks in the GOFER-project was to develop a simulation model of the traffic flow to a freight terminal in Oslo, to evaluate several priority alternatives. During the development of the simulation model, it became obvious that heavy vehicles and their interactions with other vehicles should be investigated more. This in turn lead to defining the objectives set for this PhD study.

Acknowledgements

I would like to express my sincere gratitude to NTNU and NPRA for funding this work. I would also like to thank the many people who have helped me along the way, and to the following remarkable people in particular:

All my colleagues who I have had the pleasure to work with at SINTEF, for including me in all sorts of interesting projects and teaching me the many aspects of transport research.

Roar, for always having an open door, for understanding my situation and for always being eager to help.

Solveig, for your crucial help and backing in the early stages, and for your patience as my PhD study developed into what it is today.

Børge, for your helpful advice as a member of my reference group, and for sharing your knowledge about microscopic simulations.

Sebastian, for an inspiring collaboration on our paper.

Torgeir, for your invaluable help with getting the data I needed.

Eirin, for your patience, understanding and guidance along the way. You were always there when I needed help. Thank you for sharing your time and knowledge of risk theory for our paper.

Tomas, for your friendship, knowledge and savvy. Without your encouragement and constructive criticism, I would not have been where I am now.

GB, for necessary distractions and great discussions.

My parents, for teaching me that anything is possible if you set your mind to it. I am grateful for your guidance and for always believing in me.

To Stine, for being my better half. You help me push myself beyond my limits to accomplish my goals.

Contents

List of Tables

List of Figures

Part I

Overview

Chapter 1

Introduction

Part I of this thesis describes the theoretical base and the state of the art addressed by the papers in Part II. Chapter 1 provides an introduction to the field of heavy vehicle behavior and modelling, and summarises the gaps in knowledge in the field. Chapter 2 defines the research questions for this thesis, and presents scope and limitations of the thesis. In Chapter 3, a brief summary of the main results of the papers and how they answer the research questions is given. Part I is concluded by Chapter 4, which describes the contributions from the PhD project and identifies topics for future research.

1.1   The Challenges of Road Based Freight Transport

Freight transport in urban areas is a necessity for sustaining today's way of life. Our need for goods require transport from producer to consumer. However, the increasing demand for goods has lead to an increase in the volume of freight vehicles. In the EU, the increase in road freight traffic is estimated to about 55 % from 2010 to 2050 (Capros et al. 2013). The increasing presence of freight vehicles has several negative impacts:

- Congestion in urban areas is aggravated by a growing number of freight vehicles. The large size and often lower freedom of movement of a heavy vehicle compared to a car may lead to a significant disturbance in traffic flow. Slow heavy vehicles can act as bottlenecks in a traffic stream and severely influence other vehicles (Daganzo and Laval 2005). Heavy vehicles also influence the capacity of the road (Transportation Research Board 2010, Al-Kaisy et al. 2005).

- The physical dimensions of heavy vehicles leads to damage and wear on the

3

road infrastructure. The damaging effect of a heavy vehicle is thousands of times more than a car (Fwa 2005). An increase in the volume of heavy vehicles will further increase the negative impacts on the infrastructure.

- Accidents involving heavy vehicles are usually more severe than accidents with lighter vehicles. The fatality risks when heavy vehicles are involved in an accident are significantly higher than those compared with passenger cars and other vehicles. In the EU, 15% of road fatalities result from accidents involving heavy vehicles (European Commission 2015b). Wood (1997) estimated that the relative injury risk in collisions between two vehicles of different sizes were dependent on the relative energy absorption, as well as the length and mass ratios, meaning that the injury risk increases as the physical difference between colliding vehicles increases.

- The pollution and noise from a heavy vehicle can be several times greater that from a passenger vehicle. According to the European Commission (Capros et al. 2013, p 52), "the main contributor to CO_2 emissions growth is road freight, where the increased activity surpasses improvements in specific fuel consumption, especially for heavy vehicles". Heavy vehicles have traditionally been a substantial source of NO_x-emissions, but recent tests indicate that vehicles complying with the EURO VI emission standards have a greatly reduced emission of NO_x and particulate matter (PM) compared to older vehicles (Hagman and Amundsen 2013). The external marginal cost of noise produced by a heavy vehicle was estimated by Maibach et al. (2008) to be approximately ten times greater than the noise from a car.

Clearly, the increasing volume of heavy vehicles, coupled with the related negative consequences, will create issues. Finding solutions to problems associated with the increasing traffic volumes is a challenge for the road research community, the road authorities, and heavy vehicle operators. The European Commission implemented an action plan in 2007 to deal with the present problems in the freight and logistics sector (European Commission 2007). The action plan had a positive effect, but there are still problems to be dealt with, including rising costs and the negative environmental footprint (European Commission 2015a). In the EU, the modal share of road based freigth transport is 71 %, and is projected to be 70 % by 2050 (Capros et al. 2013). By 2013, 52 % of all domestic freight transport in Norway were produced by road based vehicles (about 19 billion tonne-kilometers), a growth from 18 % in 1960 (Kolshus 2015). The Norwegian Government plans for a transition from road to sea and rail for domestic transport, but acknowledges that this is only achievable for freight trips longer than 500 km (NTP 2013). They

also state that to achieve the nations climate goals, the traffic flows where short road freight trips (less than 500 km) takes place needs to become more efficient and less polluting.

Practitioners who try to solve a transport related problem, have often several possible solutions in mind. However, the effects of alternative solutions may not be obvious, making it challenging to select the correct one. A normal approach is to construct a model of the problem for estimating the consequences of each alternative.

1.2   Modelling Traffic

"A model is a simplified representation of a part of the real world - the system of interest - which focuses on certain elements considered important from a particular point of view." (Ortuzar and Willumsen 2011, p 2)

When modelling traffic, the purpose is to model traffic flow in a specific, limited area. The model is designed to replicate driver behavior as a function of the road, the surroundings, the vehicle, the driver, and other drivers. The goal of the model user is usually either evaluation or optimisation of transportation systems, or modelling existing traffic flows and forecasting probable results of alternative designs.

A model needs input for its functions, which then predicts an outcome of the process. If the functions in the model properly replicate the real world functions, safe and controlled experiments can be simulated in the model instead of conducting real world experiments. Thus, time and money can be saved, and even more important, a more optimal solution can be found.

Historically, models of traffic flow have existed for decades. The first pioneering studies date back to the first half of the 20th century, where e.g. Greenshields (1935) studied the relationship between traffic volume and speed. Since then, models on several levels of detail have been developed. Simulation models are usually classified in three scopes: macroscopic, mesoscopic and microscopic (Alexiadis et al. 2004). Macroscopic models are suited for larger regions, as the relationships between speed, flow and density are simulated section-by-section rather than simulating individual vehicles.

Mesoscopic models combine the properties of macroscopic and microscopic models. Individual vehicles are modeled, but with less detail than microscopic models.

Microscopic simulations use stochastically distributed properties to model each vehicle by several behavioral models, with a time resolution of typically one second or less, and are thus able to evaluate the growth and dissolution of congestion. They are useful for assessing the dynamic progression of problems due to traffic congestion. Because individual vehicles are modeled, the inherent variability in the behavioral and dynamical properties of a vehicle can be included in the simulation. This PhD project focuses on the behavior modeled by microscopic simulation models.

There are many examples of microsimulation models being used to successfully model traffic. Anya et al. (2014), Momenian (2013), and Khaki and Pour (2014) used microscopic simulations to estimate emissions. Zefreh et al. (2015) investigated the effect of shared taxies on traffic flow. Chen (2014) used microsimulations to study detailed traffic and intersection operations. Simulations can also be used to evalute the effect of ITS on traffic flow, as demonstrated by Ntousakis et al. (2015). These examples show that traffic models can be helpful in studying the present and future challenges.

According to Dowling et al. (2004), microscopic simulations are suitable for small networks, typically less than 520 square kilometers. This is because simulation models are highly detailed and require a great deal of input data, which in turn needs to be checked for errors. To establish a valid model, the parameters needs to be calibrated so that the simulated features replicate actual field conditions. The calibration procedure can be a tremendous task, depending on the size of the model and the number of parameters.

Microsimulation models are available as several software packages, which are used to simulate traffic in existing or future road networks. Descriptions of the basic principles of these simulation models are commonly found in textbooks, and a fully operational microsimulation model usually consists of the following behavioral models:

- **Car-following models:** These longitudinal models replicate interactions between follower and leader vehicles. The output of these normally time-continuous models is usually the acceleration or speed of a vehicle based on current values of speed, spacing, acceleration and vehicle-specific parameters.

- **Acceleration models:** These models describe the longitudinal behavior of a vehicle where there are no constraining leader vehicles. Several car-following models describe this type of behavior as well.

- **Lane-change models:** Latitudinal models which describe the process of

decision and movements related to change of lane on multi lane highways. The decision process is a continuous query where the answer is either to stay in the current lane, or to change to an adjacent lane, depending on current speed, leader vehicle speed, desired speed, and occupancy in target lanes.

- **Gap acceptance models:** These models are mainly used in intersections with priority rules, where the behavior of finding an acceptable gap in a present conflicting traffic stream is modeled. The models are based on drivers' preferences regarding risk acceptance given the speed of conflicting vehicles and the acceleration properties of the driver.

- **Route choice models:** Every simulated vehicle in a model has an origin and a destination, and needs to find a route through the road network. Decisions made about route choice are at the strategic level, and involves estimations of fastest or shortest route.

This thesis will focus on the modelling of heavy vehicles in car-following models. There are several reasons for this choice. Firstly, on the simplest roads without intersections, and with one lane in each direction, only a car-following model is needed to model the traffic flow.

Secondly, car-following behavior is the crucial factor for creating speed profiles, which in turn are important for emission calculations. The engine fuel consumption and emissions are determined by the engine characteristics, as well as engine speed and load. These are controlled by the way the driver responds to the longitudinal road profile and nearby vehicles.

Thirdly, in urban areas, a large share of the driving task consists of car-following behavior, and there is generally more vehicles and more congestion in urban areas. Therefore, car-following models are important for modelling urban vehicle behavior.

Lastly, heavy vehicles have been overlooked when it comes to modelling in general, although constituting a significant share of traffic (Aghabayk et al. 2012). It is not hard to understand why, since car is the dominant vehicle type in road traffic. The most prominent example of the focus on cars can be found in the terminology of the most important behavioral model in the field, which are "Car"-following models. This shows that heavy vehicles are in certain ways not equally important as cars, despite being a significant contributor to emissions, congestion, and accidents. The increase in road based freight transportation calls for a proper inclusion of heavy vehicles in the modelling of longitudinal behavior, as stated by (Aghabayk et al. 2012, p 1): "Following behavior of passenger car

drivers has been modelled in many studies over the last half century. However, the existence of heavy vehicles in the traffic stream has not received the same level of attention."

Before the state of the art in heavy vehicle following behavior is explored, an introduction to car-following theory in general is given.

1.3   A Brief Introduction to Car-Following Behavior and Models

Car-following behavior can be described as the behavior of a follower vehicle given the actions of a present leader vehicle. It is a continuous process where the intervehicular distance and speed difference is constantly fluctuating. Every change in the movement of the leader will cause a response in the movement of the follower vehicle. If the gap between follower and leader vehicle is large enough, the actions of the leader will no longer affect the follower, and the follower vehicle will be in a state of free flow.

From the perspective of the follower vehicle, the driver has a hypothetical desired speed which it strives to maintain. Every vehicle in front of the follower with a lower desired speed will be an obstacle, assuming no overtaking possibilities. A safety based approach to describing this behavior would assume that the follower would avoid a collision with the leading vehicle. This implies that the inter-vehicular gap should not be too small, and that the relative velocity should not be too high. However, the gap should neither be too large, if the desired speed of the follower is not reached.

An informative description of the car-following process is a car-following spiral, in which a series of observations of gap and speed difference are plotted. An example is shown in Figure 1.1. Here we see that the typical pendulum behavior in both relative speed and distance gap results in a spiraling behavior.

The modelling of car-following behavior has gone through a long and varied evolution since the first models appeared in the middle of the 20th century. The Next-Generation Simulation Program (NGSIM) has rigorously classified the most well known car-following models in 5 types (Ni 2015), as shown in Table 1.1. These 5 types represent slightly different ways of determining a change in the speed of a vehicle, determined by the preceding vehicle. The rule-based models consist of a set of rules which triggers a certain change in speed. Psycho-physical models involve both psychological activities (e.g. behavioral thresholds) and physical behavior (e.g. accelerations and decelerations). Desired measure models are designed to ensure a safe distance between vehicles, while stimulus-response models calculate the speed (response) as a function of change in the speed of the leader vehicle (stimulus). The Intelligent Driver Model (Treiber et al. 2000) is a
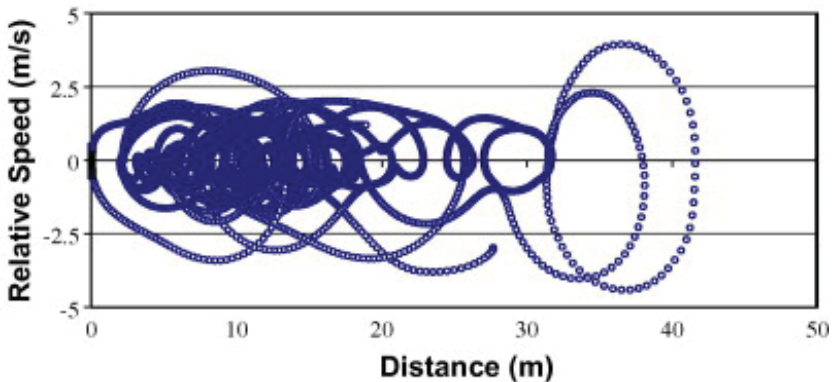
Figure 1.1: A typical car-following process visualised by a time series of relative speed as a function of distance gap. Source: Brackstone et al. (2009)

relatively complicated model which combines the ability to reach the speed limit in free flow with the ability to avoid collisions in car-following situations.

Many software packages, both commercial and open source, are developed to offer a framework for practitioners to implement the theoretical behavioral models. Table 1.1 lists different types of car-following models, and which type of model group which is implemented in the most used software packages. It is apparent that the Desired Measure-type models are most frequently used in software packages.

Table 1.1: Examples of published models, and usage of model types in software packages, as classified by NGSIM (Ni 2015).

Type	Models	Software
Rule-Based	Kikuchi and Chakroborty (1992) and Kosonen (1999)	HUTSIM
Psycho-Physical	Michaels (1963) and Wiedemann (1974)	Paramics, VISSIM
Desired Measure	Pipes (1967), Newell (1961), Gipps (1981), and Benekohal and Treiterer (1988)	AIMSUN, ARTEMIS, CORSIM, DRACULA, Integration, SimTraffic, SUMO, WATSim
Stimulus-Response	Chandler et al. (1958), Kometani and Sasaki (1958), Gazis et al. (1961), and Ceder and May (1976)	MITSIM, Transmodeler
Intelligent Driver Model	Treiber et al. (2000)	

Several guidelines exist for developing a microscopic simulation model. Before establishing a set of procedures for microscopic simulations in Sweden, Olstam and Tapani (2011) reviewed the state of the art in existing guidelines. Their review covered guidelines from USA, Germany, UK, Denmark and Sweden. Although elements from all guidelines were used, the guidelines given by FHWA (Dowling et al. 2004) were the most extensive, except for the fact that model validation is not included.

According to the guidelines from FHWA, a project which involve establishing and applying a valid simulation model is demanding, both in sense of time and data requirements. The FHWA separates the workload into several tasks, which are:

- Project scope: Project goals are defined, and plans are made for data collection, coding procedures, alternatives to be simulated, and calibration.

- Data collection: Collection and preparation of data sets needed for the model.

- Model development: Coding links, nodes, travel demand, traffic control etc.

- Error checking: Software error checking, input coding error and animation review.

- Calibration: Adjusting parameters until calibration targets are met. The model must be calibrated to ensure that the model will be able to correctly predict the traffic performance.

- Validation: According to Olstam and Tapani (2011), model validation should be covered at this point, but it is not included in Dowling et al. (2004) .

- Alternatives analysis: Description of alternatives, analytical procedures and results.

- Final report: Documentation of the project.

There are several apparent challenges when microsimulation models are developed. Two important challenges are, according to Dowling et al. (2004), insufficient managerial expertise for verifying the technical application of the model, and insufficient data/documentation for calibrating the model. They also mention that the importance of calibration cannot be overemphasized. Hourdakis et al. (2003) states that a major share of the criticism against microscopic simulation are related to calibration and validation. A survey carried out by the

MULTITUDE project revealed that 19 % of practitioners polled did not calibrate their models, and that 55% did not follow any guidelines when calibrating a model (Antoniou et al. 2014).

An evolution of models in the direction of more complexity requires even more data and effort. The amount of parameters usually increases with the complexity and size of the model. An important example of increased complexity is the inclusion of several vehicle types. Usually, cars are the dominant vehicle type in a traffic flow, but the share of heavy vehicles can in many cases be significant. Thus, for the model to produce realistic results, the behavior of heavy vehicles must be modeled sufficiently. The next section describes the state of the art in this research area.

1.4   State of the Art in Heavy Vehicle Behavior and Modelling

A prerequisite for modelling is empirical knowledge about the processes and functions within the subject of the model. Several studies have focused on describing elements of heavy vehicle dynamics, in the absence of car-following interactions. Then, only the physical and operational properties of the vehicle are responsible for the behavioral differences:

- The larger mass of heavy vehicles needs more energy to drive uphill. As shown by Fry et al. (2002), the speed of heavy vehicles decreases with increasing grade.

- A heavy vehicle can in some cases have a high center of gravity, depending on the load. This may lead to rollovers in curves, especially if the speed is too high. As stated by de Pont et al. (2004), high speed through curves were the cause of more than half of the rollovers of heavy vehicles in New Zealand and the Netherlands.

- Heavy vehicles are sometimes limited to certain speeds on highways, either by speed delimiters or by speed limits. A possible reason for this is the decreased agility due to the high weight compared to cars, in addition to safety reasons. Saifizul et al. (2011) studied the relationship between vehicle weight and speed. They found that speed decreased for heavier vehicles, and that most heavy vehicles had speeds below the speed limit.

- The engine capability of a heavy vehicle should be designed with maximum cargo in mind, to ensure a reasonable acceleration and deceleration regardless of the cargo. However, it is shown empirically by Di Cristoforo et al. (2004) that the acceleration properties of a vehicle is

related to the weight of the vehicle. Their acceleration tests of combination vehicles revealed that heavier vehicles have lower acceleration and deceleration capabilities.

The longitudinal behavior in presence of car-following interactions has been described my multiple other studies. By measuring either gap or headway between vehicle pairs, the effect of vehicle type can be determined. When only cars and heavy vehicles are present, the following combinations of vehicle pairs are possible:

- **C**ar following **C**ar (C-C). This is the most frequent pair, and also the behavior which is usually described in studies of car-following behavior.

- **C**ar following **T**ruck (T-C). The larger size of the heavy vehicle reduces the ability of the car driver to obtain information about downstream traffic conditions. However, the car presumably has better maneuverability and braking ability than the heavy vehicle.

- **T**ruck following **C**ar (C-T). The raised position of the heavy vehicle cabin gives the heavy vehicle driver the ability to see downstream movements, and thereby predict the behavior of the lead vehicle. On the other hand, the physical differences between vehicles may lead to fatal consequences in an eventual collision.

- **T**ruck following **T**ruck (T-T). As heavy vehicles are usually outnumbered by cars, this is the least occurring vehicle pair.

Brackstone et al. (2009) and Sayer et al. (2003) found that vehicles in general follow heavy vehicles closer than cars. Ye and Zhang (2009) studied statistical distributions for time headways. They found that C-C headways were the smallest, and T-T headways were largest. They also found that C-T headways were shorter than T-C, presumably because the heavy vehicle drivers could see further downstream. Ossen and Hoogendoorn (2011) found that the desired headways are lower when following a heavy vehicle than when following a car. They also found that heavy vehicles have a more robust following behavior, with less variation in speed. Nouveliere et al. (2012) developed a headway spacing estimation model based on vehicle weight data, showing that the headway increased with increasing vehicle weight. Aghabayk et al. (2012) found that speed differences between follower and leader, as well as the acceleration of both vehicles were significant stimuli on heavy vehicle following behavior. Weng et al. (2013) studied time headway distributions in work zones for different

Table 1.2: Summary of results showing the effect of vehicle pair on time headway.

Result	Source
(T-C & T-T) < (C-T & C-C)	Brackstone et al. (2009), Sayer et al. (2003), Ossen and Hoogendoorn (2011)
(C-C & T-C) < (C-T & T-T)	Nouveliere et al. (2012)
(C-C & C-T) < (T-C & T-T)	Weng et al. (2013)
C-C < T-C < C-T < T-T	Hashim et al. (2014)
C-C < C-T < T-C < T-T	Ye and Zhang (2009)

leader-follower vehicle type configurations. They found that the time headway was larger for vehicle pairs with heavy vehicle as leading vehicle. They also found that heavy vehicles tend to keep larger headways than cars when following other vehicles. A study by Hashim et al. (2014) showed that followers kept a larger distance to leading heavy vehicles than to leading cars. They also found a significant correlation between speed and time headway in situations where a heavy vehicle was either follower, leader or both. The correlation was not found for C-C interactions.

These results show that the effect of vehicle type on time headway is diverging. The summary presented in Table 1.2 display the variety in results. The empirical results show that vehicle type matters for vehicle following behavior, although Table 1.2 indicates that more research is needed to determine how vehicle type affects the choice of headway.

The car-following models presented in Table 1.1 may potentially be used for heavy vehicles as well as for cars. This requires that the relevant parameters are calibrated for heavy vehicles. However, it is unclear whether these models are able to capture the differences in behavior between cars and other vehicle types as for instance heavy vehicles. There has been a relatively small amount of studies focusing on heavy vehicle modelling compared to cars. A notable exception is in the field of modelling mixed traffic, sometimes referred to as heterogeneous traffic. Mixed traffic is characterised by multiple vehicle types present and weak lane discipline, which is commonly found in developing countries. Although mixed traffic is not primarily focused on heavy vehicle following behavior, it is an important component along with other vehicle types such as for instance bicycles and motorcycles.

There has been several past attempts to develop a simulation model for mixed traffic, focusing on either multiple vehicle types, weak lane discipline, or both.

Arasan and Koshy (2005) developed a simulation model called HETEROSIM with the purpose of modelling heterogeneous traffic, but with the capability of modelling homogeneous traffic as well. The model was revalidated by Arasan and Dhivya (2010). Gunay (2007) used Gipps' car-following model as a basis for developing a new type of model, called staggering car-following model, which included the modelling of a weak lane discipline. While most studies have chosen a conventional car-following model, Mallikarjuna and Rao (2009) used a cellular automata to model heterogeneous flow, and were able to reproduce real traffic behavior. Ravishankar and Mathew (2011) added a vehicle type parameter in Gipps' car-following model (Gipps 1981), and the results showed an improvement in comparison to the original Gipps' model. Metkari et al. (2013) further developed the work of Gunay (2007) and Ravishankar and Mathew (2011), combining their ideas into a modified Gipps' model taking both weak lane discipline and vehicle type into account. Aghabayk et al. (2013) implemented their previous findings (Aghabayk et al. 2012) in a car-following model. Using a local linear model tree approach, the resulting car-following model was able to reproduce car-following behavior depending on the lead vehicle type.

Munigety and Mathew (2016) conducted a thorough review of the state of the art in the field of modelling mixed traffic. In their road map towards a mixed traffic behavioral model, more effort is required on vehicle type dependent longitudinal movement models. This is further elaborated in the next section, where the gaps in knowledge are presented.

1.5   Gaps in Knowledge

Heavy vehicle following behavior is an important component in the field of mixed traffic, and a large share of the existing studies on heavy vehicle behavior has aimed at contributing to a better understanding of heterogeneous and mixed traffic. Therefore, it is natural to present the gaps in knowledge within this field, concentrated on the longitudinal behavior of heavy vehicles. The recent review by Munigety and Mathew (2016) identify some important research directions in the field of modelling mixed traffic, which include and further develops the gaps identified by Kanagaraj et al. (2013). These gaps can be grouped into four categories: (1) data requirements, data collection and extraction, (2) driving regimes, (3) driver behavioral models, and (4) integrated driving behavior model. They are further explained in the following sections.

1.5.1   Data Requirements, Data Collection and Data Extraction

One of the challenges in driver behavioral modelling is the identification and effect of individual and circumstantial factors, and how to incorporate them in

behavioral models. The former is attributed to the driver and vehicle, while circumstantial factors are attributed to the surrounding area. The importance of factors as a function of flow type was postulated by Ranney (1999) as shown in Figure 1.2. In congested flow, the main influence on driver behavior comes from other traffic. In free flow, external factors are more important, as well as driver characteristics.
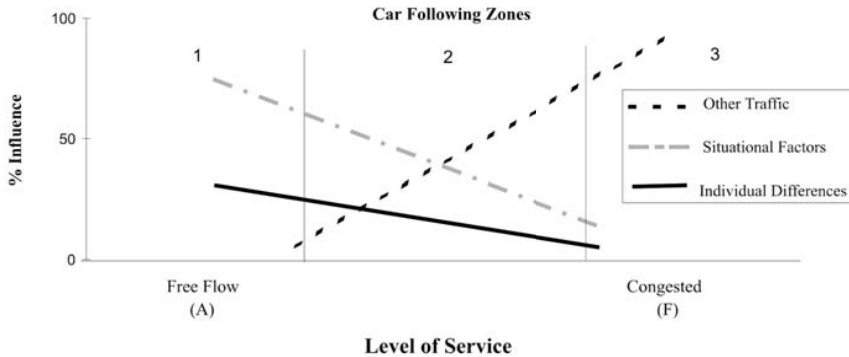
Figure 1.2: The influence of factors on vehicle behavior at different levels of service. Source: Ranney (1999)

The data collection method for describing mixed traffic should according to Munigety and Mathew (2016) be trajectory data. Then, the choice is between floating car data and video recorded data. While video recordings yield much information about driver behavior, it is labor intensive to analyse and often inaccurate. Floating car data requires an extensive instrumentation of vehicles in order to collect car following behavior data. To properly understand driver behavior, data should be collected from longer sections with variability in the vehicular and geometric characteristics. More effort should be invested in developing methods for extracting data, which is challenging in mixed traffic conditions due the occlusion caused by large variations in the physical size of vehicles and weak lane discipline.

1.5.2 Driving Regimes

As the driver behavior may change with circumstantial factors, the need for definition of boundaries between driving regimes arises. An example of a boundary is the headway threshold between car-following and free flow. These thresholds has often been set or calibrated arbitrarily, and set deterministically without regarding the diversity in vehicle and driver properties (Munigety and Mathew 2016).

1.5.3   Driver Behavioral Models

Munigety and Mathew (2016) state that of all available car-following models, collision avoidance based models, e.g. Gipps' model (Gipps 1981), seem to be the most appropriate choice for describing the car-following behavior in mixed traffic. However, there is a need to develop models which properly describes the vehicle dependent following behavior which can be observed in mixed traffic. This is also the case for vehicle dependent lateral movements observed in mixed traffic.

1.5.4   Integrated Driving Behavior Model

Longitudinal and lateral movements are in reality the results of integrated choices made by the driver. Therefore, several researches have tried to model integrated driver behavior by one mechanism. However, according to Munigety and Mathew (2016), this seems to be unachievable, and further research should try alternative approaches for modelling integrated behavior, e.g. mechanics-dynamics theory.

In the next chapter, the research questions for the PhD project are presented. They address a selection of the identified gaps in knowledge.

Chapter 2

Study Objectives

The overall goal of the research work undertaken in this PhD study is:

> *To investigate how the car-following behavior of heavy vehicles differ from that of cars, how external factors affect this behavior, and how to incorporate this knowledge in traditional car-following models.*

There are several gaps in the field of heavy vehicle following behavior and modelling which needs to be addressed. However, it is not possible with the limited resources available in a PhD study to answer all challenges raised in the introduction. Neither is it realistic to aim for developing the next generation of behavioral models. Collecting the vast amount of data for all important vehicle types in all relevant situations and locations would be an exhaustive task for a single PhD study. Additionally, theories would have to be postulated, the data would have to be analysed, and models developed on basis of the theories.

Instead, a subset of the challenges are addressed, with the goal being to improve the understanding of heavy vehicle behavior, and potentially implement some of the findings in a model.

A series of four research questions (RQ) were formulated to structure and further detail the work.

2.1 Presentation of Research Questions

The first three RQs focus on obtaining new knowledge about heavy vehicle following behavior, while the fourth RQ focus on implementing the new knowledge in a modelling framework.

-RQ1 *What is the difference between following behavior for cars and heavy vehicles, and how could this difference be measured?*

-RQ2 *How do road characteristics such as number of lanes, speed limit and traffic flow status affect heavy vehicle following behavior?*

-RQ3 *How do environmental factors such as weather, road surface cover and lighting conditions affect heavy vehicle following behavior?*

-RQ4 *How can we successfully incorporate a selection of new knowledge about heavy vehicle behavior in traditional car-following models?*

The three first RQs are empirical of nature, which implies that a data collection is needed to provide answers. To measure empirical differences between cars and heavy vehicles, variables which describe car-following behavior has to be determined. Already in the introduction, two candidate vaiables were presented, which were time gap and speed difference. These two variables are used to describe car-following behavior in the car-following spirals in Figure 1.1. They are also the main variables in many car-following models, for example Gipps' model (Gipps 1981), where speed is the output from a function where relative speed and gap are variables.

RQ1 *What is the difference between following behavior for cars and heavy vehicles, and how could this difference be measured?*

In an empirical study, the selected variables determines the data collection. To empirically describe car-following behavior, data about car-following needs to be collected. There are several ways to collect data about time gap and vehicle speeds, but the most frequently used are point data, video recorded data and floating car data.

Point data are collected at a specified cross section of a road with a sensor which detects the presence of a vehicle. Data from traffic registration sites are available in large numbers, which gives the possibility of describing car-following behavior accurately. However, each observation is from one vehicle at a time, so that individual temporal fluctuations can not be observed. Also, data from induction loops inhibit some inaccuracy, so that quality control of the data is necessary before use.

Video recorded data are collected from cameras which monitor a limited stretch of road. These recordings can potentially offer information about traffic behavior from a large number of vehicles. Although several techniques exist to

automatically extract data from images, there are some challenges especially for mixed traffic flow conditions, as mentioned in section 1.5.

Floating car data are collected from one vehicle for each data set. The strength of this method is that fluctuations in behavior are readily available for analysis. However, these data sets are expensive to collect because of the time and equipment needed to achieve observations from a representative fleet of drivers. The subject vehicles are also required to have equipment able to detect the speed and position of the leader vehicle to reveal car-following behavior.

Another possible option for data collection is driving simulators. They provide a simulated environment in which a human test subject can drive. The advantages of a driving simulator include safe driving environments, a large span in available simulated scenarios and most importantly a much higher level of data availability. However, driving simulator experiments are associated with high costs, and there is an issue regarding the validity of driving simulators.

So far the methodological approach for the first RQ is established. Car following behavior is observable through variables such as time gap, speed and speed difference, which can be measured either as point data, video recorded data or floating car data, either from real world traffic or driving simulator experiments. For the next two RQs, additional data is required.

RQ2 *How do road characteristics such as number of lanes, speed limit and traffic flow status affect heavy vehicle following behavior?*

There are several possible variables which could influence car-following behavior, as shown in Table 2.1. To study how car-following behavior is affected by every variable presented in Table 2.1, a large amount of data is needed. The NPRA (Norwegian Public Roads Administration) collect data from loop detectors across Norway, but they are usually placed on flat, straight roads (NPRA 2011). This means that additional data collection with mobile detectors is necessary to investigate car-following behavior in grades and curves. If floating car data were to be used, an even larger effort would be needed to collect data for all variables. Only a selection of variables, as presented in the next chapter, are studied in this thesis due to time and financial constraints of the PhD project.

Although the effect of a single variable is interesting, interactions between variables would also be of interest. An example of this is that the presence of congestion may have a different impact on a two-lane road compared to a four-lane road. To analyse all possible interactions calls for a even larger data collection, hence a subset was chosen.

Table 2.1: Road related variables and possible impacts on car-following behavior.

Variable	Description
Grades	The need for engine power to maintain a given speed may increase the speed, especially for heavy vehicles.
Curvature	Due to sideways acceleration and the risk of losing friction, the speed may decrease in curves.
Number of lanes	More than one lane in one direction may complicate the driving task because the driver needs to relate to parallel driving vehicles.
Lane width	Wider lanes may affect the speed sensation, and thus increase the speed level.
Area type	The increased level of traffic on urban roads relative to rural areas, as well as the urban lifestyle in general, may induce a difference in car-following behavior. This may also be the case when comparing a small city with a large city, or even when comparing two cities in different countries.
Speed limit	The speed limit will presumably affect the average speed level.
Traffic state	A congested flow can be characterised as a traffic state with low speed and high density relative to a state of free flow. The presence of many vehicles would presumably be distracting for a driver, removing focus from the car-following task and lead to change in car-following behavior.

Table 2.2: Weather related variables and possible impacts on car-following behavior.

Variable	Description
Precipitation	Rain and snow may interrupt the field of vision, causing lower speeds and increasing time gaps.
Road surface	Wet roads, snow covered roads, and ice covered roads all reduce friction relative to dry roads. This may reduce the speed level and increase vehicle gaps.
Light conditions	The effect of nightfall relative to daylight may also reduce speed and increase gap.
Wind	Strong winds may affect car-following behavior alone, but winds in combination with precipitation may drastically decrease the level of sight.

RQ3 *How do environmental factors such as weather, road surface cover and lighting conditions affect heavy vehicle following behavior?*

While road characteristics are relatively constant, except for e.g. traffic state and varying speed limits, weather and road surface conditions are usually changing. This is especially the case for Nordic countries, where snow and ice is common during winter. Models developed for sunny conditions with a dry road surface are not necessarily applicable for other conditions. Some variables which are related to weather with the possibility of affecting car-following behavior, are shown in Table 2.2.

To answer RQ3, it is not necessary to collect data from several locations, but additional data about weather is required. This means that as long the variables for describing car-following behavior are collected, an additional instrument for collecting simultaneous weather data is needed. Information about the weather conditions are important not only for meteorological purposes, but also for road maintenance. The Norwegian Public Roads Administration (NPRA) monitors several roads where adverse weather may drastically worsen the driving conditions.

As for road characteristics, interacting effects of weather variables will be of interest. Given that all weather situations of interest will occur at one data collection point or by one vehicle, only an extended period of data collection is required. However, interactions between road and weather variables would require a data collection from multiple sites with both traffic and weather registration equipment.

While the three first RQs are descriptive, the fourth research question calls for

a different approach. Munigety and Mathew (2016) propose two possible ways to achieve a vehicle-dependent movement model. The first way is to modify an existing car-following model by incorporating vehicle-type specific parameters, while the second way is to propose separate models for each vehicle-type based on discrete choice theory. This PhD study will explore the first way by answering the following research question:

RQ4 *How can we successfully incorporate a selection of new knowledge about heavy vehicle behavior in traditional car-following models?*

RQ4 builds on the knowledge obtained through answering RQ1-RQ3, by implementing a selected subset in a car-following model. This approach is to a certain degree dependent on what is actually achieved by answering the three first RQs. It also calls for an exploratory study of car-following models, and how the mechanisms in car-following behavior are affected by vehicle type and characteristics of the road and weather.

When an appropriate car-following model has been selected, then the challenge will be how to implement any new knowledge into an existing model. To make the models suitable for practical use, the large effort of calibrating a model urges any further development to not complicate or increase the calibration procedure.

Together, RQ1-RQ4 form a set of questions which, when answered, will help reach the main goal posted in the beginning of this section.

2.2   Scope and Limitations

Several limitations of scope have already been made in Chapter 1. First, the operational aspects of freight transport are not given attention, only the traffic related aspects. Second, it is mentioned that the focus is on heavy vehicles. This does not however exclude passenger cars from the thesis. It is important to describe heavy vehicle behavior relative to car behavior, as well as studying heavy vehicle behavior in the presence of cars. Third, it is already specified that the focus of the PhD study is on car-following behavior. Although driving is a complex process involving several types of behavior, car-following behavior is the omnipresent behavior. Therefore, behavior involving intersections and lane changes are not in the scope of this PhD project. As shown in Table 1.1, there are 5 main types of car-following models, with several car-following models within each type. The most commonly used model type is "Desired Measure", where Gipps' model is the dominant one. Additionally, Munigety and Mathew (2016) state that this model type is probably the best choice for describing mixed traffic. Therefore it was decided to use Gipps' model as a first choice for the exploratory study.

For the first three RQs, the limitation is generally related to data collection. The limited amount of time and resources in a PhD project means that not all variables presented in Table 2.1 and Table 2.2 may be explored. As mentioned, the collection of floating car data is a resource intensive task, and because there are no other data sets to the authors knowledge which can be used for this purpose, available point data are used. The loop- and WIM- (Weigh In Motion) detectors owned by NPRA are numerous, placed in diverse locations, and most importantly, the data from them are available.

The choice of not collecting floating car data has implications. The first one is that fluctuations in individual longitudinal behavior will not be possible to study. Only observations of vehicles passing over fixed detector locations are available outputs. However, important features of car-following behavior as time gap and speed are measured. Also, this choice of data source comes with a large amount of samples, so that a larger share of the vehicle population is possible to study.

Another implication is that not all desired external variables are possible to include in the data set. A design specification of existing loop detector sites in Norway is to avoid placement in curves or slopes. Loop detectors are generally placed on roads with a high level of traffic, which are roads with high standards, e.g. multiple lanes, high speed limits, and wide lanes. Although there is a large number of detectors placed on other road types, not all combinations of road type variables are represented. This is important when studying the effect of interactions between road variables. Examples of such non-existing combinations of variables are two-lane road with speed limit 100 km/h, and rural four-lane highways with speed limit 40 km/h. Data from these road categories are not available because they do not meet the Norwegian road standards, and in theory does not exists.

As this PhD study focus on the behavior of heavy vehicles, an increased number of data attributes concerning vehicle characteristics would presumably strengthen the study. Ordinary loop detectors usually detect vehicle lengths, but Weigh In Motion (WIM)-detectors detect vehicle weight as well. WIM-detectors are generally used by the NPRA for controlling the weight of vehicles, and are usually placed close to roadside control stations at rural highways. The number of WIM-stations are significantly lower than loop detector sites. Therefore, it may be difficult to gather data from vehicle weights from sites with different road characteristics.

The practical use of car-following models are through microsimulation software developed for practitioners, for instance those mentioned in Table 1.1. It is not in the scope of the PhD study to implement any results or findings in commercial software.

Chapter 3

A Summary of Results from the Papers

To answer the main research goal, four studies were conducted, one for each research question. They were documented through a series of four research papers, and one descriptive paper of a dataset used in one of the main papers. The full text papers can be found in Part II. The work done in the papers are three empirical studies and one case study.

The papers are numbered I to IV for how they match each other thematically, and not necessarily for the order they were written in. The following papers were written as a part of this thesis:

- **Paper I**: Hjelkrem, O. A., 2014. *Vehicle Type Characteristics During Car-Following Behavior.* (Unpublished). The work presented in this paper was done in late 2012. It was submitted in mid 2014 for the 94th Annual Meeting of the Transportation Research Board , where it was not accepted. It has not been submitted anywhere else, primarily because the other papers were prioritized over doing the work needed to improve Paper I.

- **Paper II**: Hjelkrem, O. A., 2015. *Determining Influential Factors on the Threshold of Car-Following Behavior.* This paper was written between late 2013 and mid 2014, when it was submitted for the 94th Annual Meeting of the Transportation Research Board, where it was accepted for presentation.

- **Paper IIIa**: Hjelkrem, O. A., and Ryeng, E. O., 2016. *Chosen risk level during car-following in adverse weather conditions.* Accident Analysis &

Prevention, 95, 227-235. Paper IIIa was written between mid 2014 and mid 2015, when it was submitted to Accident Analysis & Prevention. After a review process it was accepted for publication in mid 2016.

- **Paper IIIb**: Hjelkrem, O.A. and Ryeng, E.O., 2016. *Driver behavior data linked with vehicle, weather, road surface, and daylight data.* Data in Brief (Submitted). This paper was written during the review process of Paper IIIa, and submitted in mid 2016. It is still under review by the journal.

- **Paper IV**: Hjelkrem, O. A. and Nerem, S., 2015. *A Transition from Car-Following to Vehicle-Following Model.* Presented at 22th ITS World Congress, Bordeaux. (Invited and submitted for publishing in International Journal of ITS). The work presented on this paper is based on the thesis written by Sebastian Nerem (Nerem 2013), and builds on the work presented in Paper I. The paper was written between mid 2013 and late 2014, and submitted for the 22th ITS World Congress. It was presented at the congress in 2015. An extended version was submitted to the International Journal of ITS in early 2016, where it is still under review.

Paper I and Paper II were authored solely by Odd André Hjelkrem.

Papers IIIa and IIIb were written by Odd André Hjelkrem and Eirin Olaussen Ryeng. In these papers, Hjelkrem was responsible for the literature study about the impact of weather on vehicle behavior, the data procurement and the statistical analysis. Ryeng was responsible for the literature study about risk theory. The decisions about the goals and methods, and the interpretation of results was a joint effort.

Paper IV was written by Odd André Hjelkrem and Sebastian Nerem. The main idea of the study was conceived by Hjelkrem, while Nerem performed the simulations and the statistical analysis under supervision by Hjelkrem.

3.1   Presentation of Data Sets

Three data sets were collected, one for each empirical study.

The first data set was collected for the study in Paper I from a weigh in motion (WIM) detector at Stamphusmyra on road E6 in Norway. The majority of vehicles travelling between the middle and northern parts of Norway choose this route. The speed limit at the detector was 70 kph, and the road has one lane in each direction. The data attributes available for the study is presented in Table 3.1. Most of these attributes were recorded directly from the detector, but traffic volume and information about the preceding vehicle was added in post processing of the data.

The case study presented in Paper IV was based on the data set and the findings in Paper I.

Table 3.1: Data set used in Paper I and IV. N=669 820.

Attribute	Data type	Range
ID	Integer	1 to 669 820
Timestamp	Text	1.8.2012 to 30.9.2012
Lane	Integer	1 or 2
Speed	Floating point	0 to 173 kph
Length	Integer	112 to 5 201 cm
Gross Weight	Integer	10 to 127 475 kg
Traffic volume	Integer	4 to 1 252 veh/hour/lane
Weight previous vehicle	Integer	0 to 127 475 kg
Number of axles	Integer	2 to 10
Time gap	Integer	27 to 65 535 ms

The second data set was used in the study presented in Paper II. Data was collected from 14 loop detectors in Norway. Unlike the data set for Paper I, this data set did not include vehicle weight. The other data attributes are shown in Table 3.2. Information about traffic flow and the preceding vehicle was added during post processing of the data. The detectors were chosen strategically based on number of lanes, speed limit and area type. A more detailed presentation of the detector properties is given in Paper II.

The third data set is described in Paper IIIb.

Table 3.2: Data set used in Paper II. N=20 827 506.

Attribute	Data type	Range
ID	Integer	139 to 21 155 010
Detector ID	Integer	1 to 14
Timestamp	Text	29.4.2013 to 4.9.2013
Lane	Integer	1 to 6
Speed	Floating point	0 to 180 kph
Length	Floating point	0 to 25.39 m
Leader vehicle ID	Integer	139 to 21 155 009
Leader vehicle speed	Floating point	0 to 180 kph
Leader vehicle length	Floating point	0 to 25.39 m
Traffic volume	Integer	1 to 1 765 veh/hour/lane
Time gap	Integer	0 to 4 294 967 ms

In the following sections, a short description of the studies and their results are given.

3.2   Vehicle Behavioral Differences

RQ1: What is the difference between following behavior for cars and trucks, and how could this difference be measured?

As mentioned previously, time gap and speed difference are two variables describing car-following behavior. These are investigated in both Paper I and Paper II.

Paper I describes how the time gap is affected by vehicle properties during car-following behavior. The data used in Paper I was collected from a WIM-station, and included variables such as time gap, speed, vehicle weight, vehicle length, axle weights, and number of axles. About 670 000 time gaps were collected from a rural two-lane road for the study.

The first analysis in Paper I focused on the difference in time gap between vehicle pairs, as several previous studies had shown that the leader vehicle type is important, not only the follower vehicle. This behavior was investigated on the basis of the collected data, and the results showed that the characteristics of the leader vehicle does not affect the time gap as much as the follower vehicle characteristics. As shown in Figure 3.1, for situations where a truck is the follower vehicle (red lines), the distribution peak is shifted about 0.5 seconds compared to the situations with a car as the follower vehicle (blue lines).

It was further investigated if the time gap varied as a function of vehicle weight. Weight was chosen because it is important for the acceleration capabilities of a vehicle, and should thus affect the time gap choice of the drivers. The results showed that, despite large variations in the chosen time gap, there is a statistical significant, moderate and positive correlation between the weight of a follower vehicle and the time gap. An inspection of the data suggested a log linear regression model, as the time gap increases with weight up to a weight of about 20 tonnes, and then flattens out for further increasing weight. The difference in median time gap for cars and trucks is about 0.5 seconds when the truck has a weight of 20 tonnes or more. This relationship is illustrated in Figure 3.2.

Paper II also investigated the differences between cars and trucks. However, the variables of interest were slightly different. The aim of the study was to define the threshold of car-following behavior using loop detector data, based on assumptions about vehicle behavior. The first assumption was that in the car-following state, the speed difference fluctuate around a desired gap, as shown in Figure 1.1. For
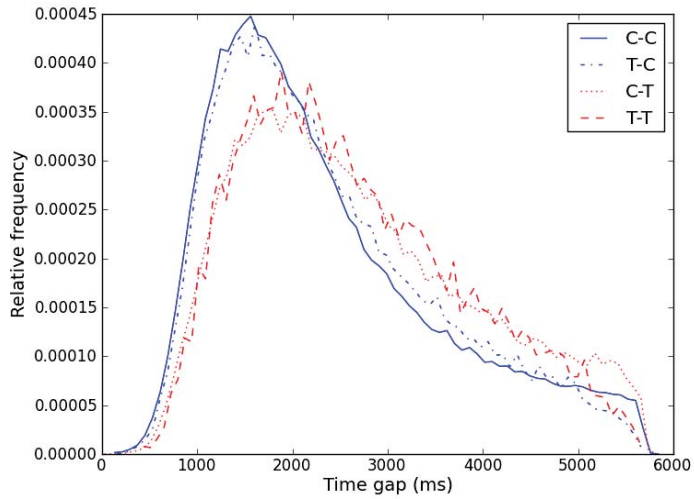
Figure 3.1: Relative frequency of time gaps for vehicle pairs, where C represents cars, and T represents trucks.
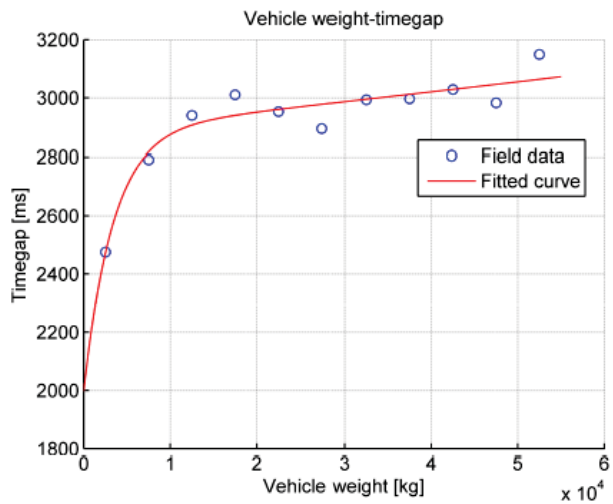
Figure 3.2: The relationship between average time gap and following vehicle weight.

gaps higher than the desired gap, the follower will increase the relative speed to reduce the gap. For lower gaps, the speed difference will be the opposite, because the driver will try to increase the gap. The second assumption was that vehicles have a desired speed choice. Eventually, a free flowing vehicle will catch up a leader vehicle with a lower desired speed, and thus have a higher relative speed while in a state of free flow. Vehicles with a lower desired speed than its leader, will at one point change from a car-following state to a state of free flow. Because the gap is increasing, the relative speed difference must be negative during this phase transition.

By investigating about 20 million observations, the threshold value and the desired speed were determined. The analyses were done separately for cars and trucks, and showed that the car-following behavior differed greatly between cars and trucks. Figure 3.3 displays the average speed difference for time gap values between 0 and 25 seconds, with one observation for each 0.1 seconds. The green shaded area was identified as the car-following state, and the threshold value was found to be on average 3.9 seconds for cars and 5.8 seconds for trucks, which conformed with other studies.
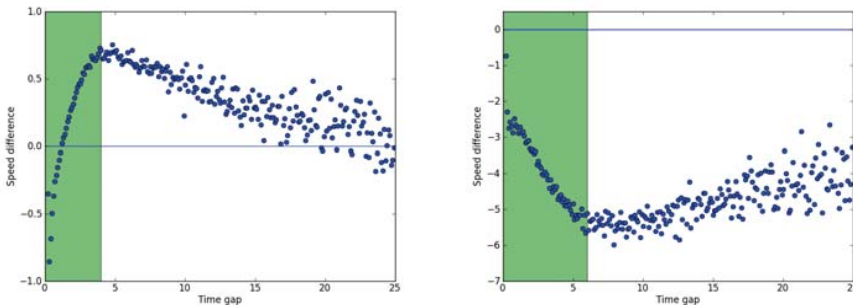
Figure 3.3: Speed difference between follower and leader as a function of time gap for passenger cars (left) and heavy vehicles (right). The green area indicates the car-following regime, while the white area indicates the free-flowing regime.

By following the assumptions about car-following behavior, the desired gap was identified as the point where the relative speed is zero. This was found to be 1.1 seconds for passenger cars. The desired gap was not possible to identify for heavy vehicles from Figure 3.3, but a further examination of the relationship between speed difference and time gap in different surroundings led to the identification of desired time gap for trucks in two specific situations. In rural areas, it was found to be 2.0 seconds, and 2.8 seconds in areas with a speed limit of 60 kph. This was the first result indicating showing that road characteristics are important for

car-following behavior.

3.3   How do Surroundings Affect Driver Behavior?

The main goal of Paper II was to find out if road characteristics affected the chosen behavioral variables: car-following threshold and desired gap. This effort was made to answer the second research question:

RQ2: How do road characteristics such as number of lanes, speed limit and traffic flow status affect heavy vehicle following behavior?

The data set used in Paper II consisted of loop detector observations from 16 detectors placed at different places in Norway. They were carefully selected for studying the impact of road characteristics, so that each detection site was unique in terms of the variables presented in Table 3.3.

Table 3.3: Range of variables used in Paper II.

Variable	Levels
Speed limit	60, 70, 80, 90, 100
Area type	Rural, Urban
Number of lanes	2, 4, 6
Traffic state	Uncongested, Congested

In the study, a factorial ANOVA was used to determine how the threshold value varies with area type, number of lanes, and traffic state for cars and trucks, and to determine any interactions between the factors. The speed limit was not included in the analysis because the data coverage was not good enough for all speed limits, and because an inspection of the data showed that the speed limit apparently had no effect on the threshold value.

The results from the ANOVA are presented in Table 3.4. For cars, the number of lanes was the only significant main effect. On two-lane roads, the threshold value was higher than for roads with more than two lanes. However, there were two significant interactions, which were between traffic state and both area type and number of lanes. This implies that in congested traffic, the threshold value will be higher on rural roads or two-lane roads, compared to urban roads or roads with more than two lanes.

For trucks, the only significant main effect was area type, which means that the threshold value for trucks will be higher in urban areas than in rural areas. There was also one significant interaction effect, which was between area type and traffic state. In urban areas, the threshold value was higher in uncongested traffic than in

Table 3.4: Significant results from the full-factorial ANOVA. The dependent variable is the car-following threshold. The level of significance is set to 0.05.

Term	Effect	Coef	SE Coef	T-value	P-value
Passenger cars:					
Constant		3.725	0.091	40.93	0.000
Lanes	-0.75	-0.375	0.091	-4.12	0.015
Area*Traffic State	0.75	0.375	0.091	4.12	0.015
Lanes*Traffic State	0.6	0.3	0.091	3.3	0.03
Heavy vehicles:					
Term	Effect	Coef	SE Coef	T-value	P-value
Constant		4.175	0.0729	57.28	0.000
Area	1.0	0.5	0.0729	6.86	0.002
Area*Traffic State	-0.75	-0.375	0.0729	-5.14	0.007

congested traffic.

This shows that to some extent, car-following characteristics vary with location. However, there might be situations where the behavior varies within one location as well, e.g. during rainfalls and snow storms. This was the topic of the next paper.

3.4   How do Weather Affect Heavy Vehicle Following Behavior?

Paper IIIa describes an empirical study which answered the following RQ:

RQ3: How do environmental factors such as weather, road surface cover and lighting conditions affect heavy vehicle following behavior?

As adverse weather is assumed to increase the risk of driving, the angle of Paper IIIa was to investigate how drivers react to adverse weather by changing their car-following behavior. An index called Chosen Risk Index (*CRI*) was defined as:

$$CRI = \frac{v \cdot w}{TG} \tag{3.1}$$

Here, *v* is vehicle speed, *w* is vehicle weight, and *TG* is the time gap. The *CRI* was calculated for each observation in the dataset, and all observations were grouped in the categories presented in Table 3.5. The main goal of Paper IIIa was to determine how each weather category affected the driver behavior, as well as interacting effects between variables. As the data were categorised, a Generalized Linear Model (GLM) was estimated, and the results were the following:

- Both car and truck drivers perceive the highest risk when driving on snow covered roads.

- For car drivers, a snow covered road in combination with moderate rain or light snow are the factors which lowers the *CRI* the most.

- For trucks, snow cover and partially covered roads significantly lowers the *CRI*

- Precipitation does not seem to affect the chosen risk level of truck drivers.

- Interaction effects were found only for car drivers. The interactions were between road status and both precipitation type and lighting conditions. While the main effects were negative, and thus decreased the *CRI*, almost all interacting terms were positive, and thereby countering the combination of several main effects.

Table 3.5: Range of variables used in Paper IIIa.

Variable	Levels
Precipitation	No preciptiation, Light Rain, Moderate Rain, Heavy Rain, Light Snow, Moderate Snow, Heavy snow
Road surface status	Dry, Wet, Snow covered, Partially snow covered
Daylight condition	Daylight, Night, Twilight

These results show that weather has an impact on following behavior. Although the *CRI* is designed to express chosen risk, it is composed of factors such as time gap and speed, which expresses car-following behavior.

The combined results from Paper I, II and IIIa comprised a new understanding of heavy vehicle following behavior. The next challenge was be to incorporate parts of this knowledge in a car-following model.

3.5   A Vehicle-Following Model

So far, several properties about heavy vehicle behavior has been shown. A subset of these have been selected for a case study to answer the final research question:

RQ4: How can we successfully incorporate a selection of new knowledge about heavy vehicle behavior in traditional car-following models?

Paper IV describes a case study where the main goal was to improve car-following models for heterogeneous traffic flow. This was done by modifying Gipps' car-following model (Gipps 1981) in order for it to better reproduce

observed behavior in heterogeneous traffic, and to reduce the calibration effort. Gipps' car-following model was published in 1982, as a model with two regimes, free flow and car-following behavior. In the car-following regime, it describes the behavior of a follower vehicle given the changes in behavior of the leader vehicle. The mathematical equation for Gipps' model in the car-following regime is expressed as the speed of vehicle n at time $t + \tau$, where τ is the reaction time of vehicle n, as:

$$v_n(t + \tau) = b_n\tau + [b_n^2\tau^2 - b_n(2(x_{n-1}(t) - s_{n-1} - x_n(t)) - v_n(t)\tau - v_{n-1}^2(t)/\hat{b})]^{0.5} \tag{3.2}$$

Here,

- b_n is the most severe braking that the driver of vehicle n wishes to undertake $(b_n < 0)$

- $x_{n-1}(t)$ is the position of the front of vehicle $n - 1$ at time t

- s_n is the effective size of vehicle n (vehicle length plus an imagined safety distance)

- vehicle $n - 1$ is the preceding vehicle

- $\hat{b}$ is the estimated deceleration of vehicle $n - 1$

In Paper IV, several choices were made to improve Equation 3.2 to better incorporate vehicle behavior without increasing the calibration effort. It was chosen to include a parameter γ, which was determined on the basis of the vehicle weight by a double exponential function:

$$\gamma_n = c_1 e^{c_2 GVW_n} + c_3 e^{c_4 GVW_n} \tag{3.3}$$

Here, c_1, c_2, c_3 and c_4 are coefficients which where calibrated, and GVW_n is the gross vehicle weight of vehicle n. The coefficients in Equation 3.3 was determined by fitting a curve to the observations plotted in Figure 3.2. The parameter γ was incorporated in Gipps' model by multiplying it with the deceleration parameters for vehicles n and $n-1$. It was assumed that the relationship between time gap and deceleration properties were the same shape as the relationship found in Equation 3.3, because drivers with low deceleration presumably maintain higher time gaps. The modified Gipps' model was expressed in the following way:

$$v_n(t + \tau) = \gamma_n b_n \tau + [(\gamma_n b_n)^2 \tau^2 - \gamma_n b_n (2(x_{n-1}(t) - s_{n-1} -$$
$$x_n(t)) - v_n(t)\tau - v_{n-1}^2(t)/(\gamma_{n-1}\hat{b}))]^{0.5} \tag{3.4}$$

Here, γ_n is the GVW-coefficient of vehicle n and γ_{n-1} is the estimated GVW-coefficient of vehicle $n-1$. The inclusion of γ has the advantage of having only one set of parameters for all vehicles in the model, instead of calibrating a set of all parameters in Equation 3.2 for each vehicle type.

A simulation environment was programmed in MATLAB, and the car-following models presented in equations 3.2 and 3.4 were simulated on a straight road section. The time gap distributions observed in the field was successfully reproduced by both models. Indeed, the distributions measured with the modified model was a slightly better fit than the original model.

From the study in Paper IV, two main conclusions can be made. First, the calibration workload is significantly reduced, and the reduction is greater for each additional vehicle type included in a simulation with Gipps' original model. Second, the modified model reproduced the time gap distributions measured in the field slightly better than the original model.

Chapter 4

Concluding Remarks

The main research goal:

> *To investigate how the car-following behavior of heavy vehicles differ from that of cars, how external factors affect this behavior, and how to incorporate this knowledge in traditional car-following models.*

and the related research questions were answered through the five papers produced during this PhD project. The behavior of heavy vehicles was examined, compared to the behavior of cars, with variation in external conditions. Finally, some of this knowledge was implemented in Gipps' car-following model.

4.1   Contribution of the PhD Project

By answering the research questions, several contributions to the state of the art were made. As described in Chapter 1, there is limited knowledge about heavy vehicle behavior. The PhD project described new aspects of the following behavior of heavy vehicles. As the previous studies focused on vehicle types at often only one location, without any variation in weather, the results from the PhD project contributed with new knowledge about how vehicle parameters influence behavior, and how the car-following behavior is affected by external factors.

As for the modelling of heavy vehicle behavior, the PhD study investigated if it is possible to change car-following models to better incorporate multiple vehicle types, without increasing the calibration effort.   The results from the MULTITUDE project showed that practitioners rarely follow guidelines for calibrating microsimulation models, and that some even skip the calibration

entirely (Antoniou et al. 2014). With several vehicle types present, the workload traditionally increases, which could lead to an even higher percentage of practitioners not calibrating their models. The work done in this PhD study showed that it is possible to decrease the number of parameters, and still be able to model heterogeneous traffic. A simpler calibration task may help to convince more practitioners to calibrate their models.

4.2   Topics for Future Research

The three first studies were empirical, and could therefore be replicated and extended by collecting more data. Some variables were found to be particularly interesting, and should be subjected to more research. The majority of the data collected for this PhD study were from uncongested traffic flows. It may be that the effect of congestion would lead to other results as demonstrated in Paper II, and could therefore be topics for further research. With an extended data collection, other external properties such as road curvature could have been examined. If WIM-detectors were more common, the variables studied in Paper I could have been examined for varying road and weather characteristics as well.

For all research questions about vehicle following behavior, floating car data could have been used as a supplementary data set. This type of data could have given information about the fluctuation of speed for individual drivers. As the acceleration capability is related to vehicle weight, it is likely that smaller fluctuations in speed will be observed for heavier vehicles. Floating car data have traditionally been very expensive to collect in a large scale, as they require vehicles to be instrumented with hardware for detecting, storing and communicating data. With the development of vehicle technology, modern vehicles are being equipped with more sensors, more computing power, and more advanced solutions for communication. If these technologies could have been used to collect data about driver behavior, then floating car data would become more available for research.

Paper IV demonstrated that it is possible to reduce the calibration effort and still achieve acceptable results. There are several key issues which are important to look further into, e.g. the relationship between vehicle characteristics and behavior in order to build better models. Further research should also be done to investigate how the findings from Paper II and Paper IIIa could be incorporated in a behavioral model.

4.3   The Future of Car-Following Models

The MULTITUDE project revealed that only 45 percent of practitioners calibrate their models according to known guidelines. This clearly states that models needs to be improved, in a sense that they need to be easier to use, but still capture important behavioral properties. Several efforts could be made, such as reducing the number of parameters needed for calibration, or improving the guidelines for calibrations. Targeted models could be made for specific conditions, such as different area and road types, or even for changing weather situations.

The world has seen the first autonomous vehicles driving in regular traffic, and it has been predicted that vehicles with human drivers will be extinct in a few decades (Litman 2015). In this case, car-following models predicting human driver behavior will be of no use. Until this happen, there are more than 1 billion vehicles worldwide today (Sperling and Gordon 2009). In the transitional period, there will be a mix of autonomous and conventional vehicles. Knowledge of driver behavior is still important for practitioners modelling traffic flows, but equally as important for designing algorithms for the autonomous cars. They need to know how other drivers behave to predict how adjacent vehicles will behave.

Bibliography

Aghabayk, C., Sarvi, M., and Young, W. (2012). Effective variables on following behaviour of heavy vehicle drivers. In *35th Australasian Transport Research Forum (ATRF)*.

Aghabayk, K., Sarvi, M., Forouzideh, N., and Young, W. (2013). New car-following model considering impacts of multiple lead vehicle types. *Transportation Research Record: Journal of the Transportation Research Board*, 2390(1):131–137.

Al-Kaisy, A., Jung, Y., and Rakha, H. (2005). Developing passenger car equivalency factors for heavy vehicles during congestion. *Journal of Transportation Engineering*, 131(7):514–523.

Alexiadis, V., Jeannotte, K., and Chandra, A. (2004). Traffic analysis toolbox volume I: Traffic analysis tools primer. Report No. FHWA-HRT-04-038.

Antoniou, C., Barceló, J., Brackstone, M., Celikoglu, H., Ciuffo, B., Punzo, V., Sykes, P., Toledo, T., Vortisch, P., and Wagner, P. (2014). Traffic simulation: case for guidelines. *Publications Office of the European Union*.

Anya, A., Rouphail, N., Frey, H., and Schroeder, B. (2014). Application of aimsun microsimulation model to estimate emissions on signalized arterial corridors. *Transportation Research Record*, (2428):75–86.

Arasan, V. T. and Dhivya, G. (2010). Simulation of highly heterogeneous traffic flow characteristics. In *Proceedings from 24th European Conference on Modelling and Simulation (ECMS)*, pages 81–87.

Arasan, V. T. and Koshy, R. Z. (2005). Methodology for modeling highly

heterogeneous traffic flow. *Journal of Transportation Engineering*, 131(7):544–551.

Benekohal, R. and Treiterer, J. (1988). Carsim: Car-following model for simulation of traffic in normal and stop-and-go conditions. *Transportation Research Record*, (1194):99–111.

Brackstone, M., Waterson, B., and McDonald, M. (2009). Determinants of following headway in congested traffic. *Transportation Research Part F: Traffic Psychology and Behaviour*, 12(2):131–142.

Capros, P., De Vita, A., Tasios, N., Papadopoulos, D., Siskos, P., Apostolaki, E., Zampara, M., Paroussos, L., Fragiadakis, K., Kouvaritakis, N., et al. (2013). EU energy, transport and GHG emissions: Trends to 2050, reference scenario 2013. Technical Report Publications Office of the European Union.

Ceder, A. and May, A. D. (1976). Further evaluation of single-and two-regime traffic flow models. *Transportation Research Record*, (567):1–15.

Chandler, R. E., Herman, R., and Montroll, E. W. (1958). Traffic dynamics: studies in car following. *Operations Research*, 6(2):165–184.

Chen, B. (2014). Application of transport hybrid modelling for new town planning. In *Proceedings from Australian Institute of Traffic Planning and Management (AITPM) National Conference, 2014, Adelaide, South Australia, Australia*.

Daganzo, C. F. and Laval, J. A. (2005). On the numerical treatment of moving bottlenecks. *Transportation Research Part B: Methodological*, 39(1):31–46.

de Pont, J., Charlton, S., Latto, D., and Baas, P. (2004). Heavy vehicle speed through curves. In *International symposium on heavy vehicle weights and dimensions, Muldersdrift, South Africa*.

Di Cristoforo, R., Hood, C., and Sweatman, P. F. (2004). Acceleration and deceleration testing of combination vehicles. Report to Main Roads Western Australia, Document Number RUS-04-1075-01-05.

Dowling, R., Skabardonis, A., and Alexiadis, V. (2004). Traffic analysis toolbox: volume III: Guidelines for applying traffic microsimulation modeling software. Report No. FHWA-HRT-04-040.

European Commission (2007). Freight transport logistics action plan. Technical report.

European Commission (2015a). Fact-finding studies in support of the development of an eu strategy for freight transport logistics lot 1: Analysis of the eu logistics sector. Technical report.

European Commission (2015b). Traffic safety basic facts on heavy goods vehicles and buses. Technical report.

Fry, J. C., Woolley, J. E., and Taylor, M. A. P. (2002). A microsimulation model of truck speeds on grades. In *Canadian Society of Civil Engineers 30th Annual Conference Proceedings*.

Fwa, T. F. (2005). *The handbook of highway engineering*. CRC Press.

Gazis, D. C., Herman, R., and Rothery, R. W. (1961). Nonlinear follow-the-leader models of traffic flow. *Operations Research*, 9(4):545–567.

Gipps, P. G. (1981). A behavioural car-following model for computer simulation. *Transportation Research Part B: Methodological*, 15(2):105–111.

Greenshields, B. D. (1935). A study of traffic capacity. In *Highway Research Board Proceedings*.

Gunay, B. (2007). Car following theory with lateral discomfort. *Transportation Research Part B: Methodological*, 41(7):722–735.

Hagman, R. and Amundsen, A. (2013). Exhaust emissions from vehicles with euro 6/vi technology. *Institute of transport economics, Report*, 1259.

Hashim, W., Arshad, A., Mustafa, M., and Kamaluddin, N. (2014). Heavy vehicles-cars interaction behavior for urban expressways. *Australian Journal of Basic & Applied Sciences*, 8(5).

Hourdakis, J., Michalopoulos, P., and Kottommannil, J. (2003). Practical procedure for calibrating microscopic traffic simulation models. *Transportation Research Record*, 1852(-1):130–139.

Kanagaraj, V., Asaithambi, G., Kumar, C. N., Srinivasan, K. K., and Sivanandan, R. (2013). Evaluation of different vehicle following models under mixed traffic conditions. *Procedia-Social and Behavioral Sciences*, 104:390–401.

Khaki, A. M. and Pour, P. J. H. (2014). The impacts of traffic signal timings optimization on reducing vehicle emissions and fuel consumption by aimsun and synchro software's (case study: Tehran intersections). *International Journal of Civil & Structural Engineering*, 5(2):144–154.

Kikuchi, S. and Chakroborty, P. (1992). Car-following model based on fuzzy inference system. *Transportation Research Record*, pages 82–91.

Kolshus, K. E. (2015). Samferdsel og miljø 2015: utvalgte indikatorer for samferdselssektoren. Report 2015/34 from Statistics Norway.

Kometani, E. and Sasaki, T. (1958). On the stability of traffic flow (report-I). *Operations Research Japan*, 2(1):11–26.

Kosonen, I. (1999). Hutsim-urban traffic simulation and control model: principles and applications. Ph.D. Thesis, Helsinki University of Technology.

Litman, T. (2015). Autonomous vehicle implementation predictions: Implications for transport planning. In *Transportation Research Board 94th Annual Meeting*, number 15-3326.

Maibach, M., Schreyer, C., Sutter, D., Van Essen, H., Boon, B., Smokers, R., Schroten, A., Doll, C., Pawlowska, B., and Bak, M. (2008). Handbook on estimation of external costs in the transport sector. *CE Delft*.

Mallikarjuna, C. and Rao, K. R. (2009). Cellular automata model for heterogeneous traffic. *Journal of Advanced Transportation*, 43(3):321–345.

Metkari, M., Budhkar, A., and Maurya, A. K. (2013). Development of simulation model for heterogeneous traffic with no lane discipline. *Procedia-Social and Behavioral Sciences*, 104:360–369.

Michaels, R. (1963). Perceptual factors in car following. In *Proceedings of the 2nd International Symposium on the Theory of Road Traffic Flow, OECD*.

Momenian, A. (2013). Influence of syncronizing traffic lights on fuel consumption and air pollution: A simulation by AIMSUN. *Life Science Journal*, 10(6).

Munigety, C. R. and Mathew, T. V. (2016). Towards behavioral modeling of drivers in mixed traffic conditions. *Transportation in Developing Economies*, 2(1):1–20.

Nerem, S. (2013). Vehicle weight in gipps' car-following model. *Masters Thesis. Norwegian University of Science and Technology, Department of Civil and Transport Engineering*.

Newell, G. F. (1961). Nonlinear effects in the dynamics of car following. *Operations Research*, 9(2):209–229.

Ni, D. (2015). *Traffic Flow Theory: Characteristics, Experimental Methods, and Numerical Techniques*. Butterworth-Heinemann.

Nouveliere, L., Stanczyk, D., Dervieux, B., Rabehi, A., Mvome, C., and Pelaud, B. (2012). Headway spacing model for a heavy vehicle based on experimental data. In *Proceedings of the International Heavy Vehicle Symposium Transport Technology (HVTT12)*.

NPRA (2011). Handbook v714: Traffic data guide. *Norwegian Public Roads Administration*.

Ntousakis, I. A., Nikolos, I. K., and Papageorgiou, M. (2015). On microscopic modelling of adaptive cruise control systems. *Transportation Research Procedia*, 6:111–127.

NTP (2013). Nasjonal transportplan 2014-2023, meld. st. 26 (2012âĂŞ2013).

Olstam, J. and Tapani, A. (2011). A review of guidelines for applying traffic simulation to level-of-service analysis. *Procedia - Social and Behavioral Sciences*, 16:771 – 780. 6th International Symposium on Highway Capacity and Quality of Service.

Ortuzar, J. d. D. and Willumsen, L. G. (2011). *Modelling transport*. John Wiley & Sons.

Ossen, S. and Hoogendoorn, S. P. (2011). Heterogeneity in car-following behavior: Theory and empirics. *Transportation Research Part C: Emerging Technologies*, 19(2):182–195.

Pipes, L. A. (1967). Car following models and the fundamental diagram of road traffic. *Transportation Research*, 1(1):21–29.

Ranney, T. A. (1999). Psychological factors that influence car-following and car-following model development. *Transportation Research Part F: Traffic Psychology and Behaviour*, 2(4):213–219.

Ravishankar, K. V. R. and Mathew, T. V. (2011). Vehicle-type dependent car-following model for heterogeneous traffic conditions. *Journal of Transportation Engineering*, 137(11):775–781.

Saifizul, A. A., Yamanaka, H., and Karim, M. R. (2011). Empirical analysis of gross vehicle weight and free flow speed and consideration on its relation with differential speed limit. *Accident Analysis and Prevention*, 43(3):1068–1073.

Sayer, J. R., Mefford, M. L., and Huang, R. W. (2003). The effects of lead-vehicle size on driver following behavior: Is ignorance truly bliss? In *Proceedings of the Second International Driving Symposium on Human Factors in Driver Assessment, Training and Vehicle Design*.

Sperling, D. and Gordon, D. (2009). *Two billion cars: driving toward sustainability*. Oxford University Press.

Transportation Research Board (2010). Highway capacity manual. *National Academy of Sciences*.

Treiber, M., Hennecke, A., and Helbing, D. (2000). Congested traffic states in empirical observations and microscopic simulations. *Phys. Rev. E*, 62:1805–1824.

Weng, J., Meng, Q., and Fwa, T. F. (2013). Vehicle headway distribution in work zones. *Transportmetrica A: Transport Science*, 10(4):285–303.

Wiedemann, R. (1974). Simulation des straßenverkehrsflusses. schriftenreihe heft 8. *Institute for Transportation Science, University of Karlsruhe, Germany*.

Wood, D. P. (1997). Safety and the car size effect: a fundamental explanation. *Accident Analysis & Prevention*, 29(2):139–151.

Ye, F. and Zhang, Y. (2009). Vehicle type-specific headway analysis using freeway traffic data. *Transportation Research Record*, 2124(1):222–230.

Zefreh, M. M., Torok, A., Mandoki, P., and Toth, J. (2015). Maneuvers analysis of shared taxi and their effects on flow characteristics. In *Proceedings from International Conference on Models and Technologies for Intelligent Transportation Systems (MT-ITS)*, pages 328–331. IEEE.

Part II

Papers

Chapter 5

Paper I

Unpublished

Vehicle Type Characteristics During Car-Following Behavior

Odd Andre Hjelkrem

Abstract

In this study, the relationship between time gap and gross vehicle weight (GVW) during car-following is investigated. Data for the study was collected using a weigh in motion detector on a two-lane road in Norway. The effect of leader and follower vehicle type is examined, both on a continuous weight scale and for vehicle categories. A log-linear regression model is used to infer a relationship between time gap and the properties of the follower vehicle. The results show a significant relationship between time gap and follower GVW. Heavy vehicle drivers tend to maintain a larger gap in order to compensate for lesser braking ability. The weight of the leader vehicle does not seem to affect the time gap chosen by the following driver. These results may affect the design of car-following models.

Keywords: Car-Following, Heterogeneous flow, Traffic flow characteristics, Weigh in Motion

1   Introduction

A frequently used type of traffic models are microscopic simulation models, which model individual vehicles. They consist of several behavioral models for each type of behavior, with car-following models for modelling the interaction between succeeding vehicles. For car-following models, the time gap is an important variable, as the follower vehicle will relate to the rear of the leader vehicle. If the time gap is large enough, the follower vehicle will stop considering the actions of the leader vehicle, and there will be no interaction between them. This is defined as the threshold between the car-following regime and the free flow regime. Reiter (1994) estimates that the threshold is at 2 seconds, The Highway Capacity Manual estimates it to be 3 seconds (Transportation Research Board, 2000), Hoban (1983) and Rahman and Lownes (2012) recommend a value of 4 seconds, Gattis et al. (1997) use a threshold value of 5 seconds, while Al-Kaisy and Karjala (2010) and Vogel (2002) estimate a value of 6 seconds.

While in a state of car-following, a driver will adjust the time gap by controlling the accelerator and brake pedals depending on the behavior of the preceding vehicle. For a follower, the continuous process of choosing a gap is mainly a compromise between two events. If the gap is too short, the risk of a rear-end collision increases. The other event is the urge to drive with the same speed as or faster speed than the leader. If the urge is not present, the time gap between the follower and leader will eventually reach a point where the car following behavior is replaced by free flow behavior.

Empirical based knowledge of time gap distributions is important in order to establish and verify vehicle behavior models. Several factors may influence a drivers choice of time gap, for example speed, traffic flow, weather, road geometry, vehicle type and driver preferences. A study by Brackstone et al. (2009) suggest that vehicle type may influence the choice of headway during car-following, and found evidence for drivers following closer behind trucks than cars. Sayer et al. (2003) have also studied the effect of vehicle type on time gap. They found that passenger cars kept a larger gap with cars as the leader vehicle as opposed to light trucks as leader vehicle type. Ossen and Hoogendoorn (2011) studied the heterogeneous car-following behavior of cars and trucks, and found indications that passenger cars have lower desired headways when following a truck as opposed to following a car. The difference in time headway distributions between vehicle types has been investigated by Ye and Zhang (2009) and Weng et al. (2014), where vehicles were classified according to length and/or number of axles. They found that trucks tend to keep longer headways than cars.

When performing analyses of transport systems with a significant share of heavy vehicles, it is important to understand how heavy vehicles affect the traffic flow. Peeta and Zhou (2005) argued that heavy vehicles can significantly affect the capacity and safety due to their physical and dynamical appearance. Regarding the car-following process, heavy vehicles may behave different than cars because of the larger GVW. A heavy loaded truck will normally have lesser deceleration abilities than a car or an empty truck. This is shown empirically by Di Cristoforo et al. (2004), who have done acceleration and deceleration tests of heavy loaded vehicles and found that the stopping distance increases with GVW. This means that the heavier the vehicle, the larger the time headway should be in order to avoid collisions. Some research has been done describing the relationship between GVW and driver behavior. Saifizul et al. (2011) describe the relationship between vehicle speed and GVW, showing that heavy vehicles tend to keep lower speeds. The relationship between time headway or time gap and GVW has to our knowledge not been analysed by other authors.

The main purpose of the study reported in this paper was to determine how the GVW of a vehicle affects the time gap. This was done by first examining the effect of vehicle type in leader follower pairs, to compare with the results reported by Brackstone et al. (2009), Sayer et al. (2003), Ossen and Hoogendoorn (2011), Ye and Zhang (2009) and Weng et al. (2014) concerning the effect of leader and follower vehicle type. The second part of the study aimed to determine the relationship between follower GVW and time gap. The study was performed by analysing empirical data of time gaps and gross vehicle weights.

2   Data

Time gap is collected by most detection equipment, but the vehicle weight is not a common data collection variable, as the measurement of weight requires more advanced equipment. The detectors need to measure the deflection of the surface in order to estimate the weight, which requires periodically calibration of the sensors.

For this study, data was collected from weigh in motion (WIM) detectors, which use piezoelectric sensors and inductive loops to measure the weight of each axle. The

equipment aggregates the axle readings into vehicle classification and weight. The detector site is located on E6 in Norway, a part of the international E-road network in Europe. There are no horizontal or vertical curves, and no interfering intersections in the proximity of this site. The speed limit is 70 kph.

A total of 669 820 gaps were measured in the registration period, covering August and September in 2012. The relationship between speed and traffic volume in each lane for 15 minute intervals is shown in Figure 1. The traffic volume in the 15 minute intervals varied between 0 and 1250 vehicles per hour per lane. It is apparent that there were no detected traffic jams.
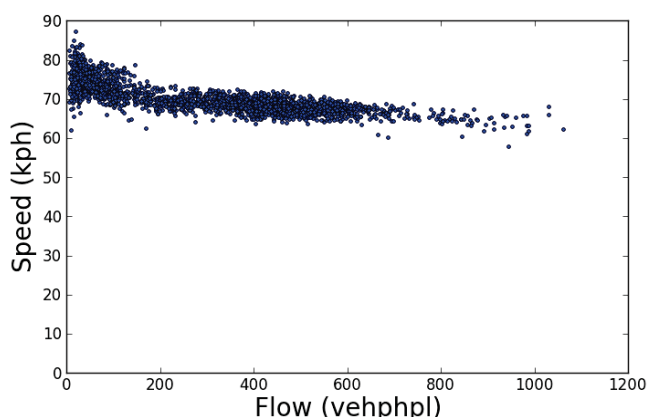
Fig. 1. Speed flow relationship of the detection period.

For the remainder of this study, the terms truck and car are used for vehicles above or below 3500 kg. With C and T representing car and truck, four leader-follower vehicle pairs C-C, T-C, C-T, and T-T can be defined. The leader vehicle type is the first character. 15 percent of the time gaps were recorded with a truck as the follower vehicle, with 59 percent of the trucks weighing less than 15 000 kg. The maximum allowed GVW on Norwegian roads is 50 000 kg, but there were some observations of even heavier vehicles. This can be explained either by vehicles ignoring weight limits, or by data error. All observations of GVW exceeding 50 000 kg were excluded from the data set.

In addition to detecting the time gap, GVW, length and axle loads of each vehicle, information about the preceding vehicle was stored for each detection event. This enables the possibility of investigating how the characteristics of the leader and follower vehicle affect time gaps during car-following behavior. 67 percent of the gaps were below 6 seconds, which is used as the threshold for car-following behavior in this study. Time gaps over 6 seconds are not used in the analysis, as only car-following behavior is

investigated. The threshold value of 6 seconds is based on the studies mentioned in the introduction, which reported values for the threshold to be between 2 and 6 seconds. By setting the value to 6 seconds, most of the occurrences of car-following behavior are included in the data set, but the risk of including vehicles in a free flow regime is present.

A summary of the data included in the study is shown in Figure 2, where the average time gap is plotted by contours as a function of leader GVW and follower GVW. The plot is produced by sorting leader and follower vehicle GVW into cells, forming a grid, and then calculating the average time gap for each cell in the grid. As most of the vehicles were cars, the number of observations decrease for increasing leader and follower vehicle GVW. In order to get enough observations in the cells in the top right corner of the grid, a cell width of 12 500 kg was necessary. The first cell row was restricted upwards to a GVW of 3500 kg, so that the differences between cars and trucks were not masked by unfortunate cell size. By arranging vehicle types in leader-follower pairs, the four distinct vehicle pairs were marked in the figure.
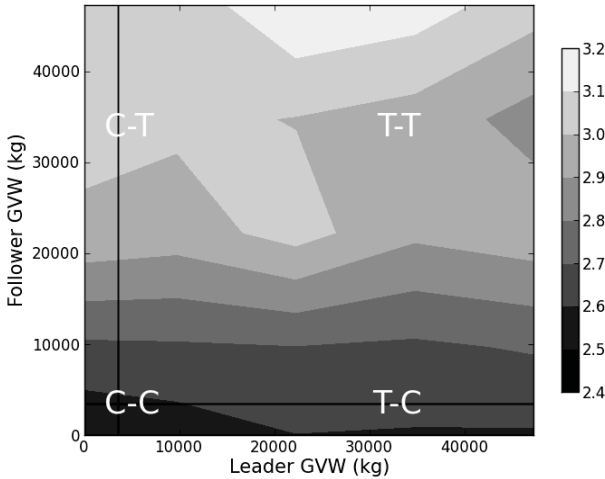

Fig. 2. Mean time gap during car-following with leader and follower GVW. The limit between car and truck at 3500 kg is drawn for both leader and follower vehicle. The color scale is time gap (s).

3 Data Analysis

The contour plot in Figure 2 form the basis for the analysis in this study, because it demonstrates the car-following behavior of vehicles by both leader and follower GVW. By examining the plot, several observations can be made.

First, we see that leader GVW seems to be less important for time gap. The contours are close to horizontal, especially in the region with low follower GVW. This suggests that in a car-following process, the follower does not care about the leader vehicle type when deciding the gap. In the region with high leader GVW, the contours tend to deviate from the horizontal pattern.

Second, we see that the average time gap increases for increasing follower GVW, regardless of leader GVW. This shows that the follower vehicle GVW is an important factor concerning the car-following behavior. The heavier the vehicle is, the larger the average time gap will be. This implies that the drivers of trucks compensate for their high weight by increasing the distance to the leader vehicle, regardless of the leader vehicle type.

Third, we see that the contour lines are denser for low GVW than for high GVW. There seems to be a boundary at about 20 000 kg, implying that the differences in time gap for follower GVW over this boundary are small. This suggests a non-linear relationship between time gap and follower GVW.

These observations are further analysed in the study. The analysis is divided into two parts, where the first part investigates further the impact of vehicle type on time gap, and the second part investigates the impact of follower GVW on time gap.

3.1 The impact of vehicle type on time gap

When observing the contours in Figure 2, it seems as the leader vehicle type is not relevant. However, the contours are based on average values, and may therefore conceal some of the properties of time gaps. The distributions of time gaps sorted by vehicle type are therefore further examined in this section to see if the observations derived from the contour plot are correct.

The total number of detected time gaps for each vehicle pair is shown in Table 1. The frequency of observations for C-C is larger than the frequency of other vehicle pairs, as expected. The table shows that approximately one quarter of all observed time gaps include at least one truck. It also tells us that most of the observations in Figure 2 are close to the edges of the contour plot, with either the follower or leader vehicle GVW below 3500 kg. Thus, the majority of the area in the contour plot is based on the 10486 observations of T-T.

Table 1. Number of observations and median of each vehicle pair.

	C-C	T-C	C-T	T-T
N	316694	51176	43840	10486
Median time gap (ms)	2.10	2.16	2.52	2.50
Mean time gap (ms)	2.40	2.42	2.74	2.68

A histogram of the distribution of time gaps for each vehicle pair is shown in Figure 3. Because of the difference in number of observations between vehicle pairs, the scale of the histograms of time gaps in each category was incomparable. They have therefore been normalised to show the relative frequency instead of observed frequency in order to compare the four distributions. The number of bins are calculated using the Freedman−Diaconis rule (Freedman and Diaconis, 1981) for the T-T vehicle pairs , resulting in 74 bins. The relative frequency is found by dividing the number of observations in each bin by the bin width and the total number of observations in the histogram. The lines in Figure 3 are drawn between the top of each bin in each histogram for the sake of comparison.

Figure 3 clearly show the difference between car as follower vehicle and truck as follower vehicle. The plotted lines for C-C and T-C are almost identical, the same applies for C-T and T-T. As shown in Table 1, the difference in median time gap is about 0.4 seconds for car and truck as follower vehicle, while the difference in mean time gap is somewhat smaller. This supports the assumption of trucks having larger time gaps than cars.
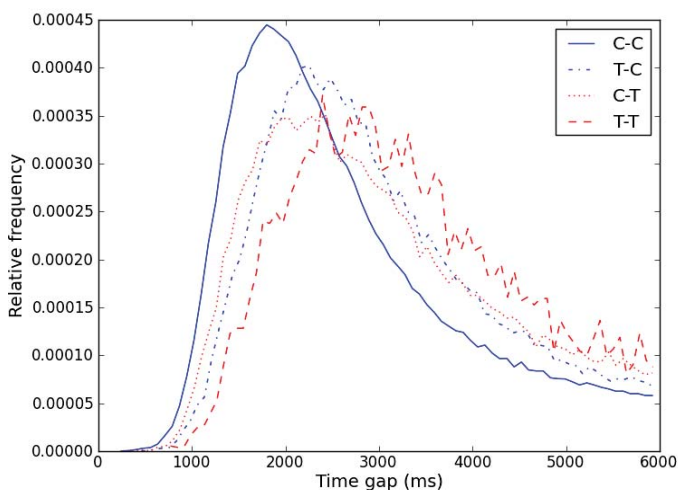
Fig. 3. Histogram of time gaps during car-following for all vehicle pairs.

These results indicate a difference in driver behavior for cars and trucks. The next step of the analysis is to further examine this relationship by analysing the car-following behavior on a continuous scale of follower vehicle GVW.

3.2   The relationship between follower GVW and time gap.

Plotting all the data points reveals no obvious correlation between GVW and time gap, as one would expect. This is shown in Figure 4. It is in the nature of time gaps that trucks may have small time gaps, and cars may have large time gaps. The correlation coefficient for the relationship between time gap and GVW is 0.102, which indicates a low correlation between the two variables. The p-value of the correlation analysis is however less than 0.001, which supports a rejection of the null hypothesis that the calculated correlation coefficient is from an uncorrelated set.
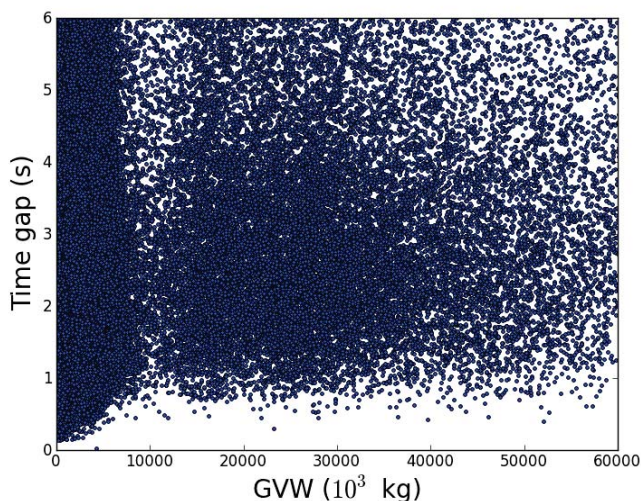
Fig. 4. Scatter plot of observed time gap and GVW.

In order to continue the analysis, the data was categorised to filter out the noise in the data. The observations were sorted into categories of GVW to investigate the relationship between median time gap and GVW. The question of the width of the weight categories then arises. In order to avoid unfortunate category width, the width is varied between 100 kg to 10 000 kg, while the relationship between median time gap and GVW is tested for correlation for each category. The results are shown in Table 2. It is clear that there exists a high correlation between median time gap and GVW. For weight categories of 100 kg, the correlation coefficient is about 0.5, which increases to about 0.9 for weight categories of 10 000 kg. The p-values for all the calculated coefficients are well below 0.001 for weight categories of 2500 kg and smaller, which means that there is a high probability for a correlation between median time gap and GVW. The p-value increases slightly for the two highest weight categories, but are still

significant at a 0.05 level.

Table 2. Correlation coefficient and p-value for correlation between time gap and GVW, for different weight category widths.

Width (kg)	Correlation coefficient	p-value
100	0.519	< 0.001
500	0.741	< 0.001
1000	0.771	< 0.001
2500	0.825	< 0.001
5000	0.821	0.00105
10000	0.846	0.0336

This motivates a further analysis of the data by performing a regression analysis, which will describe the relationship between time gap and GVW. Before a regression model could be fitted, the data was visually analysed to see if there could be a linear relationship. As seen in Figure 4, it is impossible to determine a relationship based on a plot of each pair of data. Figure 2 suggests an approximately linear relationship for follower GVW up to 20 000 kg, followed by a change in slope for higher follower GVW. This may indicate a polynomial relationship.

A linear regression model describe the data with the following equation

$$y = \alpha + \beta x, \tag{1}$$

where α and β are constants to be determined. In the case of a non-linear relationship, a polynomial relation between the variables may be appropriate:

$$y = \alpha x^{\beta}. \tag{2}$$

In order to perform a linear regression of a polynomial relationship, the data has to be transformed from polynomial to linear, which can be done using the following logarithmic transform:

$$y^* = \alpha^* + \beta x^*, \tag{3}$$

where $y^* = \log y$, $\alpha^* = \log \alpha$ and $x^* = \log x$.

Because of the lack of a theoretical model to explain the relationship, both a linear and polynomial model was fitted to the data. The polynomial model is fitted by transforming the data with a logarithmic transform. The results from the regression analysis are shown in Table 3. First, all single observations were included in the regression model. For the linear model, the result was a R^2 of 0.0102 and a p-value of less than 0.0001, while the log-linear model was slightly better with a R^2 of 0.0196 and a p-value of less than 0.0001.

Then, a linear and log linear regression model was fitted to median values of time gaps. The width of the weight categories varied from 100 kg to 10000 kg. Table 3 shows the value of the regression coefficients, R^2 and p-value for each regression. The linear regression models fit well to the data, supported by high values of R^2 and low p-values.

Table 3. Values of gradient, y-intercept and R^2 for the log-linear regression at each GVW category width.

Width (kg)	Linear				Log-linear			
	α	β	R^2	p-value	α^*	β	R^2	p-value
All points	2.43	0.000018	0.0102	< 0.0001	-0.0038	0.10208	0.0196	< 0.0001
100	2.3853	0.0000	0.2724	< 0.0001	-0.0043	0.1008	0.3855	< 0.0001
500	2.3607	0.0000	0.5760	< 0.0001	-0.0254	0.1060	0.7536	< 0.0001
1000	2.3579	0.0000	0.6405	< 0.0001	-0.0232	0.1053	0.8160	< 0.0001
2500	2.3908	0.0000	0.7121	< 0.0001	0.0215	0.0952	0.8458	< 0.0001
5000	2.4027	0.0000	0.7107	0.0006	0.0445	0.0896	0.9069	< 0.0001
10000	2.3001	0.0000	0.7441	0.0270	-0.0014	0.0996	0.9494	0.0010

The log-linear regression models also have high values of R^2 and low p-values. The results show that with a GVW category width of 500 kg, the regression has a R^2 of 0.7536. This means that even for a high resolution of 500 kg, the log-linear model explains about 75 % of the variation in the model. Choosing the best model in Table 3 is a compromise between model detail and model fit. With a category width of 10 000 kg the fit is the best, but the resolution in weight categorization is low. To meet both demands, a category width of 2500 kg is chosen to be the most promising. The data points and regression line for Equation (2) with a category width of 2500 kg is shown in Figure 5. We see that the resulting model fits well to the data. The residuals from the regression analysis is shown in a quantile-quantile plot in Figure 5. They should be on a straight line to exclude unfortunate effects in the regression analysis. There are no evidence for abnormalities in the residuals, which is supported by a R^2 of 0.97.
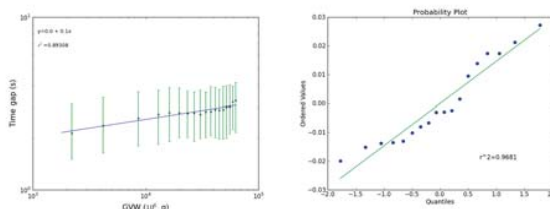
Fig. 5. a) Log-linear regression of time gap vs median GVW for a weight category of 2500 kg. b) Normal probability plot of residuals.

4 Discussion

The results from the analysis give insight to some of the characteristics of car following behavior in heterogeneous traffic. The first observation was that the leader vehicle type does not seem to affect the chosen time gap of the following vehicle. This means that in uncongested traffic flow, it does not make a difference to the chosen time gap whether

a large truck or a small car is the leader vehicle. This is in contrast to the findings reported by Brackstone et al. (2009), Sayer et al. (2003) and Ossen and Hoogendoorn (2011), who stated that the vehicle type of the preceding vehicle will indeed affect the choice of time gap. Their studies suggested that drivers tend to have smaller gaps when following trucks as opposed to following cars. Brackstone et al. (2009) suggested that drivers will increase their gap when following a car because downstream vehicles are visible to the driver. The driver may then adjust the time gap based on information about two or more downstream vehicles, and thus being able to predict the actions of the leader vehicle, which in turn results in a larger gap. When following a truck, it will shadow most of the downstream traffic. Then the follower only needs to take the truck into consideration when determining the gap, which results in a smaller time gap.

There are two main differences between this study and the studies by Brackstone et al. (2009), Sayer et al. (2003) and Ossen and Hoogendoorn (2011). The first difference is the properties of the traffic flow in the collected data. The studies by Brackstone et al. (2009) and Ossen and Hoogendoorn (2011) collected data in congested traffic, while Sayer et al. (2003) did not report the traffic flow during data collection. The data in our study did not cover congested flow. This may explain the differences in the results, if the driver behavior is different in congested and uncongested flow.

The second difference is the type of data collected in the reported studies. Brackstone et al. (2009), Sayer et al. (2003) and Ossen and Hoogendoorn (2011) used floating car data in their analyses, while point data has been used in this study. Floating car data allows the observer to analyse the behavior of vehicles over a certain period of time, but the cost of data collection often only allows a limited sample size of dependent data. Point data captures the behavior of the driver at a certain point in time. This type of data is cheap, and the sample sizes of the data are usually large. The observations are therefore able to describe the behavior for a large span in both leader and follower GVW. Point data are independent, and should therefore be more valid than a limited amount of floating car data.

While the leader vehicle type was found to be of little importance for the chosen gap in this study, the follower vehicle type was clearly important. The average driver will adjust the gap based on the weight of his vehicle, with an increasing gap for increasing GVW. The gap chosen by the driver does in some way reflect the safety distance estimated by the driver, based on the perceived ability to prevent a rear-crash with the leader vehicle. Although GVW is an important factor of the braking distance of a vehicle, the brakes are equally important. The braking system on trucks should be able to function when the truck is fully loaded, and trucks with no cargo should therefore have better braking performance than fully loaded trucks. Thus, we should expect trucks to have higher time gaps at higher load factors. As this study only incorporates GVW, and not the load factor, it is difficult to observe this effect in the data.

The coefficients in the log linear regression model are not easily described theoretically. The unit of α is $\frac{s}{kg}$, and might be interpreted as an internal resistance in the driver behavior, leading to higher gaps for higher GVW. The value of α is about 1, indicating that the dominating effect is from the exponent β, which is dimensionless.

The data from the WIM detectors are not 100 % accurate. Even though the sensors were calibrated before the data collection, there is an error margin in the data, both in gap and weight measurements. Random errors in the data should not affect the

results because of the large number of observations. Systematic errors could affect the absolute values of time gaps and GVW, but should not affect the main results because the time gaps will still increase for increasing vehicle weight. There may also be errors in the classification of vehicles, which may lead to very small headways when a truck is classified as two cars with almost zero time gap. These outliers in the data are believed to have little or no importance for this study, because the median time gap is used in the analysis. The median is not as affected by extreme values as the average. Another result of classification error is extreme weights when two trucks are classified as one huge truck. These values are not included in the study because of the maximum limit of 50 000 kg for vehicle weights. Classification errors might also occur for GVWs lower than 50 000 kg, and add noise to the data analysis. We assume however that the occurrences of these events are not frequent enough to affect the results. This assumption is based on an inspection of the registered axle loadings in the data.

The results are derived from data describing the car following behavior of Norwegian drivers. A similar analysis of data from drivers of other nationalities, or even from other parts of Norway, may yield different results. A study by Sato et al. (2009) found that English drivers were maintaining shorter headways than Japanese drivers. Although the values of time gap might differ between countries, it is not obvious that the relationship between time gap and GVW will. This study suggests that driver behavior is dependent on vehicle properties, and vehicles in Norway are probably not performing very differently from vehicles in other countries.

5   Concluding remarks

Based on an analysis of data collected from weigh in motion detectors in uncongested traffic flow, the following conclusions can be drawn from the work in this paper:

1) The leader vehicle type does not seem to affect the time gap chosen by the follower vehicle.

2) There is a positive correlation between the GVW of a follower vehicle and the time gap.

3) The relationship between time gap and follower GVW can be described by a log linear regression model. This means that the median time gap increases with GVW up to a GVW of about 20 000 kg, and then flattens out for further increasing GVW. The difference in median time gap for cars and trucks is about 0.5 seconds when the truck has a GVW of 20 000 kg or more.

These results are important for the modelling of vehicle behavior. Car-following models should be able to reproduce the results from this study when modelling more than one vehicle type. The relationships found in the study could be used to further develop existing car-following models.

As these results are only valid for uncongested traffic flow, there is a need to investigate further the relationship between time gap and GVW in congested traffic flow. The results from other studies also call for more research in this field.

Other variables may help to further explain the relationships described in this paper. As seen for trucks, there are only small differences in the time gap distributions for vehicles in the range of 20 000 kg to 50 000 kg. In order to examine this effect, detailed data about each vehicle would be necessary, not only the GVW, time headway and traffic volume. With the rapid development of new technology, it is possible to combine a WIM-detector with equipment for automatic number plate recognition (ANPR), which reads the license plate of each vehicle. The registration number of the vehicle can be used to retrieve information about the tare weight and engine power of the vehicle, and then combining the data for new analyses.

References

Al-Kaisy, A. and Karjala, S. (2010). "Car-following interaction and the definition of free-moving vehicles on two-lane rural highways." *Journal of Transportation Engineering*, 136(10), 925–931.

Brackstone, M., Waterson, B., and McDonald, M. (2009). "Determinants of following headway in congested traffic." *Transportation Research Part F: Traffic Psychology and Behaviour*, 12(2), 131–142.

Di Cristoforo, R., Hood, C., and Sweatman, P. F. (2004). "Acceleration and deceleration testing of combination vehicles." *Report No. RUS-04-1075-01-05*, Roaduser Systems PTY LTD.

Freedman, D. and Diaconis, P. (1981). "On the histogram as a density estimator:L2 theory." *Probability Theory and Related Fields*, 57(4), 453–476.

Gattis, J., Alguire, M. S., Townsend, K., and Rao, S. (1997). "Rural two-lane passing headways and platooning." *Transportation Research Record*, 1579(1), 27–34.

Hoban, C. J. (1983). "Towards a review of the concept of level of service for two-lane roads." *Australian Road Research*, 13, 216–218.

Ossen, S. and Hoogendoorn, S. P. (2011). "Heterogeneity in car-following behavior: Theory and empirics." *Transportation Research Part C: Emerging Technologies*, 19(2), 182 – 195.

Peeta, S., P. Z. and Zhou, W. (2005). "Behaviour-based analysis of freeway car-truck interactions and related mitigation strategies." *Transportation Research Part B: Methodological*, 39 (5), 417–451.

Rahman, A. and Lownes, N. E. (2012). "Analysis of rainfall impacts on platooned vehicle spacing and speed." *Transportation Research Part F: Traffic Psychology and Behaviour*, 15(4), 395 – 403.

Reiter, U. (1994). "Empirical studies as basis for traffic flow models." *Proceedings of the second International Symposium on Highway Capacity, Volume 2*.

Saifizul, A. A., Yamanaka, H., and Karim, M. R. (2011). "Empirical analysis of gross vehicle weight and free flow speed and consideration on its relation with differential speed limit." *Accident Analysis and Prevention*, 43(3), 1068 – 1073.

Sato, T., Akamatsu, M., Zheng, P., and McDonald, M. (2009). "Comparison of car following behavior between UK and Japan." *ICCAS-SICE, 2009*, 4155–4160.

Sayer, J. R., Mefford, M. L., and Huang, R. W. (2003). "The effects of lead-vehicle size on driver following behavior: Is ignorance truly bliss?." *Proceedings of the Second International Driving Symposium on Human Factors in Driver Assessment, Training and Vehicle Design*.

Transportation Research Board (2000). "Highway capacity manual." *Washington, DC*.

Vogel, K. (2002). "What characterizes a 'free vehicle' in an urban area?." *Transportation Research Part F: Traffic Psychology and Behaviour*, 5(1), 15 – 29.

Weng, J., Meng, Q., and Fang Fwa, T. (2014). "Vehicle headway distribution in work zones." *Transportmetrica A: Transport Science*, 10(4), 285–303.

Ye, F. and Zhang, Y. (2009). "Vehicle type-specific headway analysis using freeway traffic data." *Transportation Research Record*, 2124, 222–230.

Chapter 6

Paper II

Presented at the Transportation Research Board 94th Annual Meeting, 2015.

DETERMINING INFLUENTIAL FACTORS ON THE THRESHOLD OF CAR-FOLLOWING BEHAVIOUR

Odd A. Hjelkrem (corresponding author)
Department of Civil and Transport Engineering
Norwegian University of Science and Technology
Telephone: (0047) 98482278; E-mail: odd.hjelkrem@ntnu.no

Word count: 4,937 words text + 6 tables/figures x 250 words (each) = 6,437 words

15.11.14

ABSTRACT

In this study, a method for using loop detector data for empirical analysis of car-following behavior is proposed. It is demonstrated that it is possible to define the threshold of car-following behavior. The analysis is done for both passenger cars and heavy vehicles. We find the threshold to be 3.9 seconds for cars and 5.8 seconds for trucks in general. A factorial ANOVA was carried out to determine how this threshold varies with area type, number of lanes, and traffic state for both passenger cars and heavy vehicles, and to determine any interactions between the factors. The method can also be used to determine the desired gap in a car-following regime, which is found to be 1.1 seconds for passenger cars. This value is mostly influenced by the number of lanes and the speed limit. For heavy vehicles, the desired gap is found to be 2.0 seconds in rural areas and 2.8 seconds where the speed limit is 60 kph. These results are important for microscopic traffic simulation models as well as capacity analyzes.

Keywords: Driver behavior, Car-following, Desired time gap

INTRODUCTION

Car-following behavior is a term for the longitudinal interactions between vehicles in a traffic flow. When a vehicle is following another vehicle, the driver will adjust the speed so that a satisfactory time gap is achieved. In traffic simulation models, this behavior is important to model correctly, as it is an important part of driving behavior. A specific type of models, that is car-following models, has been developed for this purpose. There are several types of car-following models, see for example Toledo (1) or Wilson and Ward (2) for a review.

Car-following is a process where the speed and time gap of a follower vehicle changes over time. This means that a driver is not likely to have a constant gap, but rather fluctuate around a desired gap, as demonstrated by e.g. Brackstone and McDonald (3) who analyzed headways from floating car data recorded during car-following. At the desired gap, the speed difference between the follower and leader vehicle will be zero. This is defined as steady-state car-following behavior. Dey and Chandra (4) investigated the desired time gap during steady-state car-following. They simulated traffic on a two lane road, and found that the desired time gap increases for decreasing speed. They also found that heavy vehicles have a larger desired time gap due to their weight and lower braking efficiency.

As pointed out by Toledo (1), there is a need for determining the threshold between free flow and car-following behavior. There have been several attempts for determining this limit, and the results are varying. A study by Reiter (5) found a threshold value of 2 s. Rahman and Lownes (6) reviewed the existing literature and found several threshold values. Based on these values, they decided to use a value of 4 seconds for studying the impact of rain on speed for platooned vehicles. The values they found were 3 seconds (TRB (7)), 4 seconds (Hoban (8)), 5 seconds (Gattis et al. (9)), and 6 seconds (Al-Kaisy and Karjala (10), and Vogel (11)).

The car-following behavior can be affected by both external factors as well as vehicle characteristics. Ayres et al. (12) studied inductive loop data from a four-lane highway in varying traffic flow. They argued that several factors affect the choice of speed and time headway, such as the speed limit, grade, lane size, weather, and driver preferences.

This paper proposes a method for analyzing loop detector data to identify the threshold of car-following behavior, and the desired time gap. The method is applied on data from several different locations, making it possible to investigate potentially influential variables. The purpose of the research is to better understand the car-following process, so that car-following models can be improved.

METHOD

It is assumed that there exists one regime with car-following behavior and one regime with free flow behavior, and that they are different. In the car-following regime, the speed difference between succeeding vehicles is highly correlated to the time gap. For low time gaps, the risk of rear crash is high because of the short distance between the vehicles. The follower will then be at risk of crashing into the leader if the leader performs an emergency brake, and will decrease his speed, resulting in a negative speed difference when defining speed difference as follower speed minus leader speed. It is also expected that there exists a point where the speed difference is zero, indicating a state of desired time gap. For higher time gaps than the desired time gap, the speed difference will have positive values, because of the urge of the follower to reach the desired time gap. At some point, the relationship between speed difference and time gap will be uncorrelated, and this would mark the threshold for car-following behavior. In the free-flow regime there is no

HJELKREM, ODD A.   4

correlation between the speed difference and time gap, simply because the follower is behaving independently of the preceding vehicle. This assumption about the car-following threshold is supported by the work of Vogel (*11*), who used the correlation between vehicle speeds and headway to estimate the threshold between the two regimes.

It is also assumed that the car-following behavior of passenger cars deviates from heavy vehicle car-following behavior. The rationale behind this assumption is that heavy vehicles have different behavior than passenger cars because of the difference in size, acceleration and deceleration capabilities. Some studies show that heavy vehicles keep a larger time gap than passenger cars, e.g. Ye and Zhang (*13*), and Weng et al. (*14*), who studied time headway distributions for different vehicle types. When heavy vehicles are included in microscopic simulation models, they are often treated as a separate vehicle type. This motivates a distinction between passenger cars and heavy vehicles in this study.

Based on these assumptions about car-following behavior, a method is proposed to further investigate the threshold of car-following behavior. The data for the method is collected by inductive loop detectors. The advantages of availability and low cost of collecting point data yields an exciting new way of describing car-following behavior in several different situations. As the time gap and speed difference is the direct outcome of car-following behavior, one is able to describe the result of the process. This is not to be considered as an alternative to floating car data, but however a complementary data source. With floating car data, one can better study the individual variation in car-following behavior. This type of data is however more expensive to collect, especially when the aim is to study how the car-following behavior is affected by independent variables.

The data set was first divided by vehicle type, because of the assumed difference between passenger cars and heavy vehicles. All the vehicles observed in each data set were then grouped into bins of time gap, with a resolution of 0.1 seconds. The average speed difference between the observed vehicle and preceding vehicle was calculated for each time gap bin. The data was further coded by geometric, vehicle and traffic flow properties to examine the car-following behavior in different situations, and inspected to see if the car-following threshold and desired gap was visually recognizable. The factors were then analyzed by a factorial ANOVA to reveal any significant main effects or interactions of the factors 'area type', 'number of lanes' and 'traffic state'.

DATA

Data for the study was collected from 14 loop detectors, with properties as shown in Table 1. For each lane at each detector site, speed, time gap, vehicle length, and time were collected. The information about the preceding vehicle was also stored, so that it was possible to use vehicle pair data in the analyzis.

The detectors used in the study were strategically chosen based on unique properties of each detector. Half of the detectors were placed in rural areas, while the rest were placed in urban areas. The difference between urban and rural is in this case defined by the type of traffic travelling in the area of the detector. Traffic in urban areas are typically dominated by short distance work trips as travel mode, with congested rush periods in the morning and afternoon. Rural areas may also have rush periods, but the dominant type of travel is long distance commute, leisure and freight trips.

The number of lanes was varying, with half of the detectors having two lanes. The other half had either four or six lanes. This enabled the possibility of studying the impact of number of lanes on car-following behavior.

HJELKREM, ODD A.   5

The total number of observations was 20 827 506, with about 75 % of the observations stemming from urban areas. The heavy vehicle percentage was in general higher in rural areas. As the detectors did not measure weight, heavy vehicles (HV) were defined by a vehicle length of more than 7.5 meters.

A post processing of the data was done to calculate the traffic flow at each 15 minute interval, and this value was assigned to each data line in each interval. Hence, it is possible to study the effect of traffic state on car-following behavior. The speed flow relationship at each detector is shown in Figure 1. We see that there is great variation in traffic flow characteristics between the detectors. Most urban detectors have observations for congested traffic, as one would expect, but a large share of the data is collected in uncongested traffic.

The detectors were placed on straight and level road segments, which is a common feature of almost all loop detectors owned by the Norwegian Public Roads Administration. The existence of grades, curves or intersections would presumably have affected the vehicle behavior at the detector, which in turn could have led to different results.

TABLE 1 Detector properties. The detectors were named a to n for the sake of simplicity.

Detector	Area type	Speed limit	Number of lanes	N	Heavy vehicle percentage
a	Rural	80	2	175,729	27
b	Rural	70	2	301,435	12
c	Rural	80	2	980,486	3
d	Rural	80	2	1,006,298	9
e	Rural	80	2	179,440	7
f	Rural	100	4	1,039,161	7
g	Rural	100	4	392,523	11
h	Urban	60	4	2,878,893	6
i	Urban	80	6	2,341,110	8
j	Urban	60	2	1,086,916	7
k	Urban	90	4	3,891,076	4
l	Urban	80	2	1,267,603	7
m	Urban	90	4	2,509,480	6
n	Urban	80	4	2,777,356	6

ANALYSIS

Figure 2 (a) and (b) are aggregated plots of all observations, and show the observed car-following behavior. Figure 2 (a) is based on time gaps where passenger cars are followers, while Figure 2 (b) show the following behavior of heavy vehicles. For each interval of time gap, with an interval length of 0.1 seconds, the average speed difference between follower and leader is calculated. A positive speed difference means that the follower speed is larger than the leader speed and vice versa for a negative speed difference. By examining the figure, several observations can be made for Figure 2 (a):

- There is a local maximum for the speed difference where the time gap is 3.9 seconds.

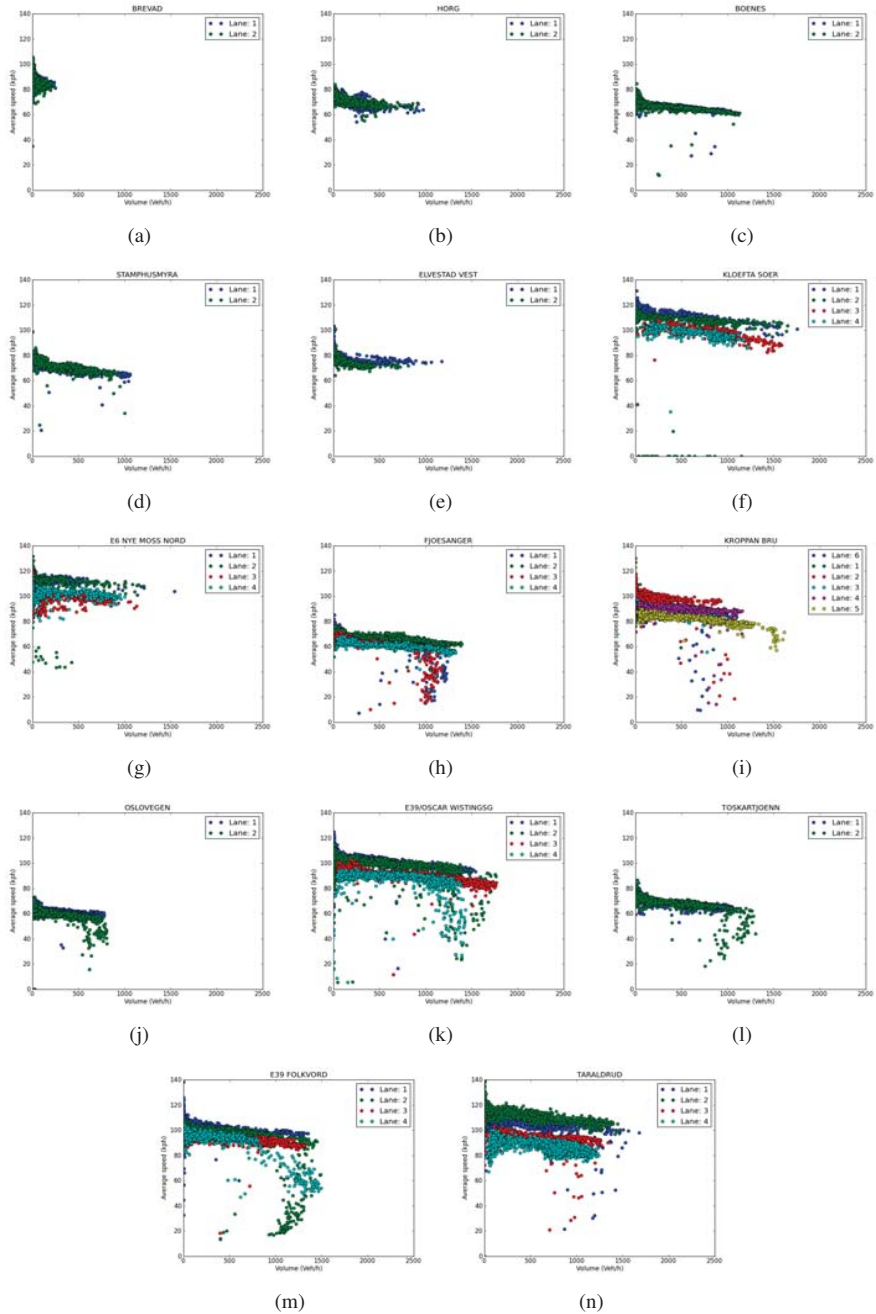- The speed difference is zero where the time gap is 1.1 seconds.

HJELKREM, ODD A.   6

FIGURE 1 Speed-flow relationships observed by the detectors a) to n).

- The slope of the curve is steeper in the green area than in the white area.

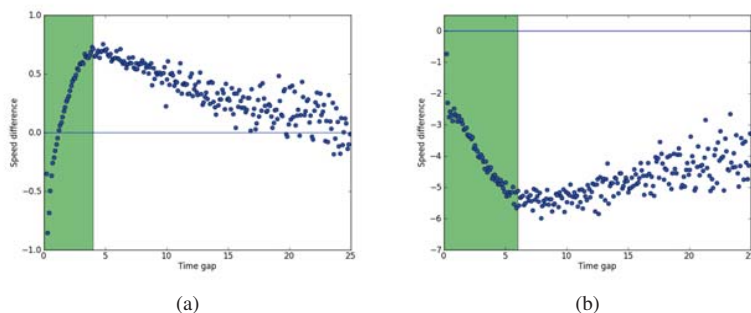(a)   (b)

FIGURE 2 Speed difference between follower and leader as a function of time gap for a) passenger cars and b) heavy vehicles. The green area indicates the car-following regime, while the white area indicates the free-flowing regime.

At the local maxima the speed difference is at its highest value, which occurs at a time gap of 3.9 seconds. This value can be interpreted as a balance point between the two regimes. Between time gaps of 1.1 and 3.9 seconds, the positive speed difference is presumably describing an urge to reach the desired time gap at the x-intercept. For time gaps higher than 3.9 seconds, the decreasing speed difference for increasing time gap presumably represent an average free-flowing vehicle. As a free-flowing is closing in on the preceding vehicle downstream from a distance, the speed difference grows in the favor of the free-flowing vehicle, until the behavior is interrupted by the appearance of a leader vehicle. Based on this interpretation of the plot, we defined the time gap of 3.9 seconds to be the threshold for car-following behavior.

The intercept with the x-axis indicate a steady state of car-following. We see that the intercept is well defined at 1.1 seconds. For lower time gaps, the follower speed is lower than the leader. This means that the speed difference grows rapidly in favor of the leader vehicle as the time gap decreases to zero, suggesting that the average follower will decelerate more than usual to increase the time gap. At higher time gaps, the follower speed is higher than the leader. This indicates that the first intercept is an equilibrium point, and we define it as the desired time gap.

In Figure 2 (b), the following is observed:

- The shape of the curve is quite different from the equivalent plot for passenger cars.

- There is a local minimum for the speed difference where the time gap is 5.8 seconds.

- In the green area, there is no intercept with the axis.

- The slope of the curve is steeper in the green area than in the white area.

While the speed difference plot for passenger cars had a maximum, the plot for heavy vehicles has a minimum. At these extreme points the behavior changes, this is interpreted as the threshold for car-following behavior. It is apparent that in average, the heavy vehicles have a lower

speed than their leader, and this speed difference increases for increasing time gaps, until the free-flow regime is reached. Because of this, it is not possible to determine a desired gap for heavy vehicles from this plot. This does not necessarily mean that heavy vehicles do not have a desired gap, but rather that it is not measurable by using this method.

The green areas in Figure 2 (a) and (b) mark car-following regimes, while the white areas are free-flow regimes. The threshold between the regimes is set to the distinct point where the slope changes. It is also possible to measure the desired gap for passenger cars, but not for heavy vehicles. The threshold value and the desired time gap will probably depend on several factors, e.g. area type and speed limit. Therefore, the same plots are created while changing several of the available variables. These plots are presented in the following section.

Impact of factors
Figure 3 show the speed difference as a function of time gap where the following factors are varied for both passenger cars and heavy vehicles: Area type, number of lanes, speed limit and traffic state. Some plots have more scatter than others, implying a lower number of observations. A large share of the observations was made in uncongested flow in urban areas where the speed limit is 80 kph, and it is apparent that the plots made from these observations have a low degree of scatter. The plots made from observations from congested flow, a speed limit of 100 kph or rural areas are however characterized by a larger degree of scatter.

Figure 3 (a) and (b) show the difference between rural and urban traffic for passenger cars and heavy vehicles. The desired time gap for cars is slightly lower in urban areas than in rural areas, while the car-following threshold is 4.1 seconds in urban areas and 5.2 seconds in rural areas. For heavy vehicles it is not possible to determine the desired gap, because all data points are negative. The threshold value is 5.0 seconds in both urban and rural areas.

The effect of number of lanes is shown in Figure 3 (c) and (d). The threshold value for cars is 5.1 seconds for cars on two-lane roads, while it is 3.9 seconds if the number of lanes is four or six. The desired time gap is 1.6 seconds on two-lane roads and 1.0 seconds for roads with four or six lanes. For heavy vehicles, the threshold value is 5.0 seconds on two-lane roads and 5.9 seconds for roads with four or six lanes. The most interesting thing about this plot is that it is possible to identify a desired gap for heavy vehicles on two-lane roads, which is 2.0 seconds.

In Figure 3 (e) and (f), there is a trend of increasing speed differences for increasing speed limits. The threshold for passenger cars is about 4 seconds for speed limits 90 kph or lower, and 5.2 seconds at a speed limit of 100 kph. The desired gap is 1.4 seconds in 60 kph, 0.8 in 80 kph, 1.1 in 90 kph and 1.2 in 100 kph. For heavy vehicles the threshold value is between 4 and 5 seconds at all speed limits, while the desired time gap is only possible to measure for a speed limit of 60 kph, where it is 2.8 seconds.

Figure 3 (g) and (h) show the effect of traffic state. It is clear that the threshold value is lower in congested traffic than uncongested traffic, for both passenger cars and heavy vehicles. The desired time gap for cars is not affected by the traffic state, while it is not measurable for heavy vehicles.

A summary of the findings from Figure 3 is that the car-following threshold for passenger cars is lower in urban areas than in rural areas, lower on four- or six-lane roads than on two-lane roads, somewhat higher at a speed limit of 100 kph than other speed limits, and quite lower in congested traffic than in uncongested traffic. For heavy vehicles, the threshold is apparently not affected by area type or speed limit, but lower on two-lane roads than on four- or six-lane roads,
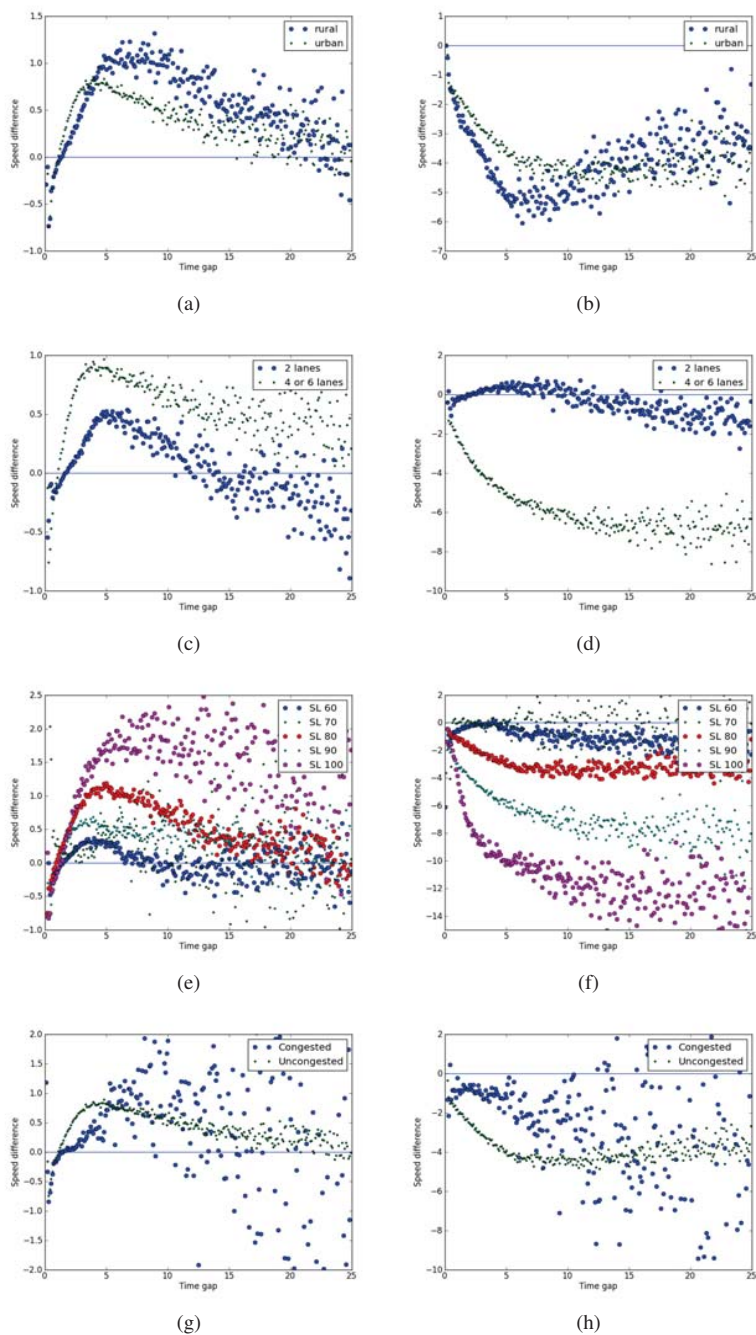
FIGURE 3 Speed difference as a function of time gap for all factors. Figure (a), (c), (e) and (g) show the speed differences with passenger car as the follower, while Figure (b), (d), (f), and (g) show the speed differences with heavy vehicle as the follower.

HJELKREM, ODD A.   10

and lower in congested traffic than uncongested traffic. These results show how the factors affect the threshold, but there might be some underlying interactions which cause the changing value of the thresholds shown in Figure 3. This is investigated in the next section.

Interactions between factors

To determine if any such interactions exist, a factorial ANOVA has been carried out on the available data set. A full 2^3 factorial design was chosen, one for passenger cars and one for heavy vehicles, resulting in a total of 16 experiments. The response of each experiment was the car-following threshold. An equally interesting response could have been the desired gap, but this could not be measured for heavy vehicles at all factor levels.

The factors included in the experiment were chosen to be area type, number of lanes, and traffic state. The levels of the factors were 'rural' and 'urban' for area type, 'two' and 'more than two' for number of lanes, and 'uncongested' and 'congested' for traffic state. The reason for using these factors was to identify eventual situations where the car-following threshold is different, depending on the characteristics of the road in question.

The speed limit factor is not included in the interaction analysis. The main reason for this is that none of the detectors were placed on four- or six- lane roads in rural areas with a low speed limit. It is also clear from Figure 3 (e) and (f) that the speed limit has relatively small impact on the value of the car-following threshold.

The experiment was carried out by calculating the speed difference as a function of time gap for each experiment, and then determining the threshold value for each graph, as demonstrated in Figure 2. The factor levels in each experiment, and measured threshold values for passenger cars and heavy vehicles are shown in Table 2.

TABLE 2 Threshold values for PC and HV in all experiments prepared for the ANOVA.

Experiment	Threshold PC	Threshold HV
Rural - Two lanes - Uncongested	4.8	3.3
Rural - Two lanes - Congested	3.2	4.3
Rural - More than two lanes - Uncongested	3.5	2.9
Urban - Two lanes - Uncongested	4.3	4.9
Rural - More than two lanes - Congested	3.0	4.2
Urban - Two lanes - Congested	4.1	4.3
Urban - More than two lanes - Uncongested	2.9	4.8
Urban - More than two lanes - Congested	4.0	4.7

The significant main effects and interactions from the ANOVA is shown in Table 3, for both passenger cars and heavy vehicles. For passenger cars, the significant main effect is the number of lanes. The results show that the threshold value will be higher on two-lane roads than on roads with more than two lanes. The significant interactions are between area type and traffic state, and number of lanes and traffic state. This means that in congested traffic, the threshold will be lower in urban areas or on roads with more than two lanes, than if the traffic was in an uncongested state. In rural areas or on two-lane roads, the threshold will be lower in uncongested traffic than in congested traffic.

From the experiments with heavy vehicles, the area type was found to be a significant main effect. In urban areas, the threshold value is higher than in rural areas. The only significant

interaction for heavy vehicles was found to be between area type and traffic state. This means that in urban areas the threshold value is higher in uncongested traffic than in congested traffic, but in rural areas the threshold value is higher in congested traffic than in uncongested traffic.

TABLE 3 Significant results from the full-factorial ANOVA. The α is set to 0.05.

Term	Effect	Coef	SE Coef	T-value	P-value
Passenger cars:					
Constant		3.725	0.091	40.93	0.000
Lanes	-0.75	-0.375	0.091	-4.12	0.015
Area*Traffic State	0.75	0.375	0.091	4.12	0.015
Lanes*Traffic State	0.6	0.3	0.091	3.3	0.03
Heavy vehicles:					
Term	Effect	Coef	SE Coef	T-value	P-value
Constant		4.175	0.0729	57.28	0.000
Area	1.0	0.5	0.0729	6.86	0.002
Area*Traffic State	-0.75	-0.375	0.0729	-5.14	0.007

DISCUSSION

The values for the car-following threshold found in this study vary between 2.9 seconds and 5.8 seconds, depending on vehicle type and road characteristics. All these values are in accordance to values found in previous studies, which were in the range of 2 seconds to 6 seconds. However, the analysis of factors showed that there were some significant effects on the threshold value. For passenger cars, the number of lanes has a significant impact on the threshold. This means that vehicles will start considering the actions of the approaching downstream vehicle sooner on two-lane roads. The reason for this behavior could be that vehicles driving on roads with more than two lanes have the option of changing lanes. Hence, they do not need to adjust their speed according to the behavior of the preceding vehicle, if there is enough space in the next lane to perform a lane change. The ANOVA also showed that the interactions between traffic state and number of lanes, as well as the interaction between traffic state and area type are significant. A surprising result of this is that in rural areas and two-lane roads, the threshold value is higher in congested traffic than in uncongested traffic. One could think that in congested traffic, the high traffic density results in a low threshold, but this is clearly not the case in rural areas or on two-lane roads.

For heavy vehicles, the area type and the interaction between area type and traffic state were found to have a significant impact on the threshold value. The interaction between area type and traffic state was also found for passenger cars, but with positive effect on the threshold. This means that the behavior of heavy vehicles is opposite that of passenger cars in congested or uncongested traffic in rural or urban areas.

The desired time gap was easily determined for passenger cars as the point where the speed difference between succeeding vehicles are zero. The reason for identifying this as the desired gap was based on the assumption that the desired gap is an equilibrium point, in which the speed difference is zero. This reasoning would have been more wavering if the number of observations were lower, and if the shape of the curve was not as well defined as it is. The observed behavior also agree with the assumed behavior of a vehicle in a car-following regime, which is described empirically from floating car data by Brackstone and McDonald (*3*).

A particularly interesting result from the analysis is that it is not possible to identify a desired time gap for heavy vehicles, except for data from two-lane roads or where the speed limit is 60. The probable reason for this is that heavy vehicles are on average not able to maintain the desired gap at high speeds, to some extent because of speed limiters installed in heavy vehicles in Norway which limits the top speed to 90 kph.

Weather conditions could also influence the data, but there has been no attempt to collect data about weather in the registration period. Because the data was registered in the summer, there were no snowy or icy road conditions. There were probably periods with rainfall when the data set was collected. This was not controlled for in the study, which implies that the results could be slightly different if the data was collected in periods with no precipitation. One should for example expect that the measured desired time gap would be lower in dry spell, because the time gap increases slightly during wet road conditions Rahman and Lownes (*6*).

At several of the detectors the road geometry allows for overtaking. This is especially the case for two-lane roads where the speed limit is 80 kph or more. On roads with more than two lanes, follower vehicles may have a larger speed than the leader vehicle because of an imminent lane change for overtaking the leader vehicle. However, the follower speed at overtaking is probably higher on two-lane roads than on roads with four lanes because of the risk of appearing meeting vehicles on two-lane roads. It is not possible to identify observations where the follower vehicle is about to overtake the leader vehicle in the data set, but we assume that these events are not frequent. If there were a large share of such events, the speed difference at very low time gaps would have been high, so that an adjusted data set without overtaking events would have a lower speed difference at low time gaps than reported in this study.

The results from the analysis are derived from the behavior of vehicles in Norway, which may be different from the behavior in other countries. As reported by Brackstone and McDonald (*3*), the average time headway is lower for French drivers than for German and English drivers. One should therefore expect that the values for the threshold of car-following behavior as well as the desired time gap vary between countries. However, this does not necessarily mean that the behavioral pattern is different, so that the same method can be used to determine these values in other countries.

CONCLUDING REMARKS

The car-following behavior of vehicle pairs was investigated in this study. By examining about 20 million observations, we conclude with the following:

- The average values of speed differences show that the car-following behavior of passenger cars and heavy vehicles are different. The threshold value for the car-following regime is higher for heavy vehicles, and the few values for desired gap which was found in the study were higher than the ones found for passenger cars.

- By studying the speed difference between follower and leader vehicle, we can accurately describe the threshold between the car-following regime and the free-flow regime. The average value is 3.9 seconds for passenger cars, which is in the scope of results reported in other studies.

- The results of the ANOVA showed that the number of lanes as well as the interactions between area type and traffic state, and number of lanes and traffic state had significant

impact of the car-following threshold of passenger cars. For heavy vehicles, the significant effects were found to be area type as well as the interaction between area type and traffic state.

- The desired gap of a vehicle is found to be 1.1 seconds for passenger cars, but this value varies depending on the number of lanes and the speed limit. For heavy vehicles, it is only possible to measure the desired time gap on two-lane roads and in speed limits of 60 kph, where it is found to be respectively 2.0 and 2.8 seconds.

The results are important for car-following models, as they should be able to replicate the results from this study. A better understanding of when drivers start to take the preceding vehicle into consideration will help to define the limits for when car-following models have to be initiated for free flowing vehicles.

We propose to perform similar studies in other areas as well, for example in other countries or at highways with higher traffic flow than observed in this study. There could also be other external factors which affect the threshold and desired time gap, for example weather, road surface conditions, time of day, and grade. It is also apparent that the car-following behavior of large vehicles should be investigated further, because of the observed differences in car-following behavior between passenger cars and heavy vehicles. The differences between passenger cars and heavy vehicles could also suggest that other vehicle properties affect the threshold, for example vehicle speed.

HJELKREM, ODD A.   14

REFERENCES

[1] Toledo, T., Driving Behaviour: Models and Challenges. *Transport Reviews*, Vol. 27, No. 1, 2007, pp. 65–84.

[2] Wilson, R. and J. Ward, Car-following models: fifty years of linear stability analysis - a mathematical perspective. *Transportation Planning and Technology*, Vol. 34, No. 1, 2011, pp. 3–18.

[3] Brackstone, M. and M. McDonald, Driver headway: How close is too close on a motorway? *Ergonomics*, Vol. 50, No. 8, 2007, pp. 1183–1195, cited By (since 1996) 16.

[4] Dey, P. and S. Chandra, Desired Time Gap and Time Headway in Steady-State Car-Following on Two-Lane Roads. *Journal of Transportation Engineering*, Vol. 135, No. 10, 2009, pp. 687–693.

[5] Reiter, U., Empirical studies as basis for traffic flow models. In *Proceedings of the second International Symposium on Highway Capacity, Volume 2*, 1994.

[6] Rahman, A. and N. E. Lownes, Analysis of rainfall impacts on platooned vehicle spacing and speed. *Transportation Research Part F: Traffic Psychology and Behaviour*, Vol. 15, No. 4, 2012, pp. 395 – 403.

[7] *Highway capacity manual 2000*. TRB, 2000.

[8] Hoban, C. J., Towards a review of the concept of level of service for two-lane roads. *Australian Road Research*, Vol. 13, 1983, p. 216?218.

[9] Gattis, J., M. S. Alguire, K. Townsend, and S. Rao, Rural two-lane passing headways and platooning. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 1579, No. 1, 1997, pp. 27–34.

[10] Al-Kaisy, A. and S. Karjala, Car-Following Interaction and the Definition of Free-Moving Vehicles on Two-Lane Rural Highways. *Journal of Transportation Engineering*, Vol. 136, No. 10, 2010, pp. 925–931.

[11] Vogel, K., What characterizes a 'free vehicle' in an urban area? *Transportation Research Part F: Traffic Psychology and Behaviour*, Vol. 5, No. 1, 2002, pp. 15 – 29.

[12] Ayres, T. J., L. Li, D. Schleuning, and D. Young, Preferred time-headway of highway drivers. In *Intelligent Transportation Systems, 2001. Proceedings. 2001 IEEE*, 2001, pp. 826–829.

[13] Ye, F. and Y. Zhang, Vehicle Type-Specific Headway Analysis Using Freeway Traffic Data. *Transportation research record*, Vol. 2124, 2009, pp. 222–230.

[14] Weng, J., Q. Meng, and T. Fang Fwa, Vehicle headway distribution in work zones. *Transportmetrica A: Transport Science*, Vol. 0, No. 0, 2013, pp. 1–19.

Chapter 7

Paper IIIa

Chosen risk level during car-following in adverse weather conditions

Odd André Hjelkrem*, Eirin Olaussen Ryeng

Department of Civil and Transport Engineering, The Norwegian University of Science and Technology, NO-7491 Trondheim, Norway

ABSTRACT

This study examines how precipitation, light conditions and surface conditions affect the drivers' risk perception. An indicator CRI (Chosen Risk Index) is defined, which describes the chosen risk level for drivers in a car-following situation. The dataset contains about 70 000 observations of driver behaviour and weather status on a rural road. Based on the theory of risk homeostasis and an assumption that driving behaviour in situations with daylight, dry road and no precipitation reflects drivers' target level of risk, generalised linear models (GLM) were estimated for cars and trucks separately to reveal the effect of adverse weather conditions on risk perception. The analyses show that both car and truck drivers perceive the highest risk when driving on snow covered roads. For car drivers, a snow covered road in combination with moderate rain or light snow are the factors which lowers the CRI the most. For trucks, snow cover and partially covered roads significantly lowers the CRI, while precipitation did not seem to impose any higher risk. Interaction effects were found for car drivers only.

© 2016 Elsevier Ltd. All rights reserved.

1. Introduction

The challenges of driving vary according to varying driving conditions. Among these are changes in weather and road conditions. Rain, snow and ice alter the friction between the tires and the road surface, while precipitation may impair the driver's visual ability to detect potential dangers, as do driving in twilight and dark hours. How do drivers perceive and respond to risk under such varying conditions?

1.1. Theoretical approach

Numerous theories and models have been developed to better understand and predict road user behaviour. Risk perception is a central component and predictor in many of these, proposing that road users' perceptions of risk influence their behavioural choices. One of these theories is Wilde's Risk homeostasis theory (Wilde, 1982) in which he suggests that individuals continuously compare their perceived level of risk to their target level of risk and take behavioural decisions in order to balance the two. The target level of risk represents the levels of risk individual drivers are willing to take. In order to maintain the balance between perceived and target risk, the theory posits that if drivers perceive an increased risk,

for example due to reduced friction, they will adjust their driving accordingly to reduce the risk they are facing. In a situation with perceived reduced friction, lowering speed or increasing the time gap could be possible strategies to avoid exceeding the desired target level of risk. The theory has, however, been mostly used to advocate that traffic safety measures have no effect since a lowered perceived risk level will be met by a more risky behaviour. Thus, a reduction in traffic accidents will only take place if the target level of risk is lowered.

Wilde's theory has been heavily discussed and criticised, and is regarded more as an interesting basis for discussion by identifying important mechanisms in human behaviour, than as an applicable model. Since it is not possible to falsify the theory, it has no explanatory value (Elvik et al., 2009). However, the notion of drivers adjusting their behaviour as a response to changes in their environment is the basis for the concept of behavioural adaptation (OECD, 1990). The concept behavioural adaptation was redefined by Kulmala and Rämä (2013) as "Any change of driver, traveller, and travel behaviours that occurs following user interaction with a change to the road traffic system, in addition to those behaviours specifically and immediately targeted by the initiators of the change". Although this concept is mostly discussed as a response to implemented measures, it is also meaningful to apply when discussing driver behaviour as a response to natural changes in weather and road surface conditions. These are changes that are easily observed and therefore likely to evoke changes in risk perception, which in turn may affect the behavioural decisions taken by the drivers.

* Corresponding author.
E-mail addresses: odd.hjelkrem@ntnu.no (O.A. Hjelkrem), eirin.ryeng@ntnu.no (E.O. Ryeng).

84   **Paper IIIa**

Van der Molen and Bötticher (1988) suggested a hierarchical risk model in which drivers' tasks take place at three levels: strategical, tactical and operational. Decisions about choice of speed and time gap belong at both strategical and tactical level. At strategical level, strategies for the journey are planned, such as general strategies for choice of speed and time gap, depending on weather and road surface conditions. At tactical level, however, these strategies are transformed into manoeuvring plans with short time spans based on the current situation. These manoeuvring plans are put into action at operational level. At both strategical and tactical level, drivers perceive information from their environments and make judgements based on their motivations and expectations. The model utilises utility functions in the decision process, in which both risk and other judgements are included. These judgements and the decision rules may vary both intra- and inter-individually. Both Wilde's risk homeostasis theory and the concept of behavioural adaptation can be integrated into this model. In both cases, risk perception is a key element. Slovic and Peters (2006) claim that risk can be perceived in two ways, both analytical and as feelings. Risk as feelings is the most intuitive way of perceiving risk while the analytical way is based on logic and reason. Risk perception at strategical level is suggested to be more analytical than risk perception at tactical level. Thus, there is a mixture of both analytical and emotional elements to risk perception when driving at adverse conditions.

1.2. State of research

Several studies have investigated how driving behaviour is affected by adverse conditions, and how the accident rates change as well. The following statements can be made based on the literature:

1.2.1. Precipitation reduces speed and increases time gap, and the speed reduction is larger for higher intensities

Rain and snow disturbs the field of view enough to influence the traffic flow. This is shown empirically by several studies. Agarwal et al. (2005) found that speed was reduced by rain and snow, and that the reduction was dependent on the precipitation intensity. In heavy rain and heavy snow the speed was reduced by respectively 4%–7% and 11%–15%. A study by Billot et al. (2009) also found that drivers reduce their speed during rain, and the impact was increasing with precipitation intensity. Rahman and Lownes (2012) found that a shift from no-rain to rain led to a speed reduction of 3.7% and an increase in time gap of 5.7%. Lam et al. (2013) studied the impact of rain intensity on the Hong Kong road network, and found that speed decrease as the rain intensity increases.

1.2.2. Precipitation increases accident rate

During rain or snow, changing driving conditions leads to more accidents. Eisenberg and Warner (2005) found that snowy days have fewer fatal accidents, but more nonfatal injury accidents. A study by Hermans et al. (2006) showed that among several weather indicators, the presence of precipitation had the most significant impact on number of accidents. Qiu and Nixon (2008) conducted a meta study of 34 papers and 78 records showed an increase in accident rate during precipitation. Snow had the greatest effect, with a possible increase in accident rate by 84% and injury rate by 75%. Karlaftis and Yannis (2010) found a surprising decrease in accident rate for increasing precipitation intensity, and suggested that a decrease in speed as well as Southern European drivers being unaccustomed to wet roads as an explanation. Strong et al. (2010) reported that snowy weather leads to a decrease in speed and an increase in accident frequency, but a decreased number of fatal accidents. They attributed this primarily to the fact that the severity of accidents decrease as the speed decreases. Mills et al. (2011)

found that precipitation in the form of both rain and snow substantially increases the risk of injury collision. Andrey et al. (2013) performed a risk analysis showing an increase in collision rate on days with snow, and a higher relative risk in rural areas than in urban areas. Bergel-Hayat et al. (2013) studied a large European dataset of weather and injury reports, and found significant correlations between weather and accident rate, but the results varied for different road types. On motorways, the effect of rainfall was direct, but on main roads, the effect was indirect through exposure.

1.2.3. Water, snow or ice on the road surface reduce speed and increase time gap

Typical values of coefficients of friction are: dry surface (0.80–1.00), wet surface (0.40–0.90), snow covered surface (0.15–0.30), and ice covered surface (0.05–0.15) (Aurstad et al., 2011). The reduced friction, either from rain, snow or ice will lead to longer braking distances and reduced handling capabilities. Strong et al. (2010) summarised the results from earlier studies on how weather affects speed and accident rate in an extensive literature review, showing how the speed reduces with increasing adversity for pavement conditions. In the worst case, which was "very icy", the speed adjustment factor was estimated to be 0.83. Dixit et al. (2012) reported that drivers behave more careful in situations with a wet road surface compared to situations with a dry surface. Kwon et al. (2013) found that road surface condition has a significant effect on free flow speed and capacity. They calibrated models based on empirical data which estimated a reduction of 17.0% in free flow speed for a snow covered road, and an 11.0% reduction for wet road surface. Kvernland (2013) observed speed at several places along a straight road section ending in a curve during winter conditions. Compared to dry surface, he found speed reductions of 5.9–13.9% on icy surface and 4.6–12.2% on snow covered surface, but hardly any changes on wet surface. The highest reductions were found just before entering the curve. However, calculations based on measured friction showed that none of these speed reductions were sufficient to fully compensate for the reduced friction.

1.2.4. Water, snow or ice on the road surface increases accident rate

The challenging driving conditions during reduced friction often lead to a loss of control of the vehicle. Keay and Simmonds (2006) investigated the impact of rainfall on daily road accidents in Australia and found that the risk is greater in wet conditions caused by rainfall. Strong et al. (2010) also found that the accident rate increased with more adverse surface conditions. In the worst condition, "very icy", their accident adjusted factor was 1600% as opposed to 100% for dry roads. A meta study by Elvik et al. (2009) derives relative accident risks for adverse lighting and surface conditions based on Norwegian studies. They found that the relative risk increased to 1.3 for wet surfaces, 1.5 for slushy roads and 2.5 for icy or snow covered surfaces.

1.2.5. Lower visibility reduces speed and increases time gap

Another important factor is the reduced sight caused by precipitation, somewhat depending of the time of day. When driving in daylight during a dry spell, the sight is usually quite good, and eventual hazards can be spotted in time for the driver to react. On the other hand, driving in heavy snowfall or fog at night will dramatically reduce the visibility. During situations of reduced sight, the ability of the driver to detect potential hazards will decrease. Hoogendoorn et al. (2010) showed that fog leads to a significant reduction in speed and a significant increase in gap. The study by Kwon et al. (2013) found that visibility, measured in sight distance, has a significant effect on free flow speed and capacity, showing an increase in speed and capacity for increasing visibility.

Table 1
Overview of vehicle detection data, limited to all observed following vehicles with time gap below 5 s.

Statistic	Value
$N_{followingvehicles}$	67 723
Truck percentage (%)	10.5
Speed limit (kph)	80
Speed all vehicles (kph) Mean/SD	80.6/8.0
Time gap all vehicles (s) Mean/SD	2.5/1.1
Speed cars (kph) Mean/SD	80.7/8.1
Time gap cars (s) Mean/SD	2.43/1.08
Speed trucks (kph) Mean/SD	80.2/7.0
Time gap trucks (s) Mean/SD	2.77/1.13
Length trucks (m) Mean/SD	16.2/3.6
Weight trucks (kg) Mean/SD	16 871/7 733

1.2.6. Lower visibility may increase accident rate

The only result found concerning this statement was the meta study by Elvik et al. (2009). They found that the impact of adverse lighting on the relative risk was 1.1 at night for accidents involving vehicles, and 2.1 and 2.2 for accidents involving bicycles or pedestrians respectively. These findings were however based on a limited number of studies.

1.3. Study objective

The statements presented in Section 1.2 are all supported by the existing literature in this field, and each statement seems logical with anticipated results. However, when put together, the statements lead to the following conclusion, which may sound surprising. Firstly, we see that adverse weather induce a change in driver behaviour. The speed decreases, and time gap increases. Secondly, we see that the accident rate increases during adverse weather, despite the compensating behaviour by the drivers. This might imply that, based on the literature presented here, drivers do not compensate enough for the reduced friction and the loss of visibility. The perceived risk by the drivers seems not to be coherent with the actual risk.

Driven by these challenges, we seek to explore some of the underlying mechanisms of the driver behaviour during adverse conditions. The main objective of the study is to examine how precipitation, light conditions and surface conditions affect the drivers' risk perception. We focus on situations on rural roads where two subsequent vehicles are interacting, also known as car-following behaviour.

2. Method

2.1. Dataset

The data used for this study was based on the data set described by Hjelkrem and Ryeng (2016), which was collected from a two-lane rural road in Norway, equipped with a dual loop detector, a Weigh in Motion (WIM)-detector, and a roadside weather station. These measurement equipment allow for studies of how weather affects driving behaviour, as the winter season with heavy snowfall, low temperatures and winds creates challenging conditions for drivers. The vehicle weight was used to classify the vehicles by labelling all vehicles under 3500 kg as cars. The heavier vehicles were defined as trucks. Table 1 shows a summary of the vehicle data included in this study.

In total, there were 67 723 observations in the data set, where each observation included information about the observed leader-follower vehicle pair, the current weather, the current road surface condition, as well as the lighting condition at that time. Table 2

shows how the numbers of observations are distributed across these varying conditions.

2.2. Measures of risk

The definition of risk and how it is measured varies in the literature from explicit variables to more complex terms. In traffic safety research, a commonly used value is the time to collision (TTC), which is defined as the time to an impact in seconds if two vehicles maintain their current speed. In car-following situations TTC can only be calculated in cases where the follower speed is greater than the leader speed. Oh and Kim (2010) developed a method to estimate rear-end crash potential by using the TTC to calculate a crash risk index. They expressed the probability of an accident as an exponential decay function of TTC, and calculated the probability in real-time based on vehicle trajectories.

Jin et al. (2011) used the percentage of TTC below a certain threshold sampled from Beijing expressways as an indicator for risk. They used this indicator to show that the risk varies between lanes and locations. Brackstone and McDonald (2007) investigated if drivers with low headways have higher TTC, in order to maintain a constant risk level. They found the opposite, which is that drivers with low headways also had low values of TTC.

Duan et al. (2013) measured perceived risk in a simulator experiment. They used time headway as a measure for perceived risk, and found that drivers decreased their headway with oncoming vehicles in the adjacent lane, thus increasing their risk.

Vogel (2003) compared time headway and TTC as indicators for traffic safety. She stated that time headway can be small without necessarily indicating a dangerous situation, while low values of TTC will always indicate danger. Time headway should therefore be used for enforcement issues, and TTC should be used when the safety of a specific situation is to be evaluated.

Hassan and Abdel-Aty (2013) and Abdel-Aty et al. (2012) used real-time traffic flow data to predict crashes due to reduced visibility. They found that changes in average speed and occupancy, as well as fluctuations in speed were valid indicators for predicting both visibility related crashes and other crashes.

2.3. Defining an index of chosen risk

In order to study drivers' risk perception during adverse conditions, we need to define a measure of risk that is applicable and based on available data. Our measure is based on an underlying assumption that risk perception is reflected in actual behaviour. Although Wilde's risk homeostasis theory (Wilde, 1982) has obvious weaknesses as a predictive model, we base our measure on the core mechanism described in his model. We assume that the target level of risk is the risk chosen when driving at normal conditions, i.e. at daylight with dry road surface and no precipitation. *Thus, any deviations in chosen behaviour compared to the normal condition express changes in perceived risk.*

2.3.1. Indicator of accident probability

It is clear that time headway, TTC and speed are recurring terms when dealing with risk during car-following. Risk is often defined as the product between probability and consequence. As reported in previous studies, both TTC and intervehicular distance in form of gap or headway has been used as a measure for probability. However, it is not obvious which of these are best to use when studying car-following behaviour on rural roads. A low value of time gap might come with a high TTC and vice versa, depending on the speed difference between leader and follower. As shown by Brackstone and McDonald (2007), there might be a correlation between the value of TTC and time headway. In our dataset we find that there is a significant positive correlation between time gap

Table 2

Observations categorised by varying precipitation, surface and lighting conditions (Daylight/Twilight/Night). Both cars and trucks are included. There were 917 observations without precipitation intensity data, which were left out from this table.

	Dry	Wet	Visible tracks	Snow cover	Sum
Clear	11591/5523/31144	3649/1138/8048	351/150/1274	18/3/229	**63 118**
Light Rain	61/7/69	190/88/339	69/26/159	41/2/201	**1252**
Moderate Rain	0/0/18	30/11/94	14/1/77	10/0/29	**284**
Heavy Rain	0/0/0	5/0/10	1/0/0	2/0/0	**18**
Light Snow	47/25/75	347/308/1065	16/7/50	0/0/24	**1964**
Moderate Snow	0/0/19	19/1/4	7/0/51	4/0/25	**130**
Heavy Snow	0/0/6	0/0/26	0/8/0	0/0/0	**40**
Sum	**48 597**	**15 354**	**2 279**	**594**	**66 806**

and TTC (p = 0.000), with a Pearson correlation coefficient of 0.361. A positive correlation between the two variables means that the time gap is the explaining factor in the TTC term. A negative correlation would have implied that the speed difference is the most important contributor to TTC. The correlation test was run for all observations where the speed difference was positive, which is the criterion for calculating TTC. Since the speed difference is not prevalent and TTC only can be calculated for positive speed differences, we decided to use the inverse time gap as the indicator for accident probability. Thus, we can utilise the whole dataset. The inverse time gap is used because the accident probability is assumed to increase with decreasing time gap.

2.3.2. Indicator of accident consequence

The potential consequence of an incident span from minor fender scratch marks to fatal accidents. The severity of an accident is to a high degree governed by the laws of physics. The higher the momentum, the more impact an object will have. As the momentum is the product of speed and mass, the severity of an accident will normally increase for increasing speeds and vehicle weight. We therefore use the vehicle speed multiplied with the vehicle weight as a proxy for the accident consequence.

2.3.3. Chosen Risk Index (CRI)

Based on the findings from the literature and the general definition of risk, where risk is a product of consequence and probability, we deduce an expression for the *risk chosen by each driver*. We call this expression the Chosen Risk Index (CRI):

$$CRI = \frac{V * W}{TG}$$

In this equation, TG is time gap, while V is speed and W is vehicle weight of the following vehicle. A decrease in time gap or an increase in speed or weight translates to an increase in CRI in a given situation.

The introduction of CRI is to our knowledge the first attempt to define an index based on traditional risk theory of probability and consequence. Compared to other similar risk indicators, it is more complex, by involving speed, weight and time gap.

2.4. Analyses

The analyses use CRI in two ways. Firstly, by defining the normal condition as 1, the relative CRI (CRI/CRI$_{norm}$) is calculated for all other conditions. The relative CRI is explored to observe and describe any trends. The chosen risk is compared between all situations where the road surface condition, weather status and lighting conditions change. Given the assumption that driving at normal conditions expresses the drivers' target level of risk, and given that drivers according to Wilde's theory (Wilde, 1982) adjust their driving behaviour to maintain their target level of risk, the relative CRI gives an indirect expression of how risk is perceived. The relative

CRI shows how much the chosen risk in a given situation deviates from the chosen risk at normal conditions. A low relative CRI corresponds to a high perceived risk, and vice versa.

The second way of utilising CRI is by performing a generalised linear model (GLM) analysis in which CRI is chosen as the dependent variable. For independent data, the GLM models the expected response via a transformation of a linear combination of covariate terms with a vector of coefficients. For a full discussion about GLM and applications, see McCullagh and Nelder (1989).

Our model estimates CRI as a function of the following variables:

- Precipitation type (PREC_CAT). Nominal variable with values "Clear", "Light rain", "Moderate rain", "Heavy rain", "Light snow", "Moderate snow" and "Heavy snow".
- Road surface status (ROAD_CAT). Nominal variable with values "Dry", "Wet", "Visible tracks" and "Snow cover".
- Time of day (TIME_OF_DAY). Nominal variable with values "Daylight", "Twilight" and "Night".

Both main effects and interactions were explored. Thus, CRI is modelled in the following way:

$CRI_{ijk} = Constant + PREC\_CAT_i + ROAD\_CAT_j + TIME\_OF\_DAY_k + INTERACTIONS_{ijk}$ i,j,k denotes the values representing each nominal variable (i.e. j denotes either "Dry", "Wet", "Visible tracks" or "Snow cover", and so on). INTERACTIONS may include both 2-way and 3-way interactions.

The GLM procedure should always have independent factors. In our dataset there might be some correlations. For example, we expect that a rainfall leads to a wet road, and that a snowfall leads to a snow covered road. However, a wet road does not necessarily mean that it is raining. To further investigate this, the correlation coefficient between PREC_CAT and ROAD_CAT was calculated to be 0.274 using Cramer's V, and the correlation was statistically significant. As the score of Cramer's V ranges from 0 to 1, where 1 implies full correlation, a score of 0.274 means that there is a moderate association between the variables, but still acceptable for using the data. The implication of the revealed association is that if only main effects are present, the parameter estimates for PREC_CAT and ROAD_CAT could be misleading. However, any interacting effects would to a certain extent represent correlations. No correlations were found between TIME_OF_DAY and the other main effects.

To find the best model, we used the backward selection algorithm. Starting with all factors and interactions, non-significant factors were iteratively removed from the analysis until a satisfactory model was achieved.

In this analysis, the normal condition is defined as the reference situation ("Clear", "Dry" and "Daylight"). Thus, all parameter estimates give direct measures of each value of each variable's contribution to changes in the CRI compared to the normal condition. Since we propose CRI as a measure of chosen risk, these parameter estimates can be interpreted, when comparing them relatively to

Table 3
Relative CRI for cars and trucks, as well as relative consequence and relative probability. N = 67 723.

		Cars			Trucks		
		CRI/CRI_{norm}	Relative cons. $(V*W)/(V*W)_{norm}$	Relative prob. $(1/TG)/(1/TG)_{norm}$	CRI/CRI_{norm}	Relative cons. $(V*W)/(V*W)_{norm}$	Relative prob. $(1/TG)/(1/TG)_{norm}$
ClearDry	Daylight	100	100	100	100	100	100
	Twilight	100	100.5	99.5	102.8	107.4	98.1
	Night	98.6	99.9	97.3	107.9	113.5	101.9
Wet	Daylight	99.3	104.2	94.2	102.2	107	97.1
	Twilight	98.3	101.8	94.7	101.4	106.7	95.9
	Night	95.4	97.3	93.5	108.8	118.2	98.5
Visible tracks	Daylight	85.7	79.8	91.2	88.9	88.5	89.2
	Twilight	93.4	95.7	91	91.1	100.8	80.2
	Night	87	88.4	85.6	99.1	108.3	89
Snow cov.	Daylight	77.7	42.7	101.2	72.5	67.3	77.3
	Twilight	68.1	51.5	81.3			
	Night	73.3	57.9	86	82.2	76.8	87.4
Rain Dry	Daylight	90	85.3	94.4	88.5	66.5	106
	Twilight	101.8	105.8	97.7	106.2	110.5	101.6
	Night	85.4	83.1	87.6	92.3	97.3	87.1
Wet	Daylight	101.3	109.6	92.2	99.3	97.1	101.5
	Twilight	96.7	99.1	94.4	107.4	116.4	97.6
	Night	95.1	99.4	90.7	52	39	62.2
Visible tracks	Daylight	76.2	68.8	83			
	Twilight	94.4	87.1	101.2	92.9	94	91.8
	Night	83.9	70.9	95.2			
Snow cov.	Daylight	59.8	50.6	67.7			
	Twilight						
	Night	76	57.5	90.8	73.7	59.9	85.4
SnowDry	Daylight	96.8	97.8	95.9	102.1	101.1	103.1
	Twilight	96.9	92.3	101.2	101.1	108.8	92.9
	Night	95.1	95.4	94.7	101.5	105.1	97.8
Wet	Daylight	96.6	100.7	92.3	93.7	81.9	104.1
	Twilight	95	99.3	90.6	113.8	126.9	99
	Night	95.4	99.1	91.6	101.8	115.2	86.3
Visible tracks	Daylight	88	75.6	98.9	78.2	69.1	86.3
	Twilight	83.1	84.2	82	62.3	64	60.5
	Night	84.4	78.9	89.5	88.6	94.1	82.7
Snow cov.	Daylight	73.9	47.5	93	96.8	88.4	104.6
	Twilight	62.1	36.9	79.8			
	Night	78.8	65	90.5	72.8	67.9	77.3

each other, as measures of each variable's contribution to the risk perception. Negative estimates correspond to increased risk.

In order to distinguish between free flow and car-following behaviour, the threshold between these regimes must be defined. Several previous studies have tried to locate this point, e.g. Gattis et al. (1997), Reiter (1994), Hoban (1983), Rahman and Lownes (2012), Al-Kaisy and Karjala (2010), Vogel (2002). The values found in these studies vary between 2 and 6 s. A recent study by Hjelkrem (2015) showed how this threshold vary with external factors, suggesting a value of approximately 5 s for two lane rural roads with speed limit of 80 kph. Based on these values, only data where the time gap was below 5 s were included in this study.

There are several differences between cars and trucks which call for separate analyses. They hold different physical appearances in weight, length and height. Truck drivers are expected to be more experienced and professional than car drivers. The number of trucks on the road is also far lower than cars, which means that the effect of trucks would probably be concealed if we treated cars and trucks as one group. Therefore, we separate between cars and trucks throughout the analyses.

3. Results

In this analysis, the normal situation is defined as daylight, no precipitation and dry road surface. The data observed at these conditions serve as a sample of a reference situation to which all other weather, light and road conditions are compared.

3.1. Results from descriptive analysis of CRI

The relative CRI was investigated first to illustrate how the CRI deviate from the normal situation when conditions change. The results are shown in Table 3 where each value is categorised according to weather, lighting and road surface condition. Several trends can be noticed.

For cars we see that the CRI tend to generally decrease for all adverse weather conditions when compared to the normal situation. The CRI decreases for more adverse precipitation type and road cover, and especially where the road surface is covered by snow or have visible tracks. By inspecting the columns showing relative consequence and probability, it is obvious that drivers regulate both their speed and gap according to changing conditions.

For trucks, the pattern is more complex. Although the general trend is in line with the results for cars, we also find that the CRI actually increase with dry or wet road surface, especially during twilight and night time. The table reveals that trucks have generally higher relative consequence at night time. An analysis of the truck data showed that the mean truck weight was 16.9 tons at night, 15.3 at twilight and 14.9 tons at daytime. As weight is a factor in the CRI, this could explain why the CRI is higher at night and twilight for trucks.

It is apparent that there are some systematical patterns in the way CRI is affected by lighting conditions, precipitation and the road surface condition. There might also be some interactions between the factors. Because the number of observations in each

Table 4
Parameter estimates for chosen risk index for cars, CRI$_{cars}$. Non-significant effects are in italic. N = 59 795.

Parameter	B	Std. Error	95% Wald Confidence Interval		Sig.
			Lower	Upper	
Intercept	21.38	0.1204	21.144	21.616	0.000
Heavy snow	*−1.768*	*3.1875*	*−8.015*	*4.479*	*0.579*
Moderate snow	−11.47	3.085	−17.517	−5.424	0.000
Light snow	−3.899	1.1376	−6.128	−1.669	0.001
Heavy rain	*2.822*	*4.3746*	*−5.752*	*11.396*	*0.519*
Moderate rain	−11.956	2.9929	−17.822	−6.09	0.000
Light rain	−2.755	1.0922	−4.896	−0.615	0.012
Snow covered	−13.984	1.7574	−17.423	−10.545	0.000
Visible tracks	−6.558	0.6456	−7.823	−5.292	0.000
Wet	−0.593	0.2368	−1.057	−0.129	0.012
Night	−0.85	0.1412	−1.127	−0.574	0.000
Twilight	*−0.130*	*0.2105*	*−0.543*	*0.283*	*0.537*
*Heavy snow*Snow covered*	*−1.833*	*9.4508*	*−20.356*	*16.69*	*0.846*
Moderate snow*Snow covered	16.606	3.7896	9.179	24.034	0.000
Light snow*Snow covered	5.033	1.6529	1.793	8.273	0.002
*Heavy snow*Visible tracks*	*1.741*	*12.7573*	*−23.263*	*26.744*	*.891*
Moderate snow*Visible tracks	10.937	3.3631	4.346	17.529	0.001
Light snow*Visible tracks	3.359	1.4362	0.544	6.173	0.019
Moderate snow*Wet	10.988	3.2727	4.573	17.402	0.001
*Light snow*Wet*	*2.416*	*1.2542*	*−0.42*	*4.874*	*0.054*
*Heavy rain*Snow covered*	*−7.609*	*7.094*	*−21.513*	*6.295*	*0.283*
Moderate rain*Snow covered	9.476	3.8917	1.849	17.104	0.015
Light rain*Snow covered	7.793	2.9258	2.058	13.527	0.008
*Heavy rain*Visible tracks*	*−6.406*	*5.0348*	*−16.274*	*3.462*	*.203*
Moderate rain*Visible tracks	9.858	3.4257	3.143	16.572	0.004
*Light Rain*Visible tracks*	*1.083*	*1.861*	*−2.565*	*4.73*	*.561*
Moderate rain*Wet	11.525	4.0737	3.541	19.51	0.005
Light rain*Wet	2.504	1.144	0.262	4.746	0.029
Snow covered*Night	3.404	1.6442	0.181	6.627	0.038
*Snow covered*Twilight*	*−1.505*	*5.742*	*−12.759*	*9.749*	*0.793*
*Visible tracks*Night*	*0.913*	*.7095*	*−0.478*	*2.303*	*0.198*
Visible tracks*Twilight	3.317	1.1552	1.053	5.581	0.004
Wet*Night	−1.046	0.2791	−1.593	−0.499	0.000
*Wet*Twilight*	*−0.555*	*0.4407*	*−1.419*	*0.309*	*0.208*

category varies greatly, the explanatory power also varies. To unveil these mechanisms, we adopt a generalised linear model (GLM) for the response variable CRI.

3.2. Results from GLM-analysis

For cars, two second order interactions were found to be significant, as shown in the resulting model:

$$CRI_{car} = \text{Const.} + PREC\_CAT + ROAD\_CAT + TIME\_OF\_DAY$$
$$+ PREC\_CAT * ROAD\_CAT + ROAD\_CAT * TIME\_OF\_DAY$$

However, this model gave a non-significant main effect from TIME_OF_DAY, with a p-value of 0.986. Although not significant, we chose to keep it in the model, as it is present in the second order interactions.

The parameter estimates of each variable in the model are shown in Table 4. For each estimate, a confidence interval and p-value is reported. A negative estimate implies that the chosen risk is decreased relative to the normal situation, expressing higher perceived risk, and a positive number imply the opposite.

We see that all significant main effects have negative coefficients, meaning that these effects help to lower the CRI. The road surface status has coefficients ranging from −13.984 to −0.593. Precipitation type range from −11.47 to 2.822, while light conditions range from −0.85 to −0.13. Snow cover is the most extreme situation with a value of −13.984, which is about two thirds of the intercept value of 21.38. The effects of moderate rain or snow are also large, with coefficients of −11.956 and −11.47, respectively. We also see that the effect of precipitation increases with inten-

sity, except for heavy precipitation. However, there is not enough data to achieve significant results for heavy rain or heavy snow. The effects of night and twilight are negligible compared to other main effects, indicating that drivers don't perceive driving in twilight and night as much riskier than driving at daylight.

All significant interactions, except for the combination of night and rain, have positive coefficients. This means that the negative coefficients found for main effects are countered by the interacting variables. The interactions with highest coefficients are interactions involving either snow covered road, moderate precipitation, or both, which have the highest main effects. This means that in situations with two strong main effects present, their interaction will counteract the impact of the CRI.

An interesting effect is the interaction between rain and night being the only significant interaction with negative coefficient. This can to a certain degree be explained with the effect water has on pavement. A wet pavement will usually become darker, and at night time, the combined effect affects the driver to reduce speed and/or increase time gap. We also see that the opposite is the case for a snow covered road at night time, with a positive coefficient of 3.404.

The estimated CRI can be calculated for all possible combinations of the three variables. When considering only statistically significant combinations, there are 35 possible situations, as "Twilight", "Heavy snow", "Heavy rain" and some second order interactions are not significant. The significant combinations and their estimates of CRI are shown in Table 5. It is apparent that drivers adjust their car following behaviour mostly in situations with a snow covered road, especially in combination with moderate rain. At night, with moderate rain on a snow covered road, the estimated CRI is more than 5 times lower than the reference situation with daylight, dry road and no precipitation.

Table 5

Estimated CRI for cars in all significant situations. The situations marked with bold are assumed to be transitional, as they represent situations with a dry road surface despite the presence of precipitation.

Precipitation type	Road surface status	Time of day	Estimated CRI
Moderate rain	Snow covered	Night	4.07
Moderate rain	Snow covered	Daylight	4.92
Clear	Snow covered	Daylight	7.40
Light snow	Snow covered	Night	7.68
Light snow	Snow covered	Daylight	8.53
Moderate rain	**Dry**	**Night**	**8.57**
Moderate snow	**Dry**	**Night**	**9.06**
Moderate rain	**Dry**	**Daylight**	**9.42**
Moderate snow	**Dry**	**Daylight**	**9.91**
Clear	Snow covered	Night	9.95
Moderate snow	Snow covered	Night	11.68
Moderate rain	Visible tracks	Night	11.87
Moderate snow	Snow covered	Daylight	12.53
Moderate rain	Visible tracks	Daylight	12.72
Light rain	Snow covered	Night	14.10
Moderate snow	Visible tracks	Daylight	14.29
Clear	Visible tracks	Daylight	14.82
Light rain	Snow covered	Daylight	14.95
Light snow	**Dry**	**Night**	**16.63**
Light snow	Visible tracks	Night	17.33
Light snow	**Dry**	**Daylight**	**17.48**
Light rain	**Dry**	**Night**	**17.78**
Light snow	Visible tracks	Daylight	18.18
Light rain	**Dry**	**Daylight**	**18.63**
Clear	Wet	Night	18.89
Moderate snow	Visible tracks	Night	19.46
Moderate snow	Wet	Night	19.46
Moderate rain	Wet	Night	19.51
Light rain	Wet	Night	19.69
Moderate snow	Wet	Daylight	20.31
Moderate rain	Wet	Daylight	20.36
Clear	Dry	Night	20.53
Light rain	Wet	Daylight	20.54
Clear	Wet	Daylight	20.79
Clear	Dry	Daylight	21.38

For trucks, the only effects found significant were the main effects of road status and lighting conditions, resulting in the following model:

$$CRI_{truck} = Const. + ROAD\_CAT + TIME\_OF\_DAY$$

The effect of PREC_CAT was not found to be significant, with a p-value of 0.29, and was therefore not included in the model.

The largest impact was found to be snow covered roads and visible tracks, as shown in Table 6. However, there were no second order interactions countering the main effects. A wet road will also probably reduce the CRI, but the 95% confidence interval includes positive values of the coefficient as well.

A somewhat surprising result is the effect of night and twilight, with positive values of 24.469 and 6.601 respectively, although the effect of twilight is not significant. As previously mentioned, the trucks at night are on average heavier than trucks driving at daylight. With the CRI increasing with vehicle weight, this can explain the large positive effect of night.

Table 7

Estimated CRI for trucks in all significant situations.

Road surface status	Time of day	Estimated CRI
Snow covered	Daylight	70.93
Snow covered	Night	95.40
Visible tracks	Daylight	108.14
Visible tracks	Night	132.61
Dry	Daylight	152.18
Dry	Night	176.65

The significant combinations and their estimates of CRI for trucks are shown in Table 7. The estimated CRI is reduced by 60% in situations with a snow covered road in daylight compared to a dry road at night.

4. Discussion

As cited in Section 1.2, previous studies have found effects of precipitation, road surface condition and light conditions on speed, time gaps and accident frequencies. By introducing the Chosen Risk Index (CRI) as an expression of speed, time gap and vehicle weight, we were able to study the combined effect of these three variables on risk perception, assuming (1) that drivers aim at maintaining their desired target level of risk when choosing speed and time gap, and (2) that the desired target level of risk is reflected in the choice of speed and time gap when driving on dry road surface in daylight without precipitation. Like for the previous studies, we also found that the surface conditions affect car-following behaviour more than do precipitation and light conditions. We found, however, interaction effects moderating the effect for cars when two states other than the normal situation were present. Interpreting these findings in the light of risk perception, our dataset implies that both car and truck drivers perceive the highest risk when driving on snow covered roads. For cars, the highest perceived risk is observed when snow covered roads are combined with moderate rain, followed by light snow. At these conditions, higher risk is perceived at night time compared to daylight. The model also implies that the effect of moderate rain or moderate snow has a large effect on the chosen risk level. However, while precipitation is present, the road surface is rarely dry. In combination with either wet road, visible tracks, or a snow covered road, the second order interaction coefficients counteract the apparently large effect from moderate precipitation.

The suitability of CRI as a tool to study risk relies on our two main assumptions, (1) that changes in perceived risk reflect in changing behaviour, and (2) that drivers strive to maintain their target level of risk. As presented in the introduction, the driving task takes place at strategical, tactical and operational level. Risk evaluations are part of the decisions made at strategical and tactical level, and risk can be perceived both analytical and as feelings. Snow covered roads are very visible indicators of reduced friction and hence higher risk, and this is common knowledge by drivers. Driving during precipitation and twilight and night limits the driver's sight vision. Since these

Table 6

Parameter estimates for chosen risk index for trucks, CRI_{trucks.} Non-significant effects are in italic. N = 7037.

Parameter	B	Std. Error	95% Wald Confidence Interval		Sig.
			Lower	Upper	
Intercept	152.177	3.1919	145.921	158.433	0.000
Snow covered	−81.243	15.5334	−111.668	−50.798	0.000
Visible tracks	−44.038	8.6643	−61.020	−27.057	0.000
Wet	*−4.619*	*3.5412*	*−11.560*	*1.702*	*.192*
Night	24.469	3.5289	17.552	31.386	0.000
Twilight	*6.601*	*5.8364*	*−4.838*	*18.040*	*0.258*

conditions often occur gradually, they might affect risk perception more intuitively, as feelings.

Our findings may thus indicate that the analytical risk dimension is dominating when driving at adverse conditions. Since risk perception is suggested to be more analytical at strategical level, this may also indicate that if judgments made on tactical level find support at strategical level, they are more likely to be addressed. There is however still a question whether the high effect of snow covered roads compared to other conditions is an indicator of analytical strategical thinking as more influential than intuitive feelings at tactical level on risk perception, or if the findings merely express that drivers adjust their behaviour intuitively in accordance to the actual risk.

The composition of the CRI was based on assumptions about how drivers react to perceived risk. A different functional form of the expression could have given other results. As an example, one could have used the inverse squared time gap as probability, or only speed as consequence. However, a closer inspection reveals that the unit of CRI is $kg\,m/s^2$, or N. While it is tempting to imagine the CRI as a force, this would probably be a mistake. However, CRI is somewhat related to the force accepted when braking a vehicle. Given a vehicle's speed and mass, a shorter time gap implies a more abrupt retardation in an emergency brake to avoid a rear end accident.

Weight is a factor included in the CRI, but in contrast to the two other factors speed and time gap, the weight is a constant value which the driver cannot change. It is however something that the driver should be aware of, especially for trucks. We also see that the average truck weight is highest at night, which automatically leads to a higher CRI at night, all else equal. This is unfortunate in the sense that we do not capture the real effect of light conditions for trucks.

One could argue that the target level of risk varies from driver to driver, and since our dataset does not necessarily include the same drivers during all conditions, we will not be able to distinguish the effects of varying conditions from the effect of individual risk preferences among the observed drivers. We argue, however, that our sample size is substantial enough for most situations to outweigh the effect of individual variations compared to the effect of varying conditions. The number of observations in each data category varies from 0 observations during rain, twilight and snow cover to a maximum of 31 144 observations for dry road with no precipitation at night time. Some situations were not frequently observed in the time period of the data collection, which is probably the reason why for example the effect of variables including twilight was not found to be significant.

With the recent development of ITS equipment for cars, it is not unlikely that some of the observed vehicles were equipped with Adaptive Cruise Control (ACC), which is a driver support system that regulates the speed of the following vehicle in order to keep a given distance to the leader car. Since the drivers set this distance by themselves, they are able to choose their preferred risk level according to the current conditions. This can be regarded as a choice at strategical level. There was no way of detecting whether ACC were in use, so we have to accept that there might be some disturbances in the data. By disturbance we mean that the distance headway may have been set long before the vehicles reached our observation site and thus been set for other road and weather conditions. A pre-set distance headway also impede the drivers' continuous adjustments of speed and time gap that takes place otherwise at operational level. We assume, however, that any such effects on the results are negligible.

When driving on a wet road at temperatures around 0 °C, it may be difficult to visually determine if the road is covered with liquid water or solid ice. Because of the severe difference in friction on the different surfaces, this will affect the handling of the vehicle. It was not possible to determine from the images alone if wet roads were

actually wet or ice-covered. However, this would also be difficult to decide for every driver in the dataset. They had to mainly rely on their eyes to decide the friction between the tires and the pavement, although a driver can get a sense of the driving conditions through physical feedback from the car.

5. Conclusions

In this study, we have defined an indicator CRI, which describes the chosen risk level for drivers in car-following situations. The CRI is defined as speed multiplied by weight and divided by time gap. It should be underlined that CRI is not a measure of actual risk, but merely an indicator of perceived risk developed specifically for this study. The lower CRI, the higher perceived risk. The use of CRI as an indicator of perceived risk rests on assumptions based on Wilde's Risk homeostasis theory (Wilde, 1982). From the analysis we see that the CRI is an effective indicator for expressing chosen risk during adverse weather conditions. With the normal situation (daylight with dry road surface and no precipitation) as a reference, we see that as the driving conditions worsen, the drivers adjust their behaviour. As a result, CRI decreases. Based on the size of the unique dataset prepared for this analysis, we achieved statistically significant GLM-models which describe the CRI for rural car-following behaviour.

For cars, the CRI is modelled by the road surface status, precipitation type, lighting conditions, the interaction between precipitation type and road status, and the interaction between road status and lighting conditions. We found that a snow covered road in combination with moderate rain or light snow are the factors which lowers the CRI the most, thus being the situation contributing the highest to the perception of risk. Due to few observations in heavy snow and heavy rain, it was not possible to significantly estimate the effects at these conditions.

For trucks, only the road surface condition and lighting conditions were found to have an impact on the CRI. Snow cover and partially covered roads significantly lowers the CRI, indicating that these conditions are perceived as the riskiest. The CRI is increased at night and twilight. This can be explained by the fact that the average truck weight in the data set increased at night, which confounds with the effect of night on CRI.

There are several aspects about this study that should be investigated in further research:

- It would be interesting to compare our measured chosen risk level to the actual accident risk to uncover any situations where the drivers underestimate the risk level. However, the actual accident risk is derived from registered accidents. In order to perform such a comparison, we need accident data which contains not only information about road surface, precipitation and lighting conditions, but also exposure data which relates traffic volumes to these conditions.
- Our definition of CRI assumes that the actions of the driver reflect his perceived risk. To investigate this further, a survey should be conducted to see if there is accordance between the perceived risk expressed by the drivers and the chosen risk levels as revealed in this study.
- Further studies including CRI may reveal whether the proposed methodology is valid as a comparative measure. If so, a possible application could be to identify areas or roads where the CRI is especially high, that may be areas where the drivers underestimate the risk. As all components of the CRI are vehicle dependent, it can be used as a measure of chosen risk level independent of location, and thus be used for identifying possible locations requiring preventive action.

- The vehicles observed in this study were driving on a rural road. Only car-following behaviour was studied, defined as a time gap less than 5 s. One could imagine that more congested states of traffic would lead to other results, especially as the time gap distribution would be different, with presumably a lower average value for time gap. It would be very interesting to perform the same analysis in congested areas, to see if the influence of adverse weather conditions is comparable.

- With the rapid development of vehicle technology, the CRI may in the future be measured as a time series for each single vehicle, and thereby provide a different data source for a similar study. Depending on the results from such a study, a long term goal could be to develop a real-time application which alerts the driver if a measurement of CRI deviates from a typical CRI for that specific driver.

References

Abdel-Aty, M., Hassan, H.M., Ahmed, M., Al-Ghamdi, A.S., 2012. Real-time prediction of visibility related crashes. Transp. Res. Part C 24, 288–298.

Agarwal, M., Maze, T.H., Souleyrette, R., 2005. Impacts of weather on urban freeway traffic flow characteristics and facility capacity. Proceedings of the 2005 Mid-continent Transportation Research Symposium.

Al-Kaisy, A., Karjala, S., 2010. Car-following interaction and the definition of free-moving vehicles on two-lane rural highways. J. Transp. Eng. 136 (10), 925–931.

Andrey, J., Hambly, D., Mills, B., Afrin, S., 2013. Insights into driver adaptation to inclement weather in Canada. J. Transp. Geogr. 28 (0), 192–203.

Aurstad, J., Larsen, Ø., Refsdal, G., Berntsen, G., Hoff, I., Lerfald, B.O., 2011. Road Operation and Maintenance Textbook. Norwegian Public Roads Administration, Report nr 53 (in Norwegian).

Bergel-Hayat, R., Debbarh, M., Antoniou, C., Yannis, G., 2013. Explaining the road accident risk: weather effects. Accid. Anal. Prev. 60, 456–465.

Billot, R., El Faouzi, N.-E., De Vuyst, F., 2009. Multilevel assessment of the impact of rain on drivers' behavior. Transp. Res. Rec. J. Transp. Res. Board 2107 (1), 134–142.

Brackstone, M., McDonald, M., 2007. Driver headway: how close is too close on a motorway? Ergonomics 50 (8), 1183–1195.

Dixit, V., Gayah, V., Radwan, E., 2012. Comparison of driver behavior by time of day and wet pavement conditions. J. Transp. Eng. 138 (8), 1023–1029.

Duan, J., Li, Z., Salvendy, G., 2013. Risk illusions in car following: is a smaller headway always perceived as more dangerous? Saf. Sci. 53 (0), 25–33.

Eisenberg, D., Warner, K.E., 2005. Effects of snowfalls on motor vehicle collisions, injuries, and fatalities. Am. J. Public Health 95 (1), 120.

Elvik, R., Vaa, T., Erke, A., Sorensen, M., 2009. The handbook of road safety measures, Emerald Group Publishing.

Gattis, J., Alguire, M.S., Townsend, K., Rao, S., 1997. Rural two-lane passing headways and platooning. Transp. Res. Rec. J. Transp. Res. Board 1579 (1), 27–34.

Hassan, H.M., Abdel-Aty, M.A., 2013. Predicting reduced visibility related crashes on freeways using real-time traffic flow data. J. Saf. Res. 45, 29–36.

Hermans, E., Brijs, T., Stiers, T., Offermans, C., 2006. The impact of weather conditions on road safety investigated on an hourly basis. In: Presented at the 85th Annual Meeting of the Transportation Research Board, Washington, D. C.

Hjelkrem, O.A. and Ryeng, E.O., 2016. Driver behavior data linked with vehicle, weather, road surface, and daylight data. Data in Brief (Submitted).

Hjelkrem, O.A., 2015. Determining Influential Factors on the Threshold of Car-Following Behavior Presented at 94th Annual Meeting of the Transportation Research Board , Washington, D.C.

Hoban, C., 1983. Towards a review of the concept of level of service for two-Lane rural roads. Austr. Road Res. 13 (3).

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. Intelligent Transportation Systems (ITSC), 2010 13th International IEEE Conference on.

Jin, S., Qu, X., Wang, D., 2011. Assessment of expressway traffic safety using gaussian mixture model based on time to collision. Int. J. Comput. Intell. Syst. 4 (6), 1122–1130.

Karlaftis, M., Yannis, G., 2010. Weather effects on daily traffic accidents and fatalities: a time series count data approach. In: Proceedings of the 89th Annual Meeting of the Transportation Research Board, January 10–14, Washington, D.C.

Keay, K., Simmonds, I., 2006. Road accidents and rainfall in a large Australian city. Accid. Anal. Prev. 38 (3), 445–454.

Kulmala, R., Rämä, P., 2013. Definition of behavioural adaptation. In: Rudin-Brown, C.M., Jamson, S.L. (Eds.), Behavioural Adaptation and Road Safety. Theory, Evidence and Action. CRC Press, Taylor & Francis Group.

Kvernland, J.K., 2013. Drivers Choice of Speed Under Different Friction Conditions. Master Thesis. The Norwegian University of Science and Technology, Dept of Civil and Transport Engineering, Trondheim (in Norwegian, summary in English).

Kwon, T., Fu, L., Jiang, C., 2013. Effect of winter weather and road surface conditions on macroscopic traffic parameters. Transp. Res. Rec. J. Transp. Res. Board 2329 (1), 54–62.

Lam, W.H., Tam, M.L., Cao, X., Li, X., 2013. Modeling the effects of rainfall intensity on traffic speed, flow, and density relationships for urban roads. J. Transp. Eng. 139 (7), 758–770.

McCullagh, P., Nelder, J.A., 1989. Generalized linear models. Monogr. Stat. Appl. Probab. 37.

Mills, B.N., Andrey, J., Hambly, D., 2011. Analysis of precipitation-related motor vehicle collision and injury risk using insurance and police record information for Winnipeg, Canada. J. Saf. Res. 42 (5), 383–390.

OECD, 1990. Behavioural adaptations to changes in the road transport system. Report prepared by an OECD Scientific Expert Group, Paris.

Oh, C., Kim, T., 2010. Estimation of rear-end crash potential using vehicle trajectory data. Accid. Anal. Prev. 42 (6), 1888–1893.

Qiu, L., Nixon, W.A., 2008. Effects of adverse weather on traffic crashes: systematic review and meta-analysis. Transp. Res. Rec. J. Transp. Res. Board 2055 (1), 139–146.

Rahman, A., Lownes, N.E., 2012. Analysis of rainfall impacts on platooned vehicle spacing and speed. Transp. Res. Part F Traffic Psychol. Behav. 15 (4), 395–403.

Reiter, U., 1994. Empirical studies as basis for traffic flow models. Proceedings of the second International Symposium on Highway Capacity, volume 2.

Slovic, P., Peters, E., 2006. Risk perception and affect. Curr. Dir. Psychol. Sci. 15 (6), 322–325.

Strong, C.K., Ye, Z., Shi, X., 2010. Safety effects of winter weather: the state of knowledge and remaining challenges. Transp. Rev. 30 (6), 677–699.

Van der Molen, H.H., Bötticher, A.M., 1988. A hierarchical risk model for traffic participants. Ergonomics 31 (4), 537–555.

Vogel, K., 2002. What characterizes a free vehicle in an urban area? Transp. Res. Part F Traffic Psychol. Behav. 5 (1), 15–29.

Vogel, K., 2003. A comparison of headway and time to collision as safety indicators. Accid. Anal. Prev. 35 (3), 427–433.

Wilde, G.J.S., 1982. The theory of risk homeostasis: implications for safety and health. Risk Anal. 2 (4), 209–225.

Chapter 8

Paper IIIb

Submitted for publishing in Data in brief.

Data article

Title: *Driver behaviour data linked with vehicle, weather, road surface, and daylight data.*

Authors: Odd André Hjelkrem and Eirin Olaussen Ryeng

Affiliations: Norwegian University of Science and Technology

Contact email: odd.hjelkrem@ntnu.no

Abstract

This article describes a data set related to the article "Chosen risk level during car-following in adverse weather conditions"[1]. In this data set, vehicle observations have been linked to data containing weather and road surface conditions. A total of 311 908 observations are collected and classified in categories of precipitation type, road status information, and daylight condition. The data is collected for a long period of time, so that several different weather situations are present, ranging from dry summer to adverse winter weather conditions.

Specifications Table

Subject area	*Transport Engineering.*
More specific subject area	*Traffic flow, traffic safety*
Type of data	*Table, .csv file.*
How data was acquired	*Detection equipment, ephemeris, visual investigation.*
Data format	*Raw, analysed*
Experimental factors	*Raw data obtained from WIM-detectors, a weather station and a roadside camera.*
Experimental features	*Image classification performed after data collection.*
Data source location	*Latitude: 62.48780N, Longitude: 7.76104E.*
Data accessibility	*Data is included in this article.*

Value of the data
- *A unique collection of linked data sources offers a large number of factors available for studying vehicle behaviour.*
- *The data set include vehicles in both free flow and car-following state, so that the impact of both traffic and surroundings can be analysed*
- *The vehicles observed are diverse in physical characteristics and driver behavior, allowing for studies of either specific vehicle types or the entire traffic flow*

- *The weather situations observed range from normal conditions to adverse conditions, such as snow during night time on snow covered roads, facilitating studies of weather related driver behaviour.*

1. Data

A presentation of the available attributes in the data set (see Supplementary Material .csv file) is shown in Table 1.

Table 1: Description and range of attributes in the data set, N=311 908.

Attribute	Data type	Range
ID	Integer	19 to 794 438
Timestamp	Text	21.03.2012 to 30.04.2014
Vehicle length	Floating point	102 to 2981 cm
Lane	Integer	1 or 2
Vehicle speed	Floating point	0 to 169 kph
Vehicle weight	Floating point	0 to 69 548 kg
Number of axles	Integer	2 to 11
Validity code	Text	
Lead vehicle ID	Integer	19 to 794 436
Lead vehicle speed	Floating point	0 to 169 kph
Lead vehicle weight	Floating point	0 to 69 548 kg
Lead vehicle length	Floating point	102 to 2981 cm
Time gap	Floating point	0 to 530 331 s
Air temperature	Floating point	-13.6 to 24.8
Precipitation type	Text	Clear, Rain, Snow
Precipitation intensity	Text	None, Low 0-1 (mm/10min), Moderate 1-5 (mm/10min), High above 5 (mm/10min)
Relative humidity	Floating point	16 to 97 %
Wind direction	Integer	0 to 360 degrees
Wind speed	Floating point	0 to 23.1 m/s
Road surface status	Text	Dry, Wet, Visible tracks, Snow covered
Time of day	Text	Daylight, Night, Twilight

2. Experimental Design, Materials and Methods

The vehicle and weather detection equipment are placed close to each other at a rural two-lane road in Norway. The speed limit at the site is 80 kph. The traffic level at the site is quite low, with an AADT of about 2000. Located about 15 km from the city of Åndalsnes, the road is an important route for road transport between Oslo and the west coast. About 10 km further east, there is a climb of about 500 meters for 25 km, which is quite steep. Still, there are no viable alternatives for heavy vehicles, so the

heavy vehicle percentage is about 10 %. The data was recorded between March 21th 2012 and April 30th 2014, although not continuously.

2.1 Observations

The vehicle detectors measured speed, time, lane number, vehicle length, vehicle weight, and number of axles for each passing vehicle. From this data, it was possible to derive time gap and information about the lead and following vehicle.

The roadside weather station measured meteorological data every 10 minutes, including precipitation intensity, precipitation type, air temperature, relative humidity, wind speed and wind direction.

The weather station was also equipped with a camera which stored a picture of the road surface approximately every 10 minutes. These pictures were used to identify the road surface conditions. All pictures in the detection period were manually investigated to classify the road surface according to the categories 'dry', 'wet', 'snow covered' and 'visible tracks' in snow, with the latter category meaning longitudinal bare strips on a surface otherwise covered by snow. The definition of snow cover is when the complete road surface is covered with snow.

Using the spatial position of the detector site and the point in time for each vehicle detection event, the lighting condition was found by looking up in an ephemeris, which is an almanac for the movements of the celestial bodies. The specific ephemeris used was the PyEphem module available for Python [2]. It can be used to determine the sunrise and sunset at a specific place and time on the planet. The lighting conditions were categorised into daylight, twilight and night. Twilight was defined as the time period one hour before and one hour after both sunset and sunrise.

2.2 Data join

The following routine was used for creating the data set:
1. Import vehicle observations into a PGSQL-database.
2. Assign time of day to each observation
3. Import weather data to another PGSQL-database.
4. Join the two databases using the time of each vehicle event and each 10-min interval of weather data.
5. Add information about the preceding vehicle (ID, speed, weight and length)
6. Add information about road status information based on the manual classification of images.

References

[1] Hjelkrem, O. A. and Ryeng, E. O. (2016*): Chosen risk level during car-following in adverse weather conditions. Accident Analysis & Prevention, 95, 227-235.*

[2] Python Software Foundation (2016): *https://pypi.python.org/pypi/ephem/*

Chapter 9

Paper IV

Presented at the 22th ITS World Congress in Bordeaux, 2015.

Invited and submitted for publishing in International Journal of ITS.

A Transition from Car-Following to Vehicle-Following Model

Odd André Hjelkrem[*1]   Sebastian Nerem[*2]

Norwegian University of Science and Technology [*1]

(Institutt for bygg, anlegg og transport, NTNU, 7491 Trondheim, +47 98482278,
odd.hjelkrem@ntnu.no)

Norconsult AS[*2]

(Postboks 626, 1303 Sandvika, +47 48607530, sebastian.nerem@norconsult.com)

The recent development in car-following behavior has turned the attention towards other vehicle types than cars, e.g., trucks, two- and three-wheelers. In this study, we propose that the next step in the evolution of both model framework and terminology should allow for the inclusion of other vehicle types. Our contribution is a modification of Gipps' car-following model, resulting in a vehicle-following model. The main change is the addition of a vehicle property dependent parameter. The modified model yields a significant reduction in number of parameters to calibrate, yet being able to reproduce realistic driving behavior. A comparison to the original Gipps' model on selected areas show that the modification leads to slightly better results. Even more importantly, the calibration effort is greatly reduced, and the reduction increases for each vehicle type included in the model.

Keywords: *Car-Following, Traffic flow, Trucks, Heterogeneous flow*

1. Introduction

Car-following models aim to replicate the vehicle behavior when in the presence of a leader vehicle. They constitute central components in microscopic simulation software developed to simulate traffic in road networks. Recent advances in this field show an increasing number of studies focusing on the role non-car-vehicles have in traffic flow. When modelling heterogeneous traffic flow, the behavior of several vehicle types needs to be properly modelled. Differences in vehicle size and performance lead to behavioral differences.

The size of a vehicle does affect the vehicle dynamics, as shown by [1]. They studied the acceleration properties of a vehicle related to the weight of the vehicle for trucks of different sizes. Their acceleration and deceleration tests showed that heavier vehicles have lower acceleration and deceleration capabilities. Other studies have investigated the effect of vehicle type on the time gap. [2] and [3] found results suggesting that vehicles follow trucks closer than cars. The explanation for this effect was that the increased distance when following a car gives the driver more information about the downstream flow, thus being capable of adjusting the speed to downstream speed fluctuations. [4] developed a headway spacing estimation model based on vehicle weight data, showing that the headway increased with increasing vehicle weight.

Vehicle properties also affect other aspects of vehicular behavior, e.g. lane-changing behavior. [5] argued that heavy vehicles have different properties than cars, and showed that the previous generation of lane-changing models was insufficient for modelling heavy

vehicles. They introduced a new model for heavy vehicles which was more accurate than the one used in the VISSIM microscopic simulation model at the time.

[6] added a vehicle type parameter in Gipps' car-following model [7]. Their attempt was probably the first to model explicitly the effects of vehicle-type behavior, and the results showed an improvement in comparison to the original Gipps' model. [8] investigated the car-following behavior of heavy vehicles. They found that speed differences between follower and leader, as well as the acceleration of both vehicles were the most significant stimuli. They also state the need for incorporating heavy vehicle behavior in a car-following model. In a more recent paper, [9] implement their previous findings from [8] in a car-following model. Using a local linear model tree approach, the resulting car-following model was able to reproduce car-following behavior depending on the lead vehicle type.

The current state of the art shows that there is a need for research on how car-following behavior is dependent on vehicle types, and how this can be implemented in microscopic simulation models. With the increase in road based freight transport, the interactions between vehicle types and the resulting effect on the traffic flow increase in importance. However, separating into vehicle types leads to a discrete distinction, with the risk of large variation in size and performance for vehicles within one vehicle type. We rather propose a redefinition of the concept by a change in the terminology from "car-following" to "vehicle-following". After all, the term "car"-following is used, even if the leader vehicle is a truck. We add to the previous work by [9] and [6] by introducing vehicle-property based parameters into Gipps' car-following

model, and thereby eliminating the need for vehicle types. The modification of Gipps' model is based on assumptions of heavy vehicle behavior, as well as relationships discovered in empirical data. The potential gain in this procedure, besides an improved vehicle behavioral model, is a reduction in calibration effort by reducing the total number of parameters in the model. The modified model is calibrated to behavior for a two-lane road with a minimum of confounding elements, such as intersections, grades, turns, traffic conditions etc. Finally the results from the modified model are compared to the results from the original Gipps' model.

2. Method

The car-following model developed by Gipps is one of the most extensively used car-following models. It is classified as a safety-distance model, meaning that modelled vehicles adjust their gap and speed to avoid a collision with any preceding vehicles [10].

According to Gipps' model, the speed of a vehicle is dependent on the vehicle status. In free flow, only the restrictions of the driver will affect the chosen speed, as there is no preceding vehicle to set restrictions. If the subject vehicle is driving at its desired speed, there is no need to change the speed, and it will maintain the desired speed until disturbed by other vehicles. The equation describing this behavior is formulated by Gipps as:

$$v_n(t + \tau) = v_n(t) + 2.5 a_n \tau \left(1 - \frac{v_n(t)}{V_n}\right) \sqrt{0.025 + \frac{v_n(t)}{V_n}} \quad (1)$$

, where $v_n(t+\tau)$ is the speed of vehicle n at time $t+\tau$, τ is the reaction time of the vehicle, a_n is the maximum acceleration which the driver of vehicle n wishes to undertake, and V_n is the desired speed of vehicle n. Note that when $v_n(t)$ equals V_n, $v_n(t+\tau)$ equals $v_n(t)$, which implies a state of constant speed.

If the subject vehicle is following another vehicle, it is in the car-following regime, and the behavior is more complex. The vehicle will then have to react to the actions of the preceding vehicle in order to maintain a safe distance. The resulting behavior is described by Gipps as:

$$v_n(t + \tau) = b_n \tau + \sqrt{b_n^2 \tau^2 - b_n \left[2[x_{n-1}(t) - s_{n-1} - x_n(t)] - v_n(t)\tau - \frac{v_{n-1}^2(t)}{\hat{b}}\right]} \quad (2)$$

Here, b_n is the most severe braking that the driver of vehicle n wishes to undertake, $x_{n-1}(t)$ is the position of the front of vehicle $n-1$ at time t, vehicle $n-1$ is the preceding vehicle, s_n is the effective size of vehicle n (vehicle length plus an imagined safety distance) and $\hat{b}$ is the estimated deceleration of vehicle $n-1$.

2.1. Proposed Model structure

A typical use of Gipps' model would involve a calibration of the parameters a_n, τ, V_n, b_n, s_{n-1} and $\hat{b}$ in equations (1) and (2) for each vehicle type. In homogeneous flow this would not be a problem, but for heterogeneous flow, the calibration effort increases for each included vehicle type. Additionally, the effects of leader and follower vehicle type are only indirectly represented through s_{n-1} and $\hat{b}$. Therefore, we propose to modify Gipps' model in order to deal with these two issues.

We chose to use the findings available in the literature as a starting point for the analysis. As previously mentioned, the weight of the vehicle is important for the braking ability. As shown by [1], the acceleration and deceleration properties are dependent on the gross vehicle weight (GVW). During deceleration,

the vehicle mass will determine the force the braking systems need to oppose in order to achieve the desired deceleration. A high GVW results in a higher opposing force, which demands better braking capabilities. By using a parameter dependent on vehicle weight, there will be no use of vehicle types, because one set of parameters could be used for all vehicle types.

Equally important, the other parameters do not affect the deceleration properties in the same way. The driver reaction time τ is assumed to be constant for all drivers, and hence not vary for heavy and light vehicles. The effective size could be used as a proxy for modelling the impact of weight on time gap, as an increase in size is the same as an increase in time gap seen from an observer's perspective. However, as the effective size is a fixed value for each vehicle, it will not affect the dynamical properties of the vehicle the same way as the deceleration parameter, as shown by [1].

There are three possible approaches for introducing a vehicle specific parameter in the equations:
1. Add a new element to the equations where the new parameter is included. A new element can be added to one or both of the equations if the new parameter has direct influence on vehicle speed. The new element must be of unit meters per second, to be in

accordance with the remaining elements of the equation.

2. Multiply one or more of the existing elements with the new parameter, or a factor which is determined by a function of the new parameter. This is useful if the new parameter does not necessarily have a direct influence on the vehicle speed, but affects one or more of the other input parameters of the model.

3. Exchange one of the existing elements, which might be useful if it can be shown that the element in question contributes to incorrect vehicle behavior.

The second approach was chosen because there was limited data to support a direct influence of vehicle weight on vehicle speed in all situations. There was neither no evidence to support that one of the existing elements causes incorrect vehicle behavior. In order to achieve complete weight incorporation in Gipps' model, the weight parameter needs to be introduced to both speed equations. We propose to introduce a new parameter γ_n, which is affected by the GVW of vehicle n. During car-following, most vehicles will be constrained by equation (2), and we will therefore focus only on this equation for the remainder of the study. When a vehicle is not affected by preceding vehicles, it is assumed that the GVW is not important. Even though GVW will affect the acceleration-parameter, most of the time spent in free flow will be with constant speed, when on a straight road with no interfering factors. In the case of a vehicle driving uphill, the GVW will be very important for the choice of speed. This is however not in the scope of this study.

As a result of the inclusion of γ_n, we propose the following equation for the modified Gipps' model:

$$v_n(t + \tau) = \gamma_n b_n \tau + \sqrt{\gamma_n b_n^2 \tau^2 - \gamma_n b_n \left[2[x_{n-1}(t) - s_{n-1} - x_n(t)] - v_n(t)\tau - \frac{v_{n-1}^2(t)}{\gamma_{n-1}\hat{b}} \right]} \quad (3)$$

, where γ_n is the GVW-coefficient of vehicle n and γ_{n-1} is the estimated GVW-coefficient of vehicle $n-1$. In order to determine the relationship between GVW and γ, a closer inspection of empirical data is necessary.

2.2. Data collection

As the study aims at investigating how well the model reproduces differences in driving behavior caused by vehicles' weight, data from vehicles with many different gross weights is needed. In order to reduce uncertainty it is also desirable to obtain data from several vehicles with the same weight. Floating car data allows the researcher to analyze time series of data, but usually only a modest amount of data is collected because of the cost. In this study, we have used data collected at a weigh in motion (WIM) detector, which use piezoelectric sensors and inductive loops to measure the axle weight. The WIM detector used in this study also measured gap, which is the spacing between two preceding vehicles.

There are several reasons for choosing data from this detector for the study. First, the data is available in very large amounts, and it is cheap to collect given that the detector is already installed. This results in a high number of observations for vehicles with all kind of weights. Second, we are able to measure the specific properties of each vehicle, such as weight, length and number of axles. Thus, we can validate the model for the whole weight scale instead of using a few probe vehicles. Third, we are measuring the speed and time gap, which are direct results from the car-following process.

To ensure that the collected data really reflect car-following behavior, only time gaps lower than 6 seconds were used in the study. The value of 6 seconds is based on previous studies reporting values between 2 seconds and 6 seconds for the car-following threshold value [11]. A total of 247 645 vehicles were identified as being in the car-following regime. For each passing vehicle, the variables GVW, speed, time gap, length and time were detected. The flow rates were found by counting the number of vehicle observations in each lane in 15-minute intervals. It is assumed that observations from the two lanes are independent of each other. These values were then multiplied by four to find the equivalent hourly flow rate. No congestion occurred during the detection period, and most flow rates were below 1000 vehicles per hour.

About 14 % of the vehicles were heavier than 3500 kg, and thereby classified as heavy vehicles. Half of all heavy vehicles weighed more than 7500 kg, and the other half were between 3500 and 7500 kg. The relationship between GVW and time gap is shown in Figure 1. Here, the vehicles are sorted in GVW categories, and the average time gap for each category is plotted in the figure. We see that time gap increases for increasing GVW until 20 000 kg, where the curve flattens out.

The weight factor γ_n has to represent how GVW affects the deceleration capabilities of vehicle n. Because we do not have detailed data about this relationship, we assume that the relationship between deceleration and GVW is of the same shape as the relationship between time gap and GVW. The reason for this assumption is that vehicles with lower deceleration capabilities will compensate by an increase in time gap. The weight factor γ_n is therefore assumed to have the following relationship with GVW, based on a regression to a double exponential function:

$$\gamma_n = c_1 e^{(c_2 GVW_n)} + (1 - c_1) e^{(c_3 GVW_n)} \quad (4)$$

Here, c_1, c_2, and c_3 are coefficients to be calibrated. The factor γ_n is dimensionless, and the value determines the effect the vehicle weight has on the deceleration. c_1 is also dimensionless, while c_2, and c_3 have unit kg^{-1}. The interpretation of this is not intuitive. The constants can for example be regarded as parameters describing resistance in deceleration, or that the coefficients c_2, and c_3 are reference weights describing some extreme situation.
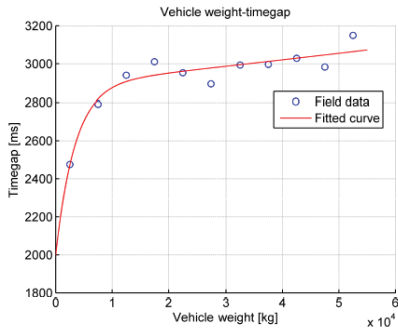

Figure 1. Relationship between GVW and average time gap, field data and fitted curve.

2.3. Implementation in a simulation model

Two models were made, one with the original Gipps' model implemented, and the other with the modified model implemented. The traffic in the original model was simulated with two vehicle types, cars and trucks. The modified model was simulated with one generic vehicle type, with a distribution of GVW in the vehicle generation sampled from the field data. Both the original and modified models were simulated in a MATLAB-script. The model consisted of a straight section with vehicle generation at the beginning of the section. A detector area was defined at the end of the section, to simulate a loop detector. The distance from the beginning of the section to the detector area was set high enough so that steady state car following behavior would occur at the simulated detector, and not be influenced by the vehicle generating arrival distribution. Figure 2 show simulated vehicle trajectories for a time period of 4 minutes. It is clear that equation (1) and (2) are both employed in the model, as vehicles in the front of a platoon will have free flow behavior, and the following vehicles will have car following behavior.

In order to simulate for the same flow rates as the field data, the traffic flow at the input was varied from 200 to 1000 veh/h in 50 veh/h intervals. For each input flow rate, a satisfying number of replication was run, and the detector data was stored for the analysis.

The simulation models were calibrated on both macroscopic and microscopic level. On the macroscopic level, the Root Mean Squared Percent Error (RMSP) developed by [12] was used to calibrate the speed-flow relationship. The RMSP should be as low as possible, preferably below 15 %. The input chosen for calibration was the desired speed, which was thought to have the most influence on the speed-flow relationship in uncongested flow. By using the Golden Selection Search Algorithm [13] for mean and standard deviation of the desired speed, the RMSP was calibrated to 0.5 % for cars and 0.9 % for trucks in the simulation with the original Gipps' model. For the modified model the corresponding value of RMSP was 0.55 %. Figure 3 shows the resulting speed-flow relationships compared to field data.
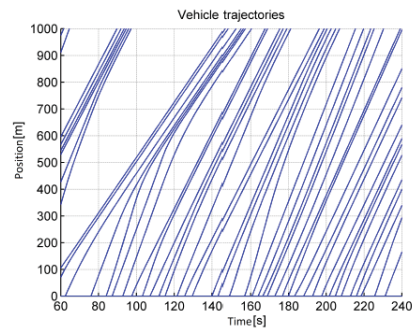

Figure 2. Vehicle trajectories from the model.

On the microscopic level, the models were calibrated to replicate time gap distributions observed in the empirical data. If data from congested flow were available in the data set, we would be able to use the procedure presented by [14] to calibrate all input parameters in Gipps' model using macroscopic variables. Since this was not available, the parameters had to be manually calibrated. Although it is not necessarily an inadequate procedure, it is time consuming. Each input parameter was tuned carefully until the time gap distributions were in correspondence to the observed data. For each change in an input parameter, the macroscopic flow-speed relationship was checked for deviations. For the original model, one parameter set was calibrated for each vehicle type. For the modified model, only one parameter set had to be calibrated. The values of the calibrated parameters are shown in Table 1. We see that only 14 parameters had to be calibrated in the modified model, as opposed to 23 in the original model. The reaction time is excluded from this number because it is not vehicle type differentiated.
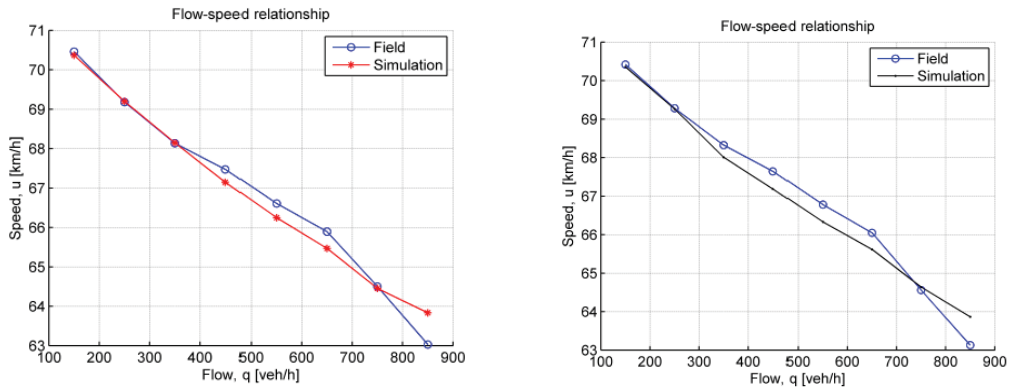
Figure 3. Speed-flow relationship for original model (left) and modified model (right) after calibration, compared to field data.

In the modified model, the vehicle length was determined using the vehicles' weight, which was picked from the weight distribution. The function was determined empirically, as the fitted curve shown in Figure 4. The curve was fitted with a second degree polynomial function shown with a black line in Figure 4. The function is shown in and Equation (5), where vehicle length l is given in meters and GVW in kg. The fit of the polynomial had a R^2 of 0.98.

$$l(GVW) = -5.88 \cdot 10^{-9} \, GVW^2 + 0.0006 \, GVW + 4.58 \quad (5)$$

A new data set was acquired for validating the calibrated models. The data was collected at the same site, but for a different time period. The RMSP for the speed-flow relationship between the validation data and the original and modified model was 0.75 % and 0.66 % respectively. These are almost the same values of RMSP as for the calibration, and the two models are therefore considered valid.
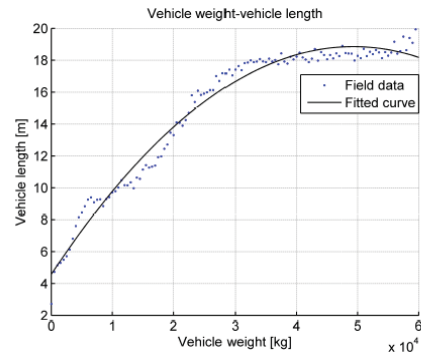

Figure 4. The relationship between vehicle length and vehicle weight for intervals of 500 kg.

Table 1. Calibrated parameters in the original and modified Gipps' model. Parameters without standard deviation were treated as constants in the simulations. The vehicle length was a function of GVW in the modified model.

Parameter	Symbol	Unit	Cars, original model		Trucks, original model		Modified model	
			Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
Max acceleration	a_n	m/s^2	3.0	0.2	1.0	0.5	3.0	0.2
Max deceleration	b_n	m/s^2	2.9	1.0	2.5	1.0	3.0	1.2
Veh. length	l_n	m	5.5	0.9	10.8	5.0	f(GVW)	
Eff. Veh. Length	s_n	m	l_n+1.1		l_n+1.0		l_n+1.0	
Desired speed	V_n	m/s	20.7	1.4	20.2	1.8	20.5	1.4
Estimated dec.	$\hat{b}$	m/s^2	6.2	1.0	5.5	0.9	6.7	1.2
Reaction time	τ	s	0.8		0.8		0.8	
Constant	c_1						0.78	
Constant	c_2	kg^{-1}					$-9*10^{-7}$	
Constant	c_3	kg^{-1}					$-2.5*10^{-4}$	

3. Results from the simulations

In order to evaluate the modified model, some evaluation criteria had to be determined. This could be how an observed vehicle in the model reacts to different maneuvers performed by the downstream vehicle. Alternatively could one or more single variables be compared. Based on the previously reviewed literature, acceleration rates, deceleration rates, and vehicle spacing seemed to be affected by the weight of the vehicle.

These variables are thus eligible for comparison. Vehicle spacing was chosen as the main comparison variable. This is an important variable because it influences how much space one vehicle occupies on the road, which again is of importance when determining road capacity. In addition, vehicle spacing may be particularly relevant for an analysis of Gipps' car-following model, because it is a safety-distance model. The foundation, upon which this type of model is built, is the following distance to the vehicle ahead.

Of the different kinds of spacing variables, time-gap is chosen for the comparison. The main reason is that this variable is independent of the length of the vehicle ahead, as opposed to the headway. Secondly, time-gap is advantageous over space-gap because it includes the vehicle's speed. It could be argued that headways should be chosen over time-gaps, as vehicle length also influences how much space a vehicle occupies on the road. However, when analyzing potential deviations between headways collected in the field and from the model, it may be difficult to determine whether the source of error is the vehicle length or the vehicle spacing. Of the two variables, only gap is solely a result of driving behavior.

As it was implemented in the modified model that the weight of the downstream vehicle should affect the estimated deceleration of the downstream vehicle, it is interesting to investigate whether this has had any effect. Therefore the vehicle spacing is also grouped by different pairs of leader and follower vehicles.

The cumulative distribution function of time gap for different weight groups is shown in Figure 5. Field data as well as results from both the original and modified model are included in the figures. For vehicle weight categories between 0 kg and 10 000 kg, we see that both the original and modified model produce results which are quite close to the field data. For vehicle weights above 10 000 kg, the modified model produces more accurate distributions, while the original model underestimates the lengths of the time gaps.

Goodness of fit tests were applied on the time gap distributions for heavy vehicles in the original and modified model. The χ^2-test was run with the null hypothesis being that the time gap distribution from the model is equal to the time gap distribution from the field data. The alternative hypothesis was that the time gap distributions were not equal. If the calculated χ^2–value is higher than a critical value, the null hypothesis is rejected. With a significance level of 0.05 and 11 bins in the distributions, the critical value was 18.31.
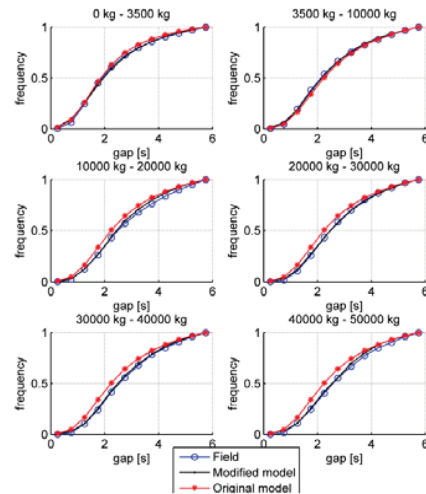

Figure 5. Cumulative distribution of time gaps in the car-following regime for vehicles in different weight groups for the original and modified model, compared to field data.

In Table 2, we see that the null hypothesis is rejected for all comparisons at a 0.05 level of significance. The table does however show that the modified model produces lower χ^2–values than the original model, and thus closer to the critical value. This supports that the modified model provides a better fit for the time gap distributions of heavy vehicles than the original model.

Table 2. Values for the χ^2–test for comparisons to time gap distributions from field data.

Weight category	χ^2 Original model	χ^2 Modified model
3500-10,000 kg	254	122
10,000-20,000 kg	826	32
20,000-30,000 kg	1310	31
30,000-40,000 kg	1610	24
40,000-50,000 kg	1598	26

The modified model includes the GVW of the preceding vehicle by multiplying $\hat{b}$ with γ_{n-1}. It was therefore investigated whether the modified model improves the accuracy of time gaps between different pairs of leader and follower vehicles where one or both are heavy. The different pairs of vehicles which were compared are: car–car (leader–follower), car–heavy vehicle, heavy vehicle–car, and heavy vehicle–heavy vehicle.
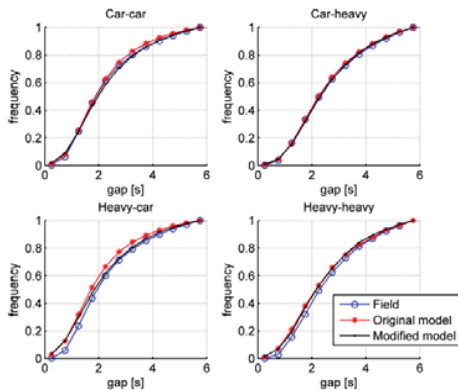
Figure 6. Cumulative distributions of time gaps in the car-following regime grouped by leader-follower vehicle pairs.

Figure 6 shows the cumulative distributions of time gaps sorted by pairs of leader and follower vehicle. The top right graph shows that both the original and the modified model produce accurate results for the case where a heavy vehicle follows a car. In situations where car follows car and car follows a heavy vehicle, the modified model produces a better fit than the original model. For the case of heavy vehicle following heavy vehicle there does not seem to be a considerable difference between the two models. In all cases of deviation the distribution curve is shifted to the right, meaning that the lengths of time gaps are underestimated.

For the sake of comparison, the average time gap was calculated for each time gap distribution, and compared to the average time gap in the field data. The results are shown in Table 3, and they are quite similar to the findings in Figure 6. The lowest deviation is found for heavy vehicle following car, and the largest improvement is found for car following heavy vehicle. The improvement for heavy vehicle following heavy vehicle is 0.1 %, and is not considered to be of significance. The largest deviations for the modified model are found in the cases where a heavy vehicle is the leader. This may be an indication that the same constants in the function determining the weight dependent reduction factor should not be used for both b_n and $\hat{b}$.

Table 3. Deviations from average time gap in the car-following regime measured in the field data.

Vehicle pair	Original model	Modified model
Car - Car	-3.4%	0.7%
Car - Heavy vehicle	-1.7%	-0.3%
Heavy vehicle - Car	-10.4%	-5.6%
Heavy vehicle -Heavy vehicle	-5.3%	-5.2%

4. Discussion of results

The results revealed several important findings. It is clear that there is a potential gain in further developing vehicular models, especially for heterogeneous traffic. By reducing the number of parameters to calibrate from 23 to 14, we show that the calibration task can be decreased, and the savings are larger the more vehicle types originally modelled. The results show that the parameter reduction does not compromise the ability to predict vehicle behavior, and in some cases even improve it. However, the study revealed some issues to be discussed.

The calibration task was performed with extensive data about the vehicle weight distribution at the model area. As WIM-sites are not very common, it could be difficult to calibrate a similar model with heterogeneous flow without such data. One could argue that average weight distributions which are assumed to be present on different road types could be used instead of weight data, but this would presumably impede the calibration.

The data used for the study is not without noise. There may be systematic errors such as overestimating vehicle weights, but this should be possible to compensate by changing the constants in the modified model. The large number of observations means that it is impossible to manually validate each data entry. Therefore, some false registrations might not have been spotted. However, the high number of observations should reduce the significance of such errors.

There are some limitations in the data set used. First, the choice of using point data instead of time series data introduces some uncertainties. The calibrated acceleration parameters were not compared to real deceleration and acceleration rates. This would certainly improve the quality of the study, but time series data from enough vehicles from the whole spectra of GVW is much more difficult to collect than the data used in this study. Second, the data is from a rural two-lane road only. There are certainly other locations with different road and traffic characteristics which would be interesting to include in the analysis, e.g. congested flow, hills, curves, urban areas, adverse weather. An important reason for this limitation is that WIM-detectors are usually placed on locations where there are no confounding factors, which means that other data collection methods should be used for further research.

There might be better ways to incorporate the effect of vehicle size in Gipps' model. We proposed three options, but only had the data to explore one of these. The implementation of the modified model was made on the assumption of declining deceleration rate for increasing GVW. Even though this assumption is supported on literature, there might be other unknown factors affecting the relationship between spacing and GVW.

There might be other types of vehicle behavior affecting the vehicle-following model. Including the model in microscopic simulation software would also be of interest, as this will show how well the model performs together with other types of models, such as lane-change models. It is not known either if the reduction of parameters limits the use of Gipps' model. It must though be expected that some degrees of freedom is lost, when a model is simplified. In the longer term, a similar analysis can be performed for other car-following models. This may show if some models are better fitted for weight incorporation than others.

The data collected for the study describe the behavior of Norwegian drivers, which may behave differently than drivers with other nationalities. A similar data set from drivers of other nationalities, or even from other parts of Norway, may produce different results. Although the data might differ between countries, it is not obvious that the relationship between vehicle-following behavior and vehicle properties will. The implementation of GVW in Gipps' model suggests that vehicle properties affect the behavior, and vehicles on Norwegian roads are not very different from vehicles in other similar countries.

5. Conclusion

This was an initial study in the attempt of improving vehicle-following models in heterogeneous traffic flow. The purpose was to modify Gipps' car-following model in order for it to better reproduce observed behavior in heterogeneous traffic, and to reduce the calibration effort. By introducing a parameter γ, which is determined on the basis of the vehicle weight, we were able to fulfil these goals. The following can be concluded:

1. When GVW is included in the model, the time gap distributions fit slightly better than with the original model.
2. The calibration effort is significantly reduced, and the reduction is greater for each additional vehicle type included in a simulation with Gipps' original model.

These results are useful for simulations with heterogeneous flow. However, several important topics are to be addressed before the modified model can be implemented, and which should be addressed in future research.

We propose to collect more data about heavy vehicle car following behavior to test the modified model in other cases, especially for congested traffic. As loop detectors are known to have issues with detecting slow moving vehicles, floating car data could be a better option. However, this type of data collection is resource demanding, especially because of the need of vehicles with a large variation in GVW.

We also propose to collect data about the relationship between deceleration and GVW in order to

verify the impact of the weight factor γ. In this study, it is assumed that this relationship is equal in shape as the relationship between time gap and GVW. By performing deceleration tests of vehicles with different GVW, it is possible to define this relationship more accurate. If the performance tests are also done on varying surface conditions, it is possible to simulate different weather conditions, as the behavior changes whether the surface is dry, wet or even icy.

6. Acknowledgements

14. References

1. Di Cristoforo, R., C. Hood, et al. (2004). "Acceleration and deceleration testing of combination vehicles."
2. Brackstone, M., B. Waterson, et al. (2009). "Determinants of following headway in congested traffic." Transportation Research Part F: Traffic Psychology and Behaviour 12(2): 131-142.
3. Sayer, J. R., M. L. Mefford, et al. (2003). "The effects of lead-vehicle size on driver following behavior: Is ignorance truly bliss?" Ann Arbor 1001: 48109-42150.
4. Nouveliere, L., D. Stanczyk, et al. (2012). Headway Spacing Model for a Heavy Vehicle Based on Experimental Data. Proc. of the International Heavy Vehicle Symposium Transport Technology (HVTT12).
5. Moridpour, S., M. Sarvi, et al. (2012). "Lane-Changing Decision Model for Heavy Vehicle Drivers." Journal of Intelligent Transportation Systems 16(1): 24-35.
6. Ravishankar, K. V. R. and T. V. Mathew (2011). "Vehicle-Type Dependent Car-Following Model for Heterogeneous Traffic Conditions." Journal of Transportation Engineering-Asce 137(11): 775-781.
7. Gipps, P. G. (1981). "A behavioural car-following model for computer simulation." Transportation Research Part B: Methodological 15(2): 105-111.
8. Aghabayk, C., M. Sarvi, et al. (2012). Effective Variables on Following Behaviour of Heavy Vehicle Drivers. Australasian Transport Research Forum (ATRF), 35th, 2012, Perth, Western Australia, Australia.
9. Aghabayk, K., M. Sarvi, et al. (2013). "New Car-Following Model Considering Impacts of Multiple Lead Vehicle Types." Transportation Research Record: Journal of the Transportation Research Board 2390(1): 131-137.
10. Toledo, T. (2007). "Driving behaviour: models and challenges." Transport Reviews 27(1): 65-84.
11. Hjelkrem, O. A. (2015). Determining Influential Factors on the Threshold of Car-Following Behavior Presented at 94th Annual Meeting of the Transportation Research Board. Washington, D.C.
12. Hourdakis, J., P. Michalopoulos, et al. (2003). "Practical Procedure for Calibrating Microscopic Traffic Simulation Models." Transportation Research Record: Journal of the Transportation Research Board 1852(-1): 130-139.
13. Dowling, R., A. Skabardonis, et al. (2004). Traffic analysis toolbox volume III: guidelines for applying traffic microsimulation modeling software.

14. Rakha, H., Y. Gao, et al. (2010). Calibration of steady-state car-following models using macroscopic loop detector data, Mid-Atlantic Universities Transportation Center.

Odd André Hjelkrem is currently pursuing his PhD at the Institute of Civil and Transportation Engineering at the Norwegian University of Science and Technology. He received a M.Sc. in applied physics in 2007 at the Institute of Physics at the Norwegian University of Science and Technology. He is currently employed as a researcher at SINTEF Transport Research. His research interests include driver behavior and modelling.

Sebastian Nerem received his M. Sc. in Transportation Engineering (2013) from the Norwegian University of Science and Technology. He is currently employed at Norconsult AS, where he works with applying and developing traffic flow and transportation demand models.