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Graduation Research Report

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Performance of Existing Integrated Car Following and Lane Change Models around Motorway ramps

Delft University of Technology

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Preface

This report contains a performance study of existing integrated car following and lane change models around motorway ramps, performed by Maarten Oud. The study is performed as part of the Master graduation procedure at the department of Transport & Planning of the faculty of Civil Engineering and Geosciences at Delft University of Technology (TU Delft). The study is performed in association with TNO, which provided the data set that was being used in this research.

First, I would like to thank ir. Aries van Beinum and dr. ir. Haneen Farah for their support and advice during the research project and for their insightful and useful reviews of the intermediate versions of the report. I would also like to thank prof. dr. ir. Serge Hoogendoorn and dr. ir. Riender Happee for their comprehensive feedback of the overall research process.

I would also like to thank TNO for providing their data for this research, which did mean a great deal for the research overall. I would like to thank professor Tomer Toledo for his efforts to share code of his model, despite the fact that I did not know how to use it properly.

Finally, I would like to thank my brother Stefan and my father Peter for giving me tips about more efficient programming, which helped me to drastically reduce the processing time of my data processing scripts to acceptable and workable levels.

Delft, February 2016

Summary

Models are an important tool for decision making. However, in order to get proper results, these models must be validated and only be used in situations where the conditions of the validation apply. Blind trust on a model can lead to unexpected and inaccurate results. Advancements can be made to reduce the number of situations where this occurs. Not only by making the models more accurate, but also by doing more field studies for validation of behavioural aspects of the traffic.

One of these aspects is the process of lane changing and car following behaviour. These two aspects determine the general longitudinal and lateral driving behaviour. Mathematical models that describe these types of movements for each individual vehicle provide the building blocks for microscopic simulation. In most models, these two aspects are modelled independently, but newer models, such as the integrated driving behaviour model (Toledo, 2003), attempt to mould this into an integral decision structure.

This research attempts to validate the lane changing and car following behaviour of three models: FOSIM, VISSIM and the aforementioned Integrated driving behaviour model. These models are compared against a dataset from TNO of the motorway A270, in situations where free flow conditions apply. The models are tested on the desired speed distribution, the merging point distribution, the accepted gap distributions and the lane change distribution. The lane changes that are being found are classified by their distinctive causes, the so-called "triggers". Six triggers are defined for lane-change classification.

The main result is that calibration and validation play a major role in the validity of the models. For all tested simulation packages, their default parameters did not reflect the observed data. This means that the driver's attitude and the traffic conditions have a large impact on the general driver behaviour. In free-flow traffic conditions, Dutch drivers tend to be risk-averse, as reflected in the low number of voluntary lane changes and the wide gap acceptance distribution. This risk-averseness is usually not part of a model's default parameter set and therefore calibration is essential to simulate the traffic correctly. Furthermore, the different triggers helped to get a clearer view about what type of lane changes occur, where, and why they occur.

The FOSIM simulation results show that this model has serious limitations. A main point is that this model is too deterministic regarding driver characteristics. Although in theory probabilistic factors could be added to the model, further advancements of the model, such as implementing probabilistic behaviour, requires reprogramming of the simulation package, which was not possible within this research.

VISSIM gave better results, but it over-estimates the number of voluntary lane changes in free flow conditions on Dutch motorways when using the default behavioural parameters. Further calibration of these parameters did partially correct this error, but the remaining estimation errors differ per voluntary lane change trigger; courtesy and speed gain related lane changes are under-estimated while lane changes to keep right were over-estimated. Furthermore, the gap acceptance behaviour was not much improved. This may indicate that other boundary conditions, such as traffic generation, where wrongly assumed in the simulation. Also, one could argue if a gap selection algorithm could improve the accuracy. Further research is required to test these hypotheses.

The Integrated driver behaviour model could not be completed within the time constraints of this research, but analysis of the car-following aspect of this model shows that this model has some limitations that could be easily solved by several counter-measures. Driver observation and acceleration behaviour issues could be solved by integrating psycho-physiological factors into the model, such as observation thresholds and multiple acceleration regimes. A main recommendation is to perform more validation research of current models to gather more calibrated parameter sets for a wide range of traffic conditions.

The used data collection method, road side cameras, was an accurate enough method to gather enough data for this research. This method can be widely applied for other researches too with different camera mounting points, such as lamp posts and sign gantries.

The triggers that have been defined in this research could be used in other studies to find if there are differences in driver behaviour for each trigger. However, within this research, 10 to 15 percent of the lane changes could not be classified in one of the six triggers. This may indicate that there is either a classification error or a missing trigger.

For VISSIM, ranges of recommended parameter values for Dutch traffic in free-flow have been found and are provided in this study.

Contents

1 Introduction

1.1 General introduction of the subject

Since the beginning of mass-motorisation, traffic problems have emerged. The ever growing number of cars causes situations where cars in traffic cannot be optimally served, and as a consequence, the traffic cannot flow freely; this phenomenon is called congestion. Over the past decades, planners and decision makers have tried to tackle congestion problems where they occurred. However, a common question that each measure posed was: "*is this measure effective?*". And even more importantly: "*can we predict problems before they occur in future situations?*". This is where models come into play as a tool to answer these questions.

Basically, a **model** is a simplified representation of reality. Models dissect certain phenomena from reality and put these in a framework of rules, assumptions and boundary conditions. One can use a model to make alternative scenarios that differ from reality. The model will explain what the effects and consequences are of these alternative scenarios. The different scenarios then can be compared with each other and with the reference scenario taken from reality and one can draw conclusions from these results.

For traffic, **mathematical models** (often analytical models) are the most common approach to tackle traffic problems. Each traffic phenomena follows a certain pattern and this pattern is being used to set up mathematical equations and parameter sets. These models do need to be tested to check their validity with reality. Over the years, many different aspects in traffic behaviour (such as route finding, traffic distribution, car following) have got their own specialised models. Different models can operate at different scales and are suitable for different situations (though hybrid models exist, see Barceló et al (2004)). The following scales are commonly considered:

- The **microscopic models** model each vehicle (or individual) as individual agents. Each agent has its own set of properties and acts on its own. These models are mainly meant to investigate individual traffic behaviour on a small scale.
- The **mesoscopic models** group vehicles together in larger entities, such as lanes. Instead of investigating individual behaviour, these models are based upon group behaviour. Because not every individual has to be modelled, these models are more suitable for larger areas, like a city network.

- The **macroscopic models** group vehicles together in even larger entities. The network has been reduced to its bare bones and therefore these models are suitable to model entire networks.

In the past, these models only existed on paper, but with the rise of computer technology, one can use numerical interpretations of these mathematical models and incorporate them into **simulation models** to simulate traffic.

Over the past decades, microscopic models have become increasingly more advanced as the calculation power of computers has grown. This increase in complexity is often (but not always!) accompanied with an increased accuracy of the predictions, which leads to a growing appliance of these models in decision making procedures. Models have become an increasingly more important in planning and managing traffic.

One aspect of these microscopic models is lane-changing behaviour which together with the car following behaviour constitute the main building blocks of these models. Although this seems a trivial aspect at first glance, a lane change is a complex task for a driver. It involves interaction with not only vehicles on the lane the driver is on, but also the lanes adjacent to the driver. Furthermore, it involves quite some planning skills to plan ahead where to make the necessary lane changes. First, there needs to be a reason to change lanes: to gain speed, necessity to change lane as the current lane the driver is on ends, the necessity to change lanes in order to follow a planned route or the need to apply to the “keep right” rule. When a driver actually wants to change lanes, he must first find a gap of an acceptable size to fit his vehicle safely in and adapt his speed to the destination lane.

For this lane change behaviour (and related to that, the car following behaviour), a mathematical framework is required to describe the decisions drivers make and the limits they are subject to. For the formulas that are used in this framework, parameters are required to give a numerical solution that can be used in the simulation. The numerical values of these parameters must be determined by gathering data from the field. This can be done by measuring devices in vehicles or by using external measuring by e.g. loop detectors and cameras. However, the parameters do not follow directly from the measured data; they need to be derived. And the more complex the model, the more parameters it requires, making it a difficult task to determine all of these parameters such that similar macroscopic conditions are achieved.

This graduation research report is about improving the lane changing behaviour in both microscopic simulation software packages that are already existing and mathematical models that have not yet been incorporated in software packages.

A literature study, presented in Chapter 2, analyses possible mathematical frameworks, as well as comparing existing software and mathematical models with each other on their strengths and weaknesses. A selection of three models - two software models and one newer mathematical model - is calibrated, tested and compared with the data gathered from the field to analyse their performance. The goal of this study is to propose improvements to existing models in order to determine and simulate lane change behaviour more accurately.

1.2 General notes about modelling

Although software models can use increasingly more calculation power and the graphical display of the model output has also been improved greatly throughout the year, looks may be deceiving. As stated before, models are simplified representations of reality and they therefore have their limits. It is very important to be aware of these limitations, because these can lead to effects that do not occur in reality, or bias from reality, leading to wrong results.

Models are far from perfect and as a result there are still a lot of improvements to be realised. Bloomberg et al. (2000) describe in a comparison study between CORSIM and VISSIM, which are two microscopic simulation software, that there is scepticism about the application of complex traffic modelling programs due to the fact that little knowledge is available about the accuracy of these models. Although this comparison study was performed 15 years ago, both applications are still used today and their underlying models did not receive major changes.

One of the behavioural aspects that all microscopic models have to address is the process of lane changing and acceleration behaviour. There are a number of different approaches to model this behaviour, each with their own assumptions and limitations. The lane changes can be split into two main categories: the lane changes that a vehicle has to make in order to follow a route or to not end up at the end of a lane (mandatory lane changes); and the lane changes that are voluntary (discretionary lane changes). Both of them can either be modelled with one model or separately.

Mandatory lane changes mainly play a role at motorway on-ramps, but discretionary lane changes (such as courtesy lane changes) also play a minor role. There are three stages in traffic behaviour regarding on-ramp merges, each defined by their area:

1. The area in advance of the on-ramp merge;
2. The area at the on-ramp merge itself;
3. The area after the on-ramp merge.

Most studies have focussed on the traffic behaviour at the second stage, but knowledge about the traffic behaviour in the first and third stage is still missing.

Another aspect that has been brought forward in previous research is the relation between accuracy and data demand. Advanced simulation models can potentially have a greater accuracy, but this comes at a price: complex models often have a large number of parameters (such as: desired headway and speed, sizes of different “behaviour zones”, driver aggressiveness). Each of these parameters must be determined and validated.

It's often not possible to measure these parameters directly in the field and some of them are even very hard to determine indirectly (such as: critical gap size, minimum headway, maximum accepted braking deceleration). Furthermore, traffic is anything but uniform and deterministic, and behaves rather stochastic. This inherent property causes that there will always be some loss in accuracy and deviations from reality are unavoidable. The best model will always remain an estimation of reality. And even if it is possible to determine all parameters, there is a risk of over-fitting; a model may fit perfectly on one data set, but can perform terrible when another data set is being given. This is something that needs to be avoided, since the performance of a model should be as consistent as possible.

This bears the question if a simpler model would have done the job better. A simpler model may potentially be less accurate, but it is more feasible to validate these models, and there is a smaller risk of over-fitting the model onto the data. Only validated models can give accurate results, so it is very important that the data collection for this validation is feasible.

Finally, several studies have shown that microscopic models often fail to reflect the behaviour of drivers properly in busy or congested conditions. Chevallier et al. (2008) describe that these models (especially the gap acceptance algorithm) are often only validated for free-flow conditions on the main road. When spillback takes place in the models, it can be argued that the results are still valid or not. Sarvi et al. (2007) describe that “The major limitation of most of the existing microscopic simulation models is that they employ a global car following model to capture the acceleration characteristics of drivers in all driving situations.” In other words, most models assume that drivers behave the same in all traffic conditions, while this is not true, as this research describes. There are several mechanisms to overcome this problem (like implementing advanced gap selection algorithms or applying a different model under congested conditions), but most software models do not take these into account. However, this research only focusses on free-flow conditions, so this is not relevant for the study itself, but it demonstrates what improvements can be made.

In brief, there are several aspects that are not taken into account or modelled inaccurately in most common software models. These models can still benefit from a lot of improvements to increase their accuracy. Newer mathematical models may offer a solution to overcome some of these inaccuracies, but more research is required for that. This research attempts to contribute in filling this knowledge gap.

1.3 Relevance of the research

Relevance to society

Although most people in society do not have to deal with models themselves, they do face the consequences of decisions that are based upon the outcome of these models. This is not only limited to just traffic models, but a wider scope of planning models (involving demography, economy, etc.). With the ever increasing importance of models in decision making, the reliability of these models will also become more important.

It is therefore necessary to periodically check the current models for their validity and to improve models. Even more important is the development (and validation) of newer and better models that take more effects into account. With the increasing capabilities of computers, models can benefit from this by using these increased capabilities to take more effects into account. This will result in more reliable and more accurate models.

Relevance to science

The driving behaviour aspects regarding lane changing has been researched before, but it is relatively much less studied compared to car following. Current software models are not able to describe the lane-changing behaviour well enough to reflect reality, with odd results as a consequence. This gives an indication that there is some essential knowledge that is missing when it comes to modelling lane-changing behaviour. It can mean that either the model methodologically is wrong or the used parameters are wrong. To find out which of the two problems is correct, a comparison with data from reality gives insight how the model deviates and can point to the underlying causes.

As stated before, the data demand of models can be a challenge, where the main challenge is that it is very hard to get precise values from measurements. Models will therefore always remain an approximation of reality. What is however possible (and relevant to this study) is to improve this approximation and therefore improve the reliability of the model results. One can find better ways to describe certain phenomena, gather certain parameters or to validate models.

A clear and well defined methodology is needed for processing the collected data in order to get the desired results which would allow a proper comparison between the data sets from reality and from the models. One has to design how exactly to process the data based upon the available input and desired output data. The computer processing needs a mathematical framework for the processing methodology. The result will give an indication of the best approach to get the most accurate model estimation, and thus improve the reliability of model results in the future.

1.4 Research questions

Since modelling is such a broad subject, the scope of this research is set more specific. To narrow down the research, proper research questions are specified to tackle the subject and to narrow down the subject to only the elements that are relevant for the research, in this case, the lane change behaviour of traffic near motorway on-ramps and how models can be improved upon replicating this behaviour.

A few existing models were selected for this research. For the simulation software packages, possibilities to improve the models within their current programming framework have been investigated; reprogramming was not possible in this research. The main goal was to give an overview of shortcomings and deviations of current models and ways to improve them.

The core research questions are divided into two main categories:

1. How realistic is the modelling (for both software and mathematical models) of the driving behaviour of merging traffic in the following three stages:
    1.1 upstream of the merge area
    1.2 within the merge area
    1.3 downstream of the merge area
2. What is the best course of action to improve current microsimulation models?

These core research questions will be further divided into more specific research questions in Chapter 3.

2 Literature Study

To better understand the subject and identify the research gaps, a literature study is conducted. This provides more insight about the current knowledge of the subject and what has been researched recently. The literature study can be split in three parts: the first part, section 2.1, involves earlier research about driver behaviour; the second part, section 2.2, involves mathematical models that exist to describe driver behaviour; the last part, section 2.3, involves currently existing microscopic software models. Each part is discussed in the subsections below.

As a general note regarding the terminology used in the next subsections, a driver is considered to make only two types of movements:

- **longitudinal movements**, e.g. acceleration and car following; these type of movements only involve a single lane.
- **lateral movements**; these movements involve lane-changes and thus multiple lanes.

2.1 Driver behaviour research from the field

To understand how to model traffic behaviour properly, a first step is to research the actual behaviour of the traffic in the field. After all, the main goal of a model is to imitate the behaviour of real traffic. Several studies have been performed regarding the movement behaviour of vehicles, both longitudinally and laterally. Other researches from the literature describe how one can measure this driver behaviour. Below is a summary of the conclusions and lessons learned from the literature.

2.1.1 Longitudinal movements

One of the longitudinal movements is **car following.** Olstam et al. (2004) define car following behaviour as the behaviour that occurs when a vehicle is constrained by a preceding vehicle, and driving at the desired speed will lead to a collision. In general, drivers want to keep a safe distance to the vehicle in front of them, but also do not want a too large gap that someone can enter this gap (causing the headway distance to decrease drastically, which is not desired). Therefore, drivers have to follow their predecessor by adapting their speed and thus their distance to the predecessor.

Hoogendoorn et al. (2011) revisited a common psycho-physical model, the **Wiedemann-model**. The Wiedemann-model is revisited by comparing it to traffic behaviour by using remote sensing (a helicopter) to follow vehicles. The main conclusion from this research is that there is a strong indication that the general assumption of drivers accelerating smoothly is not valid; the acceleration turned out to be more linear and piece-wise. This is caused by the fact that the driver generally does not pay attention to the car following activity all the time and that drivers do not have a precise control over the acceleration of the vehicle. This result implies that most car following models, like the Wiedemann-model, are not as accurate as previously thought. This implies that next to imperfect perception, imperfect control over the vehicle is also a factor that needs to be taken into account in future models.

Saifuzzaman et al. (2014) mentions that most car following behaviour researches (and models, for that matter) focus on physical signals. However, psychological signals also play a significant role; these signals determine the driver's attitude and characteristics. Most drivers have a driving strategy that is adequate at the most. Incomplete knowledge of the traffic conditions and the lack of time to evaluate all alternatives are the main cause of these sub-optimal strategies. Models often assume that drivers do have full knowledge and spend all resources to evaluate alternatives. Both of these assumptions contradict reality. Context and driver heterogeneity are factors that influence the behaviour, influencing perception, aggressiveness, risk averseness and safety constraints. For instance, in congested conditions, the safety constraints tend to be more loose and headways tend to be smaller than the safety distance.

The following driver characteristics can be found in various literature sources, as mentioned by Saifuzzaman et al. (2014):

1. Socio-economic characteristics (e.g., age, gender, income, education, family structure).
2. Reaction time.
3. Estimation errors: spacing and speeds can only be estimated with limited accuracy.
4. Perception threshold: human cannot perceive small changes in stimuli.
5. Temporal anticipation: drivers can predict traffic situation for the next few seconds.
6. Spatial anticipation: drivers consider the immediate preceding and further vehicles ahead.
7. Context sensitivity: traffic situation may affect driving style.
8. Imperfect driving: for the same condition drivers may behave differently in different times.
9. Aggressiveness or risk-taking propensity.
10. Driving skills.
11. Driving needs.
12. Distraction.
13. Desired speed.
14. Desired spacing.
15. Desired time headway.

It is however very hard to research this with external vehicle data; for these kind of researches, full driver participation is required, which limits the possibilities of measuring methods that can be used. It also limits the number of observations, because full driver participation limits the sample size of the research by default. This may also be the reason why these factors tend to be ignored in other researches and models: "The primary data source used for developing CF models is loop detector data or trajectories at best, which can only provide basic vehicular information. Driver characteristics, which are critical for deciphering drivers' thinking processes during the CF procedure, cannot be extracted from this type of data. This serious data limitation often leads to the fact that human factors are usually over-simplified in the few CF models that indeed considered human factors. These models relied on only one or two parameters to indirectly capture the total impact of drivers' individual characteristics and cognitive features." (Saifuzzaman et al. (2014))

Although these factors are important, this research will not consider them due to the fact that full driver participation is not an option in this research.

2.1.2 Lateral behaviour

One of the main lane-changing movements are merging movements. This type of movement involves a vehicle merging with traffic on another lane. This implies that the driver also needs to pay attention to the traffic on the other lane in order to find a large enough gap to fit his vehicle in and to adapt the speed to the target lane, whilst still keeping attention to his own lane . Daamen et al. (2010) and Marczak et al. (2013) performed research in this particular subject. Daamen et al. (2010) found several peculiar aspects in this merging behaviour. First, the position of the merge differs under different traffic conditions: in free flow, traffic tends to merge earlier than in congested conditions; during congestion, the merging takes place further down the acceleration lane than in free flow conditions, maximising the use of the length of the acceleration lane. This is because it is more difficult to find an acceptable gap in the other lane in congested conditions; the drivers only change lanes when it is necessary.

Another effect that Daamen et al. (2010) observed are the necessity and relaxation effects. The **necessity effect** is defined as the need to change lanes, and is strongly related to the lane change demand for obligatory lane changes. If this necessity is high, the driver has no other option than to change lanes. The higher the necessity, the higher the demand and the smaller the gaps are that drivers are willing to accept. This implies that the minimum accepted gap, also defined as the **critical gap**, is not a constant value, unlike common gap acceptance theories describe. Instead, it is a variable, related to the desire to change lanes. This effect can complicate the determination of the critical gap. After the lane change, the drivers will let the distance between the vehicles grow again. This effect is called **relaxation**.

Daamen et al. (2010) observed one example of a common model limitation; while in reality a vehicle will always find a gap to merge, no matter how small, the vehicle in most simulation models will come to a standstill at the end of the merging lane and wait there until a gap, that is large enough, has been found. This example shows that models can show different behaviour compared to reality, in this case, the lack of the necessity effect. This also bears the question if the traffic flow upstream and downstream of an on-ramp or off-ramp is realistically simulated.

Marczak et al. (2013) investigated merging behaviour on motorways on two different locations and in two different countries (Bodegraven in the Netherlands and Grenoble, France). One of the key aspects here is that this study does not only look at accepted gaps, but also at **rejected gaps** (gaps that the driver rejects for fitting his vehicle in for a lane change). This study showed that by taking rejected gaps into account, a peculiar effect appears: there is a high chance that a rejected gap of a vehicle is larger than the finally accepted gap. It implies that the critical gap can vary depending on the situation. In this case, it’s the end of the merging lane that is approaching, which increases the necessity to change lanes and therefore decreases the minimum gap size the driver is willing to accept.

This is mainly caused by the aforementioned necessity effect. Taking this effect into account, the findings of this study are not completely surprising; the necessity effect already implies that the critical gap can shift and therefore the rejected gaps that are larger than the finally accepted gap are likely to occur when the critical gap is larger (usually when the lane change desire is low). The desire to change lanes increases as the end of the acceleration is approaching, leading to a monotonously decreasing critical gap size. Figure 2.1 shows a graph that shows this relation.

The study created a logistic regression model based upon the earlier found results. This model attempts to predict the acceptance or the rejection of all the gaps that are offered. This logistic model had a high prediction accuracy; it was able to correctly predict the acceptance and rejection in 98% of all cases. What is surprising is that not all factors are significant between the two data sets; dependent on the road geometry and traffic conditions, that play an important role change. For the shorter acceleration lane in Grenoble, the distance to the end of the acceleration lane plays a large role, while in Bodegraven the possible length of an acceptable gap plays a larger role. This means that merging behaviour can differ between ramps.

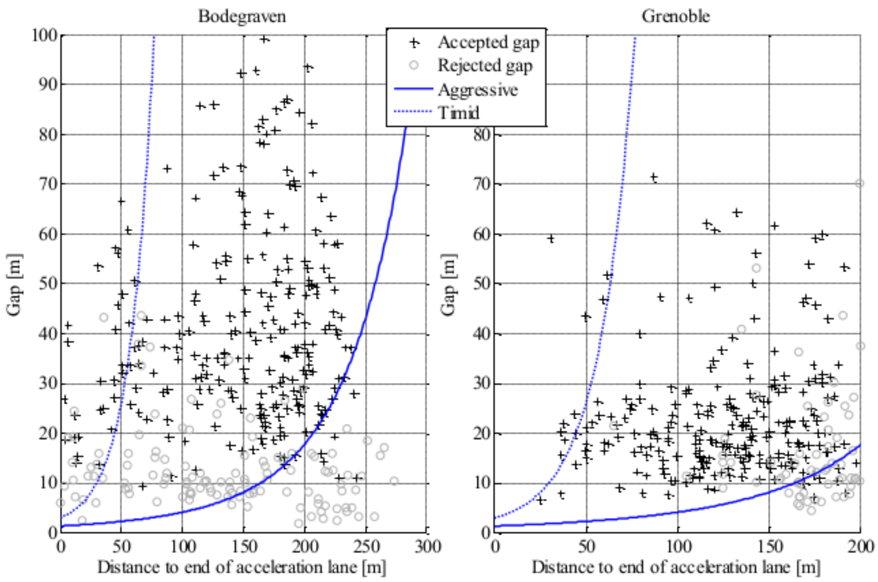

Figure 2.1 Distribution of the accepted and rejected gaps relative to the end of the acceleration lane. It's visible that the critical gap decreases as the end of the acceleration lane is approaching (Marczak et al., 2013)

Marczak et al. (2013) falsify the general assumption that the accepted gap is larger than each rejected gap due to consistent driver behaviour. In models where common gap acceptance theories are applied, it is possible that vehicles stop at the end of the acceleration lane, because they were unable to find an acceptable gap. In reality this does not occur, as measurements in this study have shown that vehicles do not slow down at the end of the acceleration lane and no vehicle was unable to find a gap.

2.1.3 Existing time series data sources

In the past, multiple time series have been recorded for model calibration and validation. Several studies have been done in isolated situations to isolate several behavioural aspects (Brackstone et al. (1999)). Other studies – mainly regarding validation – have been performed in the field.

One of the these large data sets that have been collected is the **Next Generation Simulation (NGSIM)** data set, which was collected in 2005. This is a data set collected by the Federal Highway Administration (USA) and is publically available. The data has been collected at three locations:

- **Interstate 80 Freeway, San Francisco Bay area in Emeryville, CA**
  This data set is recorded on April 13, 2005 and encompasses a 500 meter long stretch of a 6-lane motorway and one weaving area.
- **Lankershim Boulevard, Universal City neighbourhood, Los Angeles, CA**
  This data set is recorded on on June 16, 2005 and encompasses an urban arterial road, with a recording area of about 500 meters.
- **US Highway 101 "Hollywood Freeway", Los Angeles, CA**
  This data set is recorded on on June 15th, 2005 and encompasses a 640 meter long stretch of a 6-lane motorway and one weaving area.

Several studies have used this data to calibrate and validate their models (e.g. Alexiadis et al. (2004)). Although these data sets are quite extensive, they do have a few limitations:

- The recorded area is most likely too small to capture turbulence effects before and after on- and off-ramps, since the ramps within the captured areas are near the ends of the captured area.
- The recorded time periods are rather short: only 15 minutes.
- The recorded areas have uncommon lane and ramp layouts, which raise the question to what extent the conclusions drawn from this dataset are applicable to more common layouts.
- Traffic behaviour in the USA is most likely not relevant to Dutch traffic, or European traffic in general. For instance, the traffic rule to keep to the right side of the road, which is common in Europe, is not commonly found in the USA. Driver attitudes may also hugely differ between countries.

Therefore, the NGSIM data will not be used in this study.

2.2 Mathematical models

Mathematical traffic models attempt to explain and reproduce human traffic behaviour. These mathematical models can be categorised in three groups:

- Longitudinal behaviour models
- Lateral behaviour models
- Integrated behaviour models

Each category and models that fall under these categories will be explained in the sections below:

2.2.1 Longitudinal behaviour models

Longitudinal behaviour models are exclusively about behaviour of vehicles that are in the same lane. This behaviour contains car following and free flow acceleration.

Free flow acceleration behaviour

When car following does not occur, vehicles want to drive at their desired speed v_d. This only applies to models where cars can be in a non-following state, i.e. the Wiedemann model and MITSIM (Olstam et al. (2004)). A general approach is to apply constant acceleration rates. A vehicle has a desired acceleration rate $a_{d,acc}$ and a desired deceleration rate $a_{d,dec}$. A general rule (also formulated in the free-flow regime in MITSIM (Olstam et al. (2004))) that can be applied here is:

$$a = \begin{cases} a_{d,acc} & \text{if } v < v_d \\ 0 & \text{if } v = v_d \\ a_{d,dec} & \text{if } v > v_d \end{cases}$$

A note is that the desired acceleration, deceleration and speed have to be assumed based upon the vehicle's characteristics. There is no generic approach to do this other than using a deterministic value or a random distribution amongst all drivers. Other acceleration formulations (such as linear acceleration) could also be used, but since their relevance is not large enough for this research they will not be described into further detail.

When car following does occur, other models need to be used.

Car following models in general

There are different ways to approach car following behaviour. Olstam et al. (2004), Saifuzzaman et al. (2014) and Brackstone et al. (1999) describe seven different categories of approaches that car following models are using:

- **Gazis-Herman-Rothery models (GHR)**. These models state that the following vehicle's acceleration is proportional to the speed of the follower, the speed difference between follower and leader and the space headway.

The follower will respond to every change in behaviour of the leader, no matter how minor and the model assumes that the follower knows everything regarding the leader speed, distance and acceleration, which is an oversimplified assumption. An example of this is the car following model of Ahmed (1999).

- **Safety-distance/collision avoidance models**. Safety distance models are based on the assumption that the follower always keeps a safe distance to the vehicle in front. A safe distance is defined as a distance that is larger than what a car needs to come to a full stop when the leader "behaves unexpectedly". This will avoid accidents from occurring. The Gipps car following model is an example of this (Gipps (1981)).
- **Linear models (Helly)**. These models are quite similar to GHR models, but with a difference that it looks further ahead and also follows the second leader (the car in front of the first leader). It will adapt its acceleration when one of these two is braking. Helly's car following model from 1959 was the first of its kind (Brackstone et al. (1999)).
- **Optimal velocity models (OV)**. These models assume that each vehicle has their own optimal (safe) velocity, depending on the distance to the predecessor and that the acceleration of the n^{th} vehicle can be determined according to the difference between the actual velocity and the optimal velocity. An example of this type of model is IDM, as described by Treiber et al. (2000).
- **Psycho-physical car following models (PP)**. These models use perception thresholds. This means that a difference in e.g. visual angle of the leading vehicle needs to be large enough to be "noticed" by a driver, e.g. distance between the leader and follower. The headways may fluctuate, but it is realistic to assume that the perception of the follower is imperfect. However, these type of models are hard to validate due to the same imperfections. An example of this model is the Wiedemann model, as described in Olstam et al. (2004).
- **Fuzzy logic models**. These models rely on logic statements, but the boundaries on which these statements make decisions are no static values, but distributions. Though these models are relatively new, the methodology of these models is still questionable regarding its realism.
- **Cellular automation (CA) based models.** These models discretise time and space in pre-defined areas called cells; each cell can either have an occupied (1) or empty (0) state. The traffic behaviour is modelled by the interaction between these cells.

Brackstone et al. (1999) conclude that despite of extensive studies and conceptual bases supported by empirical data, all models are limited due to a lack of time-series following behaviour. Due to the limitations of the models, it can be argued whether these models are sufficiently valid or not.

It should also be noted that the reaction time of the driver is taken into account in all models, but most models use a single log-normal distribution reaction time for all drivers. (Olstam et al. (2004)). However, reaction times and reaction intensity differ from driver to driver and are different in different regions or even traffic conditions. One may be more alert during congestion than during free-flow, leading to shorter reaction times. It is argued that it may be beneficial to use different acceleration models for different traffic flow conditions.

Intelligent Driver Model (IDM)

Treiber et al. (2000) proposed a model that is similar to GHR models, but this model incorporates a desired speed. IDM is used in combination with the MOBIL lane changing model (see section 2.2.2). The main IDM equation is defined as:

$$\dot{v}_\alpha = a^{(\alpha)}\left[1 - \left(\frac{v_\alpha}{{v_0}^{(\alpha)}}\right)^{\beta} - \left(\frac{s^*(v_\alpha, \Delta v_\alpha)}{s_\alpha}\right)^2\right]$$

where:

- $\dot{v}_\alpha$: current acceleration/deceleration of the subject vehicle α.
- $a^{(\alpha)}$: maximum acceleration/deceleration of the subject vehicle α.
- v_α : current speed of the subject vehicle α.
- Δv_α : current speed difference of the subject vehicleα and its leader.
- ${v_0}^{(\alpha)}$: desired speed of the subject vehicle α.
- s_α : current net space headway of the subject vehicle α.
- $s^*(v_\alpha, \Delta v_\alpha)$: desired space headway of the subject vehicle α.
- β : calibration parameter.

The desired headway is defined as:

$$s^*(v_\alpha, \Delta v_\alpha) = {s_0}^{(\alpha)} + {s_1}^{(\alpha)} \cdot \sqrt{\frac{v_\alpha}{{v_0}^{(\alpha)}}} + T^\alpha v_\alpha + \frac{v_\alpha \cdot \Delta v_\alpha}{2\sqrt{a^{(\alpha)} \cdot b^{(\alpha)}}}$$

where:

- s_0 : bumper-to-bumper distance in congested traffic.
- s_1 : calibration parameters
- T^α : safe time headway
- $b^{(\alpha)}$: the deceleration rate of the subject vehicle α.

The model is quite simple and its parameters are quite intuitive. However, not all calibration parameters are clearly defined. Furthermore, this model is deterministic and assumes that drivers are fully aware of the traffic conditions and their own state, while in reality this is a matter of perception. Schakel et al. (2012) incorporated a modified version of this model in their LRMS model, which also incorporates relaxation effects, lane change desire and synchronisation.

Wiedemann-model

The **Wiedemann-model** is a psycho-physical car following-model that uses different perception thresholds to trigger different actions. In figure 2.2 a diagram is shown of the different behavioural regimes. The regime thresholds (as defined in Olstam et al. (2004)) are described as follows:

- The desired distance between two stationary vehicles, AX. This threshold consists of the length of the front vehicle and the desired front-to-rear distance and is defined as:

  $$AX = L_{n-1} + AX_{add} + RND1_n \cdot AX_{mult}$$

  where AX_{add} and AX_{mult} are calibration parameters. $RND1_n$ is a normally distributed driver dependent parameter;
- The desired minimum following distance at low speed differences, ABX:

  $$ABX = AX + BX\ ,$$

  $$BX = (BX_{add} + RND1_n \cdot BX_{mult}) \cdot \sqrt{v}$$

  where BX_{add} and BX_{mult} are calibration parameters. The speed v is defined as:

  $$v = \begin{cases} v_{n-1} & \text{for } v_n > v_{n-1} \\ v_n & \text{for } v_n \leq v_{n-1} \end{cases}$$

- The maximum following distance, SBX:

  $$SDX = AX + EX \cdot BX\ ,$$

  $$EX = EX_{add} + EX_{mult} \cdot (NRND - RND2_n)$$

  where EX_{add} and EX_{mult} are calibration parameters. $NRND$ is a normally distributed random number and $RND2_n$ is a normally distributed driver dependent parameter;
- Approaching point, SDV. This threshold is used to describe the point where the driver notices that he or she approaches a slower vehicle. SDV is defined as:

$$SDV = \left(\frac{\Delta x - L_{n-1} - AX}{CX}\right)^2,$$

$$CX = CX_{const} \cdot \left(CX_{add} + CX_{mult} \cdot (RND1_n + RND2_n)\right)$$

where CX_{const}, CX_{add} and CX_{mult} are calibration parameters;

- Decreasing speed difference, $CLDV$, which implies the perception of small speed differences at short, decreasing distances. $CLDV$ has a similar modelling setup as SDV. However, Olstam et al. (2004) do not give a mathematical formulation of $CLDV$;
- Increasing speed difference, $OPDV$. This threshold describes the point where the driver observes that he or she is traveling at a lower speed than the leader. This threshold is defined as:

$$OPDV = CLDV(-OPDV_{add} - OPDV_{mult} \cdot NRND)$$

where $OPDV_{add}$ and $OPDV_{mult}$ are calibration parameters.

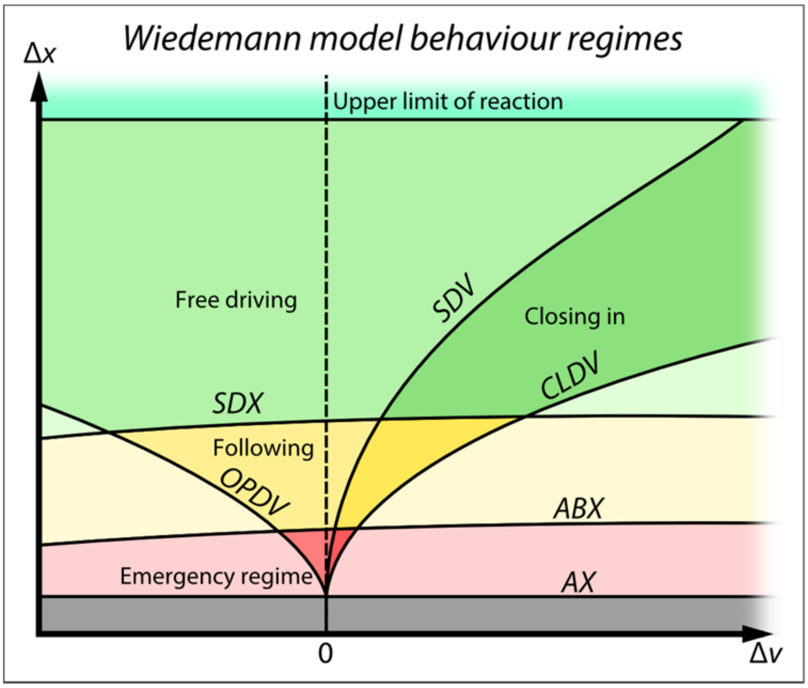

Figure 2.2. The regime zones and borders [*adaptation from Olstam et al. (2004)*]

Consequently, the following car following regimes occur:

- **Free driving**. The vehicle is not bound by other vehicles and will use maximum acceleration to gain its desired speed. When the vehicle has reached its desired speed, the acceleration is set to a random value close to zero to model inaccurate acceleration control of the driver. The regime's bordering thresholds are SDV and SDX.
- **Closing in**. The vehicle notices that it is closing in on a slower vehicle when the SDV threshold is passed and will start to decelerate.
- **Following**. The vehicle attempts to maintain the distance to the leader. The regime's bordering thresholds are ABX , SDX, SDV and $OPDV$. To model the fact that the driver does not have accurate control over his acceleration, the vehicle has a close to zero (but not zero!) acceleration.
- **Emergency regime**. When the headway distance is smaller than ABX, the driver will brake to avoid collision.

The perception-based model of Wiedemann offers a realistic framework for car following behaviour by incorporating human factors like perception and inaccuracies. However, this model does have a large number of calibration factors, which does make the validation of this model more challenging.

2.2.2 Lateral behaviour models

Several dedicated lateral behaviour models have been developed in the past decades. These models often have different base principles, such as thresholds or utility functions. The sections below give an overview of a selection of those models:

The Gipps-model

One of the earlier models for lateral movements is the **Gipps-model**. Gipps' (1986) analysis starts with three basic questions:

- Is it possible to change lane?
- Is it necessary to change lane?
- Is it desirable to change lane?

Though the first question must always been answered with "yes" in order to make a lane-change (to prevent collisions), the other two questions are not necessarily relevant in all cases. A driver encounters many conflicts that can interfere with his desires (e.g. keeping a certain speed or to be in the correct lane for a particular lane manoeuvre). Other conflicts can arise at points where lanes have a restricted access (e.g. bus lanes). Gipps identified a number of factors that influence the lane-change behaviour and therefore the relevance of these questions, namely:

- The physical possibility to change lanes and to change lanes safely.
- The location of permanent obstructions
- The presence of transit lanes
- The driver's intended turning movements
- The presence of heavy vehicles
- Speed of the vehicle and the traffic

The model gives each vehicle a pre-determined destination choice. Relative to this destination, the model identifies three zones with different driving behaviour:

- The **remote-zone** has no influence on the route choice, since the decision point is too far away here. The driver only changes lanes when it's desirable (for instance, to gain speed).
- The **middle-zone** slightly alters this behaviour by steering the driver towards his destination; the driver ignores opportunities to gain speed if these would mean that he changes to the wrong lane, so in theory, the driver should be in the correct lane or the lane next to it at the end of this zone
- In the **near-zone**, the driver is only interested in following his route to his destination and ignores all other lane-change incentives.

Although this suggests that there are three clear and distinct zones, the transitions between the zones are slightly vague and they are not the same for every driver. However, the model is not very sensitive to the exact positions of these zones.

Next, a series of questions are asked that will decide whether or not to change lanes. A flow-chart of these questions is shown in figure 2.3.

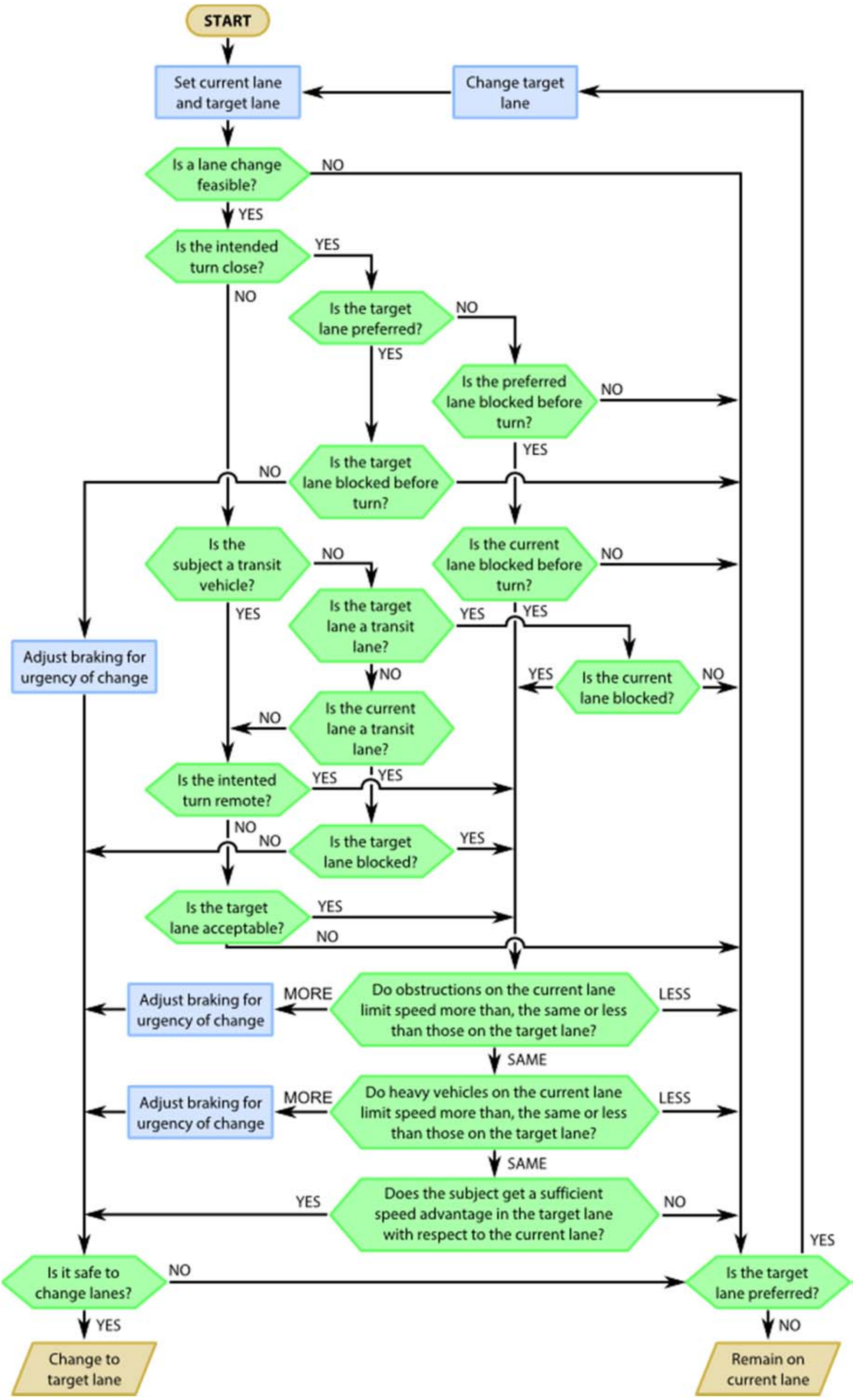

Figure 2.3 Gipps' flow chart for lane change decisions [*adaptation from Gipps (1986)*]

Gipps laid down a good basis for lane change models; it gives a clear reasoning logic of what decisions a driver has to make and it prevents that cars will collide when changing lanes (or during car following). However, this model is almost thirty years old; it does not take all relevant effects into consideration (e.g. necessity growth) that have been researched recently. Furthermore, a big limitation is that the vehicles only change lanes when it is safe and there is a sufficient headway (Zheng (2013)). The interaction between the vehicle and it's follower is limited in this model. In reality, there is much more interaction between the lane changer and its followers and this can open more opportunities to change lanes.

The MOBIL model

Kesting et al. (2007) developed the **MOBIL-model** ("Minimizing Overall Braking Induced by Lane changes"), which is partially based upon the Gipps model. A main difference is that the rules in MOBIL are acceleration-based instead of headway-based. This allows a greater interaction between drivers and can make the modelled drivers more altruistic in their behaviour. The model evaluates the advantages and disadvantages of a lane change based upon these acceleration-based rules and triggers a lane change when it is safe to change lanes and the advantages outweigh the disadvantages.

Drivers in the MOBIL-model do not only consider the consequences of a lane change for themselves, but also the consequences of their followers in the origin lane and the destination lane. The parameters in this model will determine how much the driver weighs the consequences for its followers.

In all cases, the safety criterion must be met. This is formulated as:

$$\tilde{a}_n \geq -b_{safe}$$

Where $\tilde{a}_n$ is the theoretical acceleration after the lane change and b_{safe} is the safety limit. This will prevent that vehicles crash into each other as long as b_{safe} is lower than the maximum breaking rate of the vehicle b_{max}. Even when drivers behave purely egoistic, this constraint prevents the occurrence of accidents.

MOBIL contains two rule-sets, one for symmetric passing rules (where one can pass both left and right) and one for asymmetric passing rules (where one can only pass on the left lanes). Since the latter applies to this research's focus area (the Netherlands), only the asymmetric rule set will be covered. The following rules regarding passing are assumed:

1. **Passing rule.** The passing states that traffic is only allowed to pass on the left, unless there is congestion. If the speed drops under v_{crit}, the symmetric passing rules are applied. Since this research is not focussing on congested situations, the symmetric passing rules will not be taken into account.
2. **Lane usage rule.** Vehicles should desire to go to the right lane and only use the left lane for overtaking.

Each of these rules have their own mathematical descriptions.

The first rule is mathematically described as:

$$a_c^{eur} = \begin{cases} \min(a_c, \tilde{a}_c) & \text{if } v_c > \tilde{v}_{lead} > v_{crit} \\ a_c & \text{otherwise} \end{cases}$$

Where:

- a_c : the current acceleration of the vehicle;
- $\tilde{a}_c$: the acceleration of the vehicle after an implied lane change;
- v_c : the current speed of the vehicle;
- $\tilde{v}_{lead}$: the speed of the leader on the adjacent lane;
- v_{crit} : the minimum speed of the traffic that can be considered as free-flow;

This formulation makes sure that the keep-right rule only applies when there is no congestion ($\tilde{v}_{lead} > v_{crit}$) and when the vehicles on the left lanes are faster ($v_c > \tilde{v}_{lead}$). If these two conditions do not apply, congestion is implied.

The second rule has two mathematical descriptions, depending on whether the vehicle moves from left to right or from right to left. The formulations for these rules are:

$$\text{Left} \rightarrow \text{Right: } \tilde{a}_c^{eur} - a_c + p(\tilde{a}_o - a_o) > \Delta a_{th} - \Delta a_{bias}$$

$$\text{Right} \rightarrow \text{Left: } \tilde{a}_c - a_c^{eur} + p(\tilde{a}_n - a_n) > \Delta a_{th} + \Delta a_{bias}$$

Where:

- p : politeness factor
- Δa_{th} : threshold level of the advantages to avoid fluctuations.
- Δa_{bias}: additional bias to motivate the traffic to keep right
- a_o : the current acceleration of the follower in the origin lane
- $\tilde{a}_o$: the acceleration of the follower in the origin lane after the lane change
- a_n : the current acceleration of the follower in the new lane
- $\tilde{a}_n$: the acceleration of the follower in the new lane after the lane change

In this formulation, the follower in the right lane is neglected, since by definition, the left lane is faster than the right one. This has consequences for the interpretation of the politeness factor; it will prevent lane changes from left to right if it's too disadvantageous for the follower in the left lane, even when the leader in the current lane is slow (where the value of p determines how strong this consideration is). Furthermore, when a vehicle is changing from the right lane to the left lane, the follower on the origin lane is taken into account, since they can pressure slow vehicles on the left lane to move to the right. According to Kesting et al. (2007), this is realistic behaviour as observed in Germany, where there is a great distribution in desired speeds on motorways.

Ketsing et al. (2007) used the following parameter values in their model for tests:

- $p = 0 \dots 1$
- $b_{safe} = 4 \text{ ms}^{-2}$
- $\Delta a_{th} = 0.1 \text{ ms}^{-2}$
- $\Delta a_{bias} = 0.3 \text{ ms}^{-2}$

It is recommended to use these values as initial parameter values and tweak those to make a better fit.

An important note here is that the acceleration itself is not calculated by the MOBIL model. Instead, MOBIL is dependent on a car following model to calculate these accelerations. MOBIL only evaluates the occurrence of lane changes.

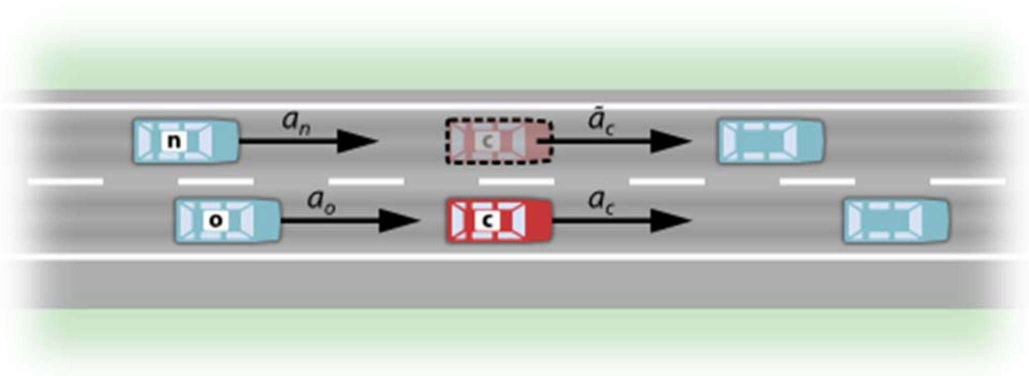

Figure 2.4 Designation of all relevant vehicles in MOBIL. The current vehicle (c) has an acceleration of a_c and an implied acceleration of $\tilde{a}_c$ after a lane change. The follower in the origin lane (o) and the follower in the destination lane (n) are affected by the decisions made by vehicle c and in return, vehicle c is influenced by the implied effects upon its followers. [*adaptation from MOBIL (2007)*]

2.2.3 Integrated behaviour model

An **Integrated behaviour model** combines car following and lane changing into one undividable behavioural model. Since the two behavioural aspects are strongly dependent on each other, they might as well be considered as one coherent behavioural aspect.

Toledo's integrated driving behaviour model (Toledo (2003)) is based upon three elements: the short-term goal, the short-term plan and the driver's actions. The short-term goal is defined by the target lane of the driver; the driver will then construct a short-term plan to reach its goal. It will select a target gap to change lanes. Finally, the driver will take action by adapting his acceleration and change lanes when they have reached their selected gap. When a driver does not need to change lanes, it can decide to follow the leader or to accelerate to/maintain the desired speed.

Figure 2.5 gives an overview of all the decisions the drivers in this model have to make. Not all decisions can be observed; the driver's actions are observable, but the short-term goal and the short-term plan – also called latent behaviour in the literature – are unobservable.

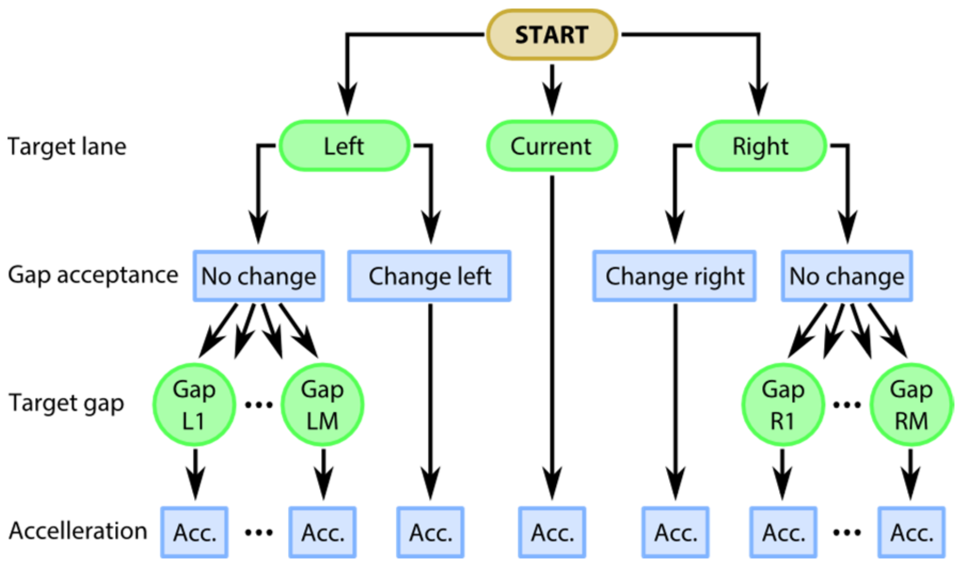

Figure 2.5 Structure of Toledo's integrated driving behaviour model. The round entries in the table are unobservable choices, while the square entries in the table can be observed. [*adaptation from Toledo (2003)*]

Lane changes and acceleration are modelled differently in the model. Acceleration is modelled as a continuous function, while lane changes are modelled as a discrete function. The assumption for the discrete modelling of lane changes is that only one lane change can be performed during one time interval. Since the time intervals are smaller than the execution time of the lane change, this is a realistic assumption.

The model contains several mechanisms to capture inter-dependencies between the various decisions made in the model. Decisions that are made at lower levels of the driving behaviour decision process (e.g. acceleration) are conditionally set by the driving decisions made on higher levels (e.g. short term plan). In other words, high-level decisions govern the outcome of low-level decisions. To specify the choices made at high-level decisions, an expected maximum utility (EMU) is being used to evaluate the effects of all low-level decision alternatives. Furthermore, the model also captures variable driver characteristics (e.g. aggressiveness, time headway thresholds, reaction times) being randomly distributed over all the drivers. Finally, the model re-evaluates the short-term plans after every time step in order to be able to cope with changing traffic conditions, but this does assume that all state dependencies are captured by the explanatory variables used in the model.

The model has a large set of sub-models, each covering a part of the driving behaviour. For the sake of keeping the model description brief, this report will not go into further detail of this model. Further information can be found in chapters 3 and 4 of the study of Toledo (2003).

2.3 Current software models

A tool to predict driving behaviour in future situations, models have been developed to estimate driver behaviour as accurately as possible. There are several approaches to gain this accuracy. However, the effectiveness of each approach differs in terms of data demand. Below is a summary and a critical assessment of models from the literature study.

AIMSUN

AIMSUN is a software package that is a hybrid between a microscopic and mesoscopic simulation (Barceló et al. (2004)). The main part of the simulation is mesoscopic with a small area being simulated microscopically. This model tries to combine the speed of large-scale models with the detail level of microscopic models. This particular combination of different scales in one model is quite unique, as most models tend to limit themselves to only one scale.

AIMSUN uses a lane-change model that is an advancement of the Gipps-model. The main components about decision modelling and the usage of different fixed zones with different behaviour are still main components of the model. The zones are defined as zone 1 to 3, where zone 1 is the farthest away from the decision point and zone 3 is the nearest to the decision point.

An addition to this model is that on ramps are modelled slightly differently when it comes to the assignment of the zones. First of all, the model ensures that the acceleration lane is never used for overtaking from the normal lanes; vehicles can only leave the lane and vehicles from the main line cannot enter it. An extra parameter has been added to the model, called *TimeDistanceOnRamp*. Barceló et al. (2004) define this as: “the distance (in seconds, converted into distance as before) from those lateral lanes considered to be on-ramp lanes, in order to distinguish between a common lateral lane, that is a long lane used for overtaking which drops down, from the proper on-ramp lanes, which are never used for overtaking.” If a vehicle is too far from its area, it will behave corresponding to the behaviour of zone 1 when no other conditions apply (e.g. other lane ends or obstructions). When it is in the on-ramp area, it will seek for a gap to merge, as this is a mandatory lane change.

Another feature that has been added into the model is the patience factor. This factor influences the gap acceptance of the drivers. The simulated driver has a defined maximum waiting time (this assigns for each driver a value randomly taken from a set distribution) that will define how long a driver is willing to wait before getting impatient and accept smaller gaps. There is however no specification in the manual from Barceló et al. (2004) how this works in detail. The inner workings of this model are a “black box”, since Barceló et al. (2004) remain quite vague about the exact underlying models of this simulator. Therefore, this model is not fit for this research.

CORSIM

CORSIM is a microscopic simulation developed for urban and motorway corridors (Bloomberg et al. (2000)). This model is developed and maintained by the American road authority, the FHWA. The model integrates two sub-models within its framework: **NETSIM** (for urban corridors) and **FRESIM** (for motorway corridors).

CORSIM can define up to ten different user types, each with their own behaviour parameters (Bloomberg et al. (2000)). This influences car following and lane changing. Each driver type has its own desired headway and a minimum headway it wants to keep while being constrained to traffic control devices and regulations.

CORSIM uses global gap-acceptance variable parameters for each type of turn or lane change movement (Bloomberg et al. (2000)). These parameters are assigned to each of the ten driver types. Each of these gap acceptance decisions are independent decisions, considering just one personal gap acceptance value of one driver. A lane change requires a large enough lead and trailing gap in the adjacent lane (Middleton et al. (1999)). The gap acceptance of the lead gap is determined by the amount of deceleration a vehicle has to perform to avoid a collision with the leading vehicle on the other lane.

The sub-model FRESIM considers three types of lane changes: mandatory, discretionary and random lane changes (Middleton et al. (1999)). During every time step of the model, each vehicle is scanned if there is any desire to change lanes. If the vehicle has changed lanes, it will remain in that lane for at least three seconds (to avoid unrealistically quick-following lane changes) if there is no other mandatory lane change. For on-ramps, FRESIM also assigns a desired free-flow speed to vehicles entering the motorway. This free-flow speed is based upon the average speed in the adjacent lane to facilitate smooth lane merging.

Since CORSIM is developed and only validated in the United States, CORSIM likely does not capture traffic behaviour commonly found in Europe. For instance, it does not have the “keep right” rule, which is commonly found in Europe, and therefore CORSIM would simulate less lane changes from the left lane to the right compared to what occurs in reality. Therefore, CORSIM could potentially give wrong results when it comes to lane change behaviour in European circumstances. Furthermore, CORSIM does not consider relaxation and has a limited set of driver classes.

FOSIM

FOSIM is a microscopic simulation model developed in the Netherlands, specialised in modelling Dutch motorways (Dijker et al., (2006)). The model has been developed at the TU Delft, and its focus is on modelling motorway corridors. Although the latest version of the model has been published in 2006, the core of the model only received small changes since 1997. Dijker et al. (2006) summarises the driving behaviour in FOSIM as follows:

- The driver has a desired speed (this speed is linked to the road);
- If the desired speed is not feasible, the driver will try to change lanes in order to pass slower traffic;
- If lane changing is not possible, the driver will adjust speed and follow the leading vehicle with a desirable time headway;
- Drivers will change lanes if it is necessary to follow their route;
- Vehicles prefer to be in the right-most lane if no other conditions and limitations apply (this not mentioned explicitly by Dijker et al. (2006) in the summary, but it is a part of the lane change model).

A vehicle will only change lanes if there is a desire to do so. This will take the following factors into account:

- **Route following:** vehicles must follow their route;
- **Physical limits:** ending lanes, accidents and other physical obstructions imply mandatory lane changes;
- **The acceleration and speed of the current leader:** if the current leader has speed close to the desired speed of its follower or if it accelerates so much that an overtaking vehicle cannot pass it quickly, no lane change will be performed;
- **The deceleration required from the vehicle, as well as its follower on the adjacent lane,** to avoid collision with the leader on the adjacent lane in case a lane change will be performed. There is a maximum value of deceleration a vehicle will accept for itself and its follower when changing lanes.

If the conditions are met, the vehicle is willing to change lanes. However, it will only do so if it can gain benefits from doing so or when it is necessary. On acceleration lanes, the maximum deceleration the vehicle accepts increases linearly from zero (at the beginning of the acceleration lane) to the maximum value (at the end of the acceleration lane). This will ensure that a gap will always appear at some point. This looks similar to the effect of growing necessity , though the traffic may react more severely on the smaller gaps than they should do.

Although this model has been validated for traffic situations in the Netherlands, the core model is almost twenty years old and may not be up-to-date to the current level of knowledge about lane changing behaviour. Also, the simulation is limited to five vehicle types; three types of cars and two types of HGVs.

VISSIM

VISSIM is a stochastic microscopic simulation model developed by PTV (Fellendorf et al. (2009)). The model is suitable to simulate not only motorway corridors, but also complex intersections (with the possibility to use an external traffic light controller) and a wide range of traffic modes (e.g. cars, trucks, trams, buses, bicycles and even pedestrians). This makes this particular model very suitable to simulate complex urban traffic and unconventional at-grade intersections; it can detect vehicle conflicts on crossing stream in conflict areas. These conflicts will be resolved by priority rules (which a user can define explicitly) and resolve the conflict when it occurs, so collisions will be avoided in this model. The same principles. can also be used for motorway corridors, which are actually much less complex than urban corridors.

VISSIM uses the aforementioned Wiedemann-model as a car following model. For lateral movements, VISSIM considers three elements:

- **Lane selection:** the vehicle will look for mandatory lane changes to follow its route. At a certain given distance, the driver becomes aware that he needs to make a mandatory lane change and will attempt to move to another lane. The possibility of changing lanes is considered, with a gap acceptance based upon *time-to-collission*. If this is not the case, the model will check if a discretionary lane change can be applied. It will check the lane conditions of the current lane and the adjacent lane and compare which lane has the best conditions in terms of speed, route following and time to collision . VISSIM has no random lane changes.
- **Lane-changing:** the model determines if it's desirable to change lanes. Just as in FOSIM, it considers the deceleration the vehicle forces on itself and its new follower. The maximum acceptable deceleration is determined by the necessity to change lanes, often the proximity of the decision point on the route; if the vehicle comes too close to the decision point without being in the right lane, it will make an emergency stop. The driver will become more aggressive the closer it gets to the decision point.
- **Continuous lateral movement within one lane:** this element makes VISSIM unique; the model is able to detect if it can physically move laterally to pass a vehicle without the condition that it has to move to another (predetermined) lane. If a road has wide lanes or even a roadway no specific lane separation, vehicles will still make lateral movements to pass other vehicles based upon the physical size of the lanes and vehicles. By decoupling lateral movements from lanes, the lanes have become more of a guideline and the model allows lateral movements and passing other models would not even consider, but real drivers would; given enough space, a driver will make lateral movements regardless if the lanes are explicitly marked. Or in case of the Netherlands, this model is able to simulate cars passing bike traffic.

VISSIM does not only consider the above aspects for lane changing. The following aspects are also defined:

- **Waiting time before diffusion:** this defines the maximum waiting time of a vehicle at the emergency stop position before it will be removed from the simulation.
- **Minimal front/rear headway:** this defines the minimum distance to leading and following vehicle on the adjacent lane that must be available for a lane change in standstill condition.
- **To slower lane if the collision time is greater than a certain value:** when "keep right" traffic rules are applied, this value describes the minimum time headway towards the next vehicle on the slow lane to make the vehicle consider changing lanes to the slower lane.
- **Safety distance reduction factor:** the reduction factor is the factor that will be used for safety distances during lane changes. After a lane change the model applies the original safety distance again.
- **Maximum deceleration for cooperative braking:** this defines the maximum deceleration the vehicle would use in case of cooperative braking to allow a lane change of another vehicle into its own lane.

VISSIM can set gap acceptance values specifically per location (Bloomberg et al. (2000)), which makes this variable very flexible. Furthermore, the number of vehicle types VISSIM can handle is practically unlimited. The only problem with VISSIM is that it has a large set of behavioural parameters, over 50 in total. Therefore, it can be hard to calibrate and validate this model.

Conclusions of the models considered

In the previous sections, various models have been discussed and analysed. From this, the following conclusions can be drawn:

- All models have their flaws. Most importantly, they all assume that the car following behaviour is the same in all traffic conditions, while this is not necessarily the case;
- None of the models considers necessity effects explicitly;
- AIMSUN combines micro-scopic and meso-scopic modeling. Although this might be an interesting combination for other studies, its microscopic simulation is not interesting enough for this study, because the parameters for lane changing behaviour are too vaguely defined and therefore, this part of the model is a "black box", and that is something that is not desired for this research;
- CORSIM may not suit well in this study because it is designed for American roads and regulations. The other models may reflect the Dutch situation better;
- FOSIM is validated for Dutch motorways, but the main core of the model is getting old and may not give the best results. Still this simulation model is considered due to its main focus, namely Dutch motorway corridors;
- VISSIM is probably the most advanced model available and has a great potential to be applied in this study due to its wide range of possibilities. This wide range of possibilities comes with a price of a large number of parameters, which can be hard to calibrate.

For the remainder of the study, FOSIM and VISSIM will be used and both of them will be compared with data collected from the field.

Table 2.1. Advantages and disadvantages of the software model packages.

Simulator	Advantages	Disadvantages
AIMSUN	• Combined microscopic and mesoscopic model	• Inner working are too much a black box
CORSIM	• Simple model setup • Prevents unrealistically quick-following lane changes	• May miss traffic rules that are commonly applied in Europe • Limited number of driver classes
FOSIM	• Calibrated for the Netherlands • Specialised in motorway corridors	• Core program is about 20 years old • Limited number of driver classes
VISSIM	• Huge flexibility • Can use different behaviour on different locations.	• Hard to calibrate due to the large number of parameters.

2.4 Final conclusions of the literature study

Concluding from these researches, the following aspects deserve further attention during the research:

- Necessity is a significant effect. It suggests that gap selection rather than gap acceptance is the driving factor behind lane changing. Gap acceptance theories may therefore be invalid. It is therefore recommended to take rejected gaps into account to assume that the critical gap is variable;
- Psychological factors may have a significant effect. Although it is acknowledged, this research will not take this into account in later steps due to the fact that it requires full driver participation for research.
- There are many different car following models. Their methodologies are sound, but all of them have a limited validity. There are also methodological difficulties to validate these models, since several parameters can either not be measured (or it is infeasible to do so) or derived from other measurable units;
- Driver behaviour changes in different traffic conditions and other geometric layouts. Different models or parameter settings are likely required.
- The two model types, car following and lane changing, are often explicitly modelled separately. Their decision-making processes are independent; only the boundary conditions of one process change under influence of the other process. Integrated models combine the two processes to take advantage of tweaking the vehicle's acceleration with its lane choice, therefore combining the two decision making processes into one;
- Most simulation models are not completely clear how they exactly work and are therefore "grey" and "black boxes". Especially AIMSUN is vague in that regard, and FOSIM and VISSIM in lesser extent in their details.

3 Research methodology

Based on the research questions and the gained knowledge from literature, a research methodology is formulated. This methodology describes the steps that are taken to perform the research and to get the desired results. Section 3.1 describes the research gaps indicated by the literature. Section 3.2 formulates the research questions following from the research gaps. Section 3.3 describes the approach to answer these questions. Section 3.4 enlists the desired results from the research.

3.1 Research gap indicated by the literature

The literature study in the previous chapter has indicated that most software models lack the ability to adapt their model to the traffic conditions, as described in Sarvi et al. (2007), Chevallier et al. (2008) and Saifuzzaman et al. (2014). Most software models work with a single model for all traffic conditions. The problems are most prevalent at congested conditions; simulated vehicles are using model parameters for free flow conditions, which can lead to the situation that these vehicles will have a hard time finding a gap in congested conditions. But even in free-flow conditions this effect does occur, though to a lesser extent, when the flows are high. The latter situation is the condition this research will try to focus on.

Another research gap is that the latest mathematical models have rarely or not yet been compared with current software models. The current software models often work with more aged models than the current mathematical models, but this also bears the question if the new mathematical models really perform better than the current software models. Therefore, a comparison between the latest mathematical models and the software models would give an indication of how significant the improvements in the latest models are.

Finally, most studies focus on the merging area itself, but the behaviour upstream and downstream of the merging area is often overlooked. This research will also attempt to get a better insight about that in general.

3.2 Reformulation of the research questions

The first step before setting up a research plan is to examine again the research questions. The main research questions are formulated as follows:

1. How realistic is the modelling (for both software and mathematical models) of the driving behaviour of merging traffic in the following three stages:
    1. upstream of the merge area
    2. within the merge area
    3. downstream of the merge area
2. What is the best course of action to improve current microsimulation models?

These research questions are formulated in generic statements. In order to answer these questions, more specific questions that tie in with the main research questions are formulated. The list below contains more specific questions about the subject:

- What differences are there in the behaviour of simulated vehicles compared to the behaviour of vehicles from the field, and how big are these differences…
    - … when using microscopic simulation software packages?
    - … when using the latest mathematical models?
- Which behavioural aspects can be quantified and compared?[1] Examples:
    - Lane change movements (trajectories)
    - Lane change incentives
    - Distribution of lane change incentives over space
    - Acceleration and deceleration in a time slot before, during and after the lane change
    - Driving speeds
    - Headways
    - Co-operative braking
    - Gap acceptance
- What data is required to make this comparison? Examples:
    - Raw data of vehicle trajectories
    - Geometric layout of the road
    - Processed data of the rejected and accepted gaps
    - Behavioural zones (predefined zones where different behaviour and incentives are expected)
    - Lane change locations, times and incentives.

These specific questions help to set up a proper methodology.

[1] Due to complexity, heterogeneity aspects will not be considered in detail in this study.

3.3 Approach

Following from the research questions, an approach is taken with a goal to answer these questions comprehensively and completely. The following sub-sections explain how the previous detailed list of questions will be answered.

3.3.1 Research setup and definitions

A first step is to set up definitions for the research and a structure for taking the next steps in the research. These definitions will be used throughout the entire research. The subsections below will describe all the definitions, sorted in the order of the research questions they relate to.

Size of observed area for research

In order to make proper observations, it is important to know in what area the relevant effects occur. Earlier research from Hovenga (2014) has observed that turbulence effects at on-ramps occur 600 meters before the on-ramp and 900 meters after the on-ramp, so in total an area of 1500 meters. Therefore, this research will set these dimensions as the minimum dimensions for observation.

Vehicle trajectories

Vehicle trajectories require four data dimensions: the vehicle ***ID*** and the ***x*** and ***y*** position at each time step ***t***. Combining the *x*,*y*,*t*-data from each vehicle creates a vehicle trajectory.

Geometric layout

The geometric layout of the road will be simplified to only three aspects, namely:

- Roadway central axis (*x*,*y*)
- Lane central axis (*x*,*y*)
- Lane type (continuous, diverging, merging, weaving)

All other aspects about the geometric layout are not relevant for this research.

Gap distributions

The accepted gaps, rejected gaps, and critical gaps are not assumed to be deterministic values. Instead, it is assumed that each behavioural zone has its own gap distribution parameters.

The following gaps will be distinguished by location of occurrence (i.e. driving lane) relative to the observed vehicle:

- **Current leader gap**, defined as the gap between the leading vehicle in the current lane and the observed vehicle, measured from the front of the observed vehicle to the rear of the leading vehicle.
- **Current follower gap**, defined as the gap between the following vehicle in the current lane and the observed vehicle, measured from the front of the following vehicle to the rear of the observed vehicle
- **Adjacent leader gap**, defined as the gap between the leading vehicle in the target adjacent lane and the observed vehicle, measured from the front of the observed vehicle to the rear of the leading vehicle.
- **Adjacent follower gap**, defined as the gap between the following vehicle in the target adjacent lane and the observed vehicle, measured from the front of the following vehicle to the rear of the observed vehicle.

It is to be expected that for lane changing, the adjacent follower gap has a much tighter distribution than the leader gap, since vehicles will try to change lanes when they have the follower on the adjacent lane in sight in their front mirrors, which means that they have enough space to change lanes.

The following gap distributions will be distinguished by function:

- **Accepted gap**, defined as the gap that has occurred when a vehicle decides to change lanes.
- **Rejected gap**, defined as the largest gap that appeared before the lane change, but without being accepted.[2]
- **Critical gap,** defined as the theoretical distribution of the minimum of the accepted gap (this needs to be derived from the other two distributions.

Since the latter two distributions are harder to determine reliably (they both require indirect observations), only the accepted gap distribution will be used for this research.

[2] This includes cases where necessity plays a role. In those cases, the rejected gap can be larger than the accepted gap.

Triggers for lane changes

There are several incentives (**triggers**) to change lanes. It is important to distinguish between different lane change triggers. Each trigger appears on a different part of the road and causes different behaviour. Each of these triggers has its own traits, which will be helpful to identify these triggers from the data. The following triggers are expected to occur in the data set:

- **Physical obstacle**. This triggers a mandatory lane change due to a physical obstacle, such as an ending lane. In this situation, a vehicle will change lanes no matter what the costs may be, because there is no other sensible option; Only when speeds are low and flows are high, the vehicle considers to stop. The hypothesis is that the closer the obstacle gets, the smaller the critical gap.
- **Route following**. This trigger is mainly applicable at weaving areas and exit ramps. A vehicle has to make a mandatory lane change to follow its route. What makes this different from the above lane change trigger is that the vehicle needs to move towards a selected target lane instead of moving away from a certain origin lane. Most of the route following lane-changes take place before the actual decision point and in case of exit lanes, there is usually a free movement to the exit lane (no cars that limit the gap size). Therefore, the most interesting part for this trigger can be found before the decision point.
- **Speed gain / maintaining speed**. Vehicles want to drive at their desired speed for the most time as possible. If the leading vehicle in the current lane is significantly slower than the desired speed of the vehicle, it will try to pass it on the adjacent lane when possible. According to the Dutch traffic regulations, vehicles can only be passed on the left. This incentive is especially true when faster person's vehicle try to avoid following slower trucks.
- **Keep right rule.** When a vehicle is not on the right-most lane and when the right lane is free, according to the Dutch traffic regulations, vehicles should switch to the rightmost lane.
- **Courtesy behaviour**. Some vehicles change lanes to the left to make room for vehicles coming from the on-ramp. The benefit for the driver that changes lanes here is that it does not need to constantly watch for the entering vehicles that will try to merge and to deal with creating gaps for them. This may look similar to speed gain trigger, but in this case, not all conditions are met regarding the headway and the speed of the leader in the current lane.

Table 3.1 gives an overview of the different lane change triggers and their identifiers. Figure 3.1 displays a flow diagram to correctly identify these triggers, which will be used later on in the data processing.

Table 3.1. Overview of lane change triggers and their identifiers. The direction and the obligation to change lanes are the main identifiers for the triggers; for further distinction, other identifiers are specified if necessary.

Type	Direction	Mandatory	Other identifiers
Physical obstacle	Away from the lane with the obstacle	Yes	
Diverging	Towards target lane	Yes	• Target lane has been reached at the end of the lane change;
Route following	Towards target lane	Yes	• Lane changes are monotonous in direction; • Target lane is **not** reached yet at the end of the lane change.
Speed gain / maintain speed	Left	No	• Leading vehicle is slower than the desired speed of current vehicle / current vehicle is not traveling at desired speed; • Headway to leading vehicle is less than 5 seconds; • Leading vehicle in adjacent lane is faster than the leading vehicle in current lane
Keep right	Right	No	• Leader on right lane is at desired speed or has a headway larger than 5 seconds
Courtesy	Left	No	• Lane change conditions for speed gain and route-following are not met • On-ramp is nearby
Free	Any	Any	• None of the previous conditions to change to the left lane are met

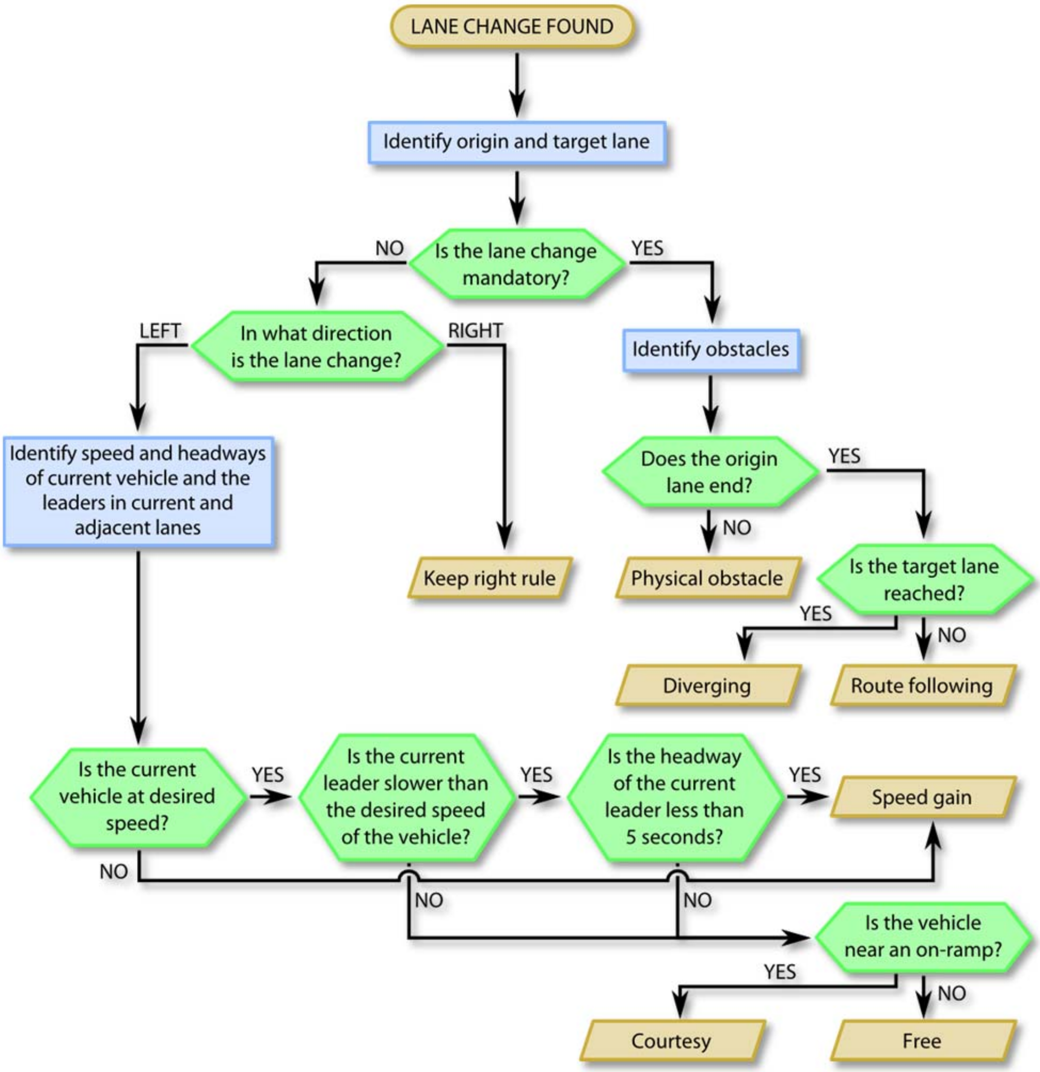

Figure 3.1. Flow diagram of the lane change triggers and identifiers

Behavioural zones

The observed roadway can be divided into several zones. These zones are bordered by discontinuities in the road configuration and can contain physical obstacles and decision points. For mandatory lane changes, the action must be completed before the end of the zone. Not all zones will appear in all layouts. Table 3.2 gives an overview of all zone types and their traits. The borders of these zones are not strict and either need to be assumed or determined empirically. Since the latter is very hard to do, the zone borders will be assumed.

Table 3.2. Overview of behavioural zone types.

Zone	Area type	Present lane changes triggers	Traits
1	Continuous	• Speed gain • Keep right rule	• No nearby merging or diverging areas • No discontinuities
2	Pre-diverging	• Route following*) • Speed gain • Keep right rule	• Always advances a diverging area • Route following in preparation for the next zone • No discontinuities
3	Diverging	• Route following • Speed gain • Keep right rule	• Discontinuity: added lane that diverges from the main line • Route following must be complete before zone end
4	Pre-merging	• Courtesy • Speed gain • Keep right rule	• Always advances a merging area • Courtesy behaviour in preparation for the next zone • No discontinuities
5	Merging	• Physical obstacle • Speed gain • Keep right rule	• Discontinuity: added lane that merges with the main line • Merging must be complete before zone end
6	Post-merging	• Speed gain • Keep right rule	• Always follows a merging area or weaving area • Extra turbulence of merged traffic attempting to gain more speed and thus re-arranging the traffic distribution over the lanes. • No discontinuities
7	Pre-weaving	• Route following*) • Courtesy • Speed gain • Keep right rule	• Always advances a diverging area • Courtesy and route following behaviour in preparation for the next zone • No discontinuities
8	Weaving	• Route following • Speed gain • Keep right rule	• Discontinuity: added lanes that merge and diverge with the main line (weaving) • Route following must be complete before zone end

**) exception to the rule that mandatory lane changes need to be completed before the end of the zone; in this case, the action must be completed before the end of the next zone.*

Processing

All data that has been collected requires processing. This research contains a design for a computer-based processing methodology. This design is done in general terms, in order to make it robust and widely applicable on a large variety of data sets. The results of the processing will be used to fine-tune the parameters from different mathematical and software models. These models will then be tested for their validity and accuracy. The models will be tested with data from Dutch motorways and therefore their validity is limited (though the methodology itself can be used on data sets from other countries to test the validity in that situation). The result will give an indication of the best approach to get the most accurate model estimation, and thus improve the reliability of model results in the future. A more detailed description of the methodology is explained in chapter 5.

3.3.2 Comparison criteria

To compare the results of the models with the empirical data, proper comparison criteria need to be set. These criteria need to be comprehensive, replicable and consistent. However, one has to note that these criteria will always show a slight deviation, because the traffic conditions can never be fully replicated in the models.

The following criteria have been chosen:

Frequency of lane changes (by trigger type)

The first criterion is to check how many lane changes occur. This will show if the model predicts too many or too few lane changes, which would indicate how sensitive the (modelled) drivers are for lane changes. To make a further distinction, the lane change frequencies can be split by trigger type to see if one or more aspects of lane change behaviour are not properly simulated.

Accepted gap distribution

The accepted gap distribution will show how risk-averse or risk-seeking the simulated drivers are compared to the empirical data. This can be related to the shape and location of the distribution of gap sizes.

Space distribution of merging lane changes

One focus point of this research is merging behaviour. For this aspect, it's interesting to look where the vehicles start to merge with the main line. Since not every vehicle will merge at the same point, this will be a distribution over space, which could be represented by a scatter plot or a histogram. When a model is accurate, it should approximate this distribution. However, when it does not, one can also see where and how it deviates.

Acceleration of influenced vehicles before, during and after the lane change

When a vehicle changes lanes, it will not only affect its own speed and acceleration, but also the speed and acceleration of its new follower. The interaction ranges between a timeframe from few seconds before the lane change to few seconds after the lane change which can tell how intense the reaction is of the simulated drivers and how much deceleration they accept.

3.4 Desired results

To conclude the methodology, an overview of the desired results is enlisted in this subsection. The desired results set a goal for the data collection and processing. From these desired results a formulation has been made in chapter 4 what data is required and how to obtain these results from the data. The following results are desired from all data sets:

- Each lane change is linked to an observed vehicle, direct neighbouring vehicles, time stamp, origin lane, destination lane and trigger
- Each lane change will have information about the accepted gap and the acceleration and speed of the observed vehicle and its follower in the destination lane in a time frame around the lane change.
- All lane changes will be analysed by trigger type to get the lane change frequency.
- In the merge area, each lane change from the merge lane will be given a start position to check the distribution

From these desired results, a data collection plan will be formulated in the next chapter to get the necessary data to be able to produce these results.

4 Data collection

One of the main aspects in this research is to gather data from the field to be able later to calibrate the parameters' values for the different simulation models. In order to get this data, a data collection plan needs to be set up. This plan will determine what type of data needs to be collected and what methods will be used to collect and process the data. The data collection is structured in the following order:

- First, the **data demand** describes what kind of data is necessary to perform the research. It specifies the types of data to collect and why this type of data is selected. The data demand also sets demands to which the measuring area needs to conform with.
- Second, the **data collection plan** describes how this data is collected. It describes what methods will be used to collect the data. It also describes what data can be measured directly and what data needs to be derived from other data. The data collection plan also defines the exact locations of the measuring areas.
- Third, the data collection plan is executed.

Each of these steps are described in detail in the sections below.

4.1 Data demand

The first step is to determine what kind of data is required for the rest of the research. The data demand has been specified in the following two ways:

1. Data demand following from the desired results
2. Data demand following from the simulation model (VISSIM and FOSIM)

Each of these two points will be elaborated in the section below.

4.1.1 Data demand following from the research questions

A proper method to start constructing the data demand is to review the desired and determine for each of these questions what data is needed to get each result. Below is a list of the desired results and the data they demand:

1. Each lane change is linked to an observed vehicle, direct neighbouring vehicles, time stamp, origin lane, destination lane and trigger
   - Unique vehicle IDs
   - Vehicle trajectories (*x, y, t, v, a*) from all involved vehicles
   - Road configuration
   - Data about following and leading vehicles in the origin/current lane
   - Data about following and leading vehicles in the destination/adjacent lane
2. Each lane change will have information about the rejected gap, accepted gap, the derived critical gap and the acceleration and speed of the observed vehicle and its follower in the destination lane in a time frame around the lane change.
   - All data from result #2
   - Gap sizes (accepted and rejected)
3. All lane changes will be added by trigger type to get the lane change frequency.
   - All data from result #2
4. In the merge area, each lane change from the merge lane will be given a start position to check the distribution
   - Vehicle trajectories (*x, y, t*) from all involved vehicles

The majority of the results are dependent from the outcome of result #2. This means that there is a large overlap in data demand. This is beneficial for the data demand; the smaller the data demand, the more feasible it is to collect the demanded data.

4.1.2 Data demand following from the simulation model

The next step is to take the selected simulation model and determine what kind of data needed to calibrate the parameters of the lane-changing model in the selected simulation model. This already overlaps the currently found data demand and only the additional data demand will be mentioned. Since the remainder of the research uses FOSIM and VISSIM, a good way to start is to check what is required to know to set up these models.

FOSIM requires the following data:

- The maximum accepted deceleration of the current vehicle and the following vehicle.
- Acceleration and speed of the current leader.

VISSIM requires the following data:

- Minimal headway in case of an emergency stop (not an interesting factor for this study, so this can be ignored)
- Headway distance before changing to the slow lane.
- Safety reduction factor relative to car following (can also be tweaked by trial and error)

All this data can be derived from the data mentioned earlier.

4.1.3 Summary of the complete data demand

Following from the previous sections, a summary of the complete data demand can be constructed. The following data is required in the continuation of this research:

- Unique vehicle IDs
- Vehicle trajectories (*x, y, t, v, a*) from all involved vehicles
- Road configuration
- Data about following and leading vehicles in the origin/current lane
- Data about following and leading vehicles in the destination/adjacent lane
- Safety reduction factor relative to car following

Not all data can be directly measured; a significant portion needs to be derived, e.g. speed and acceleration can be derived from position data. Therefore, the list below gives an overview what can be measured directly:

- Vehicle trajectories (x, y, t)
- Road configuration

All other data types can be derived from these data entries:

Directly observed data	Data derived from observed data
1. Vehicle size	• Net headways (combination with (2))
2. Vehicle trajectories (*x*, *y*, *t*)	• Vehicle speed and acceleration (*v*, *a*) • Followers and leaders in current lane • Followers and leaders in adjacent lane • Gross headways • Co-operative breaking
3. Road configuration	• Behaviour zone locations • Obstacle locations • Vehicle's current lane (combination with (2))
4. Generated data	• Unique vehicle ID

4.1.4 Data resolution demand

For each of the four data entries, a certain resolution in the data is required. This resolution determines how accurate the data should be measured and it determines what measuring methods are suitable. Below is a list of each data entry and its demanded accuracy:

- **Vehicle ID**: each vehicle needs an incremental unique ID. This is an integer.

- **Vehicle position (x, y):** a high spatial resolution is required to follow the path of a vehicle. A rough estimate about the order of size that's required for this is about a tenth of the vehicle's length, or about 0.5 meters. This is to make sure that errors in position and speed are not too large and inaccurate. If this is not manageable, one can always apply smoothing to level out noise and sharp deviations.

- **Time stamp (t):** a high time resolution is also required to follow the path of a vehicle. At least 4 time steps per second would be recommended.

- **Road geometry:** the road geometry should minimally have the same spatial resolution as the vehicle position data.

4.1.5 Demands for the measuring area

In order to get proper and clear data samples, demands for the measuring area need to be set. These ensure that the data collection is feasible and the number of unwanted side-effects causing noise in the data is minimised. The data needs to be complete, unambiguous and concise as possible with minimal disturbances.

The following demands have been set for the measuring area:

- **The research limits itself to motorways only.** Secondary roads usually have intersections that follow up each other closely, leading to too much turbulence across intersections. It is hard to isolate turbulence effects in those situations. Motorways have more spaced out discontinuities, making them more suitable to isolate turbulence effects of a single ramp.
- **The research limits itself to weaving, diverging (exit ramp) and merging (entrance ramp) lane movements near ramps.** Weaving will not be investigated within this research.
- **The ramps have a single lane when they exit or enter the motorway.** We do not want turbulence effects of tapers or merges on on-ramps that can disturb the rest of the system.
- **The situation that is being investigated is an isolated ramp system with no other turbulence effects.** This involves elements like lane endings not involving the ramps or other ramps nearby.
- **There should be no obstructions in the area that can obstruct the view for more than 1 second when following a car (such as: tunnels, wide overpasses, overhead constructions).** This is to prevent that essential data cannot be measured.
- **The area must have busy traffic conditions.** Otherwise almost all offered gaps are accepted, while it is also important to know which gaps are rejected. This is also necessary to determine the critical gap distribution.

4.2 Data collection plan

From the aforementioned data demand, a plan is needed for the collection of the data . The data collection plan describes the methods that will be used and what measures and means are considered.

4.2.1 Considered data collection methods

Several data collection methods have been considered. What these data collection methods have in common is the use of video cameras. Other data collection methods require full participation of all vehicles (in-car GPS/GSM data) – which is practically infeasible – and they do not offer a high enough data resolution (such as: detector loops). Multiple video camera methods have been considered, which can be categorised into two groups, distinguishing the angle in which the camera is mounted:

- The **perpendicular method**, where the camera faces straight down onto the road.
- The **angular method**, where the camera is pointed in the bisection of the top corner of a triangle.

Both methods are visualised in figure 4.1. An overview of the advantages and drawbacks of each method are described in the sections below.

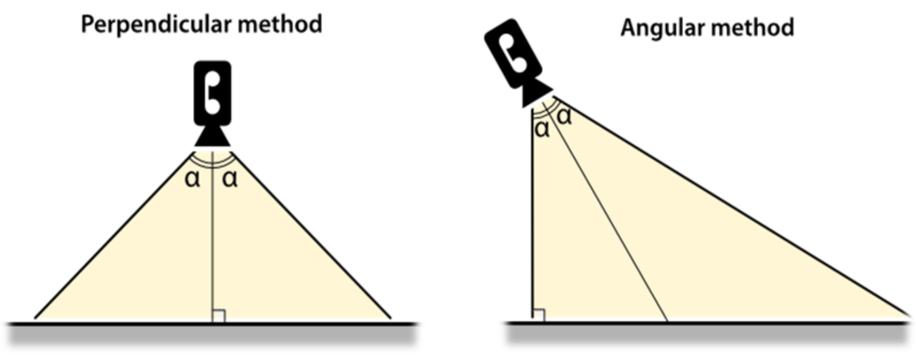

Figure 4.1. Visualisation of the camera mounting methods.

The cameras can be mounted in multiple methods. The following mounting methods have been considered:

- Static cameras mounted on gantries or lamp posts
- Static cameras mounted on tall buildings or structures.
- Static cameras mounted on a crane.
- Cameras mounted on a static helicopter
- Cameras mounted on a moving helicopter

Appendix I explains all camera mounting methods with their up and downsides in detail.

4.2.2 Selected data collection methods

The previous sections explained all the available data collection methods and their characteristics. From these methods, two have been selected for testing.

1. **Mounted cameras on posts, angular method.** TNO has a dataset available from the A270 using this method. This data set has been pre-processed to *x*,*y*,*t*-co-ordinates for each vehicle. Although this dataset is suitable for this research and the road itself has a suitable layout (one exit and one entrance ramp), this data set is only from one road and thus one location. A second data collection method is required for other research locations.
2. **Helicopter, static, hybrid method.** By using a hybrid method to mount the cameras (see figure 4.2), the best of both the angular and perpendicular method are united. By using large overlap areas, only one of the cameras needs a focus point for stabilisation, which makes it easier to stabilise all three cameras by using the overlap information. In case only one laptop is required to store the footage of all three cameras, the timestamp of the footage would also be synchronised, which is also a huge advantage. The helicopter itself can be deployed in a large range of locations and its height makes the pixelation-issue less problematic. Three HD cameras (4000 pixels) will be used. This is to ensure that the vehicle size on the footage is not too small.

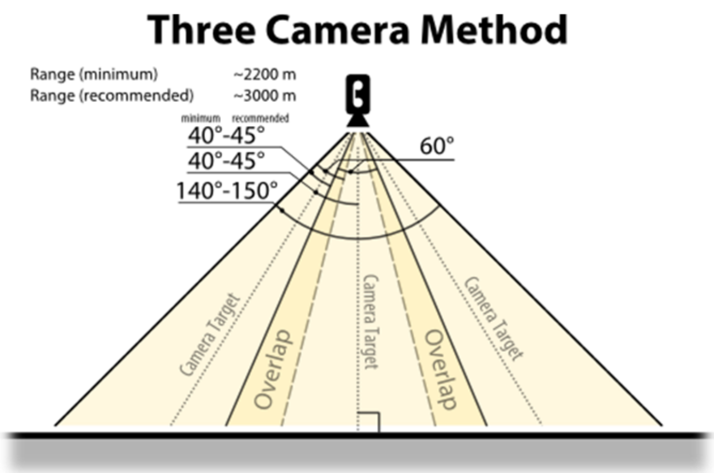

Figure 4.2. Diagram of the chosen method for the helicopter

Other methods all had some problems that made them less attractive than the two options that were selected:

- There were an insufficient number of high points close to the road to mount cameras. Therefore, the high-point method is a barely feasible option.
- The crane is a good option from a technical standpoint, but the price of hiring a crane is much more expensive than the price of hiring a helicopter. Therefore, this method is too expensive.
- Just a perpendicular camera mounted on one helicopter does not allow a sufficient range for this research without having serious deformations or a too low resolution.
- Camera footage of a moving helicopter is almost impossible to stabilise. This makes this method infeasible.

4.2.3 Availability of selected data sources

Both selected data sources have a limited availability. For the helicopter data, the helicopter must be rented and a camera mounting mechanism must be designed and constructed. The A270 data requires permission from TNO to receive and use the data. The availability of the data determines which data set will be primarily used for this research.

On beforehand, it was quite clear that the helicopter data would take a much longer time to receive an usable data set than from the A270; TNO already had formatted data sets and the only obstacle was the permission to get this data. This data set was available before the helicopter flight to collect the data by that method. Therefore, the A270 data will be primarily used for this research.

4.3 Conclusions about the data collection

After analysing several methods, the hybrid helicopter camera setup and the roadside camera setup from TNO have proven to be the best suitable methods to collect the data. However, due to the unavailability of the helicopter data within the timeframe of the research, the roadside camera setup has been selected.

This completes the main research structure. Figure 4.3 shows a schematic overview of the research.

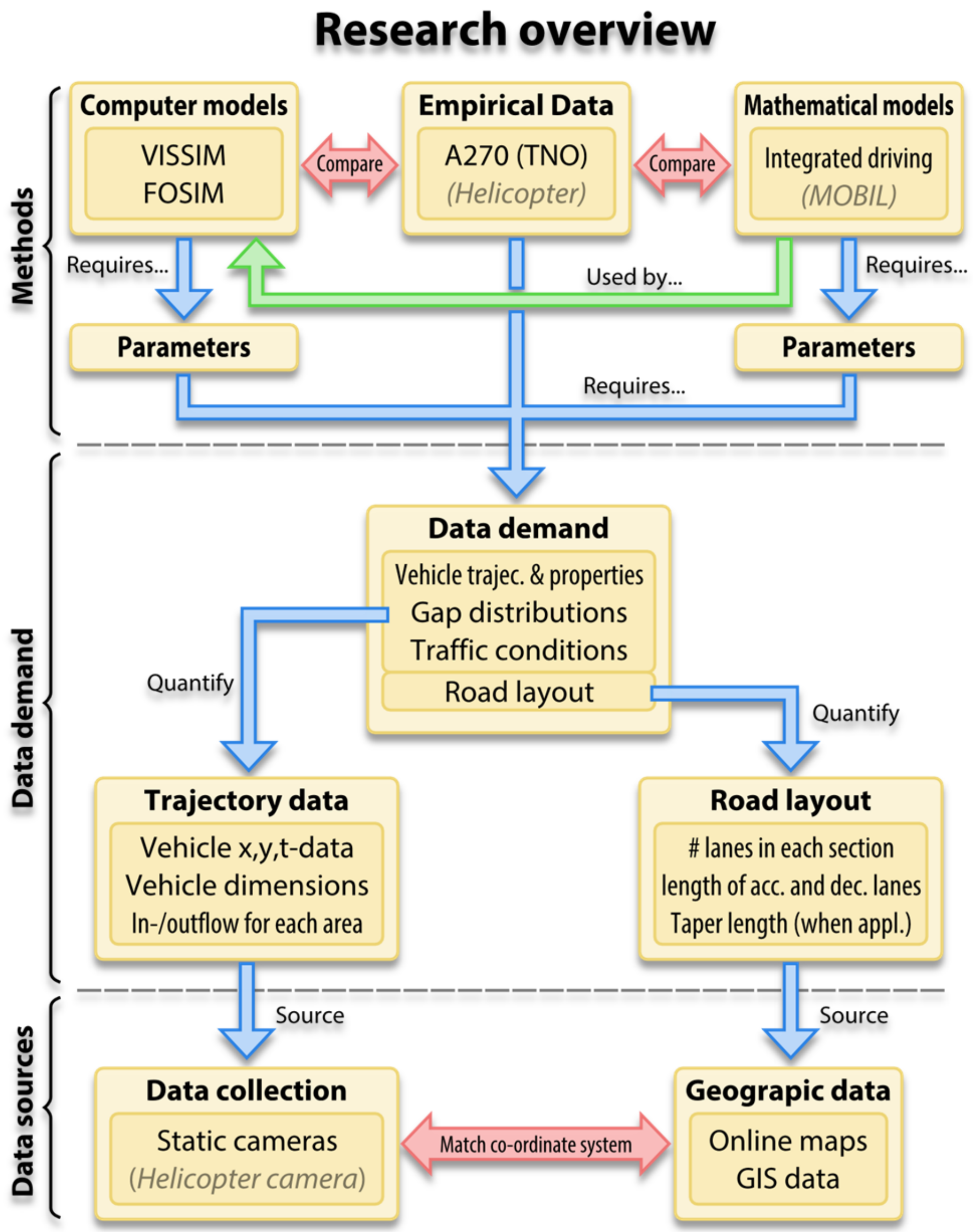

Figure 4.3. Schematic overview of the research. Research models and data collection methods between brackets were considered, but no

5 Data processing

After the data has been collected, it requires processing to give the information that is required to answer the research questions. This chapter explains the methodology of the data processing that is being used in this research. This methodology applies to both measured and virtually generated data sets.

5.1 The raw pre-processed data format

At the start of the data processing, all data that is available is a raw input data set. This raw data is directly measured and thus it does not include derived data. The processing will convert the raw dataset to a usable format to derive data from this set required to answer the research questions and to compare different data sets in a proper manner. Every data set that will be used for this research has already been pre-processed to vehicle-based data. The data includes:

- Vehicle IDs
- Vehicle *x* and *y* positions
- Timestamps

This information is usually available in most data sets that describe vehicle trajectories. For this research, MATLAB is being used for the data processing.

5.2 Specifying the desired data units

Before the processing can start, the desired results stated in section 3.4 need to be quantified in concrete data units. This determines what units the desired end-result of the processing will encompass and what steps are necessary to gain these results.

In figure 5.1 is an overview of the desired data units. The units can be categorised in three different types

- Vehicle-based data. This is the information regarding the status of a single vehicle.
- Vehicle interaction data. This data describe all the relations and interactions between different vehicles.
- Statistical data resulting from these vehicle interactions

The following data desired data set will be derived and processed in section 5.3. The data entries marked with $^{(*)}$ are given before the processing:

- **Vehicle-based data**
  - ($\boldsymbol{x}$, $\boldsymbol{y}$) position in the Cartesian x,y-space $^{(*)}$.
  - Timestamp $\boldsymbol{t}$ $^{(*)}$
  - Speed $\boldsymbol{v}$ and direction $\boldsymbol{\theta}$
  - Acceleration $\boldsymbol{a}$
  - Lane position $\boldsymbol{i}$
- **Vehicle interaction data**
  - Headway to leader $\boldsymbol{h_{leader}}$
  - Headway of follower $\boldsymbol{h_{follower}}$
  - Headway gap of leader in the adjacent lane $\boldsymbol{i}$, $\boldsymbol{h_{gap,leader,\,i}}$
  - Headway gap of follower in the adjacent lane $\boldsymbol{i}$, $\boldsymbol{h_{gap,\,follower,\,i}}$
- **Statistical data**
  - Accepted gap distribution $\boldsymbol{d_{ag}}$
  - Desired speed distribution $\boldsymbol{d_{v0,n}}$
  - Lane change frequencies, by trigger $\boldsymbol{\tau}$ and area $\boldsymbol{z}$, $\boldsymbol{f_{lc\ \tau,z}}$

This completes the desired data set.

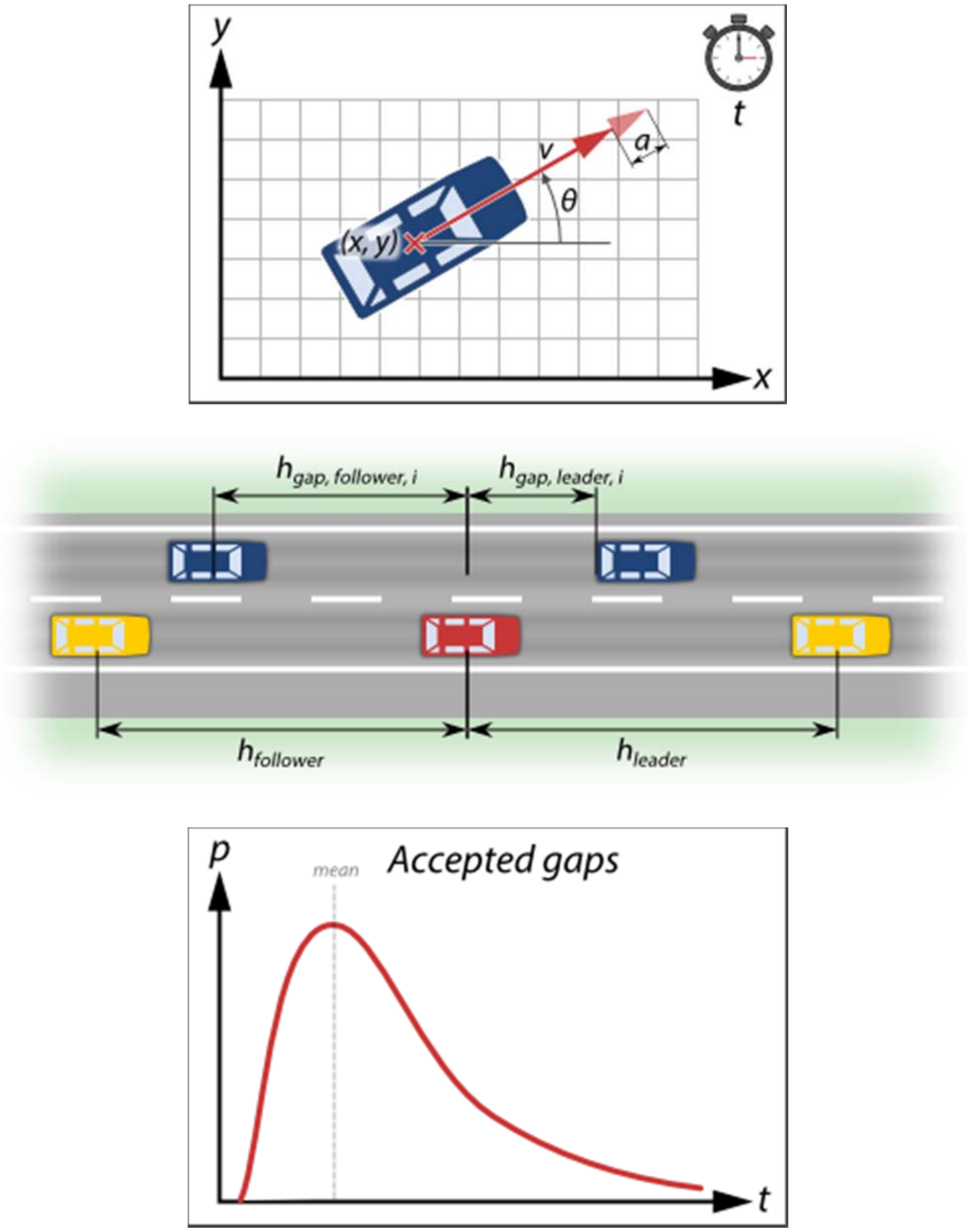

Figure 5.1: the desired data units on vehicle basis (top), vehicles interactions (centre) and the statistical data from these interactions.

5.3 Processing methodology

In the following section, several methods are explained how to derive the desired data from the raw data set. All methods are described below in order of processing appliance. This means that the methods that are described first are applied earlier in the processing.

5.3.1 Deriving the vehicle based-data

At the beginning of the processing, all that is known is the raw data. Though this data set is fairly limited, it contains enough data to derive all the other data units. The next sub-sections explain how to derive all data required for the vehicle.

Centre point

In the VISSIM data set, only the front and back of the vehicle are given, but not the centre point of the vehicle. This can be derived by using simple averaging:

$$x_{center} = \frac{x_{front} + x_{back}}{2}, \qquad y_{center} = \frac{y_{front} + y_{back}}{2}$$

All other data sets only have the centre point as a vehicle co-ordinate.

Speed, acceleration and direction

Speed, acceleration and direction of a vehicle are a little bit harder to determine. To ensure that the processing can be applied on a wide range of different data sets and to be able to cope with curves, this formulation, and all the following ones regarding vehicle interaction, need to be defined as generally as possible. Therefore, the speed and direction are defined in polar co-ordinates, where the speed v is the length of the vector and the direction θ is the angle relative to the Cartesian x-axis going counter-clockwise. The co-ordinates are based upon the difference in x,y-postions between two time steps in t, where:

$$v = \frac{\sqrt{\Delta x^2 + \Delta y^2}}{\Delta t}$$

$$\theta = \operatorname{atan2}(y, x)$$

This will ensure that the vehicle's speed is always positive. The direction has a range between $-\pi$ and π. These range limits can be a problem when comparing the differences between two angles θ, but these cases have been covered by either adding or subtracting 2π to one of the two angles and pick the absolute minimum difference:

$$\Delta\theta = \min\ (|(\theta_2 + n\pi) - \theta_1|), \qquad n \in -1, 0, 1$$

Acceleration can be easily derived from speed:

$$a = \frac{\Delta v}{\Delta t}$$

Lane position and lane layout

Finally, one needs to know in which lane the vehicle is driving. This can be done by determining a centre line of each lane. To determine which lane a vehicle belongs at a given time *t*, one has to pick the minimum distance between a vehicle *n* and a point *j* on lane *i*:

$$l_{cur,n}(t) = \arg_{i} \left\{ \min_{\forall\, i,j} \left(\sqrt{\left(x_n(t) - x_i(j)\right)^2 + \left(y_n(t) - y_i(j)\right)^2} \right) \right\}$$

The lane *i* where the minimum distance is found is assigned to that vehicle at that time step. Additionally, the two closest adjacent lanes can be found by using the same method, excluding the lane the vehicle is already on. The information about which lanes are adjacent to the current lane will be used later for vehicle interactions.

However, for this, you need a lane layout to say where these centre lines are. One can use GIS data for this, but with enough vehicles, these lanes will also become visible by emergent behaviour. Assuming that vehicles follow the centre of the lanes at the majority of the time and only change lanes occasionally. From this assumption, one can expect that when one draws the trajectories of all vehicles in a plot, the lanes will automatically show up as lines where a large number of trajectories are clustered. In figure 5.2, such a plot is displayed. It's visible that this assumption is apparently valid in practice.

For this research, a script has been written to convert (a sample of) the trajectories from the MATLAB format to SVG-format (Scalable Vector Graphics). The user has to manually draw the lanes in an graphical vector image editor (e.g. InkScape or Adobe Illustrator). The lanes are then converted back to vector format.

A fully automated method has been attempted, but this automated method was much slower (30-60 minutes) and gave less accurate results that what humans would produce from the same data set in a much shorter time span (5-10 minutes).

This completes all the data we need from the vehicles themselves.

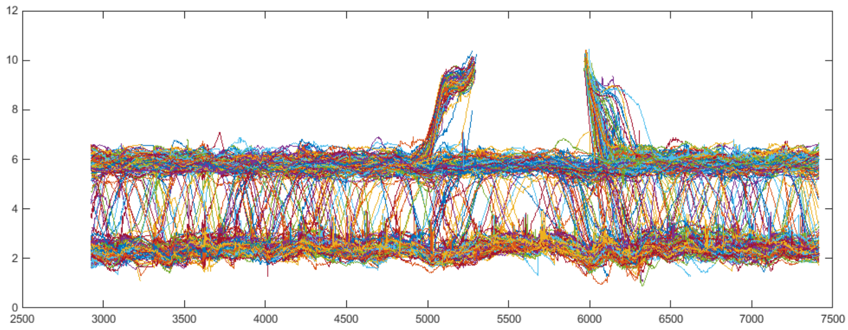

Figure 5.2. An x,y-plot of all trajectories of the A270 sample data set, where the x-axis is the length axis of the road. The lanes can be recognised as thick lines where a large number of trajectories are cluttered.

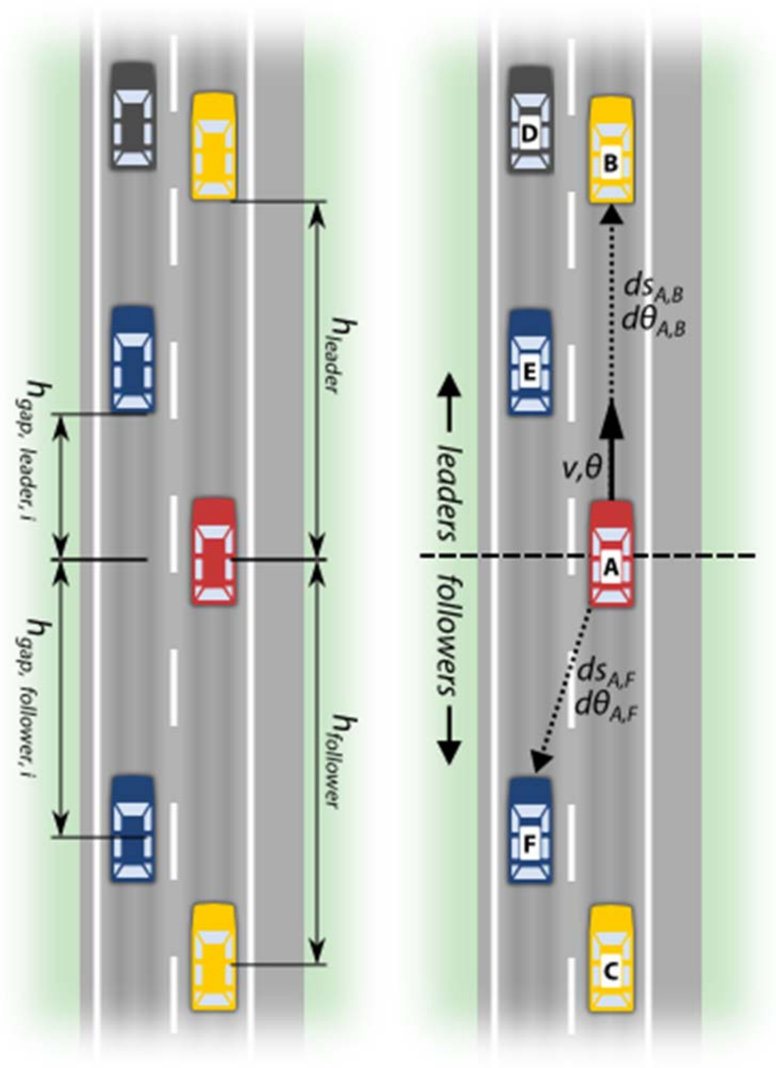

Figure 5.3. Headways of the interactions (left) and the determination of leaders and followers (right).

5.3.2 Determining the vehicle interaction

Now that all data from the vehicles have been processed, the interactions between the vehicles must be determined. This will determine the gap sizes and headways and it identifies all leaders and followers. As complex as the driving task is, so is the processing of this complex interaction. The next sub-sections explain how to determine these interactions.

Identifying the leaders and the followers

Before the headways can be calculated, the leader and following vehicles must be identified for each vehicle at each time step. This information is required to determine which vehicle needs to be compared to determine the headway. (figure 5.3, left)

By definition, the leading vehicle is the closest vehicle in front of the observed vehicle that is in the same lane. The follower is by definition the closest vehicle behind the observed vehicle that is in the same lane. Additionally, this is also true for the leaders and followers in the adjacent lane; only the observed vehicle is in a different lane in that situation. Therefore, to determine these leaders and followers, one needs to know if this vehicle is leading or following and if it's the closest vehicle in that lane.

Figure 4.3, right, shows a demonstration of this process. The observed vehicle is the red car A. Car B and C are in the same lane and car D, E and F are in the adjacent lane. Perpendicular to the driving direction, a line is drawn. This is the border between the "front" and "back" of the vehicle. The relative position of a vehicle *m* relative to vehicle *n* at time step *t* can be determined by the difference in *x,y* position. This difference gives another polar vector, with a length $\boldsymbol{ds_{n,m}}$ and an angle $\boldsymbol{d\theta_{n,m}}$. This can be used to determine the distance between the leader and the follower and the status of the leader and the following:

$$\Delta\theta_{n,m} = \min\left|\theta_n - d\theta_{n,m} + c\right|, \qquad c \in -2\pi, 0, 2\pi$$

$$\begin{cases} \Delta\theta_{n,m} < \pi \Rightarrow & \text{vehicle } m \text{ is a leader} \\ \Delta\theta_{n,m} \geq \pi \Rightarrow & \text{vehicle } m \text{ is a follower} \end{cases}$$

This will give two results: the closest leader and the closest follower. A similar method can be used to find the vehicles on the adjacent lane (where $\boldsymbol{i_n}$ needs to be replaced with the lane identifier of the adjacent lane).

In the demonstration figure, everything beyond the border line in the driving direction are leading vehicles; everything on the other side are following vehicles. Car B, D and E are therefore leaders and car C and F are followers. Car B and C are the leader and follower in the lane of the observed vehicle A and car E and F are the leader and the follower of the adjacent lane. Car D is not the closest vehicle in that lane and is therefore rejected as a leader for car A.

This method is formulated in such a general manner that it works for any direction vehicle A is travelling in, even when it does not follow any axis of the Cartesian co-ordinate system. The determination of the leaders and followers can also be accurately determined in curves by this method. The only situation this method fails is when the curve is a tight hairpin curve, where the leader has already fully passed the curve and the observed vehicle is not in the hairpin curve yet. However, this situation does not occur on any motorway, only at their on and offramps. Since the ramps themselves do not fall within the focus of this study, this method is practically fail-safe.

Time headway determination

Now that the leaders and followers are identified, the headways between these vehicles can be determined. Since the size of the vehicle is not available in the data set, only the gross headway can be determined.

The headways determination is determined by the distance between vehicle *n* and *m* and the speed of vehicle *n*:

$$h_{n,m} = \frac{ds_{n,m}}{v_m}$$

This equation can be used to determine the time headway on the current lane. It can also be applied to determine the headway on the adjacent lanes. In that case, the vehicle's current position is projected on the adjacent lane to determine the leader and follower gaps.

Lane change determination and frequency

A lane change is simple to determine: this is the point where the closest lane for that time step is a different lane then the closest lane on the previous time step:

$$\delta_{lc,n} = \begin{cases} 1 & l_{cur,n}(t) \neq l_{cur,n}(t-1) \\ 0 & otherwise \end{cases}$$

Where $\delta_{lc,n}$ is a binary flag to describe if vehicle n made a lane change or not.

The lane change frequency is the number of lane changes within an area z, normalised by time (hour) and length (kilometre). This frequency is sub-categorised by lane change trigger τ. The trigger τ is determined by the method given in section 3.3.1:

$$f_{lc,\tau,z} = \frac{lc_{\tau,z} \cdot l_z \cdot (t - t_0)}{l_{norm} \cdot t_{norm}}$$

Desired speed determination

The **desired speed** v_0 is the speed a vehicle wants to drive in free flow conditions. To determine if a vehicle is not following another vehicle, the headway must surpass a limit where the leading vehicle is too far away to cause hindrance for the currently observed vehicle. Hoogendoorn (2004) researched this subject. He concluded that almost all vehicles with a headway distance greater of 4 seconds are not showing car following. Therefore, it will be assumed that any vehicle with a lead headway of 4 seconds will attempt to get to its desired speed.

To determine the desired speed of each vehicle, the median value of all relevant observed speed entries will be taken. The valid entries are subject to the following filtering conditions:

- The speed of the vehicle is larger than 50 km/h; it does not make sense that the desired speed is any lower than the minimum speed on the motorway.
- The leader headway is larger than 4 seconds.

By doing this for all vehicles a headway distribution will appear. It should be noted that slower vehicles are over-represented in the free speed data points since they are less likely to follow a vehicle. However, in case that the observed distribution follows a normal distribution and only one speed per vehicle is picked, the reduced number of data points on the high end should not be a problem. In that case, a normal distribution can be fitted on the data set, and confirmed to be valid by a Kolmogorov-Smirnoff test.

5.4 Data selection

The field data set contains observation errors. This is partly caused by issues on the observation side and partly caused by issues on the pre-processing side of TNO.

Observation issues are:

- Camera resolution limits (represented physical size of one pixel)
- Noise effects (fog, compression of the images, etc.)
- Random, unforeseen events (e.g. birds flying right in front of the camera obscuring the view, cars stopping at the emergency lane, broken equipment)

Pre-processing issues from the side of TNO are:

- Limitations of the vehicle recognition software
- Errors in the coordinate conversion software
- Errors and limitations in the trajectory linkage software

These imperfections cause disturbances in the data. Therefore, a careful data selection must be performed to get the most valid data entries for the data analysis. To do this, each vehicle will get a **Validation Index ($\boldsymbol{VI}$)** assigned. This index is related to the validity of the data of one vehicle and all the vehicles it interacts with. If this value surpasses a pre-set threshold, it will be accepted as a valid entry. A detailed mathematical formulation of this is given in Appendix II.

6 Analysis of the field data

The processed data can be analysed for behavioural characteristics around motorway ramps. Section 6.1 presents the observed traffic behaviour. Section 6.2 presents the preliminary expectations of what behaviour is expected on beforehand and describes the results that have actually been observed in the field. Section 6.3 summarises the conclusions derived from the previous sections.

6.1 Observed traffic behaviour

The processed data give insights in different aspects of traffic behaviour. From the processed data, the following behavioural aspects can be analysed, as stated in section 3.3.2 as comparison criteria:

- Desired speed
- Lane change frequency
- Spatial and speed distribution of the merging lane changes
- Acceleration behaviour

Each aspect will be elaborated in the subsections below. But first the preliminary expectations are presented.

6.2 Results of the observed traffic behaviour

Before the analysis starts, a set of preliminary expectations regarding drivers' behaviour around motorway ramps have been made. These expectations are made to reflect whether the observed and processed data makes sense or not. After that, the analysis will show if the expectations are met or disproven. The following sub-sections describe the expectations of each tested driving behaviour in more detail.

6.2.1 Desired speed

For the desired speed, two distributions are expected to occur: a desired speed distribution for the cars with a relatively large variance, and another desired speed distribution with a smaller variance for the trucks. It is expected that the speeds are normally distributed due to differences in perception that are not bound on any side of the distribution, following Hoogendoorn (2004). The average values of these distributions are below the speed limit for both vehicle classes. For cars, this is 100 km/h; for trucks, this is 80 km/h. The main explanation why this speed is lower is due to the fact that most speedometers in vehicles have an offset towards higher speeds for safety reasons (in other words, the speedometer often gives a higher speed than the actual vehicle's speed).

This hypothesis has been tested against data from TNO from the A270. From a selection of 10 weekdays of 2 hour long morning peak periods, only 5 days had enough vehicles per day that surpassed the data selection validation index threshold of 0.60, which means that the vehicle and all the vehicles it interacts with have been found accurate enough to surpass the validation threshold (see Appendix II). A selected sample of 2062 validated vehicles have been tested on their desired speed. The observed desired speed is indeed a normal distribution; as figure 6.1 shows, the desired speed distribution fits closely to a normal distribution. This distribution has an average desired speed of 92.38 km/h and a standard deviation of 5.31. A Kolmogorov-Smirnoff test yields $p = 0.051$, which means that the distribution is significantly valid at a 95% confidence interval. A small portion of the vehicles (7.6 %) have a desired speed that is higher than the speed limit. This means that the vast majority respect the speed limit of 100 km/h.

However, what is quite noticeable is that there is no significant peak at around 80 km/h, which is the truck speed limit; this can indicate that the truck traffic intensities are low and therefore have a small contribution to the total traffic amount (and therefore the desired speed distribution). But since there is no data available on the vehicle type of each data point, this indication cannot be validated with the current data set. Future studies should gather data regarding the vehicle type to get a better picture of the truck influence.

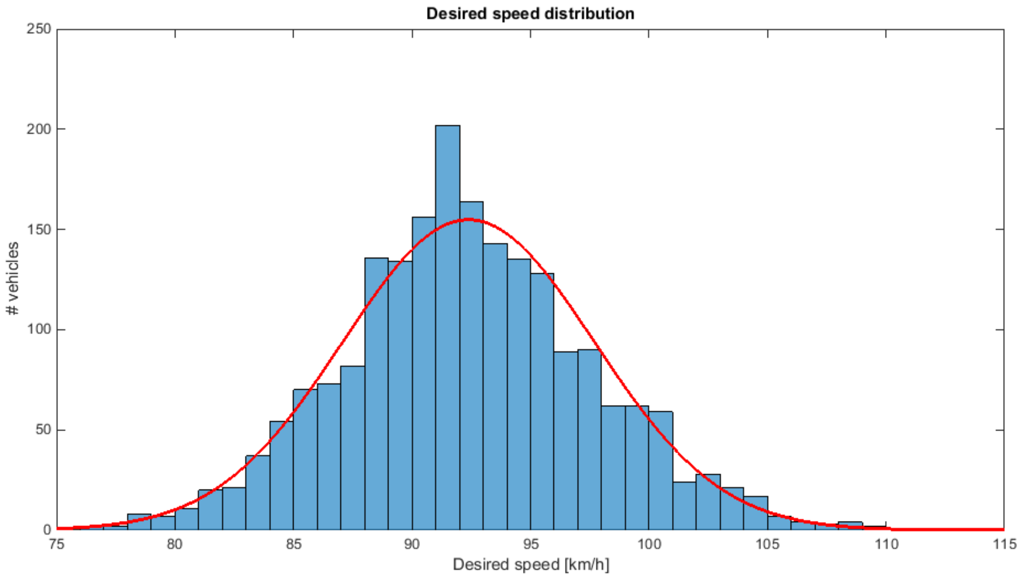

Figure 6.1 Desired speed distribution of the observed data on the A270, using the validated vehicles only. The red line represents the fitted normal distribution.

6.2.2 Spatial and speed distribution of merging lane changes

One of the focus points in this study is the behaviour of merging traffic. It is to be expected that the merging speed also follows a similar distribution as the desired speed, though with another mean and standard deviation due to the restricting traffic conditions. Based upon the findings of Daamen et al. (2010), the expected peak in the merging point distribution in free flow conditions should occur near the beginning of the merging lane.

From the validated data, 1243 merging lane changes have been found. Figure 6.2 shows that the merging speeds have a larger variation than the desired speed, although the vast majority will merge at speeds of 80 km/h or higher. The distribution does not follow a normal distribution; the best fit yields $p = 1.6 \cdot 10^{-3}$ on a Kolmogorov-Smirnoff test. However, when comparing the two graphs graphically, it is shown that this is still a close estimate, although the observed data seems to be biased towards lower speeds.

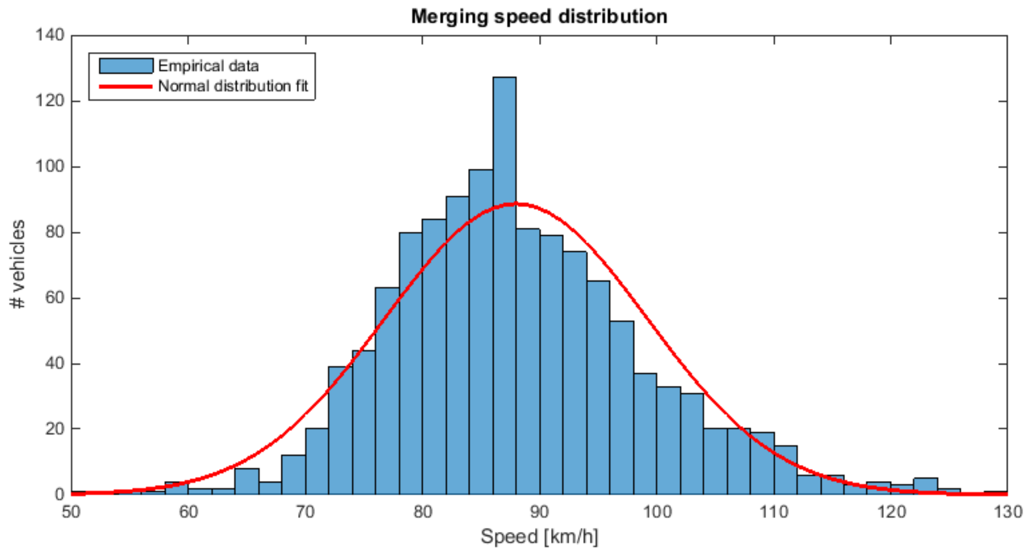

Figure 6.2 Speed of the merging vehicles when they changed lanes. The data is based upon the observed data on the A270 , using the validated vehicles only.

Figure 6.3 shows the spatial distribution of the merging lane changes. The majority of the lane changes do occur near the beginning of the merging lane, which indicates that most drivers do not use the full merging lane length (as most driving instructions recommend), but take the first acceptable gap they can find. The distribution approaches a log-normal distribution with $(\mu, \sigma) = (4.85, 0.40)$, although the best fit yields $p = 1.5 \cdot 10^{-3}$ on a Kolmogorov-Smirnoff test. However, when comparing the two graphs graphically, it is shown that this is still a close estimate. The findings are in accordance with the findings of Daamen et al. (2010).

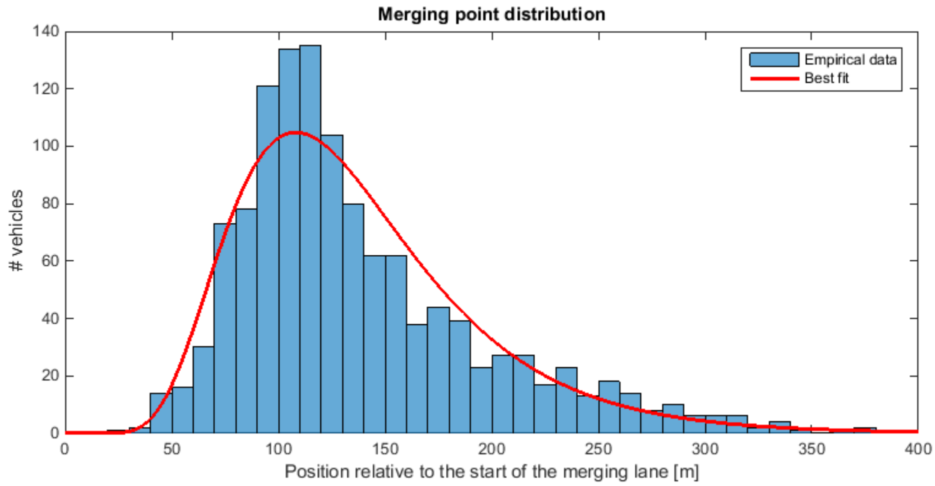

Figure 6.3 The spatial distribution of the lane changes on the merging lane. The data is based upon the observed data on the A270, using the validated vehicles only.

Figure 6.4 plots the merging speed and the spatial distribution against each other. A correlation pattern occurs where the merging speed at the end of the acceleration lane is in general higher than at the beginning, though this correlation is weak. This does make sense, since the vehicles had more time to gain speed on the acceleration lane when they are approaching the end of the acceleration lane. Multiple polynomal polynomial regression have been performed to see if a good fit occurs, but due to the weak correlation of each one, this regression is likely not reliable

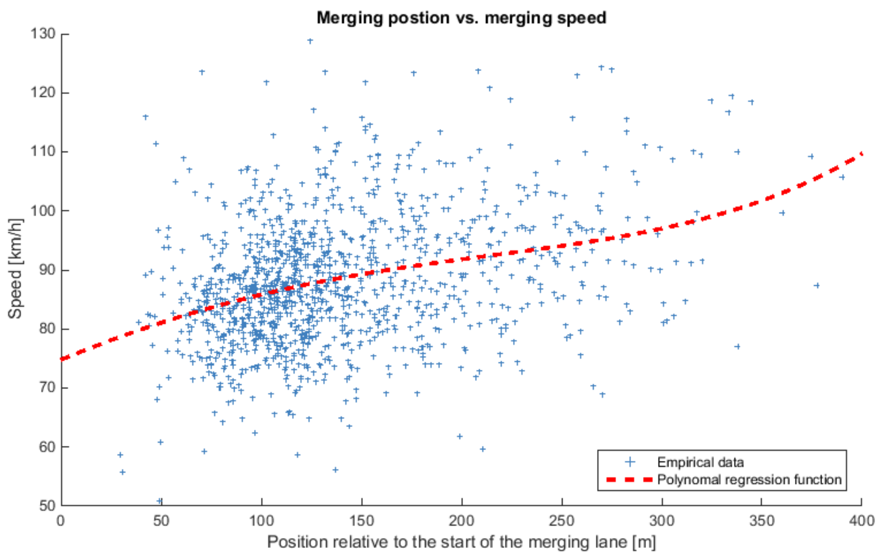

Figure 6.4 The spatial distribution of the lane changes on the acceleration lane plotted against the speed of the vehicles at the lane change. The data is based upon the observed data on the A270, using the validated vehicles only.

6.2.3 Lane change frequency

Along the observed area, several different behavioural patterns are expected regarding diverging and merging. The off-ramp is located at 5050 m and the on-ramp is located at 5950 m. It is to be expected that vehicles start to change lanes to the right around 600 metres before the off-ramp[3], so at 4450m, in order to exit later on. It is also to be expected that most courtesy lane changes appear between the end of the off-ramp (5300 m) and the start of the on-ramp (5950 m). The area between 3000 and 4000 m is used as a neutral reference.

Figure 6.5 shows the results of the lane change analysis. It occurs that there is a significant portion of the lane changes[4] that could not be categorised as courtesy or speed gain. This means that the earlier set up methodology to determine the triggers does not fully explain the lane change behaviour incentives. Another striking result is that the lane change frequency in the area before the merging lane is lower than in the rest of the zones instead of higher due to courtesy behaviour. Even the lane changes related to courtesy are not much higher in that zone in relation to other zones. Furthermore, the mandatory lane changes are dominating the lane change behaviour and the amount of route-following related lane changes is relatively low.

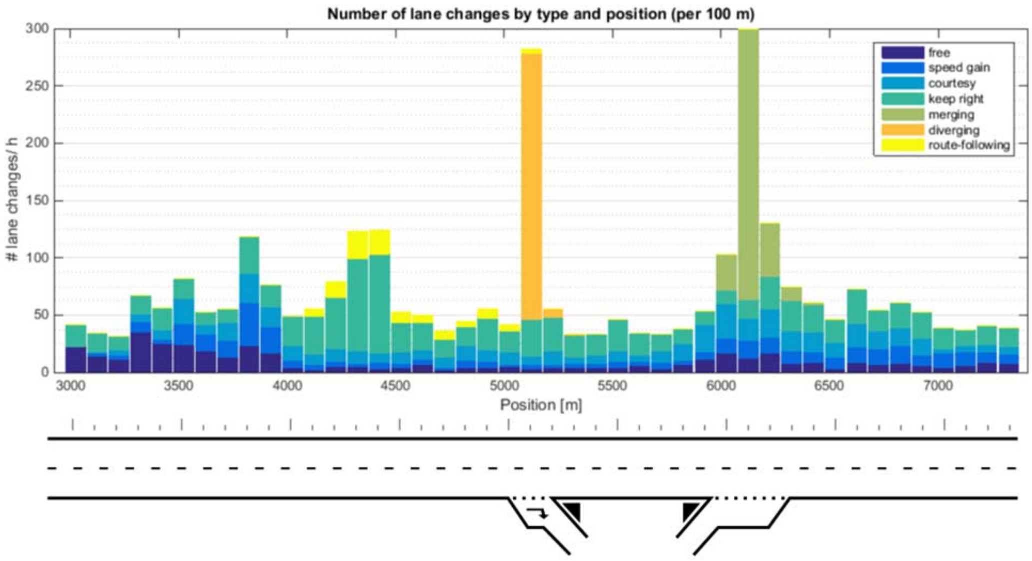

Figure 6.5 Lane change frequency. The values are per 100 metres and per hour, subcategorised by trigger type. A simplified representation of the road layout is presented below the graph for clarification.

[3] *Assuming the found values for on-ramps by Hovenga (2014). This may not be true for off-ramps, but for a lack of a better estimation, Hovenga's values for on-ramps will be used here.*

[4] *Especially in the first few 100 meters, where the amount of these lane changes raises to 25 or even 50% of all the lane changes there.*

6.2.4 Acceleration behaviour

The acceleration of the vehicle that changes lanes is to be expected to have a positive mean. It is to be expected that the acceleration of the following vehicle is not influenced by the new leader due to free flow conditions.

Figure 6.6 shows the acceleration distributions of the vehicle that changes lanes and its follower. The median of the lane changing vehicle is around 0 and there is no correlation found between the acceleration and the lane changes. The same can be said about the acceleration of the new follower.

Various attempts have been made to filter the sampled acceleration graphs to each lane change incentive or changing the percentile borders, but each of these graphs show a similar noisy pattern. This could be expected on beforehand; the position data could not be accurately measured, and since the acceleration is the second derivative of the position over time, the error has grown quite large, resulting in this noise effect. The real effect is either not present or not large enough to show itself through the noise. Therefore, this comparison criterion is not useful for further research and tweaking.

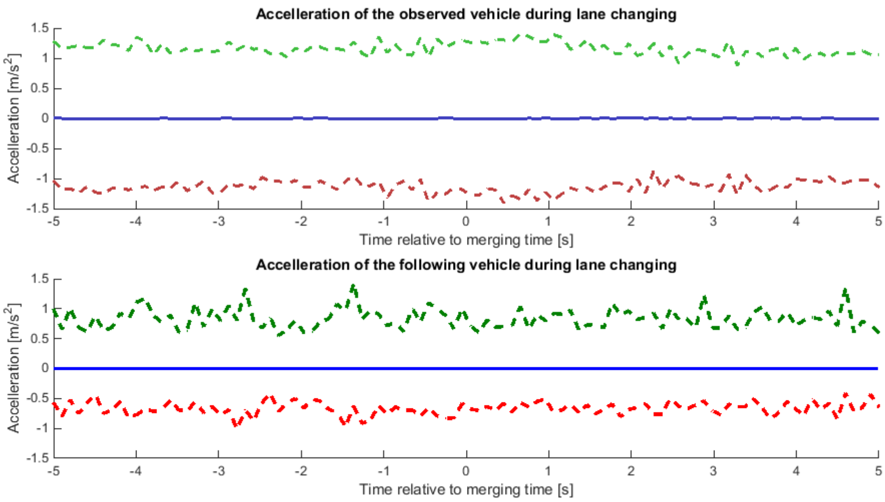

Figure 6.6 Acceleration rates of the vehicle changing lanes and its new follower. The dashed green and red lines represent the 15th and 85th percentile of the acceleration data. The blue line in the centre represents the median value.

6.3 Findings and conclusions

From the data analysis, most behavioural aspects behave like expected. Below is a summarised list of all the findings:

- All speed distributions can be estimated by normal distributions.
- The merging point can be estimated by a log-normal distribution.
- There is no correlation between the merging point and merging speed.
- Mandatory lane changes are dominating the lane changing behaviour.
- The number of lane changes in the zone before the merging lane is surprisingly low.
- Around 10 to 15% of lane changes can be explained with the lane change triggers defined in section 3.3.1. Most of these occur at the start of the observed area.
- There is no clear correlation between the lane changes and the acceleration behaviour in free flow for the involved vehicles.

7 Model implementation and testing

With the observations made from the field, the models can be set up, tested and compared. In chapter 4, FOSIM and VISSIM were selected as software models to be tested. For each of these models, the network has been reconstructed within the software model. Since there is nothing known about the truck composition in the traffic on the road, all vehicles were assumed as cars. Furthermore, the traffic flow is assumed to be uniformly distributed within the time window. The OD-matrix is based upon the OD-data from the A270 field data.

The initial test run, where only the default values have been used, will be discussed in section 7.1. This to see where the most obvious parameter mismatches are. These will be changed, and following from that a more educated test run will be done, which will be discussed in section 7.2. From this test run, the differences between the model and reality will be analysed. Further calibration has been performed after that, which will be discussed in section 7.3. Finally, section 7.4 will evaluate the results after the calibration and conclusions will be drawn about how to improve the behaviour based upon the differences still present.

7.1 Initial test runs with the software models

The first test run will analyse the general behaviour of both models. In this test run, the only things that were set manually were the network, the traffic composition and the OD-matrix. The subsections below describe the results from the first test runs.

Desired speed

When looking at the desired speed distribution, FOSIM and VISSIM show radically different behaviours, as shown in figures 7.1 and 7.2. VISSIM shows a distribution that's not normally distributed (a KS-test yields $p = 1.33 \cdot 10^{-24}$) by default and has its peak beyond the speed limit when setting the desired speed to 100 km/h with the default settings. This can be solved by changing the distribution of the desired speeds, which is a possibility VISSIM offers

FOSIM does not show any distribution at all; a KS-test yields $p = 9.0 \cdot 10^{-132}$. Instead, all desired speeds are deterministic per driver class, showing very narrow peaks. This raises the question if FOSIM is really suitable for improvement, since unlike VISSIM, FOSIM does not offer a possibility to change these deterministic speeds into one distribution. FOSIM is in this aspect too simplistic and requires reprogramming to improve this.

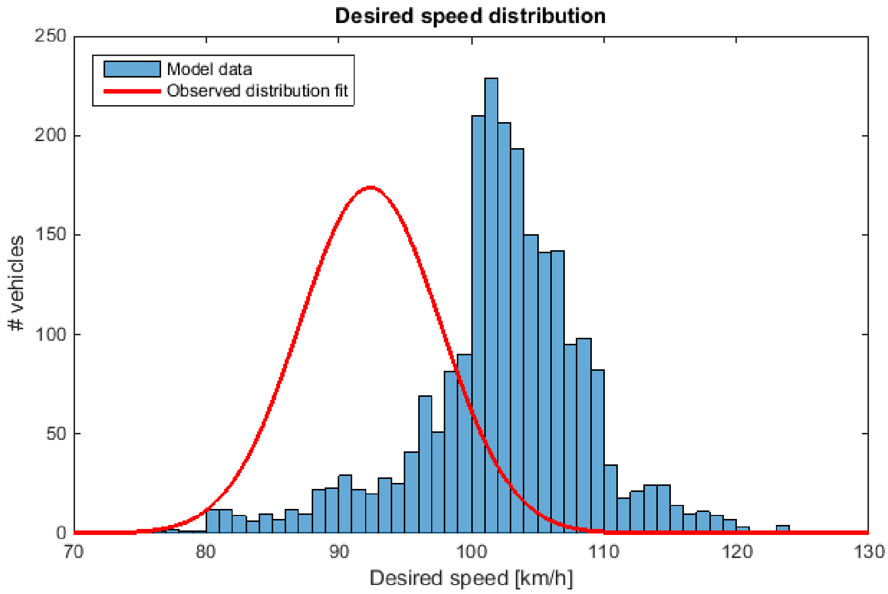

Figure 7.1 Desired speed distribution of VISSIM at the initial test run.

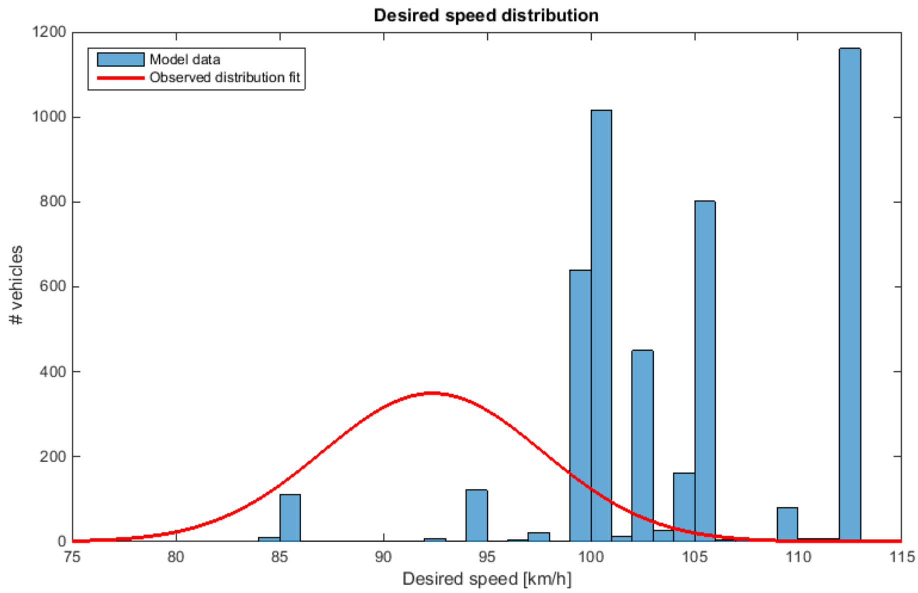

Figure 7.2 Desired speed distribution of FOSIM at the initial test run.

Merging point distribution

The merging point distribution also yields interesting results for both simulation models, as shown in figures 7.3 and 7.4. In VISSIM, the traffic merges halfway down the merging lane. The cause of this is that with the default settings, the traffic will notice the discontinuity only 200 meters in advance. Therefore, this should be changed to a length where the whole merging lane is covered.

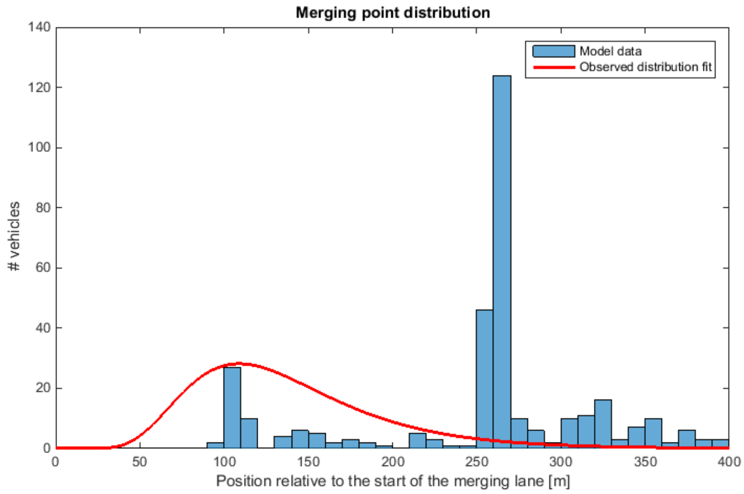

Figure 7.3 Merging point distribution of VISSIM at the initial test run.

In FOSIM, traffic merges immediately when it can merge. However, this is again quite deterministically distributed, which in turn raises doubts about possibilities for improvement within the current software application; the only way to add probabilistic distributions is to change the program's code, which is not possible within this research. At this point, it has been decided to stop with further efforts to improve FOSIM due to the fact that it behaves too deterministically.

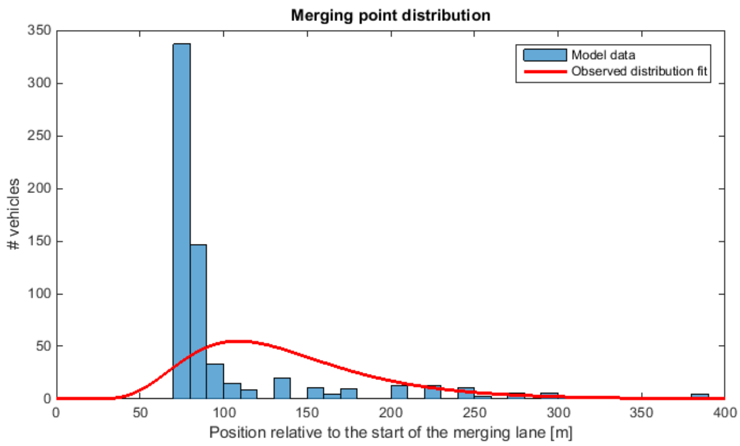

Figure 7.4 Merging point distribution of FOSIM at the initial test run.

7.2 Educated guess runs with the software models

With the information gathered from the previous section, the VISSIM model has been changed to overcome the initial issues. The following has been changed:

- The discontinuity attention range has been extended from 200 meters to 500 meters for the onramp, so that the vehicles notice the merging point on the complete merging lane and anticipate immediately to merge, as seen from the observations. For the off-ramp, it has been extended from 200 to 800 meters from the diverging point. This is to ensure traffic starts to anticipate to get in the right lane at the point where the exit sign at 600 meters from the start of the exit lane is located.
- The desired speed has been adapted to follow the distribution found in section 6.3.2. The desired speed can be adjusted manually in VISSIM by editing the cumulative speed distribution in a graph editor.

The subsections below describe the results from the educated guess runs.

Desired speed and merging behaviour

The first step is to check if the changes that are applied have the desired effect. Figures 7.5 and 7.6 show the results of the desired speed and the merging point distribution. The desired speed now follows a normal distribution, with $(\mu, \sigma) = (92.3, 5.61)$. The KS-test yields a value of $p = 0.31$, which means this is a very good fit. This is to be expected, since the normal distribution from the field data is used as the input distribution. The result only deviates slightly due to statistical noise.

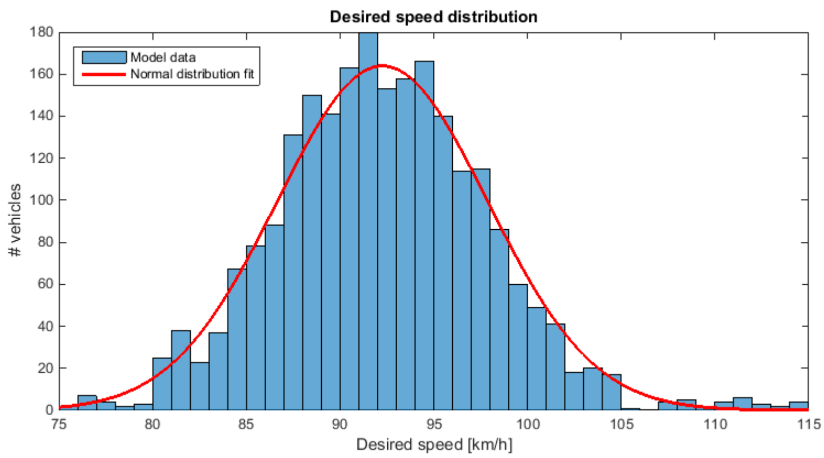

Figure 7.5 Desired speed distribution after the educated guess.

The merging point, although at the right location, is still quite sharply distributed, most definitely not log-normal; a KS-test yields a result of $p = 9.52 \cdot 10^{-33}$. The latter may be related to the gap acceptance, because that describes sensitivity and therefore the threshold of when a vehicle accepts to change lanes.

Another point to note is the small peak that appears at the end of the merging lane. These are stopped vehicles that could not find a gap to merge. In the observed data, such a peak does not occur. This means that one way or another, drivers in the real world will force themselves to accept a small gap and make a lane change without stopping at the end of the merging lane. Courtesy also plays a role, as it can create gaps for merging traffic. This is the necessity effect as described in chapter 2. something that clearly does not exist in VISSIM.

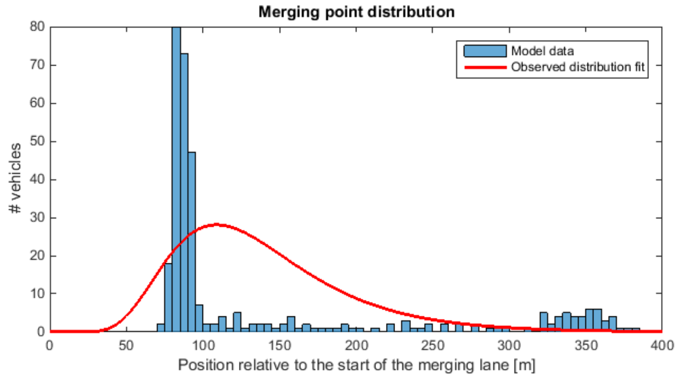

Figure 7.6 Merging point distribution after the educated guess.

Accepted gap distribution

Next is the comparison of the accepted gap distribution of the VISSIM model against the observed accepted gaps. Figure 7.7 shows a plot of the leader and follower gap of both the observed data and the model data. It is clearly visible that the accepted gap distribution of the model is much sharper than the observed one. This implies that the simulated drivers are less conservative about their time headways than the observed drivers. The gap acceptance parameters should be set to higher thresholds in order to correct this, though this may negatively affect the behaviour of the stopped vehicles at the end of the merging lane.

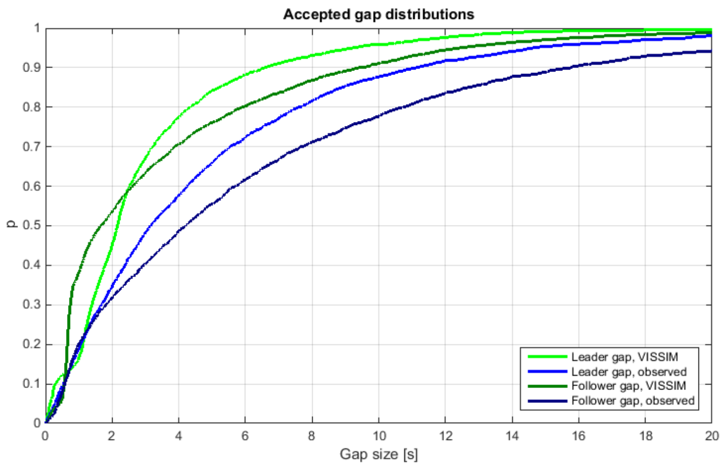

Figure 7.7 the accepted gap distributions of VISSIM (green) compared with the observed data.

Lane change frequency

Finally, the lane change frequency is checked in VISSIM. Figure 7.8 shows the lane change distribution of VISSIM. One notable difference is that the number of mandatory lane changes remained the same (logically), but the number of voluntary lane changes have increased drastically; they are more than doubled compared to the reference data. There is a peak at the start, which is explained by the fact that VISSIM distributes traffic from the traffic sources uniformly and therefore the traffic needs to re-distribute itself first.

However, the rest of the increase in lane changes indicate that VISSIM is much more sensitive to lane change incentives than what has been observed. This means that the lane changing behavioural parameters should be changed to make lane changes less attractive for the simulated drivers. It is very likely that this is related to the smaller accepted gaps found in the model data.

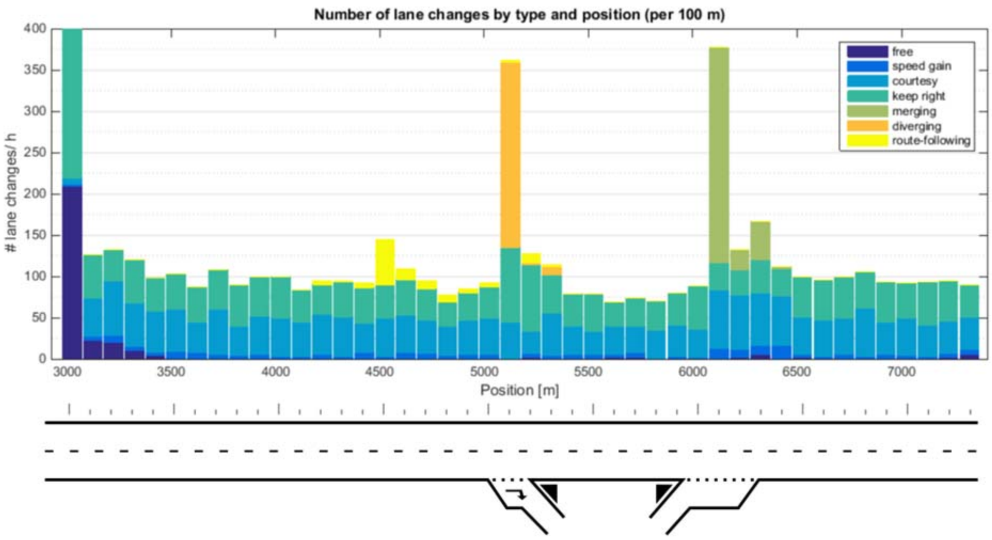

Figure 7.8 Lane change frequency in VISSIM after the educated guess run. The values are per 100 metres and per hour, subcategorised by trigger type.

Summary of the found results

The sections above show that a few of the tweaks resulted in the desired effects; the desired speed distribution and the merging location are closer to reality now. However, large deviations can be seen in the gap acceptance and lane change frequencies, especially discretionary lane changes. The gap acceptance also causes a narrower distribution of the merging point location and thus are these two aspects related to each other in that regard. The calibration for this research should attempt to minimise the deviations on this front as much as reasonably possible. The calibration will be explained in the next section.

7.3 Calibration of VISSIM

In the previous section there is a clear indication that the discretionary lane changes are strongly overestimated and the gap acceptance distribution is too biased to small gaps. This means that the calibration should focus in reducing these two deviations.

From a theoretical point of view, the two effects are correlated: a small gap acceptance means that the probability of a large enough gap occurring in the traffic is large, and therefore the chance that a vehicle can change lanes. However, this does not imply automatically that smaller gap acceptances lead to more lane changes, since it only affects the possibility to change lanes. Discretionary lane-changes are mostly governed by lane change demand, which means that lane changes only occur when the conditions are such that another lane is more attractive. This makes them fundamentally different from obligatory lane changes, which just have to happen when first possibility to leave an ending lane or to access the target lane occurs.

This suggests that for calibration, the following two aspects require attention

- The gap acceptance
- The lane change demand for discretionary lane changes

Knowing this, a parameter selection can be made for calibration.

Parameter selection for calibration

VISSIM has a large range of traffic behaviour parameters. There are over 50 parameters that can be changed in the current version of VISSIM. However, tweaking them all would require too much time and not all parameters are relevant. Therefore, selecting parameters to tweak for the calibration can help to narrow down the problem to just a few parameters.

Based upon the results found earlier, the following five parameters were chosen:

- **Look ahead distance**. This will influence how much traffic a driver will notice ahead of him and will anticipate on that.
- **The number of observed cars**. This determines how many vehicles a driver can pay attention to.
- **Desired headway for car following**. Not only does this determine the follow distance, but also determines the nominal gap size a driver is willing to accept.
- **Free driving time (FDT)**. This is a *time to collision*-threshold on the slower lane that a driver is willing to accept to change to the slower lane.
- **Safety distance reduction factor (SDRF)**. This factor (between 0 and 1) determines how much a driver is willing to accept a smaller time gap to the lead vehicle relative to the desired headway when changing lanes.

Description of the calibration process

The calibration process is being performed in a trial and error process. For a quick evaluation of the goodness of fit of each parameter set, the total number of discretionary lane changes to the left and right are summed separately and are compared to the reference data set.

First, all parameters are tweaked separately to show how much effect the change of a parameter has on the model results. From these initial test runs, the direction of change and the parameter significance can be determined. Table 7.1 shows the results of the initial test run. It is clear that the desired headway and the FDT have a large effect on the goodness of fit. The SDRF has a smaller, yet significant effect. The look ahead distance and the number of observed vehicles seems to have little effect and their change is unclear. Therefore, these will not be tweaked any further and the research continues only with three remaining parameters to tweak.

Table 7.1. Results from initial test run

Parameter	Scale of effect	Suggested direction of change
Look ahead distance	Barely significant	↕ Unclear
No. observed vehicles	Barely significant	↕ Unclear
Desired headway	Very significant	↑ Increase
FDT	Very significant	↑ Increase
SDRF	Moderately significant	↑ Increase

Continuing the calibration, the parameters have been increased up to values where they were not overcorrecting the results or became unrealistically large. Table 7.2 shows the default parameter values and the values found in three best fits:

- **Best fit #1**. High desired headway and SDRF.
- **Best fit #2**. Alternative set with lower SDRF and desired headway values to avoid the risk of over-fitting.
- **Best fit #3**. The same as one, but without any safety distance reduction. A value of 1.0 of the SDRF means that the critical gap is equally as large as the desired headway.

Table 7.2. Results from initial test run

Parameter	Defaults	Best fit #1	Best fit #2	Best fit #3
Desired headway [s]	1.1	1.5	1.2	1.5
FDT [s]	11	40	40	40
SDRF [-]	0.6	0.95	0.9	1.0

Validation process

The new parameter sets were found by comparing the model to the data set of one day. The validation process, where more days were tested and compared will determine if these parameters set fits by coincidence or by a proper estimation.

For the validation, multiple days were simulated and compared with the field data set from the corresponding day. Each simulation run of each day had its own OD-matrix based upon the field data. From the ten days of data that were gathered by TNO, only five had enough valid vehicles in their data set. There were three days with a similar traffic intensity, one day with a higher intensity and one with a lower intensity. The mean relative deviations from the field data was taken to see how well the parameter set fits over multiple days.

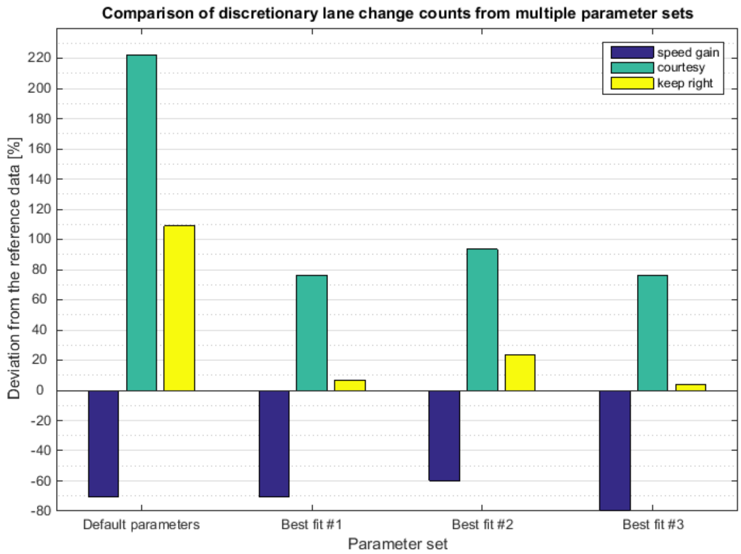

Figure 7.9. Comparison between the goodness of fit of each parameter set. The number of discretionary lane changes per trigger type are scaled relative to the observed values. Positive values represent overestimations; negative values represent underestimations.

Figure 7.9 shows the results of this validation. One thing that can be clearly seen is that the default parameter set overestimates courtesy lane change types. In any of the parameter sets, speed gain is either underestimated or misclassified as courtesy. All the other parameter set still have estimation deviations, but in lesser extent than the default parameter set, especially for keep-right lane changes. Several other parameters have been tested, but the remaining estimation differences could not be levelled out. From all the parameter sets, best fit #1 seems to have the best compromise between the overestimation on one hand and the underestimation on the other, but the difference with best fit #2 is not that large. From the five days that were compared, three days had about the same amount of traffic. Day 2 had about 25% less traffic and day 5 had 25% more traffic compared to the other three days. Figure 7.10 shows an overview of the differences under these traffic intensities.

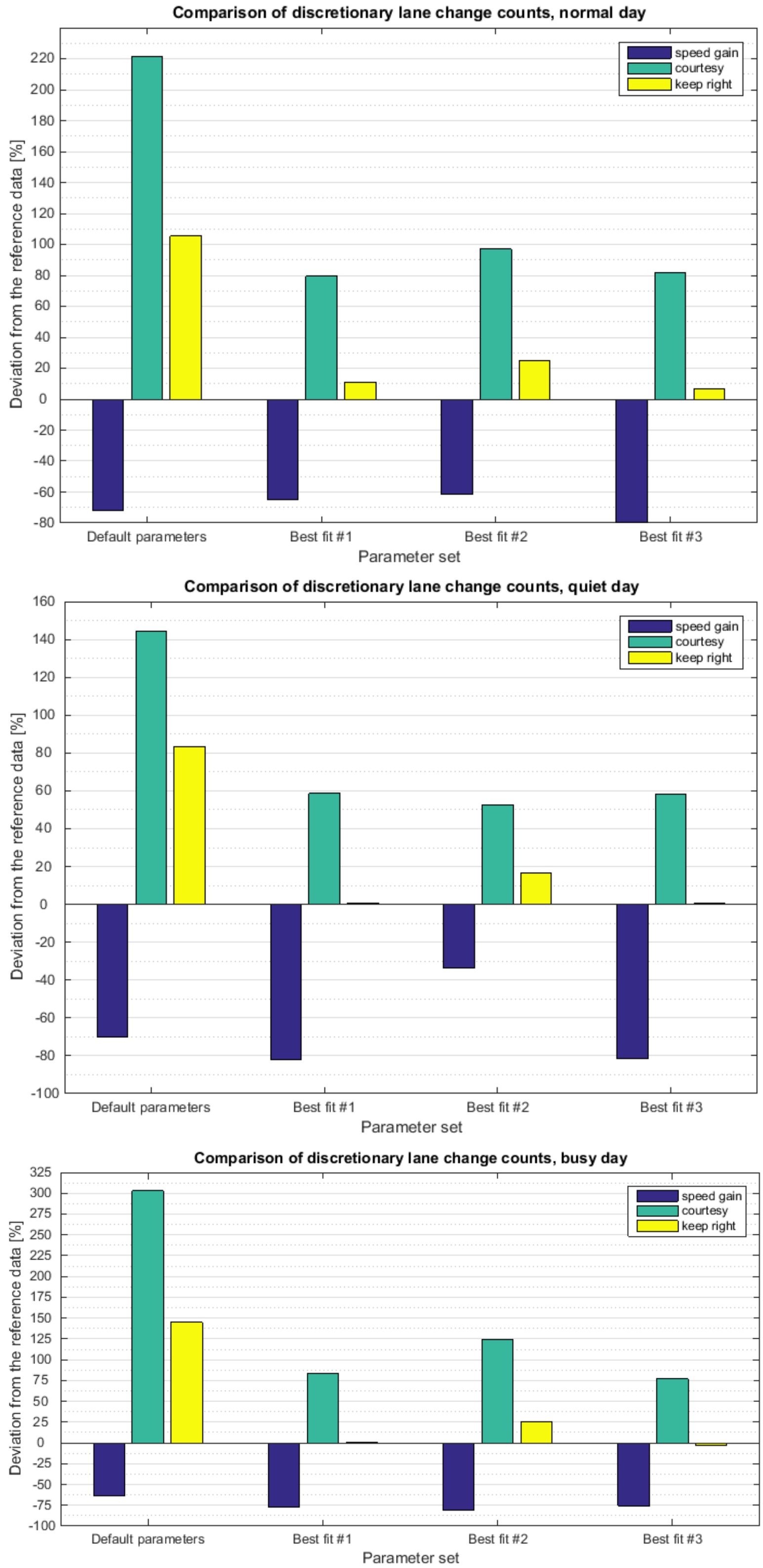

Figure 7.10 Comparison of the different parameter set performances under different traffic conditions.

It is visible that the size of the deviations do not only increase in absolute terms, but also relative terms with increasing traffic intensities. But in all three different conditions, the new parameter sets perform significantly better than the default parameter set.

Figure 7.11 shows a comparative overview of the different parameter sets compared to the reference.

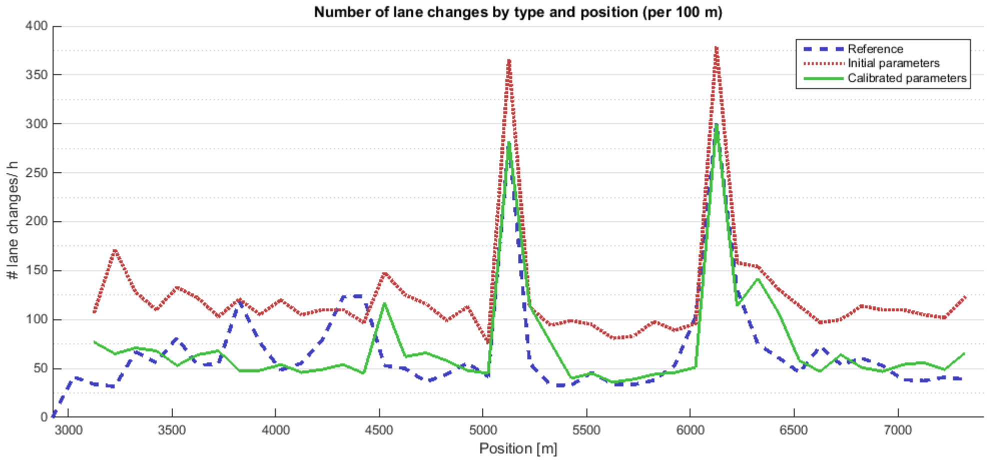

Figure 7.11 Comparison plot of the summed lane change frequencies of the reference data set, the VISSIM default parameter set and the calibrated parameter set (best fit #2).

Gap acceptance analysis

A final check of the calibration is to check the model's gap acceptance. Figure 7.12 shows a comparison of the new gap acceptance behaviour compared to the VISSIM default parameters and the observed data. Unfortunately and surprisingly, there appears to be little improvement on this part of the model, despite the fact that two of the three calibrated parameters alter the desired headway at a lane change; the gap distribution is a little less sharp compared to the default parameters, but it still deviates significantly from the observed data. One explanation for this is that VISSIM does not take gap selection into account and only considers adjacent gaps. This could lead to an underestimation of lane changes when the gap distribution is correctly fitted and vice versa (like in this example). Another explanation could be that the traffic conditions in the simulation (especially the generation) are too uniformly distributed compared to reality, which in turn leads to a narrower headway distribution. Figure 7.13 shows the flow over of both the observed data (left) and the simulated data (right). Although their OD-matrix is the same, the distribution of traffic over time and space is clearly different.

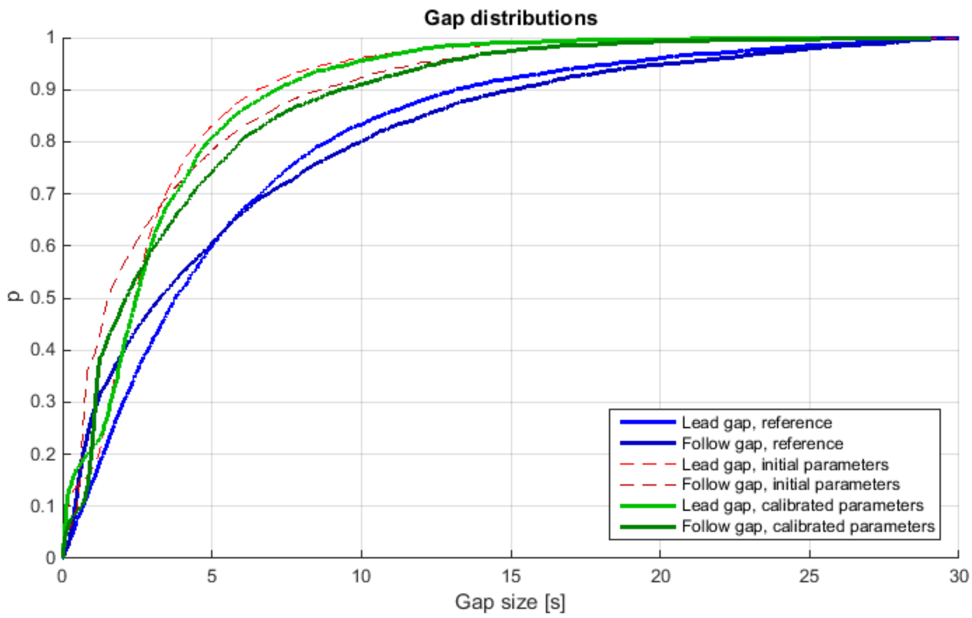

Figure 7.12. Comparison graph of the gap acceptance of the reference data set, the VISSIM default parameter set and the calibrated parameter set (best fit #2).

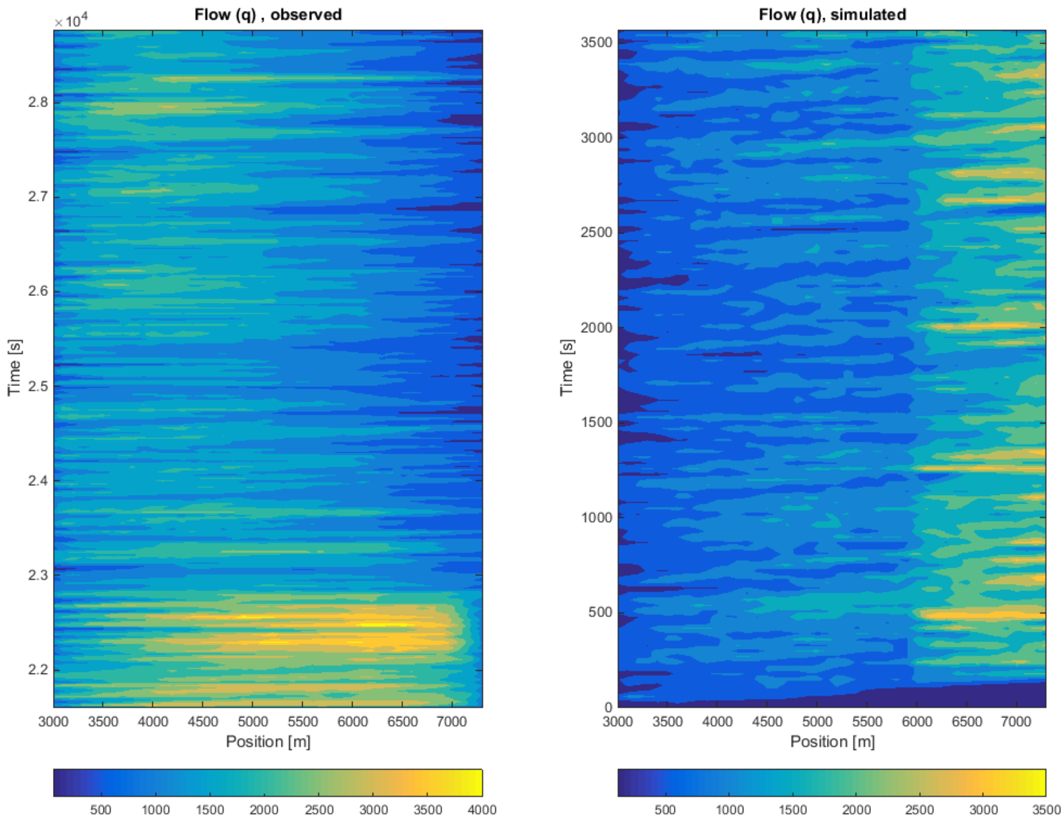

Figure 7.13. Comparison contour plot of the traffic flow from the observed data (left) and the simulated data (right).

7.4 Findings and conclusions

The model implementation shows some surprising results and demonstrates that there is a lot to be done to improve the accuracy of these models. This section summarizes the findings of the implementation.

FOSIM behaves quite deterministic in the aspects this research compares. The desired speed, as well as the merging point, seems to either focus on a small area or is limited to static values. FOSIM, in its current software package, is therefore unfit for further advancements by means of parameter tweaking. Advancements of this model requires reprogramming - which is not an option within this research - to incorporate probabilistic driver behaviour.

VISSIM has more probabilistic behaviour, but with the standard settings, it represents the traffic quite poorly. The number of discretionary lane changes is drastically overestimated and the gap acceptance distribution is too biased towards small gaps. By changing three of the behavioural parameters, the deviation in lane change frequency can be significantly improved. The found lane change behavioural parameters all suggest that Dutch drivers are risk-averse and keep their lanes in free flow condition. The recommended values are shown in table 7.3.

However, the speed gain related lane changes are systematically under-estimated. This can either mean that this trigger occurs less in the simulation or it is too often misclassified as courtesy, which still remains overestimated. This can mean that there is one or more phenomena that have not been taken into account which causes this difference. Another cause for the differences can be the assumptions that were made in the model. The current model assumes a uniform distribution of traffic entering the network. In reality, the traffic comes in waves, since the A270 ends on a traffic light controlled intersection. This may cause that near both ends of the road, the traffic density is higher than in the simulation. This density can influence the attractiveness of changing lanes. Finally, the deviation can also be caused by the deviations in the gap acceptance, which is too sharp, even after the calibration.

A final note is that these results are only valid in free flow conditions on Dutch motorways. For other countries and other traffic conditions, the parameters are most likely not valid and further research is required on that front. This also requires field data from these other locations and other traffic conditions to compare the simulation results with.

Table 7.3 Recommended parameter values for Dutch traffic in free flow.

Parameter	Recommended value ranges
Desired headway [s]	1.2 – 1.5
FDT [s]	~ 40
SDRF [-]	0.9 – 1.0

8 Mathematical model implementation

For the mathematical model, the integrated model of Toledo (2003) has been selected to perform this research. The Toledo model is implemented in MITSIM[5], but this was not available for this research. This means that in order to test the Toledo model, the model has to be programmed first. Although it was initially a goal to create a software simulation of the Toledo model, this could not be completed within the time constraints due to technical setbacks; the car following part of the model is working properly, but the lane changing behaviour is still very sensitive and unrealistic; vehicles where changing lanes to gaps that were not there and lead to collisions, or cars were ping-ponging between lanes constantly.

However, during the development of the car following part of the model, some observations could be made about the basic principles and mechanics of the model. These observations will be discussed in the subsections below.

8.1 Responsiveness of the following vehicle.

The car following model of Toledo is based upon the car following model of Ahmed (1999). This is a GHR-car following model, which is based upon the stimulus-response framework (see chapter 2), in this case, the speed difference, observed density and the space headway between the observed vehicle and its leader. This type of model has its limitations and unrealistic assumptions.

First and foremost, the follower reacts on even the slightest difference of its leader speed or headway, which is unrealistic due to the fact that drivers are not able to notice such small differences (Koutsopoulos & Farah (2012)). Furthermore, according to the model, the driver will respond to these small changes even if the leader is far away. Toledo did solve this issue by setting a headway threshold between car following behaviour and free-flow behaviour. This means that with a large enough headway, the follower is not constrained by its leader anymore and acts independently. This model could be improved by adding perception thresholds, but this would mean that this model would become a de facto hybrid psycho-physical car following model.

[5] https://its.mit.edu/software/mitsimlab

8.2 The (lack of) minimum headway distances

Another point is that the relation between speed and headway distance is treated as a multiplicative relation in the car-following model. This means that with small differences in speed, the influence of the headway distance to the acceleration is also reduced. In extreme cases, where the speed difference is 0, the headway does not even play a role anymore. This means that two vehicles following each other with the same speed can have extremely short headways, which contradicts the fact that most drivers prefer to keep a safe distance from their leader in case of an emergency.

A way to mitigate this problem is by splitting the car following regime into three sub-regimes, all determined by time headway:

- **Regular following regime**. The acceleration rules as described in the GHR-car following model are applied.
- **Relaxation regime.** When the vehicle is closing in to the leader up to the point that the headway is smaller than its perceived minimum distance, the vehicle will enter the relaxation regime. The maximum acceleration is capped to make sure that the follower will at least build up its headway slowly. The acceleration cap is set to a small value to simulate the deceleration achieved by lifting the foot from the gas pedal without further braking. The vehicle will still respond on situations that will require more severe braking.
- **Emergency braking regime.** If the driver is approaching an even smaller headway (0.3 seconds) or when the speed difference is so large that it would need to brake immediately to avoid collision, the vehicle enters the emergency braking regime where maximum braking is applied to avoid collision.

This will also make the car following behaviour more realistic without making too many changes to the model.

8.3 Car-following trains

It is quite common that there are multiple vehicles in a row that follow each other. This will be defined as a **car following train** (see figure 7.9). In a train, only the first vehicle – the **train leader** – is unconstrained and the rest of the vehicles within the train follow each other. The vehicles in the car following train will eventually all approach the speed of the train leader. If however the speed of the train leader changes, the rest of the train will respond with a slight delay due to the reaction time of each vehicle.

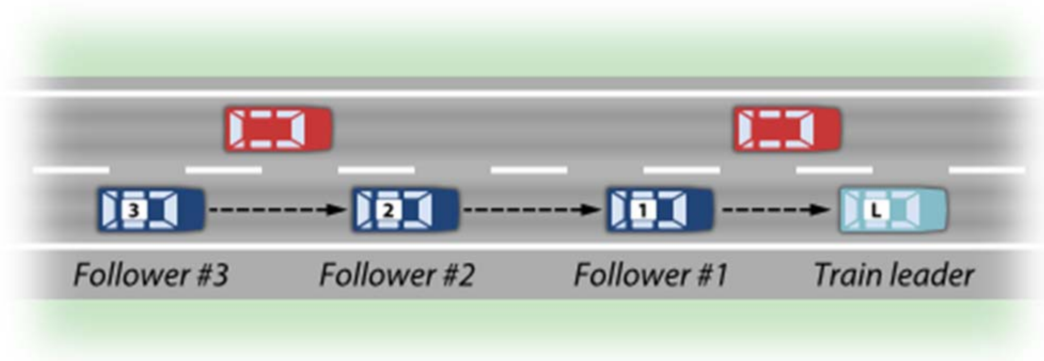

Figure 8.1 Example of a car following train with 4 vehicles. All three followers will eventually approach the speed of the train leader L.

However, the model does have a limitation that vehicles only take their direct leader into account explicitly and the rest of the train implicitly by density. The two factors also have multiplicative relation within the acceleration function, just like the speed and headway distance. This means that if the speed difference between the leader and the observed vehicle is 0 (which is a property of a car-following train), the observed vehicle does not respond to anything what happens in front of the leader. Within a train, this can be a problem; if a faster car following train is approaching a slow train, the two trains should combine in theory. And while it does within the model, it is not without problems; if the speed difference is large enough, the first few vehicles may be able to slow down in time, but there comes a point when one of the vehicles responds too late (because it only responded on the leader's braking) and crashes into its leader, and this will continue for a few more followers. In reality, this should not occur, because drivers do respond upon a few more vehicles in front of their leader when they are driving in a train, even when their leader still has the same speed as they do.

A way to counteract this problem is to add the influence of the indirect leaders to the acceleration behaviour. Their influence should be small, but large enough to make a vehicle brake when the whole train in front of him is braking. The effect is also partially mitigated (but not completely!) by adding the three car following sub-regimes as described in the previous sub-section, which increases the minimum headways between the vehicles, giving them more time to respond to the situation.

8.4 Summary

During the development of the mathematical Toledo model, some limitations of the car following model were identified. Most of these limitations require simple solutions (such as stimulus thresholds, multiple car following regimes and weighted multi-leader following) to create a hybrid model that can deal with these issues. Further research is required to check the lane changing behaviour and to calibrate the entire model. This could not be fully implemented within this research because of time constraints.

9 Conclusions and recommendations

In the previous chapters, a research has been performed about the performance of Existing Integrated car-following and lane-changing models around motorway ramps. This chapter will give the conclusions and recommendations from this research. Section 8.1 presents the conclusions drawn from this research, while section 8.2 presents the recommendations for further developments of these models and for practice. Finally, section 8.3 will give recommendations for future research to fill in the remaining knowledge gaps.

9.1 Conclusions

In the introduction of this research, it is stated that decision makers might sometimes rely too much on the outcomes of a simulation model, while the model might not be accurate. This research has proven that if one does not know the limitations and assumptions of a model, the model results can deviate drastically from reality in the field. If proper calibration has not been done, the trust in the model is unfounded and the model results are therefore inherently invalid. Calibration and validation are highly important to gather proper model results.

A demonstration of this statement is from VISSIM in this research. It has been shown that in free flow conditions on Dutch motorways, the model over-estimates the number of voluntary (discretionary) lane changes. This deviation is most notable in areas before and after on and off-ramps. This over-estimation leads to a less stable traffic flow and therefore does not represent the traffic conditions correctly. Experimental trial and error parameter tweaking does show that the behaviour can be improved, though courtesy behaviour and situations where no acceptable gap can be found are still aspects VISSIM has trouble in replicating realistically. Therefore, recalibrating the model for this is essential. For Dutch drivers, a parameter set representing more risk-averse behaviour yielded the best results for the lane change frequencies. However, the gap acceptance behaviour could barely be improved. This may be related to the assumed uniform distribution of the traffic generation in the simulation, which most likely does not occur in reality.

FOSIM has serious limitations on simulating probabilistic aspects of microscopic traffic behaviour, mainly the driver characteristics. Although the model could be adapted to handle this, it cannot be done without reprogramming the software package, which was not possible within this research. FOSIM is mainly calibrated upon macroscopic behaviour of Dutch motorways, something that FOSIM does simulate quite accurately. But at microscopic level, it is already outclassed by other software packages and more recent mathematical models. Just like VISSIM, FOSIM also predicts a too sharp gap acceptance distribution, but this may also be related to the uniform distribution of the traffic generation in the simulation. The only way to improve FOSIM is to update the core program to include probabilistic distributions of driver characteristics. This could also offer an opportunity to implement extra algorithms (such as gap selection algorithms).

The integrated vehicle model from Toledo may have some potential, but since this model could not be constructed within the time constraints of the research, not much can be concluded from this. The only conclusions that have been drawn is that the car-following behaviour can easily be improved by adding factors often seen in other types of car-following model. With a few simple changes, such as the implementation of multiple car-following regimes and perception thresholds, a hybrid model may give a much better results than the original model.

A proposed course of action to improve simulation models is to gather more local data about discretionary lane changes and calibrate the corresponding behavioural parameters accordingly. For models still in development, it is recommended to check if different parameter sets are required for different lane change triggers.

9.2 Recommendations for practical applications

The following recommendations for practical applications are proposed:

- Before performing a research with a model, it is recommended to gather information first about on which kind of situations the model is calibrated and validated. If the validated situation does not apply to the subject of the research (in general terms), a validation study must be performed first to find the proper parameters, or another model should be used that is calibrated to the subject traffic situation.
- The overestimation of lane changes in VISSIM suggests that the lane change behavioural parameters should be adapted to reduce the number of lane changes on motorways to half of what the default parameters would reproduce. For Dutch traffic in free flow, it is recommended to use the values of Table 9.1

Table 9.1 Recommended parameter values for Dutch traffic in free flow.

Parameter	Recommended value ranges
Desired headway [s]	1.2 – 1.5
FDT [s]	~ 40
SDRF [-]	0.9 – 1.0

- The core of the FOSIM software package, which is almost 20 years old, could use maintenance and reprogramming to improve the microscopic behaviour of that model. This could also offer the opportunity to implement new insights and algorithms into the model, which could turn this simulation package from an outdated model into a state-of-the art model.
- Developers of new models or developers that improve existing models could add a distinction between the proposed lane-changing triggers in the lane-change model. This could add different sensitivities to different lane-change incentives, if this was not already in place.
- Road side cameras can provide a proper data set, as the dataset from TNO has demonstrated. These cameras are mounted on dedicated posts on the A270, but alternatively on other locations, mounting cameras on sign gantries or lamp posts could also be considered.

9.3 Recommendations for future research

The following recommendations for future research are proposed to fill in the remaining knowledge gaps:

- More calibration and validation studies should be performed to existing models to cover a wider range of traffic conditions and therefore improve the accuracy of the model results. The literature study also supports this statement, since often for these models, time series for validation are lacking.
- A portion of the lane-changes found could not be classified with one of the six given triggers. Further research can investigate whether this is a classification error or if there is another trigger that has been overlooked.
- Further research could also determine whether or not there are behavioural differences for the different lane-change triggers, such as acceleration patterns during the lane change, desired gap length, etc.
- More research in the field should be performed to investigate to what extent the gap selection process plays a role in lane-changing processes, as opposed to only considering the adjacent gaps (as most models do).
- The current research only tested two models against the empirical data from the A270. More models could be tested and calibrated against this data set.
- Further research could be done for VISSIM to investigate if changing the traffic flow to a less uniform distribution has a significant positive effect the lane-change behaviour and gap-acceptance or not.
- The lane-change behaviour of the Toledo integrated driving behaviour model could not be analysed within this research and therefore could not be calibrated. Future research could attempt to investigate this behaviour and calibrate the model.

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Image sources

Front page:	Edited photo “taper-2” by ChrisZwolle on Flickr: http://farm5.static.flickr.com/4082/4824331415_bed2a459e4_b.jpg
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Figure 2.2	Adaptation of Olstam et al (2004), figure 4.
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Appendix I: Detailed description of camera based data collection methods

Considered data collection methods

As mentioned in section 4.2, multiple video camera methods have been considered, which can be categorised into two groups, distinguishing the angle in which the camera is mounted:

- The **perpendicular method**, where the camera faces straight down onto the road.
- The **angular method**, where the camera is pointed in the bisection of the top corner of a triangle.

Both methods are visualised in figure I.1. An overview of the advantages and drawbacks of each method are described in the sections below.

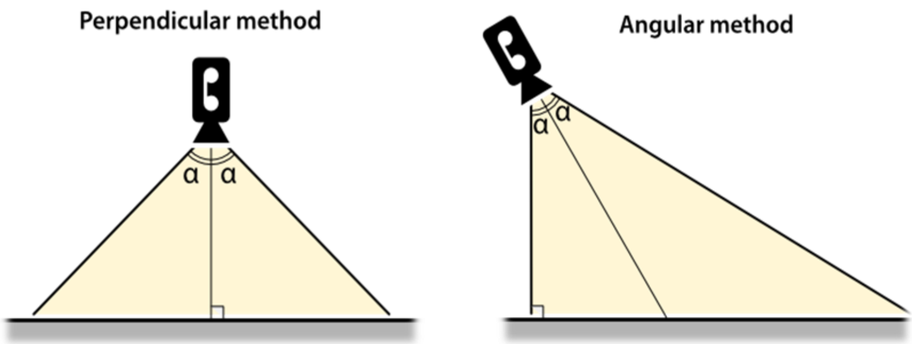

Figure 4.1. Visualisation of the camera mounting methods.

Camera position methods

Perpendicular method

The perpendicular method monitors all vehicles in the monitored range from a top-down view. This reduces all visual data to a horizontal plane. Since traffic only goes horizontally, this method allows to get all data that is necessary (i.e. the trajectories of the different vehicles on the road); from this view, the size and position of each vehicle is practically unambiguous. At small camera angles (below 60°), the perspective deformation is negligible, which simplifies the data processing.

This method does have a limited range, and it requires a high altitude to get a sufficient range. The larger the camera angle, the larger the range. At large camera angles, the curvature of the lens plays a role. This curvature can cause deformations near the edges of the captured area. Perspective will also play a role near the edges, which eliminates the aforementioned advantage of data processing simplification.

In table I.1 is an overview of the captured ranges (in meters) with different camera angles and mounting heights (in meters). This range is calculated by:

$$R = h \cdot 2 \cdot \tan(\alpha)$$

Table I.1: Overview of the captured ranges (*R* [m]) with different camera angles (2α [°]) and mounting heights (*h* [m]).

Height	70	80	90	100	110	120	130	140	150
10	14	17	20	24	29	35	43	55	75
15	21	25	30	36	43	52	64	82	112
20	28	34	40	48	57	69	86	110	149
25	35	42	50	60	71	87	107	137	187
30	42	50	60	72	86	104	129	165	224
40	56	67	80	95	114	139	172	220	299
50	70	84	100	119	143	173	214	275	373
75	105	126	150	179	214	260	322	412	560
100	140	168	200	238	286	346	429	549	746
150	210	252	300	358	428	520	643	824	1120
200	280	336	400	477	571	693	858	1099	1493
300	420	503	600	715	857	1039	1287	1648	2239
400	560	671	800	953	1143	1386	1716	2198	2986
500	700	839	1000	1192	1428	1732	2145	2747	3732

Angular method

The angular method puts the camera in a bisection of the top angle of a (fictional) triangle. Because the camera is placed at an angle, the camera can record a larger range with a smaller camera angle, which reduces deformation caused by wide-angle lenses. Although perspective correction is required here, there is a software application available to correct this. This does require a stable camera position to make correction feasible.

However, since there is no top-down view, it's harder to measure the vehicle's length. When given a large recording range, there is a risk that vehicles in the distance become so small (in terms of pixels), that their position and size may not be measured accurately enough; this will be referred to as the "pixelation"-issue.

The height differences of the road can also play a role here. Therefore, slopes in the road can cause deformations and inaccuracies. But not only that; depending on what point you take when measuring the vehicle (commonly the bumpers are the focus points), the measured position of the vehicle can deviate from its actual position. This deviation gets larger when the vehicle moves further away from the camera, since the angle of the vehicle relative to the camera changes. And finally, from this perspective it is possible that larger vehicles (such as trucks) can obscure the view of smaller vehicles, which can cause gaps in the data collected, although this can be countered by interpolation.

In table I.2 is an overview of the captured ranges (in meters) with camera angles and mounting heights (in meters), where $R = h \cdot \tan(\alpha)$

Table I.2: Overview of the captured ranges (*R* [m]) with different camera angles (α [°]) and mounting heights (*h* [m]).

Height	45	50	55	60	65	70	75	80	85
10	10	12	14	17	21	27	37	57	114
15	15	18	21	26	32	41	56	85	171
20	20	24	29	35	43	55	75	113	229
25	25	30	36	43	54	69	93	142	286
30	30	36	43	52	64	82	112	170	343
40	40	48	57	69	86	110	149	227	457
50	50	60	71	87	107	137	187	284	572
75	75	89	107	130	161	206	280	425	857
100	100	119	143	173	214	275	373	567	1143
150	150	179	214	260	322	412	560	851	1715
200	200	238	286	346	429	549	746	1134	2286
300	300	358	428	520	643	824	1120	1701	3429
400	400	477	571	693	858	1099	1493	2269	4572
500	500	596	714	866	1072	1374	1866	2836	5715

Camera mounting methods

The cameras can be mounted in multiple methods. The following mounting methods have been considered:

- Static cameras mounted on gantries or lamp posts
- Static cameras mounted on tall buildings or structures.
- Static cameras mounted on a crane.
- Cameras mounted on a static helicopter
- Cameras mounted on a moving helicopter

Each mounting method will be described in the sections below.

Static cameras on gantries and lamp posts

The first mounting method is to mount cameras by the aforementioned angular method on multiple locations along the stretch on roadside structures, such as gantries or lamp posts. A quite large portion of the Netherlands (especially within the Randstad area and in Noord-Brabant) has gantries and lamp posts placed frequent enough to allow this method to be used. At some locations, cameras from Rijkswaterstaat (mainly near peak lanes) or TNO (at the A270) are already available and at a relatively high frequency (~100 meters) to make them suitable for this application. Each camera records only a part of the motorway stretch, and the data of these recordings need to be stitched together during the processing.

The biggest advantage is that these cameras are very stable. Although the structures they are mounted on do wobble a bit due to wind influence, the intensity of these wobbles is pretty low, and the frequency of the wobbles is also low. External power supply by the electricity grid or field generators is quite feasible for these types of cameras, making the recording time less of an issue. And since the cameras are not very visible for the drivers, the measuring system will not distract the drivers.

However, this method also has some drawbacks. The low height does come with a limited range (100-200m per camera), which means that a lot of cameras will be required. Furthermore, the low height also cause strong perspective related issues, such as covering and deviations in car position due to the camera angle. Pixelation is an issue, but due to the low range it is not very bad.

Static cameras on tall buildings or structures

Another option with static cameras is to place them on tall structures or buildings This method has the same advantages as mounting the cameras on lower structures, with an extra advantage that due to the height, perspective related issues are reduced. With a tall enough mounting point, only two or three (wide angle) cameras on that single mounting point are required to record the whole 1500 meter stretch.

However, the pixelation issue is much more present, since a lot of the recorded traffic is far away and therefore will produce a very small image. Furthermore, this method requires a tall structure (80 meters or higher) near a motorway, and there are not many buildings or structures in the Netherlands that fulfil both requirements; the number of potential locations is therefore very limited.

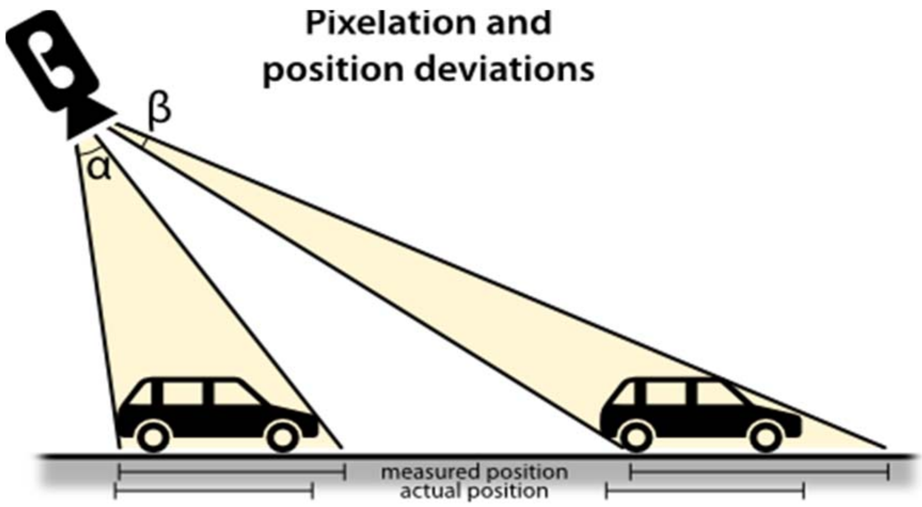

Figure I.2. Visualisation of both the position deviation and the pixelation issue. When the vehicle is near, the vehicle covers a large viewing angle on the camera, resulting in a large image of the vehicle (more pixels) and the deviation between the measured position and the actual position is small. As the vehicle moves further away, the deviations become larger and the camera viewing angle becomes smaller (which means less pixels per vehicle).

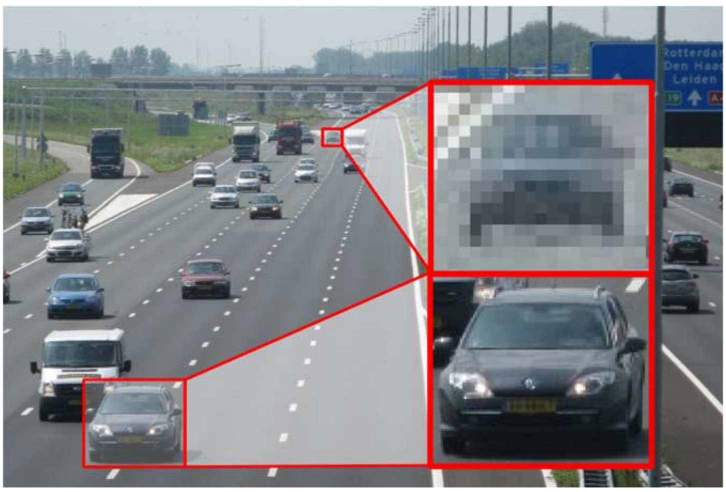

Figure I.3. Visualisation of the pixelation issue. The further away a vehicle is, the more blurred and pixelated it becomes. This is visualised in the above image where two cars are resized to the same size. It is clearly visible that the physical representation of the size of one pixel is much larger for the car in the top picture than on the bottom one, which means that the accuracy is much less when a vehicle is far away.

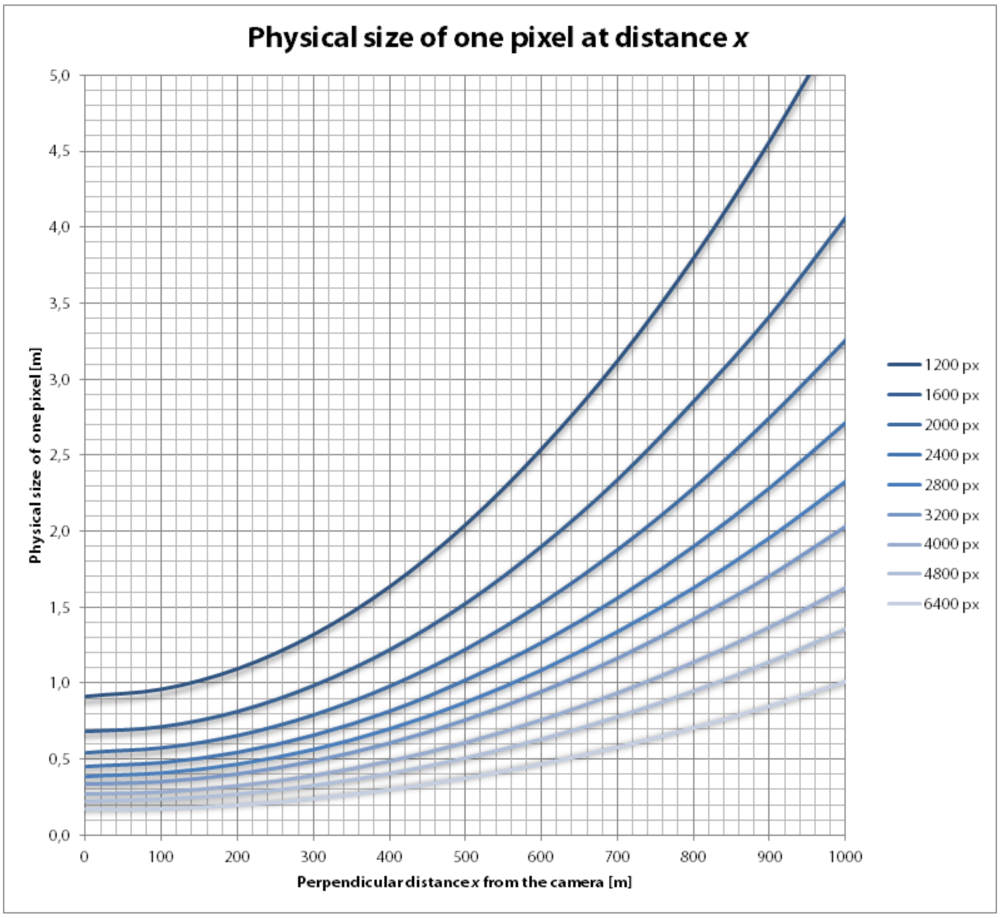

Figure I.4. The effect of the pixilation issue displayed in a graph. The pixilation issue can be reduced when the resolution is increased, but the improvements of a higher resolution become increasingly less effective, while the effect of the issue increases rapidly with the distance.

Static cameras on a crane

Instead of selecting an existing tall structure from a limited set of structures, one can always create their own high point. By using a mobile crane, the cameras can be mounted on a high point along almost any motorway stretch, given a large enough area to park the mobile crane vehicle. The cameras are mounted on the top of the crane arm, which will be raised to the desired height. The crane height can go up to 140 meters. The required space for the crane to be placed is 20.7 meters × 12.3 meters. Extra space in the length-dimension will be required to manoeuver the crane into the right position and rotation.

The drawback of this method other than pixelation are that the camera can hardly be connected to an external power supply and thus most likely requires batteries. Furthermore, the presence of the crane vehicle is very noticeable and can distract drivers. Finally, this camera is less stable since its mounting point is not rigid.

Cameras mounted on a static helicopter (perpendicular method)

Another option is to move to an even higher altitude with helicopters (or blimps). By increasing the altitude, the range of the camera can be increased without having to use wide angled lenses. Especially when using the perpendicular mounting method, this is a big advantage; this method has no issues with perspective. All vehicles will keep the same size at any point on the stretch in the recording, which makes the determination of the size and position easy. One camera is needed in this case to cover a range of 500 meter length.

However, helicopters are less stable, so a stabilisation algorithm needs to be adapted on the video footage. Although the range of the helicopter may be larger, it's still limited to 500 meters. Furthermore, pixelation does play a (minor) role due to the height, which makes all vehicles small on the recording (though unlike the previous methods, the deviations caused by pixelation are constant). The helicopter although visible for traffic, may lead only to minor distractions from drivers. Finally, the recording time is limited, not only due to lack of external power supply to the camera, but even more by the fact that the helicopter can run out of fuel and that it is a hard task for the pilot to keep the helicopter steady at one position.

Cameras mounted on a static helicopter (angular-hybrid method)

Instead of using the perpendicular mounting of the camera as described in the previous method, an alternative is to add extra cameras to extend the recording range. This does come at the cost of adding again some perspective issues (since the angular mounted cameras add perspective due to their angle), including pixelation issues of vehicles that are far away. Also, these angular cameras will be even harder to stabilise, since the angle changes during the recording due to the instability of the helicopter.

Cameras mounted on a moving helicopter

Another option is to let the camera move along with the traffic and go back and forth along the stretch. With a limited range, one can still follow a group of vehicles all the way along the 1500 meter stretch. The moving “window” extends the range of the camera. It is an easier task for a helicopter pilot to move along with the traffic than to keep the helicopter static. The drawback is that not all vehicles can be recorded at the whole stretch at the same time. Another disadvantage is that with a moving camera, stabilisation becomes almost impossible: most stabilisation algorithms need a static background or calibration points that are visible all the time. Since the camera is moving, both of these are impossible to achieve.

Other possible methods that will not be used

There are some other methods to track vehicles. For the sake of completion, these methods will be mentioned here, but will not be taken into account in the method selection for this research. The reason for this is that this research mainly focusses on camera data. Furthermore, some other camera methods are infeasible on beforehand. The other methods that are considered methods are:

- Using drones instead of helicopters. Drones have the advantage that they can be considerably cheaper than helicopters, but their light weight causes high wind influence. Moreover, there are also legal issues that limit the deployment of this method, such as the continuous line of sight between the pilot and the drone and the prohibition to fly directly above roads.

- Sonar/radar installations, mounted on gantries or lamp posts. These can measure the speed and position of a vehicle using the Doppler effect, but may have problems when they are dealing with multiple lanes.

- Stereo sonar/radar; by adding a second channel, the difference between the two can be used for a better estimation of a vehicle's position.

- Laser detectors on guard rail level; state-of-the-art technology that can detect a vehicle's position with high accuracy in time and space, but this technology is still experimental and expensive.

Summary

In Table I.3, a summary of all mounting methods and their characteristics can be found. The characteristics are denoted whether they have a positive effect on the data collection or a negative effect.

Counter-measures to reduce the drawbacks

Some drawbacks can be reduced by counter-measures. Each one of the counter-measures, enlisted below, tackle a specific drawback.

Record multiple sessions with the perpendicular method by helicopter

For the perpendicular method by helicopter, the range can be a limiting factor. A way to counter this, is to record multiple sessions where each session captures a different part of the road. This means that with only one camera, you can get a quite stable image of the entire stretch. However, since each session is recorded at a different time, one cannot follow a vehicle through the entire stretch and therefore cannot determine some causality relations for driver behaviour between two different sessions.

Table I.3. Overview of all mounting options and their effect on the characteristics. All characteristics are denoted by whether they are affected positively or negatively.

	Static (gantries / lamp posts)	Static (High point)	Static (crane)	Helicopter (perp.)	Helicopter (hybrid-angular)	Helicopter (fly-by)
Power supply	+ +	+ +	+ / -	-	-	-
Recording time	+ +	+ +	+	- -	- -	- -
Range	- -	+ / -	+	-	+	+ / -
# required cameras	-	+	+	+ +	+	+ +
# potential locations	+	-	+	+	+	+
Stability	+ +	+ +	+	-	- -	- - -
Pixelation	+ / -	- -	-	+	-	+
Perspective issues	- -	-	-	+	+ / -	+
Unwanted notability	+	+	- -	-	-	-

Legend:

+ +	Very positive
+	Mildly positive
+ / -	Neutral
-	Mildly negative
- -	Very negative
- - -	Extremely negative; practically infeasible

Use overlap to counter covering issues

Covering is a problem with angular cameras. To counter this, one can use "redundant" with cameras to track the same vehicle at the same location from another view, to make sure each vehicle is visible for at least one camera all the time. This does require more cameras and each camera adds more processing time. The question is whether or not simple interpolation is an acceptable enough replacement for this.

Use overlap to improve stability

One of the main problems with the helicopter data with the angular method is that it is hard to stabilise. To overcome this issue, one can try to overlap areas from multiple cameras. This way, only one camera requires a calibration point; the rest can synchronise based upon the overlap.

Overcome pixelation issues with extra zoomed-in cameras

Vehicles will become small on camera images when they are far away. A way to counter this is to simply make them appear larger by using a zoomed in camera. These zoomed in cameras have a smaller range, but can make vehicles that are too small for the normal camera better visible. Because the smaller zoomed in range overlaps completely with the same range of the not-zoomed-in camera (and the fact that the ratios within the area do not change between the two images), the two can be linked. This improves the accuracy of the vehicles that are at a greater distance from the cameras.

Use detector induction loop data to correct speed and time deviations

Detector loops are placed too sparsely (usually ±400 meters) to measure vehicle trajectories, but they can support the camera data. One of the issues that angular cameras cope with are deviations in position due to the angle. A detector loop can accurately detect the speed and time the vehicle passes that particular detector loop. The traffic patterns from these loops are quite unique and distinguishable in time, so it is easy to find the right data entries for this. Not only can this data be used to correct the vehicle's speed and position, but it can also be used to synchronise the time between multiple cameras. This means that the data from multiple cameras can be linked even when their clocks are de-synchronised.

Appendix II: Mathematical description of the Validation Index

The **Validation Index (VI)** is a numerical value between 0 and 1 describing how undisturbed the data entries of the referenced vehicle -and all other vehicles it interacts with - are. The higher the VI, the better the data set. The selected vehicles for the analysis must have a VI that exceeds a threshold value ($VI_{theshold}$) to be taken into account:

$$valid_n = \begin{cases} 1 & VI_n \geq VI_{theshold} \\ 0 & VI_n < VI_{theshold} \end{cases}$$

The VI is composed out of two parts: the vehicle's own validity (VI_{own}) and the validity of all vehicles it interacts with (VI_{ia}):

$$VI_n = VI_{own,n} \cdot VI_{ia,n}$$

The vehicle's own validity is determined by the presence of a selection of data disturbances. The disturbances that are identified and taken into account are:

- **Sample size.** The number of time steps a vehicle has. Short samples are deemed not to be significant or a result of noise.
- **Jumps in the trajectory**. If a vehicle moves too fast ($v_n > v_{jump}$) between time steps, it will count as a jump for each time step this occurs.
- **Backwards driving**. The distance a vehicle has travelled in the wrong direction between time steps. This is measured in meters.
- **Slow driving**: if the speed of a vehicle v_n falls below a speed threshold ($v_n < v_{slow}$) , it can be assumed that this vehicle is not driving in free-flow conditions.

The $VI_{own,n}$ is being given by:

$$VI_{own,n} = VI_{smp,n} \cdot VI_{jump,n} \cdot VI_{back,n} \cdot VI_{slow,n}$$

Where:

$$VI_{smp,n} = 1 - \frac{1}{(w_1)^{smp_n}}$$

$$VI_{jump,n} = \frac{3}{(w_2)^{j1,n} + (w_3)^{j2,n} + (w_4)^{j3,n}}$$

$$VI_{back,n} = \frac{1}{(w_5)^{sb_n}}$$

$$VI_{back,n} = \frac{1}{(w_6)^{slow_n}}$$

- smp_n sample size of vehicle n
- $j_{1,n}$ jumps of vehicle n where: $v_{jump} < v \leq 1.5 \cdot v_{jump}$
- $j_{2,n}$ jumps of vehicle n where: $1.5 \cdot v_{jump} < v \leq 2.5 \cdot v_{jump}$
- $j_{3,n}$ jumps of vehicle n where: $v > 2.5 \cdot v_{jump}$
- sb_n total distance covered driving backwards by vehicle n
- $slow_n$ total number of samples of vehicle n where $v < v_{slow}$
- $w_1 \dots w_6$ weight factors

The $VI_{ia,n}$ looks at the interactions between vehicles by taking the VI_{own}-value of each vehicle and weighs it by the time length of the interaction. The $VI_{ia,n}$ is being given by:

$$VI_{ia,n} = \sum_{q=1}^{6} \left(\frac{steps_{q,0}}{6 \cdot smp_n} + \sum_{k=1}^{m} VI_{own,k} \cdot \frac{steps_{q,k}}{6 \cdot smp_n} \right)$$

Where:

- q interaction type, related to leader/follower state and lane[6]
- m number of vehicles conforming to the interaction state
- $steps_{q,0}$ number of time steps of the interaction q without any vehicle
- $steps_{q,k}$ number of time steps of the interaction q with vehicle k

[6] *This is a relative lane reference, where 1 = current lane, 2 = left lane, and 3 = right lane. Combined with the leader/follower state, there are 6 different interaction types in total.*