Development, Simulation and Evaluation of In-car Advice on Headway, Speed and Lane

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Preface

For over 4000 days, the faculty of Civil Engineering and Geosciences at Delft University of Technology has been the place where I have been able to build on my professional career. For more than half of this time, this has been at Transport and Planning. First as a Master student, later as a PhD candidate. It was during my Master project that my supervisor Serge Hoogendoorn mentioned the opportunity of doing a PhD, about which we had a few conversations, for which I would like to thank Serge. I actually ended up doing a PhD with Bart van Arem in a dual role as promotor and daily supervisor. I would like to thank Bart for his constructive guidance and efforts. You showed enthusiasm whenever I presented some idea, and was able to help me whenever I felt stuck. I would also like to thank Rob van Nes for helping me in the initial phase of my PhD, and Hans van Lint for helping me improve the quality of this thesis.

Besides my supervisors, I would like to thank all my colleagues at Transport and Planning for providing a fruitful environment and relaxed atmosphere. I would like to thank Olga, Tamara, Niels, Adam, Meng, Gijs, Erik-Sander, Jeroen, Kakpo and Luuk, who were all at some point my roommates, for providing both casual and professional conversation. I would also like to thank everyone who used my microscopic simulation framework in any way, but especially Bernat, Meng and Lin. I had great fun in discussing the many details involved in implementing your ideas in simulation. A final colleague who I would like to thank is Victor. Your input surely helped in winning the Greenshields Prize.

The majority of my PhD involved work in the Connected Cruise Control project, an excellent opportunity to not only evolve as a scientist, but also to gain practical experience. For this I would like to thank all the people who participated in this project, and who were able to teach me a thing or two regarding implementation of an advisory in-car system.
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I would like to thank my family for their support. In particular I would like to thank my brothers Menne and Hendrik for being my paranymphs. I would like to thank my children Lena and Falco. Truthfully, I enjoy watching you observe, learn, be stubborn and show bad behavior, even more than I enjoy observing drivers not watching, not learning, being stubborn and show bad behavior. Finally, I would like to express my biggest thanks to my wife Priscilla, who supports me through all the stresses and wonderful moments that come with having busy lives and raising two children.

Rather than stating what I would like to do, let me in conclusion actually do it: thank you!

Wouter Schakel, April 2015
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<th>Description</th>
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<tbody>
<tr>
<td>ACC</td>
<td>Adaptive Cruise Control</td>
</tr>
<tr>
<td>ADAS</td>
<td>Advanced Driver Assistance System</td>
</tr>
<tr>
<td>AHS</td>
<td>Advanced cruise-assisted Highway System</td>
</tr>
<tr>
<td>ASM</td>
<td>Adaptive Smoothing Method</td>
</tr>
<tr>
<td>CA</td>
<td>Cellular Automata</td>
</tr>
<tr>
<td>CACC</td>
<td>Cooperative Adaptive Cruise Control</td>
</tr>
<tr>
<td>CLC</td>
<td>Cooperative Lane Change</td>
</tr>
<tr>
<td>DLC</td>
<td>Discretionary Lane Change</td>
</tr>
<tr>
<td>DRIP</td>
<td>Dynamic Route Information Panel</td>
</tr>
<tr>
<td>DTA</td>
<td>Dynamic Traffic Assignment</td>
</tr>
<tr>
<td>EGTF</td>
<td>Extended Generalized Treiber-Helbing Filter</td>
</tr>
<tr>
<td>FLC</td>
<td>Free Lane Change</td>
</tr>
<tr>
<td>HMI</td>
<td>Human Machine Interface</td>
</tr>
<tr>
<td>HOV</td>
<td>High Occupancy Vehicle</td>
</tr>
<tr>
<td>IDM(+)</td>
<td>Intelligent Driver Model (adapted)</td>
</tr>
<tr>
<td>IRSA</td>
<td>Integrated full-Range Speed Assistant</td>
</tr>
<tr>
<td>ITS</td>
<td>Intelligent Transportation Systems</td>
</tr>
<tr>
<td>LMRS</td>
<td>Lane change Model with Relaxation and Synchronization</td>
</tr>
<tr>
<td>MDTM</td>
<td>Microscopic Dynamic Traffic Management</td>
</tr>
<tr>
<td>MLC</td>
<td>Mandatory Lane Change</td>
</tr>
<tr>
<td>OBU</td>
<td>On-Board Unit</td>
</tr>
<tr>
<td>OOP</td>
<td>Object Oriented Programming</td>
</tr>
<tr>
<td>OVM</td>
<td>Optimal Velocity Model</td>
</tr>
<tr>
<td>RMSE</td>
<td>Root Mean Squared Error</td>
</tr>
<tr>
<td>RSU</td>
<td>Road-Side Unit</td>
</tr>
<tr>
<td>SLC</td>
<td>Synchronized Lane Change</td>
</tr>
<tr>
<td>SPECIALIST</td>
<td>SPEed ControllIng ALgorIthm using Shockwave Theory</td>
</tr>
<tr>
<td>VMS</td>
<td>Variable Message Sign</td>
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1 Introduction

There are high expectations for Advanced Driver Assistance Systems (ADAS) to combat traffic congestion, maintaining a high level of mobility, which is at the basis of modern economies and welfare. ADAS are in-vehicle systems, which assist the driver with the driving task. Aims of ADAS are various including driver comfort, safety, fuel economy, emissions and traffic efficiency. Various parts of the driving task may be assisted including: car-following, lane keeping, adhering to the speed limit, etc. Since ADAS are usually consumer products, they mainly focus on individual gains. Traffic efficiency is a common goal and therefore often not a goal of ADAS. Simulation studies have however shown that significant traffic efficiency gains can be achieved. Minderhoud (1999) performed extensive simulations to assess capacity based on a full range Adaptive Cruise Control (ACC) system and found that at a three-lane freeway with on-ramp the capacity increased with 25% while a two-lane freeway had an increase of 12%. Significant gains are already achieved at intermediate penetration rates. Similarly, van Driel and van Arem (2010) found a 30% reduction of travel time delay at a lane drop, already at 10% penetration rate. Minderhoud (1999) and van Arem et al. (1996) have however also shown that if the system is not correctly designed, capacity may not significantly change at all (e.g. headway settings, maximum deceleration, etc.), or even deteriorate. Treiber and Helbing (2001) showed that by doubling the maximum acceleration and by halving the desired headway, congestion is reduced by 80% with only 10% penetration rate, and congestion is diminished with 20% penetration rate. As such settings might not be in line with desires of drivers (i.e. comfort and perceived safety), a more advanced approach is presented by Kesting et al. (2008) where the settings of an ACC controller are dynamic and depend on the situation. Only if required, larger acceleration and smaller headway settings are used. More specifically, this is in bottlenecks and while accelerating out of congestion. The maximum deceleration is also dynamic and used for a safety increase while decelerating towards congestion. Similar results as earlier studies are achieved, while driver preferences are respected for the majority of time.
These studies show that driver inefficiency can be reduced by taking over (part of) the driving task. Another option is to advice or inform drivers, without actually taking over part of the driving task. This thesis focuses on an advisory approach, for reasons explained in the description of the advisory system (section 1.3).

To improve traffic flow, an understanding of inefficiencies in traffic is required. From literature, several contributing aspects are known such as lane changes and the resulting distribution of traffic over the lanes (Laval and Daganzo, 2006; Knoop et al., 2010), traffic flow instability (Ranjitkar et al., 2003; Sugiyama et al., 2008; Tampère et al., 2005a) and the capacity drop (Treiber et al. 2006a; Tampère et al., 2005a). For a significant part, these aspects belong to the tactical scale of driving. The tactical scale contains behavior based on a short-term mental forecast of traffic and includes game-theoretical considerations, e.g. given what other divers may do, how can you optimize your speed and comfort. Surrounding traffic is considered for aspects such as intended speed, lane choice, path planning, headway selection, gap searching, etc. This is further explained in chapter 2.

The tactical scale is in between the operational scale (e.g. vehicle control) and the strategic scale (e.g. routing, trip planning). Many systems that improve traffic flow efficiency operate at either the strategic or operational scale, such as route guidance by use of navigation devices or information panels alongside the road, and such as cruise control systems which control the vehicle longitudinally. The reason is that sensors in the traffic system mainly supply information (reliably) for the operational and strategic scale. For the operational scale this involves many in-car sensors, including radar systems for advanced cruise control systems. For the strategic scale information such as travel times and flows are available. With advice on the tactical scale (tactical advice), based on a combination of in-vehicle and road-side information, this thesis fills some of the void on the tactical scale regarding traffic flow improvement.

The difficulty of improving traffic efficiency with ADAS, especially advisory ADAS, lies in the possible conflict between (perceived) individual benefits and the common goal. Drivers may not be willing to purchase an ADAS or may not adhere to it. The latter is referred to as driver compliance. On the tactical scale this may be a stronger problem than the operational scale, as drivers cannot perceive directly what the reasons for their advice may be. This dilemma will not be investigated in this thesis. It should however be mentioned that not all ways to improve traffic flow actually form a dilemma with the individual benefits. First of all, a number of advices can be imagined which are expected to improve traffic flow and improve the individual situation. For example, accelerating more like an active ACC out of congestion or changing lane to avoid overcrowded lanes. Second, the net effects may be beneficial to all road users, though possibly more beneficial to drivers without ADAS.

This thesis will investigate how traffic flow efficiency may be improved by an advisory ADAS that gives advice on headway, speed and lane, without assuming any particular level of consumer purchase or driver compliance. The effects are assessed for various levels of penetration (percentage of drivers having the system) and compliance (the amount in to which drivers adhere to advice).
1.1 Research questions and scope

The research is this thesis is aimed at answering a number of research questions. The central research question is:

To what extent can traffic flow efficiency be improved with in-car advice on headway, speed and lane?

To help answer this question, the following partial questions will be answered in the various chapters:

- Chapter 2: What is the current state-of-the-art on theory of traffic flow dynamics and the Intelligent Transportation Systems that influence this?
- Chapter 3: What aspects of traffic flow can be improved with advice on headway, speed and lane and which advices can be given for these aspects?
- Chapter 4: What driver models can be used (and possibly should be developed) for the behavior of drivers without advice?
- Chapter 5: What simulation software can be used (and possibly should be developed) to assess the central research question?
- Chapter 6: What level of traffic flow efficiency can be achieved with an advisory system, and in what situations?
- Chapter 7: Is the system feasible in a real implementation?

The scope within which these questions will be answered is shown in figure 1.1 in which four areas are indicated. The aim of this scope is to synchronize the reader’s expectations with the content of this thesis.

![Figure 1.1: Overview of the research scope.](image-url)
Although many parts of the driving task could be influenced by advice in order to improve traffic flow, this thesis will focus on headway, speed and lane advice, which correlate to the three driving tasks indicated within the scope. Since these tasks concern the tactical scale this advice is referred to as tactical advice. In line with the scope regarding impacts, safety tasks are excluded such as collision avoidance and gap-acceptance, although these also correlate to headway and lane (changes). Impacts are assessed on traffic flow efficiency, mainly travel time delay, while assuming that safety will not deteriorate. Advice is only provided to drivers of passenger cars on freeways, advice in urban settings or advice for truck drivers is out of the scope. Furthermore it is assumed that if in-car advices are beneficial for traffic flow efficiency, a reduction of congestion will make it also beneficial for emissions.

Finally, regarding driver behavior a ‘first order’ approach is applied. For the different advices it is assumed that drivers will respond in a particular manner, mainly based on driver simulator experiments and available literature. Secondary learning effects, or compensation behavior by non-advised drivers, are not considered. It should also be mentioned that no level of penetration rate and compliance rate will be assumed. Instead, these will be varied and the impacts of in-car advice are assessed for various scenarios of penetration and compliance rate.

1.2 Contributions

The research that was performed to answer the research questions has theoretical, methodological and practical contributions. The objective of this research has been a real-world implementation. Besides a solid theoretical and methodological basis, this implies that the findings of this research have been implemented in an actual system, of which follow-up systems are operating in practice at the time of writing. This section describes the main theoretical, methodological and practical contributions.

1.2.1 Theoretical contributions

New insights on the effects of tactical advice on traffic flow dynamics

This thesis provides insights into the complex effects of advices on the tactical scale. This is particularity relevant as the tactical scale is a relatively uncharted area. From simulations it is shown that:

- In-car advice can significantly improve traffic flow by delaying traffic flow breakdown and by reducing the capacity drop.
- In-car advice on lane may deteriorate traffic flow and strong indications are found that aggregated and delayed detector data as currently available is not sufficient for robust lane advice.
- In car-advice to accelerate more effectively from congestion shows robust results and has almost solely beneficial effects on traffic flow.
- There can be complex interference between different infrastructural aspects to which advice is related. Particularly it was found that moving traffic towards the right-hand lanes for a lane drop may result in larger disturbances with nearby downstream ramps.

Driver responses on advice

A new theory is provided on how drivers respond to different advices. These responses include a compliance rate which makes it explicit how advice influences headway, speed and lane use. These assumed behaviors can be better quantified, or even falsified, as empirical or driver simulator data regarding the given advices becomes available.
Chapter 1 - Introduction

Theoretical framework of traffic flow dynamics
A new theoretical framework is developed which describes the causal relation between known aspects of traffic flow dynamics. This framework is used to categorize ITS in the state-of-the-art regarding their approaches on traffic flow dynamics. Furthermore, it forms the theoretical basis on which the tactical advice to improve traffic flow dynamics is designed.

1.2.2 Methodological contributions

Lane specific short-term traffic state prediction
A new and effective method to predict the traffic state at individual lanes is developed. The method is also able to perform data fusion of different data sources, where data from different sources has a speed dependent reliability.

Rule based advice algorithm
A new rule-based advice algorithm is developed which generates in-car advices based on a traffic state prediction to improve traffic flow.

Microscopic simulation framework
As part of this research, a new software framework for microscopic simulation has been developed. Besides the purpose of being used for this research, the framework has also been developed to be used for other research and ITS applications. An extensive overview of requirements for this is included in this thesis. No existing simulation framework meets all requirements.

Models
Microscopic simulation is used in order to evaluate the effects of in-car advice. New models were developed for both the longitudinal and lateral movement of vehicles with non-advised drivers.

- A new car-following model for microscopic simulation is proposed which has good stability characteristics. Furthermore it is able to reproduce realistic macroscopic quantities with plausible microscopic parameter values.
- A new lane change model for microscopic simulation is proposed:
  o Contrary to most existing lane change models, lane change preparation is included in the form of speed adjustment (synchronization) and yielding for another vehicle (i.e. gap-creation).
  o Contrary to most existing lane change models, relaxation is included by allowing for smaller than regular following headways to be accepted when changing lanes.
  o A new generic framework is developed and used where a set of lane change incentives results in a single level of lane change desire. Both synchronization and relaxation are linked to this desire. The set of lane change incentives can be extended.
- The integrated model is calibrated with a new and automated calibration method which has predictable and stable behavior for a unsmooth solution space. In particular, steps towards new parameter values do not rely on local gradients.

Based on the theory for driver responses on advice, models for advised drivers are also implemented. This behavior, as well as the behavior of non-advised drivers in traffic with a high penetration rate of advised drivers, has not been observed in the field, nor been
extensively researched in driver simulators. Consequently, the results in this these are to some extent speculative. However, a number of principles have been used in the development of these models leading to, in our view, face validity at least:

- Behavior is based on parsimonious models of existing behavior that reproduce important aspects of traffic flow dynamics.
- Responses to advice have been modelled by affecting a minimum of factors that i) affect behavior in relation to the circumstances investigated in this research, and ii) that adjust interpretable variables (e.g. desired speed or lane change desire threshold).
- Where possible, the response to advice has been developed in line with, to some extent, comparable situations (e.g. acceleration of attentive drivers is benchmarked with saturation flow at traffic lights) or with small-scale driver simulator tests (Risto, 2014).

1.2.3 Practical contributions

Significant improvement of traffic efficiency
Advice on the tactical scale is shown through simulation to have a considerable potential in improving traffic flow efficiency and may reduce travel time delay up to some 40-50%. This is an important practical contribution as it adds societal value.

Implementation of traffic flow optimization algorithms
Both the traffic state prediction algorithm and the advice algorithm have been implemented in simulation and in the actual pilot system, showing that an in-car advisory system is technically feasible with existing technologies for example for communication. From the pilot system an empirical analysis is performed concerning the validity and crediblity of advices in the real world. The implementation in the pilot system, as well as the findings from the empirical analysis, is a basis for further developments.

Microscopic simulation framework
The new simulation framework can be used for ex-ante evaluations of other ITS. The main benefit over existing simulation tools are inherent flexibility and support for typical types of ITS components.

1.3 In-car advisory system

This section explains the ITS application which, among other functions, provides the in-car advices. It is a system intended to improve freeway efficiency without changes to the road system. Many ideas on how to improve the road system require extensive changes. For instance, taking the driver out of the loop (i.e. controlling vehicles that are fully automated) could significantly reduce headways and therefore increase road capacity. However, reliable systems, also for adverse conditions such as heavy rain, snow, missing lane markings etc., have not yet been developed. Infrastructure to guide vehicles, for instance through magnetic markers indicating the lanes, constitutes an expensive and extensive change of the road system. Using advice keeps the driver inside the loop, meaning that the driver is still actually driving the vehicle. This is not only convenient for implementation, but also for legal issues. If an automated vehicle causes an accident, is the driver or the manufacturer to blame? Of course keeping the driver in the loop is likely to show less improvement from the current road system than these sometimes utopian systems. How much is exactly the main question of this thesis.
Keeping the driver in the loop means that driver behavior needs to be influenced in order to change traffic flow dynamics. This can be performed by supplying information to the driver in the form of warnings or advices. Warnings are usually safety related. The advisory system aims to improve traffic flow efficiency by giving advices without deteriorating safety. The effects on traffic safety have been assessed by Van der Gulik (2012) and are outside of the scope of this thesis. Clearly, overloading a driver with advices will form a too high mental workload which will deteriorate safety. Therefore advices should not be given too frequently and only at crucial locations for the road performance. In line with this advice frequency, advices are on a tactical scale, i.e. on situations about 1-2km downstream. This is different from many other systems that either work on the operational scale (e.g. vehicle control) or on the strategic scale (e.g. departure time choice, route choice, etc.). As such, advising on the tactical scale solves a missing link problem. Advices are given on three aspects of driving which are headway, speed and lane. The addition of lane advice is a benefit of an advisory system over purely longitudinal systems. In particular, the unbalanced lane use that is often found when traffic breaks down (Knoop et al., 2010) may be changed such that spare capacity on underutilized lanes is also used. The use of headway advice may, similarly to overtaking systems such as ACC, improve stability and saturation flow.

When advising drivers, compliance of the drivers is an issue, especially when the benefit of the advice is on system rather than individual level. In this thesis, no assumption of the compliance rate is made as this is simply unknown. Rather, the effects at various compliance rates are investigated. The system integrates both individual and system benefits. Individual benefits are included by increasing comfort and safety. This is depicted in figure 1.2 where additional system elements such as the digital map and the on-board camera are shown. With these elements features such as the current (dynamic) speed limit, upcoming curve warning, dynamic map updates, etc. are provided. These features may tempt more drivers to obtain the system. The focus of this thesis is on the advice server and on the driver.

![Figure 1.2: Overview of the advisory system.](image-url)
Although not provided in the initial setup of the system as developed, it would be logical to combine it with route navigation. Moreover, knowing what route the drivers will (most probably) take may improve the effectiveness of advices, especially lane advice. Route advice is also used to improve road performance. However, route advice is at strategic scale while the considered advices are at the tactical scale. The system can be positioned between systems such as Adaptive Cruise Control (ACC), Cooperative Adaptive Cruise Control (CACC) and route guidance. ACC and CACC look one or a few vehicles ahead and smooth disturbances for more stable traffic which delays or prevents traffic breakdown. Route guidance may advice some drivers to take a different route such that demand is efficiently spread over a network. The advisory system works on a range in between, namely about 1-2km. At this scale, the workload for the driver can be kept at an acceptable level and the driver has sufficient time to adjust speed or headway or to change lane. Effectively, the system allows drivers to respond to (potential) problems 1-2km downstream, which are usually not visible to the driver. It is expected that this allows drivers to improve traffic flow efficiency where it is suboptimal, for instance through smoother lane changes. This may be beneficial as Ahn and Cassidy (2007) show that all moving jams of their study were initiated by lane changes. On the other hand, Goñi Ros et al. (2013) show that at uphill sections the majority of breakdowns (89%) is caused by longitudinal behavioral changes. By creating a smoother lane change process, some of the moving jams may be prevented, but it may depend on the location how effective this is.

The purpose of this work within the project is to assess the effects of the system on freeway performance, as well as to develop the algorithms on the advice server which derive which advices to give based on the available traffic data. Assumptions are made on drivers responses, partially based on driver simulator studies (Risto and Martens, 2011), which are implemented in simulation to scale the system up to various penetration rates. The simulations are performed in a dedicated simulation environment.

1.4 Reading guide

This thesis contains 8 chapters that can be divided over five sections as depicted in figure 1.1. Chapter 1 and 2 provide an introduction and background into the subject of this thesis. Chapter 1 describes the research questions, scope, contributions and outlines the advisory system, while chapter 2 provides a state-of-the-art.

In chapter 3, the design of relevant parts of the system is discussed in detail. The algorithms developed to improve traffic flow are described. Appendix A provides an overview of how these algorithms are implemented in the real system, besides functioning in simulation.

Chapters 4 and 5 describe how the simulations to evaluate the effects are performed. The regular driver behavior, which is the default behavior in the simulation framework, is presented in chapter 4. Chapter 5 discusses a new simulation framework for development and evaluation of Intelligent Transportation Systems (ITS).

The evaluation is performed in chapters 6 and 7. In chapter 6 the simulation setup, assumed driver responses and effects at various rates of penetration and compliance are evaluated using simulation. Chapter 7 is an evaluation of the system as it runs in reality, where advice patterns in time and space are evaluated.

Finally, chapter 8 concludes this thesis by giving the conclusions and recommendations.
Parts of chapters 2, 3 and 6 have been published in:


Parts of chapters 4 and 5 have been published in:


Parts of chapter 7 have been published in:

2 State-of-the-art of on-trip traffic flow efficiency oriented ITS

Parts of this chapter have been published in: Schakel, W.J., B. van Arem (2014) “Improving Traffic Flow Efficiency by In-Car Advice on Lane, Speed, and Headway”, IEEE Transactions on Intelligent Transportation Systems, Vol. 15, Issue 4, pp. 1597-1606.

This state-of-the-art will reference ITS from the view of a two-dimensional space as in figure 2.1. The anticipation scale is the scale at which a system anticipates traffic and, in correlation, tries to influence traffic. This dimension is divided in three regions which have been taken from Michon (1979): operational, tactical and strategic. The operational scale involves vehicle control while the strategic scale involves route choice, destination choice, departure time choice, etc. The intermediate tactical scale concerns lane selection, speed selection, courtesy to other drivers, etc. This state-of-the-art will show that there is a lack of systems on the tactical scale, especially regarding systems which are used in practice. The second dimension is distinction, with which the selection of drivers receiving information is meant. Again, this state-of-the-art shows a gap as most current systems work in-car, providing information to a single driver, or from the road-side, providing information to all drivers. These two extremes have limitations in obtaining optimal traffic control as different drivers may need to perform different, but coordinated, actions.

A further categorization of ITS is provided with the aspects of traffic flow dynamics that the various systems aim to influence. This can be perceived as a third dimension in figure 2.1. To this end, this chapter will first provide a theoretical framework describing the process of traffic flow dynamics, identifying six general solutions that ITS can use. This state-of-the-art shows that in-car advice has the potential to cover a wide range of solutions.

From the viewpoint of the two-dimensional space of figure 2.1 and the theoretical framework of traffic flow dynamics, the state-of-the-art will cover existing ITS, including both road-side
and in-car systems. The solutions and lessons that these systems provide are a basis from which the next chapter can design in-car advice in order to improve traffic flow.

![Anticipation scale and distinction space of ITS.](image)

**Figure 2.1:** Anticipation scale and distinction space of ITS.

### 2.1 Theoretical framework of traffic flow dynamics

#### 2.1.1 Theoretical framework

Traffic management is used to achieve a number of goals in traffic such as increased safety, decreased environmental impact and increased throughput. The focus of this thesis is on increased throughput. Different traffic management measures try to achieve goals not only with different means, but also by targeting different aspects of the process of traffic flow dynamics. This process is depicted in figure 2.2. In this paragraph, this process is explained such that the various measures as found in the state-of-the-art can be put in their context. The aspects in figure 2.2 will be defined, simultaneously explaining the traffic flow dynamics.

![Theoretical framework of the traffic flow dynamics process.](image)

**Figure 2.2:** Theoretical framework of the traffic flow dynamics process.

*Inflow:* As can be seen in equation (2.1) inflow \( I \) is the number of vehicles \( n \) that moves over a cross-section per unit of time \( \Delta t \). In the theoretical framework, this explicitly concerns a single lane.

\[
I = \frac{n}{\Delta t}
\]  

(2.1)

*Capacity:* A clear and universal definition of capacity does not exist, but the general concept of capacity is that it is the maximum inflow that a road or lane can facilitate. The Highway Capacity Manual (HCM2010) by the Transportation Research Board is a widely used reference work to determine the capacity (and level of service) of transportation facilities, but
its formulas are rules of thumb determined by empirical data rather than a theoretical definition. Since inflow depends on $\Delta t$, so does capacity. In mathematical terms, capacity is often defined as the reciprocal of the average (over a set of drivers) minimum gross headway $h_{\text{min}}$ that drivers are able to drive with, as in equation (2.2). Due to both inter-driver and intra-driver differences, capacity is a stochastic value. Other causes for the capacity being stochastic are circumstances such as differences between roads, weather, light conditions, etc.

$$C = \frac{1}{h_{\text{min}}}$$  \hspace{1cm} (2.2)

Consequently, capacity is usually considered over some time $\Delta t$ to average headways as an approximation of $h_{\text{min}}$. Note that $h_{\text{min}}$ is not simply a desired headway, but rather a result of both the desired headway (including the vehicle length of the leading vehicle) and the stability properties of drivers. Without already explaining disturbances and stability, here capacity is defined as the maximum undisturbed inflow that can be maintained over time. This thus pertains to a different headway, namely the average minimum gross headway that drivers are able to drive with without disturbances $h'_{\text{min}}$. This is only a theoretical value since there are always minor disturbances in traffic. It does however effectively eliminate the influence of disturbances (and stability) on capacity, allowing us to define capacity and stability independently.

$$C = \frac{1}{h'_{\text{min}}}$$  \hspace{1cm} (2.3)

**Disturbance**: Traffic flow can be disturbed by various causes, leading to a fluctuation in speed. Such causes can be inherent fluctuations of drivers as found by Sugiyama et al. (2008), lane-changes which cause drivers to decelerate (Ahn and Cassidy, 2007), etc. Here, a disturbance is quantified by the minimum speed $v$ that a vehicle $k$ has over some arbitrary time period, see equation (2.4). As an analogy, suppose we have a glass filled with liquid as in figure 2.3. The glass contains a certain volume (i.e. the inflow) and has a maximum undisturbed volume it can contain (i.e. the capacity). Disturbances can be perceived as tapping the glass or blowing at the surface, leading to ripples at the surface with some amplitude. If the combination of volume (inflow) and ripple amplitude (disturbance) is sufficiently large, the liquid will spill.

$$v_{\text{min}}^k = \min(v^k)$$  \hspace{1cm} (2.4)

![Figure 2.3: Traffic flow analogy with a glass of liquid.](image-url)
In the glass analogy, a disturbance is defined by the ripple amplitude, while a disturbance in traffic is defined by a minimum speed. To clarify, note that we assume a constant average inflow, and that traffic will have a corresponding equilibrium speed for this level of inflow. A change in amplitude around this equilibrium speed is equal to a change in the minimum, which allows an intuitive definition for stability without requiring the inflow or equilibrium speed to be known. Moreover, for the same level of inflow, a lower value of \( v_{\text{min}}^k \) reflects a larger disturbance. When comparing situations with different inflow, \( v_{\text{min}}^k \) cannot be used to compare disturbance strengths. Rather, the amplitude should be used then. Note that frequencies and complex liquid dynamics including resonance are not considered in the glass analogy.

**Stability**; Stability means that a fluctuation of speed (and headway) as a response to a perturbation is damped out and equilibrium will eventually return, given no intermediate additional disturbance. This requires that as a disturbance propagates to upstream vehicles (i.e. decreasing \( k \)) the value of \( v_{\text{min}}^k \) increases on average. Different forms of stability are mentioned in literature and terms to identify them are sometimes interchangeably used, or may actually refer to different types of stability. The different forms of stability have to do with the frame of reference through which the minimum of fluctuations progresses. Table 2.1 indicates for four types of stability as found in literature, how these are referred to with different terms. The four types of stability are:

- **Single vehicle**; Given a leading vehicle with constant speed, any disturbance in the speed of the follower will damp out. Note that if this is not true (instability), a collision will occur. Therefore, this type of stability is often used in linear stability analyses of car-following models to show whether they are collision free or not. Assuming that collisions occur due to mechanical failure or driver error rather than being intrinsic in car-following, traffic can be assumed to be stable in this sense. Mathematically, this can be defined as equation (2.5), where \( t_n \) and \( t_{n+1} \) indicate two consecutive fluctuations of the same vehicle \( k \), i.e. the time over which \( v_{\text{min}} \) is determined covers a single fluctuation. One such fluctuation, in case of single vehicle stability, is indicated with (1) in figure 2.4

\[
v_{\text{min}}^k(t_{n+1}) > v_{\text{min}}^k(t_n)
\]  

(2.5)

![Figure 2.4: Single vehicle stability (1) and upstream vehicle instability (2).](image-url)
• **Upstream vehicle:** In this case stability infers that a particular follower \((k-1)\) is able to have a higher minimum speed \(v_{min}^{k-1}\) than its leader \((k)\). This is mathematically expressed in equation (2.6). In figure 2.4 an unstable case of **upstream vehicle** stability is indicated by (2), as the speed of the follower reaches lower values.

\[
v_{min}^{k-1} > v_{min}^{k}
\]  

(2.6)

• **Upstream vehicles:** This is an extension of the case for an upstream vehicle. One can speak of stability if the minimum of fluctuations is increased *on average* as one progresses from one vehicle to the next upstream vehicle. Individual followers may thus be unstable, so long as \(v_{min}\) will increase on average as the disturbance progresses upstream through a platoon. Wilson and Ward (2011) further distinguish different forms of stability depending on whether the absolute position of a disturbance is moving upstream or downstream. They conclude that car-following models should be unstable in this sense (what they call string instability), and should show upstream moving instabilities only (besides stability), in order to comply with empirical findings. Mathematically this type of stability can be expressed with equation (2.7) where \(K(k)\) is a number of vehicles upstream of \(k\) for which one can find that the disturbance has decreased. It is important to recognize that the upstream vehicle has to be part of the same platoon to distinguish with the final form of stability.

\[
v_{min}^{k-K(k)} > v_{min}^{k}
\]  

(2.7)

• **Upstream platoon:** This form of stability also considers gaps that are between platoons of vehicles. Even if platoons are unstable, the gaps may be sufficiently large such that the leader of the next platoon is less affected than the leader of the previous platoon. This is expressed in equation (2.8) where vehicle \(l\) is a platoon leader and \(L(l)\) is the size of this platoon in number of vehicles. Vehicle \(l-L(l)\) is thus the leader of the upstream platoon. This form of stability depends on the size of the platoon, the amount of (in)stability within the platoon and the size of the gap in between the platoons. Whether traffic is stable is then dependent on inflow since high inflow infers larger platoons and smaller gaps.

\[
v_{min}^{l-L(l)} > v_{min}^{l}
\]  

(2.8)

Note that equations (2.5)-(2.8) all denote stability. In real traffic, one will however find instability regarding the upstream vehicles, i.e. regarding equation (2.7). For a single follower or regarding the upstream platoon one may find both stable and unstable cases in reality, i.e. regarding equations (2.6) and (2.8).

Table 2.1: Different forms of stability and how they are referred to.

<table>
<thead>
<tr>
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<tbody>
<tr>
<td>Single vehicle</td>
<td>Local or platoon stability</td>
<td>Local stability</td>
</tr>
<tr>
<td>Upstream vehicle</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Upstream vehicles (within a platoon)</td>
<td>String stability</td>
<td>Platoon, asymptotic or string stability</td>
</tr>
<tr>
<td>Upstream platoon</td>
<td></td>
<td>Traffic stability</td>
</tr>
</tbody>
</table>
Here, by improving stability we mean improving on the second and hence the third type of stability which is commonly referred to as string stability. Consequently, increasing stability means improving car-following properties. Reducing inflow may also increase stability of the fourth kind (i.e. traffic stability), but in this thesis this is simply referred to as lowering inflow. Coming back to the glass analogy, (string) stability can be seen as the viscosity of the liquid. The higher the viscosity, the higher the level of liquid or the larger a tab on the glass can be before liquid will spill.

**Breakdown:** Breakdown is a disturbance not being damped out, which means that speeds drop. Traffic is thus unstable relating to the fourth kind of stability, i.e. traffic stability. This requires string instability or average follower instability. The result is congestion, i.e. breakdown is the transition from free flow to congestion. Within congestion, further disturbances and instability may cause stand still traffic. For the glass analogy, breakdown means liquid spilling out due to a combination of a high level of liquid and a sufficient tab on the glass. This is as far as the glass analogy goes. For the remaining aspects of traffic flow dynamics it is abandoned.

**Congestion:** In explaining the traffic flow dynamics, the exact definition of congestion is not important. Generally, it can be described as a traffic state in which all drivers are bounded, i.e. they cannot reach their desired speed, which is associated with relatively low speeds.

With the six aspects of traffic flow dynamics discussed so far, it can be described what is required for congestion to occur, i.e. the left side of figure 2.2.

- Inflow which is close to capacity.
- A disturbance which is sufficiently large so that traffic is unable to damp it.

These two factors are also mentioned by Treiber and Kesting (2013), who also mention that congestion is triggered by a disturbance if inflow circumstances are right. They also mention the requirement of a bottleneck. This is however implicit in the first requirement as at a bottleneck either the capacity on a lane drops (e.g. uphill section or narrow lanes) or the inflow on the lanes increases (e.g. onramp or lane-drop). The size of the disturbance which triggers congestion can be smaller as inflow is nearer to capacity. In fact, since capacity is the undisturbed maximum inflow, even the smallest disturbance will trigger congestion if inflow is equal to the local and momentary capacity. Once traffic is congested, there are two effects which will further deteriorate traffic, which are spillback and the capacity drop.

**Spillback:** Spillback occurs when congestion on one road grows upstream past any kind of node (intersection, off-ramp, roundabout, etc.) after which it also affects traffic that does not have the bottleneck on its route. For example, if congestion on an off-ramp spills back on the main freeway, also traffic that will not take the off-ramp will stand in queue, and therewith contribute to the length of the queue and consequently possible further spillback. Spillback is an important source of degenerating flow at network level (Schakel et al., 2010a), increased travel times (Knoop et al., 2008) and the gridlock process (Daganzo, 2007). This is the reason that efforts were made to include spillback in macroscopic dynamic traffic assignment (DTA) models such as the model by Bliemer (2007). In extreme cases, typically in urban road networks with many nearby nodes, spillback may lead to gridlock. In that case spillback has a circular pattern, i.e. a queue in front of one intersection is blocking itself indirectly through a number of other intersections. Spillback can be prevented or reduced by giving a queue a larger buffer area or, in case of urban networks, by reducing the amount of traffic that will
stand still at conflict areas. The latter is useful as traffic that will not turn onto a road creating spillback, can simply pass the intersection towards another road.

**Capacity drop:** The capacity drop $\Delta C$ is a phenomenon that has been observed in traffic by many scientists (e.g. Cassidy and Rudjanakanoknad, 2005; Kerner and Rehborn, 1997; Bertini and Leal, 2005) and is the fact that flow out of congestion (referred to as queue discharge rate or in this thesis as saturation flow, $C_{sat}$) is lower than capacity $C$, as in equation (2.9). The capacity drop occurs as soon as congestion occurs. Given an equal inflow, the capacity drop means a queue is longer in space and remains longer in time than it would without the capacity drop. Traffic flow is thus further deteriorated. The causes, and their relative contribution, to the capacity drop are subject of debate. A number of hypothesized causes are: lane changes by vehicles from slower lanes (e.g. Laval and Daganzo, 2006), bounded acceleration (e.g. Lebacque, 2003; Tampère et al., 2005a), reaction time, increased headways in congestion (e.g. Treiber and Helbing, 2003) or the fact that drivers need a stimulus to accelerate (Tampère et al., 2005a; and according to stimulus-response car-following models) in the form of a larger than desired headway. Furthermore, it is known that at incidents, the capacity drop is much larger than usual (Knoop et al., 2009). The capacity drop is thus by no means a fixed drop in flow. This gives rise to the idea that the capacity drop may be reduced by influencing drivers (reducing reaction time, reducing desired headway, increasing acceleration, etc.) or by more efficient automated vehicle control.

$$\Delta C = C - C_{sat}, \quad C_{sat} < C$$

### 2.1.2 Methods to improve traffic flow

Using the theoretical framework of traffic flow dynamics as in figure 2.2, we can identify different solutions that ITS can have to improve traffic flow. This is in many ways equal to the work of Hoogendoorn and Bertini (2012) who identify four types of solutions:

- Prevent spillback
- Increase throughput
- Effectively distribute traffic across the network
- Regulate the inflow of traffic

This categorization can be tailored towards the traffic flow dynamics described earlier. Using the aspects in the traffic flow dynamics process, six solutions to improve traffic flow are identified and depicted in figure 2.5. These can be considered from two different groups: preventive solutions and curative solution.

---

**Figure 2.5:** Theoretical framework of the traffic flow dynamics process and solutions.
The first group of preventive solutions consists of:

- **Reducing inflow**: With a lower inflow at critical locations, these critical locations become more stable as, for a fixed level of string stability, the traffic flow stability increases as disturbances are reduced in between platoons. Lowering inflow can be achieved by reducing inflow longitudinally (e.g. route guidance, influencing departure time, an artificial upstream bottleneck, etc.) or laterally by influencing lane changes to reduce the peak lane inflow.

- **Increasing capacity**: Traffic will only break down if inflow is sufficiently close to capacity. Increasing capacity can be done by automat ing vehicle control such that vehicles follow each other closer than human driven vehicles, or for instance with peak-hour lanes if one considers capacity at road level.

- **Reducing the number and extent of disturbances**: Traffic breakdown is triggered by disturbances. The chance of traffic flow instability is reduced if the extent and/or number of disturbances is reduced. This can for example be achieved by automatic vehicle control which reduces speed fluctuations, or by facilitating lane changes that cause smaller decelerations, for example by helping with gap selection or matching the speed with the target lane.

- **Increasing stability**: More stable longitudinal movement of driver-vehicle units may possibly allow the same disturbance to be damped out instead of the opposite. A well designed Adaptive Cruise Control for example shows more stable car-following behavior than drivers, i.e. string stability is improved.

The second group of aspects can be targeted by solutions which try to reduce the negative effects of congestion.

- **Reducing the capacity drop**: This may be achieved in a number of ways that will all result in shorter queues and therefore less travel time delay. It can for example be achieved by an artificial upstream bottleneck (where the saturation flow is larger) or by making the acceleration process more efficient by automating vehicle control or increasing the speed inside congestion.

- **Reducing spillback**: This will reduce the number of vehicles that is affected by, and will contribute to, congestion. This reduces the travel time delay of these vehicles, and of the vehicles in congestion as the queues are shorter. Spillback can be prevented by prioritizing flow with for example traffic lights or ramp metering, or by splitting traffic upstream of an intersection or junction which experiences spillback. In the latter way, traffic which will not turn into the direction of a road with spillback is not influenced.

In the next section, a number of traffic management measures in terms of ITS is listed and it will be evaluated which aspects of the traffic flow dynamics process are targeted by these systems, as well the location in figure 2.1 (anticipation scale and distinction). With these systems, and the lessons that are learned from them, an in-car advisory ITS is designed in the next chapter.
2.2 State-of-the-art of on-trip traffic flow efficiency oriented ITS

Many efforts have been undertaken to improve traffic flow efficiency. These efforts can be divided as in figure 2.6. This division is used to indicate what types of ITS are included in this state-of-the-art. Pre-trip ITS are efforts such as advertisement campaigns and various applications on the internet such as routing services. Pre-trip ITS will not be considered in this state-of-the-art as it has little overlap with an in-car advisory system. Road-side systems operate by providing all drivers with information through various information panels alongside the road. These systems are included as they usually try to improve traffic flow by advising, or at least informing, drivers. In-car systems are inside the vehicle and may provide individual information to the driver, or overtake (a part of) the driving task. Some in-car systems may communicate with road-side systems. Since the in-car advisory system of this thesis is an example of an in-car system, these systems are included in the state-of-the-art. In-car systems can be divided in several ways. One way is by individual and cooperative systems. The difference is that vehicles with cooperative systems share information either in order to achieve a common goal, or to achieve individual goals more effectively.

![Figure 2.6: Categorization of ITS. ITS within the box, i.e. on-trip, is considered in this state-of-the-art.](image)

In-car ITS is often referred to as Advance Driver Assistance Systems (ADAS), since these systems assist the driver regarding one or several sub tasks of the driving task. Some ADAS are safety related while others may increase comfort. Not many ADAS exist which aim to improve traffic flow efficiency, even though they are a potentially effective tool. This overview focuses on systems that aim to improve traffic flow efficiency. The in-car advisory system of this thesis is the first to our knowledge regarding in-car advice on the tactical scale (see figure 2.1), that is, on the scale of 1-2km. Therefore, this state-of-the-art will cover systems at smaller scale and systems at a larger scale. Besides advisory systems, other systems in the subdivision which constitutes intervening, warning and informative systems are also covered. Intervening systems take over a part of the driving task whereas warning and informative systems supply information to the driver with different urgencies. For warning systems this may include haptic communication through the seat, steering wheel or acceleration pedal. Although the systems mentioned in this state-of-the-art are not advisory systems on the tactical scale, they can give the context to assess whether in-car advice is efficient and effective.

The next sections will discuss 3 in-car systems (ACC, CACC and Microscopic Dynamic Traffic Management) and 4 road-side systems (AHS, Dynamic speed limits, Ramp metering and Variable Message Signs, i.e. for route guidance). These systems provide insight regarding the design and expectations of in-car advice, and also show that in-car advice has some unique possibilities, filling gaps in the two-dimensional space of anticipation and distinction.
2.2.1 Adaptive cruise control

A standard cruise control system is intended to increase driver comfort by maintaining a preset speed. It is still up to the driver to decelerate in case a slower vehicle is in front. Adaptive Cruise Control (ACC) extends a regular cruise control by sensing a predecessor usually using radar and by lowering the speed accordingly if required. As such, ACC takes over the longitudinal driving task. This is shown in figure 2.7, where the acceleration of the following vehicle is based on the headway with the leading vehicle $h_1$ (front bumper to rear bumper), the speed of the leading vehicle $v_1$, and of course the speed of the following vehicle itself, i.e. the ego-velocity.

\[ \frac{dv}{dt} = f(h_1, v_1, v_0, v) = \min \left( \alpha(v_0 - v), \beta(v \cdot T - h_1) + \gamma(v_1 - v) \right) \]  

Figure 2.7: Adaptive Cruise Control.

If there is no leading vehicle (nearby) ACC is able to maintain a desired speed $v_0$. Including the ego-velocity $v$, the acceleration is a function of 4 inputs as in equation (2.10), which shows a simple example ACC function. This example uses three sensitivity parameters namely acceleration to the desired speed $\alpha$, a deviation with the set following time headway ($T$) $\beta$ and for a deviation with the speed of the leading vehicle $\gamma$.

\[ \frac{dv}{dt} = f(h_1, v_1, v_0, v) = \min \left( \alpha(v_0 - v), \beta(v \cdot T - h_1) + \gamma(v_1 - v) \right) \]  

Though intended for increased comfort, ACC can also have significant positive and negative consequences on traffic flow efficiency. Not only the headway setting $T$ is of direct influence on road capacity, the car-following rule implemented also determines the stability of traffic flow, e.g. the values of $\alpha$, $\beta$ and $\gamma$ in equation (2.10) or the mathematical function itself. Several scientific studies have raised awareness of this strong relationship between ACC and traffic flow, both positive and negative. For instance, Treiber et al. (2006a) mention that an appropriate ACC can be used to mitigate the distinct increase in time headways encountered at the head of congestion, being directly related to the capacity drop. Kesting et al. (2010) build upon this concept by introducing an ACC with settings that depend on the situation. This system for instance decreases $T$ in a bottleneck, or increases acceleration at the head of congestion. An interesting conclusion from this study is the linear increase of capacity with increasing penetration rate combined with a non-linear growth of saturation flow. Saturation flow grows slowly for low penetration rates due to blocking of non-equipped vehicles. A consequence of this is an increased capacity drop as can be seen in figure 2.8. This is unfavorable as a larger capacity drop also means less robust travel times, the opposite of what is desired by policies at least in the Netherlands.

Other benefits of ACC over human driving are the more accurate speed and headway control, i.e. the speed and headway showing less severe fluctuations around the intended speed or headway (van Driel and van Arem, 2010). This mitigates over-reactive decelerations and unintentional drops in speed due to distraction. These behaviors may cause, or at least contribute to, traffic breakdown in saturated traffic.
Minderhoud (1999) performed an extensive study on the capacity effects of ACC using various systems differing in the operational speed range, acceleration range and automatic or manual reactivation. Capacity increases of up to 12% were found, but only for a rather low headway setting of 0.8s. Smaller benefits were found starting at headways of 1.2s. This is not common practice for ACC systems that are available, where larger headway settings are used for the confidence of both the manufacturer and the user. Another issue is the operational speed range. Many available ACC systems do not operate below a speed of about 40 km/h as these systems are then not sufficiently reliable. To investigate the effects of a full-range ACC (that is from 0 km/h up to some speed), van Driel and van Arem investigated a system called Congestion Assistance (Van Driel, 2007). It consists of an active pedal that operates when approaching congestion and a stop-and-go function that takes over the car-following task below 50 km/h and releases control above 70 km/h. If the stop-and-go is not active the driver is controlling the vehicle. A reduction in travel time was found for both headway settings of 0.8s and 1.2s. At 50% penetration rate the congestion even disappeared as the lane-drop capacity exceeds demand. Important to note also from the research into Congestion Assistance is that mandatory systems have significant larger impact than voluntary systems (Van Driel, 2007).

From the above systems it follows that ACC is able to mitigate some unfavorable aspects of human driving, but that correct settings are required to actually increase capacity and saturation flow. For an advisory system this is more difficult as the driver is still in control. Nonetheless, making drivers aware of congestion, and especially the head of congestion, may mitigate the unfavorable aspects into some extent.

Since ACC is only aware of the leading vehicle and only controls the ego-vehicle, i.e. the vehicle itself, ACC has a limited reach in anticipation range and distinction. It is however able to improve many aspects of traffic flow dynamics. Capacity and stability may be increased with correct settings, and disturbances are reduced as the vehicle control is more exact and constant as with human drivers. Furthermore, the capacity drop may be reduced as ACC is more efficient in following the leading vehicle during acceleration out of congestion.
2.2.2 Cooperative adaptive cruise control

An extension of ACC is Cooperative Adaptive Cruise Control (CACC), where vehicles communicate with one another using vehicle to vehicle (V2V) communication. The shared information can be used to optimize vehicle movements regarding different goals, where individual or common goals can be evaluated. CACC systems are not commercially available but may further enhance the benefits of ACC. Information from several vehicles ahead, including velocity and acceleration, may be used to better resolve deceleration waves, increasing the stability of traffic and possibly delaying traffic breakdown. A comparison between the information flow of ACC and CACC is presented in figure 2.9. For ACC, the headway $h$ and velocity $v$ is obtained from the direct predecessor. With the shown CACC, there are other choices possible, additional information is obtained consisting of the speed and acceleration of a number of equipped predecessors. It is also possible that information is forwarded regarding (unequipped) vehicles in between, such as for example $h_2$ and $v_2$ in figure 2.9. CACC systems usually respond only to speed and acceleration of all but the direct predecessors, as their positions are unknown. A further complication for CACC is that it is unknown how many unequipped vehicles are in between of the known predecessors, which is something a practical CACC controller has to deal with.

![Figure 2.9: Information flows for ACC and CACC.](image)

The main benefit for traffic flow from CACC over ACC is that CACC can operate at shorter time headways. For instance, Nowakowski et al. (2010) used a prototype CACC which adapts input into a factory ACC (Bu et al., 2010) which could operate at headway settings as low as 0.6s. Moreover, this study showed that most participants would select such low settings after only about 2-3 days of getting acquainted with the system. A remarkable finding is also that men were more prone to select the lower settings than women, who had a larger average headway setting.

Similar to most ACC systems, CACC control functions are usually linear response functions. The Integrated full-Range Speed Assistant (IRSA) controller is an example (Van Arem et al., 2007). Wilmink et al. (2007) evaluated this controller and found positive effects on capacity and comfort. Also Van Arem et al. (2006) found positive capacity effects at a lane-drop, though lane changes were made more difficult due to vehicles following each other more closely. Schakel et al. (2010b) investigated the traffic flow stability aspects of IRSA. The main finding is that CACC may significantly increase the speed of deceleration waves upstream through traffic. In mixed traffic, this may result in non-CACC vehicles changing their behavior as anticipating for multiple vehicles ahead is a significant aspect of human driving (Treiber et al., 2006b). Besides a decrease in car-following model validity, this may
give rise to safety and efficiency issues, as non-CACC drivers either have an increased chance of collisions or increase their time headway, possibly even resulting in net negative results. Note however that this effect is controller dependent, thus other controllers may cope with this in a more robust manner. For in-car advice this is however not an issue as drivers are still in control of the vehicle and no significant change in response time to disturbances in traffic is to be expected.

CACC deals with the same aspects of traffic flow dynamics as ACC. But as the anticipation scale concerns multiple leaders rather than one, it does so more effectively as large deceleration is more effectively avoided, i.e. CACC has better string stability.

2.2.3 Microscopic dynamic traffic management

Daamen et al. (2011) introduced the hypothetical idea of Microscopic Dynamic Traffic Management (MDTM). In the study two types of suboptimal behaviors are identified.

- Large decelerations when approaching slower traffic
- Platoons hindering merging vehicles

To prevent these behaviors from occurring, MDTM assumes that through satellite or a similar technique the position of every vehicle is known. At some central facility this information is processed and the above two situations may be detected. In that case, messages to individual cars are sent.

For the first situation a message to start coasting is given within 500m upstream of at least two vehicles driving below 60 km/h. Although the number of moving jams was reduced, which indicates improved traffic flow stability, no significant benefits in capacity or travel time were found regarding this situation.

Facilitating the merging process in case of platoons on the freeway did show significant improvement. In case a platoon and merging vehicle are expected to arrive at the onramp around the same time, the second vehicle in the platoon is advised to increase the headway to allow a high speed merge. Also a sufficient gap behind the platoon should be available to prevent disturbance on the freeway due to the headway increase. Through this principle travel time delay was reduced by 50%, the number of moving jams was reduced by 50% and the average moving jam length was reduced by 25%.

In-car advice can follow the same basic philosophy as MDTM which is to notice suboptimal road use and to advice individual drivers to improve the situation. However, the in-car advice system in this thesis is not microscopic in the sense that the positions of individual vehicles are unknown, except for the equipped vehicles but then still with a low data resolution and significant delay. It is thus not expected that the in-car advisory system is able to reach similar results, especially when penetration rate and compliance rate are taken into account. Still, MDTM shows that only a few small actions can significantly improve traffic flow.

Through the use of a central operator, MDTM extends the anticipation range relative to ACC and CACC from the operational scale to the tactical scale, and is therefore able to show significant results with small individual actions. Moreover, MDTM only influences disturbances regarding traffic flow dynamics, indicating that traffic flow can be improved further by targeting other aspects. However, in terms of the extent and precision of available data, as well as regarding driver behavior, these results were obtained in an idealized system.
2.2.4 ITS to mitigate congestion at sags

Advanced cruise-assisted Highway System (AHS) is an advanced form of ITS that is being developed in Japan. It has multiple levels: information, control and automated cruise. Hatakenaka et al. (2006) used AHS to develop a system which advices drivers about lane utilization regarding congestion at sags, which (together with tunnels) form 40% of congestion on expressways in Japan. In this research they focus on a road-side approach which utilizes sensors to determine when drivers should be advised to use the left (slow) lane, as congestion at sags usually occurs in the fast lane. When vehicles slow down at the uphill section of the sag, this may cause disturbances which propagate and increase backwards as the fast lane is saturated with large platoons.

In Xing et al. (2012) this concept is implemented using Variable Message Signs (see also section 2.2.7) to advice drivers regarding lane use. Based on a field test, the capacity of a three lane sag section increased from 4789 veh/h to 5079 veh/h (+6%), mainly by increasing flow on the underutilized lanes. Traffic flow stability (not string stability) was increased as platoon sizes were also significantly reduced. Furthermore, after traffic breakdown, the VMS showed information regarding the location of the head of the queue in order to stimulate drivers to accelerate. This is in line with Sato et al. (2009) where these messages increased saturation flow with 1.6-7.0% at different locations.

Although sags cause most congestion in Japan, as opposed to the Netherlands where this is a relatively unknown phenomenon, the research and field tests in Japan show some interesting insights. The first is that advising drivers (from the road-side in this case) can have significant effect on the occurrence of congestion, although compliance is often an issue for advisory ITS. Of course compliance might be culturally determined, but the research shows that only moderate effects in lane use and acceleration behavior can result in significant improvements for capacity, the capacity drop and the amount of congestion.

The anticipatory scale of these measures is on a tactical scale, since it advices on lane use and downstream conditions, which is similar as with in-car advice. However, since these systems are on the road-side, there is no distinction between drivers. The solutions regarding traffic flow dynamics that are used are a reduction of peak lane inflow and a reduction of the capacity drop.

2.2.5 Dynamic speed limits

Dynamic speed limits in the Netherlands were initially intended to increase safety by warning drivers of upcoming congestion (Middelham, 2006). Since then, they have occasionally been used in attempts to increase traffic flow dynamics as well. Here, two of these attempts are mentioned.

Homogenization

Van den Hoogen and Smulders (1994) describe an experiment in which freeway sections with a length in the order of 10km receive dynamic speed limits as to homogenize traffic, i.e. reduce the inter-lane and intra-lane speed differences. The goal is to achieve a more even distribution of traffic over the lanes and to reduce the number of moving jams (also known as wide moving jams or phantom jams), i.e. decrease disturbances. Some effects found were a more even distribution of traffic over the lanes, less very small headways and overall less hectic traffic. Although safety appeared to have improved, no effects on traffic flow could be found.
Generally two types of congestion can be found on freeways which are i) congestion with a fixed downstream location correlated to a bottleneck and ii) moving jams of which both the head and tail move upstream. To solve the latter type, Hegyi et al. (2008) developed an algorithm called SPECIALIST (SPEed ControllIng ALgo rIthm using Shockwave Theory). The theory that the algorithm is based on is the following.

Consider a moving jam as in phase I in figure 2.10. The moving jam has a state of low speed and low flow, state 2. States 1 and 6 are free flow states down- and upstream of the moving jam. As soon as the moving jam is detected, an area upstream of the moving jam gets a lowered dynamic speed limit resulting in state 3 during phase II. As the density cannot change instantaneously, and as the speed is reduced, the area with state 3 lowers the inflow into the moving jam which will eventually resolve at the end of phase II. Upstream of area 3 traffic is still flowing in with a higher flow resulting in an area with state 4. The moving jam has been effectively translated from a short queue with very low speed (state 2) into a longer queue with only a moderately reduced speed (state 4). However, from this significantly higher speed, drivers are able to reach a higher saturation flow as in state 5. This is in line with the bounded acceleration theory of Lebacque (2003) which could be summarized by the fact that the longer the acceleration process, the bigger the resulting time gaps between vehicles. For as long as state 5 has a higher flow than state 6, the area of state 4 will disappear. The original moving jam has then been translated into a high flow forward moving area with state 5, i.e. phase IV.

![Figure 2.10: Overview of phases in the SPECIALIST solution scheme. [Source: Hegyi and Hoogendoorn, 2010.](image)](image)

The moving jam detection is done using inductive loop detectors and the dynamic speeds are given by matrix signs on gantries. This system has been field tested, the results of which are presented by Hegyi and Hoogendoorn (2010). The final parameter settings, which were tuned during the course of the field test, resulted in 72% of the moving jams being resolved and 46% of other congestion (presumably of when the system triggered).

To enhance the detection speed and accuracy, as well as compliance to the speed limits, SPECIALIST in-car has been developed (Hegyi et al., 2013). It extends the basic system with
floating car data and video based monitoring. Using a filter to fuse the different data sources, moving jams are detected earlier and more accurately. Consequently, tuning parameters can be determined with less margin for error as the estimated properties of the moving jam are more robust, resulting in shorter (in space and time) solution schemes. This reduces unnecessary speed reductions that the original system requires to be sure that the moving jam is actually solved, reducing travel time delay further. Additionally, given some available space in which the solution scheme has to fit (due to upstream onramps and weaving section) more moving jams are solvable with the shorter schemes.

The relation between in-car advice and SPECIALIST is twofold. Both systems could be integrated as for the driver SPECIALIST (in-car) simply results in a speed advice. Second, the effectiveness of SPECIALIST strongly indicates that the acceleration process out of congestion is one where gains are to be reached, i.e. the capacity drop can be reduced. This can be done in two manners: i) shortening the acceleration process by preventing instabilities (i.e. drops in speed) and ii) targeting the acceleration process itself.

As a road-side system, dynamic speed limits make no distinction between users, but it does influence drivers on a tactical scale, i.e. adjusting to downstream conditions. SPECIALIST is specifically designed to resolve moving jams by reducing the capacity drop through shortening the acceleration process. The used solutions regarding traffic flow dynamics are thus limited. Homogenization is broader as it attempts to influence both inflow (more even lane distribution) and disturbances.

2.2.6 Ramp metering

Ramp metering is a network management tool which is widely used in the US and has also been used in the Netherlands since 1989 (Middelham and Taale, 2006). With ramp metering, traffic is buffered on a ramp to prevent a temporary peak of inflow which may either oversaturate a nearby bottleneck or may cause disruption through many merging maneuvers (i.e. the onramp is the bottleneck). For both situations ramp metering is able to increase the bottleneck capacity by several percentages, increase the speed on the freeway and reduce travel time.

The reason of the success of ramp metering lies in the fact that it effectively prevents the capacity drop from occurring. Any disturbance in traffic, for example from a momentary peak of inflow, which lowers the speed significantly, will trigger the capacity drop after which system performance is reduced. Obviously, onramps have only limited buffer capacity and for a full evaluation the underlying network also has to be evaluated, or a strict limit on the queue length needs to be adhered to. Ramp metering has effect on the routes that drivers choose and therefore the full effects of a local ramp metering control is not fully understood, let alone optimal. Papageorgiou and Kotsialos (2002) show that a coordinated extension of the well-known ALINEA ramp metering controller, named METALINE, significantly reduces congestion on the ring road of Amsterdam by utilizing limited buffers of multiple onramps, including also buffers on the freeways connecting to the ring. One of the main strengths lies in the distributed storage which also minimizes disturbances on the underlying network.

What ramp metering particularly shows is that by mitigating the capacity drop, a lot is to be gained. This fact can be used for in-car advice where smooth lane changes can for example be facilitated. Driver behavior may also be changed such that the acceleration process is more efficient which leads to a smaller capacity drop.
Ramp metering can be applied locally, or in a coordinated fashion, such as by Papageorgiou and Kotsialos (2002). However, the coordination only concerns reducing inflow further downstream in the network as a solution regarding traffic flow dynamics. Concerning a reduction in disturbances by merging vehicles, ramp metering only concerns the limited onramp in question. Also, in practice, most ramp metering is not coordinated. Therefore the anticipation scale of ramp metering is considered to span only a single onramp.

2.2.7 Variable message signs for route guidance

Variable Message Signs (VMS) are electronic panels next to the road with dynamic information that can be presented on them. They are used for various purposes, but here the most interesting purpose is rerouting traffic for a more optimal use of a road network. Regarding this purpose they are sometimes called Dynamic Route Information Panels (DRIPs). For this purpose they can contain descriptive information or prescriptive information. Descriptive information simply notifies a driver about the current or expected travel time or delay on a certain route. This is used in practice in the Netherlands with some positive results (Middelham, 2006). Prescriptive information prescribes which route to take for a certain destination. With prescriptive information, and a known compliance rate, DRIPs can be used to improve road use from a user-equilibrium towards a system optimal solution (Zuurbier et al., 2006). This is done by finding an optimum in which, given the compliance rate, messages move the optimal amount of traffic to different routes, i.e. for compliance rates below 100% more traffic is advised to change route than would be optimal. Note that due to limitations of DRIPs (i.e. their fixed location and lack of distinction between users) the optimal solution is not equal to the system optimum, but better than user-equilibrium.

In-car advice can be used to provide advices on the tactical scale, i.e. lane use, headway and speed to maintain. Route choice is on the strategic scale and falls outside of the scope of such in-car advice. However, it can be imagined that on both the tactical and strategic scale advice could be given by an integrated system. For this purpose, in-car advice should at least be able to deal with a route, especially regarding lane advice near splits in the road network.

Rerouting traffic in a network only targets the solution of lowering inflow regarding traffic flow dynamics. In theory, spillback could also be considered in prescriptive routing information, but this is not done in practice.

2.2.8 State-of-the-art overview

The state-of-the-art has listed a number of systems and research that have some similarity with in-car advice, but none could be said to be highly similar. Figure 2.11 shows for example that distinction between users is different for in-car advice than road-side systems or individual in-car systems. Road-side systems can only provide advice to all users whereas the individual in-car systems only affect a single vehicle. For in-car advice, although also an in-car system, advice may be sent to a group of users. Regarding the anticipation scale, in-car advice has some overlap with road-side systems which are in place for a specific problem. Probably MDTM is most similar to in-car advice, though it only exists in simulation.
Insights that have been gained from the experience with the systems mentioned in this state-of-the-art can be used to develop in-car advice and to create reasonable expectations. The main insights are:

- Mandatory systems have more effect than voluntary systems.
- Voluntary systems can still be effective.
- Changing the behavior of only few individuals may have significant impact on the overall traffic flow.
- Mitigating or reducing the capacity drop is an effective way to improve road performance.
- Smooth and more spread lane changes help in mitigating the capacity drop.
- Balancing lane use prior to traffic breakdown may increase capacity significantly.
- Models for drivers in unequipped vehicles are probably still valid with advised drivers in the traffic flow.

From the theoretical framework of traffic flow dynamics, a number of solutions follow that ITS can use in order to improve traffic flow, see section 2.1.2. In Table 2.2 an overview is provided of which solutions are used by the various ITS discussed in the state-of-the-art. The ITS that take over the longitudinal part of driving (ACC and CACC) influence capacity, disturbance, stability and the capacity drop. Both capacity and stability are difficult to be targeted by the other driver assisting systems, as these follow from human capabilities. Except for in-car advice, all driver assisting ITS only target one or two solutions for traffic flow dynamics. This usually follows from a system being developed from the idea of tackling a specific aspect of traffic flow dynamics. Using multiple solutions may however have significant benefits. In-car advice can use the following solutions:

- **Inflow**: with lane advice the peak-lane inflow may be reduced.
- **Disturbance**: more stable speeds or smoother lane changes can be advised.
- **Capacity drop**: drivers can be made aware of the end of congestion, increasing their willingness to accelerate.
- **Spillback**: lane advice may create circumstances in which spillback from off ramps affects freeways later.
Table 2.2: Overview of traffic flow dynamics solutions that different ITS use.

<table>
<thead>
<tr>
<th>ITS</th>
<th>Traffic flow dynamics solution</th>
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<tbody>
<tr>
<td></td>
<td>Inflow</td>
</tr>
<tr>
<td>ACC</td>
<td>✓</td>
</tr>
<tr>
<td>CACC</td>
<td>✓</td>
</tr>
<tr>
<td>MDTM</td>
<td></td>
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<tr>
<td>AHS</td>
<td>✓</td>
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<tr>
<td>Homogenization</td>
<td>✓</td>
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<tr>
<td>SPECIALIST</td>
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<tr>
<td>Ramp metering</td>
<td>✓</td>
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<tr>
<td>VMS</td>
<td>✓</td>
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<tr>
<td>In-car advice</td>
<td>✓</td>
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</tbody>
</table>

2.3 Conclusions

This chapter has presented a theoretical framework of traffic flow dynamics, as well as a state-of-the-art on ITS focusing on traffic flow improvement. Different ITS use different solutions within the traffic flow dynamics process, where the non-overtaking systems only target one or two. Giving in-car advice can be considered a new approach in a number of ways. Not only does it target all possible aspects of traffic flow dynamics, it also works on the tactical scale (i.e. 1-2km) while most current ITS operate at smaller (operational) or larger (strategic) scale. Furthermore, any desired selection of users can be given different advices, which provides much more flexibility than road-side or individual in-car systems. Finally, from the state-of-the-art a number of insights have been gained on which the advices to give to drivers can be based. The next chapter elaborates on the design of the in-car advisory system.
3 Development of an in-car advisory system

Parts of this chapter have been published in: Schakel, W.J., B. van Arem (2014) “Improving Traffic Flow Efficiency by In-Car Advice on Lane, Speed, and Headway”, IEEE Transactions on Intelligent Transportation Systems, Vol. 15, Issue 4, pp. 1597-1606.

The previous chapter has shown that advising drivers in-car on a tactical scale provides some unique opportunities for traffic flow improvement. This chapter will discuss the algorithms through which traffic data is translated into advices for individual drivers, based on the presented theory of traffic flow dynamics and the insights obtained in the state-of-the-art. This chapter will therefore first discuss an overview of the ITS application which enables in-car advice, as has already been introduced in chapter 1, but from the viewpoint of traffic flow improvement. The next two sections will elaborate on the two main algorithms to obtain advice, which are traffic state prediction and an advice algorithm.

3.1 System overview

The ITS application that enables in-car advice has been introduced in chapter 1. The application is the context for which the algorithms are designed and as such it gives some constraints. The application includes both road-side and in-car elements, but regarding the optimization of traffic flow, many in-car aspects are not of interest (e.g. curve warning, speed limit information, etc.). From the viewpoint of traffic flow improvement, the system is conceptualized in figure 3.1, which shows the control loop. With available data the traffic state prediction determines the traffic state sometime in the future. Based on the predicted traffic state, the advice algorithm determines to which drivers, where, when and which advices should be given. The advices are accordingly sent to the in-car devices. For a more technical explanation of how data is transferred between different parts of the system, the reader is referred to appendix A.
The control loop of figure 3.1 is conceptual and given by the ITS application. To further specify the system, a number of requirements, constraints and design decisions will now be discussed.

Requirements for traffic state prediction:
- The traffic state prediction should allow advices to be determined for the tactical scale.
- The predicted traffic state should allow phenomena to be recognized that tactical advices may want to avoid. This requires inflow and speed per lane with sufficient longitudinal precision to match the locations of problem and advice.
- Data from different sources and of different types needs to be fused into a single traffic state prediction. This should be flexible as in the future additional data sources may become available.
- The predicted traffic state needs to be robust to common measurement errors and simulation errors (if simulation is used).

Requirements for the advice algorithm:
- The advice algorithm should produce advices that do not overlap in validity, e.g. no more than one advice should be valid for a single user at any single time.
- Advices should not overload the users with information and should not significantly increase the mental workload.

Constraints:
- The system will operate in the Netherlands where it is practice that detector data is aggregated every minute and contains flow and average speed at lane level. The data is available within 75s after the aggregated minute (see also appendix A). For very low penetration rates, this data should be sufficient to determine the traffic state.
- The traffic state prediction and advice algorithms should have a running time of a matter of seconds or shorter as they will operate in a live system.

Besides specific design choices concerning the traffic state prediction and advice algorithm there is one design choice concerning the whole control loop. We have chosen to run the loop every 60s following these considerations:
- The system gives advice on a tactical scale of 1-2km, which on freeways is about 30-60s (in free flow) of travel time.
• Detector data is aggregated and sent every 60s. In case of low penetration rate, very little floating car data is available, making detector data the main data source.
• In order to prevent a large workload for drivers, advices should not be given too frequently.

This also means that the traffic state estimation will estimate the traffic state for 60s in the future, and that advices are based on this traffic state, in line with the tactical scale. Estimating the traffic state further in time would reflect a larger scale where the traffic state is less reliably estimated, and where compliance with tactical advice may be expected to deteriorate. Note that detector data is synchronized, i.e. data from all detectors concerning a particular minute is received simultaneously. The frequency of floating car data, as well as the frequency at which a batch is sent, are settings in the system. The traffic state prediction will run with the available data at the moment it starts running. Given that the algorithm runs every 60s, this is the same frequency with which advices can be presented to a particular driver. However, as the advices are meant to only be given in crucial situations, it is not expected that this is a typical advice update frequency. This is confirmed by the empirical analysis of the advisory system in chapter 7. The next two sections will discuss the development and design of the traffic state prediction and advice algorithm as they function in the context of the presented system.

3.2 Traffic state prediction

3.2.1 Selection of prediction technique
Traffic state estimation, or traffic state prediction if the traffic state sometime in the future is concerned, is an essential part of many ITS solutions. It is required if an ITS solution needs to know a quantity which cannot be directly measured, or which cannot be measured at all relevant moments and locations. If in such cases the required quantity can be derived from available data, traffic state estimation is used to do so. Traffic can be estimated using a number of different methods. Van Lint and van Hinsbergen (2012) provide a comprehensive overview of such models using a categorization with three categories: 1) naïve methods, where no model assumptions are used, 2) parametric methods, which essentially means the use of models of which parameters are fitted to data, and 3) non-parametric methods, which are data driven approaches for which the structure itself is also fitted to data (e.g. the degree of a polynomial). This categorization is arbitrary, many methods are actually a hybrid form of these categories. For the selection of a prediction method we use the following categories:

• Analytical models; These models describe traffic with analytical equations directly obtained from theories, such as kinematic wave theory (i.e. shockwave theory). Note that most analytical models require a numerical implementation to become operational. These numerical implementations are discussed in the category of simulation models. Here, analytical models that do not require a numerical implementation are discussed. For instance in SPECIALIST (Hegyi et al., 2008) kinematic wave theory is used directly to determine how traffic states will propagate, where the set measures (i.e. dynamic speed limits) are included. As such the system is able to determine whether a moving jam can be solved. Analytical models are a subset of the parameterized methods.
• Interpolation filters; Interpolation filters (or extrapolation) can be used if a quantity is known at some locations, and needs to be known at other locations. A typical example is the interpolation of loop detector data, which is only available at a limited number of locations. Techniques from image processing are often used in practice for this
purpose (van Lint and Hoogendoorn, 2010). These techniques are however not very precise as they are not based on any traffic flow theory. In fact, they implicitly assume that traffic states move instantaneously. For this reason, Treiber and Helbing (2002) developed the Adaptive Smoothing Method (ASM), which interpolates while taking account of the direction in which perturbations in traffic flow move (forward under free-flow conditions and against the direction of traffic in congestion). The ASM is a hybrid method. It takes a naïve approach considering that it extrapolates the current traffic state without regarding the fact that traffic states change. However, for the extrapolation a model of movement for the traffic state is used. Finally, as the name suggests, the approach also performs smoothing on the data, which is typical for data-driven approaches.

- **Data-driven approach:** Data-driven approaches find correlations between quantities and describe them with parameterized mathematical equations. This varies from simple regressions to complex neural networks. The major difference with other categories is that no underlying traffic theory or causality is assumed. One example is the estimation and prediction method described by Antoniou et al. (2013). In this work large quantities of data are used to train a model by defining different clusters, i.e. traffic regimes, and determining a time-series based model per regime. New data is then assigned to a cluster and the traffic state is accordingly extrapolated. Data-driven models require a large amount of data and may result in a considerable number of parameters to be estimated. These parameters generally have no physical meaning.

- **Simulation models:** This category of traffic state estimation uses traffic flow simulation, either macro- or microscopically. These simulations are numerical implementations of analytical models that are based on traffic flow theory. However, as the simulation needs input, in the form of an initial traffic state, simulation models are usually only used to predict a traffic state. One of the above techniques is used to estimate the initial state for the model. Also, besides the initial state, other boundary conditions need to be estimated. For simulation models this is for example demand, which itself can be predicted or estimated in various manners such as for example using historic data. Simulation models for traffic state prediction thus form a hybrid method. Another example, which is often used, is Kalman filtering (e.g. Wang and Papageorgiou, 2005) where a model’s prediction is corrected with actual data in an iterative approach. Research has shown that for this approach, a Lagrangian representation is suitable to incorporate floating car data, and provides a more efficient and accurate estimation, particularly around capacity (Yuan et al. 2012).

The requirements mentioned earlier for traffic state prediction are now recapitulated and made more concrete given the design choices.

1. A prediction horizon of 135s relative to the data is required given 75s delay plus a prediction of 60s in to the future in case no floating car data is available.
2. The estimation needs to be fast as it is used in a live application.
3. Both loop detector data and floating car data need to be fused and it should be possible to add data sources in the future.
4. The spatial precision of the derived traffic state should be sufficient to base advices on. It is estimated that a spatial precision of roughly 100m is sufficient.
5. The traffic state of individual lanes is required.
6. The estimated traffic state needs to be robust, i.e. not highly sensitive to parameter values and measurement errors.
Given the requirements both arguments for the use of interpolation filters and simulations models can be given. However, to our knowledge, no simulation model is available which meets with requirements 2, 5 and 6. Requirements 2 and 6 excludes the use of microscopic models, as these i) require more calculation time for any given simulation period, and ii) are stochastic and therefore require multiple runs in order to be robust. Moreover, microscopic models provide many degrees of freedom for which relatively little data is available to estimate it. Macroscopic models meet with requirements 2 and 6, but these models are usually not designed to operate at lane level. Some macroscopic models on lane level, meeting with requirement 5, are available, but these do not meet with requirement 6. For instance, Laval and Daganzo (2006) present a macroscopic model with lane changes. The model attributes the capacity drop to lane changes by vehicles merging at lower speeds. These are modeled as a moving bottleneck without dimension. Since these vehicles merge at lower speed, a large gap is created in front of them. This conflicts with empirical findings. For example, Hidas (2005) and Daamen et al. (2010) found that both the speed differences and the gaps between merging vehicles and their new leaders are small. This indicates that merging vehicles require less space than non-merging vehicles, which conflicts with the underlying theory in the model by Laval and Daganzo. We consider the validity too limited, and therefore it does not meet with requirement 6. One important benefit of using a simulation model is that it can create new traffic states, e.g. breakdown at a merge.

Filtering and data-driven techniques are capable of meeting with requirements 2, 5 and 6, as well as 3 (data fusion) and 4 (spatial precision). The extent into which requirement 1 can be met may or may not be sufficient depending on the prediction horizon. The prediction horizon of 135s is not large, and it should be possible to extrapolate the current traffic state with reasonable accuracy. New traffic states during the prediction horizon will not be predicted, but this is not a requirement. In fact, a phenomenon such as traffic breakdown is stochastic, so even if a model is used, a predicted breakdown is only an indication, and a lack of a predicted breakdown does not guarantee that there will be no breakdown in reality. The major drawback of data-driven techniques is the need for large quantities of data that may not always be available. Additionally, these techniques result in many parameters while filtering techniques have very little. Although this is not a requirement, it is favored to have a small set of interpretable parameters. Finally, some analytical models do not meet with requirement 4 (spatial precision), as traffic states over large areas are considered constant. For other analytical models, granularity is not an issue. However, these require precise data which is usually not available, failing to meet requirement 6.

With the above considerations it has been decided to use a filter to predict the traffic state. The next three sections explain how the filter is used to determine the traffic state on a single data source, and how the estimates from different data sources are combined.

### 3.2.2 Prediction filter – overview

The filter is based on the ASM which has been shown to be robust to missing or erroneous data, as well as to the used filter parameters (Treiber and Helbing, 2002). Furthermore, the filter can easily be extended to fuse different data sources, such as for example in the Extended Generalized Treiber-Helbing Filter (EGTF) by Van Lint and Hoogendoorn (2010). Note that the Treiber-Helbing Filter is synonymous to the ASM.

The time at which the traffic state is estimated is 1 minute in the future, based on requirement 1. Although the ASM is designed as an interpolation filter, it can also be used as a predictive extrapolation filter, so long as the forecast is short-term (Treiber and Helbing, 2002). The
method to combine data sources is equal to the EGTF, except for the way in which the speed-dependent reliability of a data source is defined. First, it is discussed how data from a single data source is used to estimate the traffic state, which is equal to the ASM except that data does not have to be from a fixed grid in space-time. Note that although these filters are usually applied on road level, it is applied to individual lanes here to meet with requirement 5. Also, to meet with requirement 4, the state is estimated for every \( \Delta t' \cdot v_{\text{max}} \), where \( \Delta t' \) is a time step setting and \( v_{\text{max}} \) is the maximum driven speed at a particular section on the freeway\(^1\).

### 3.2.3 Prediction filter – a single data source

The ASM is based on two universal notions from traffic which are that i) traffic states in free flow move forward with a constant speed of \( c_{\text{free}} \), which is usually in the order of 80-85km/h, and that ii) traffic states in congestion move backwards with a constant speed of \(-c_{\text{cong}}\), which is usually in the order of 15-20km/h. Stating that traffic states move with either of these two speeds is a simplification of reality, which has been shown by the authors of the ASM to be a reasonable approximation. In fact, this theory corresponds to a triangular fundamental diagram, the basis of the Cell Transmission Model (Daganzo, 1994) which is widely used for traffic simulation. By presuming either free flow or congestion, it makes sense to give a higher weight to measurements around a position \((t, x)\) in the direction of either \( c_{\text{free}} \) or \( c_{\text{cong}} \). This is the main difference with classical orthogonal methods, which value measurements higher in the direction of \( c = 0\)km/h and \( c = \infty \)km/h. However, since it is unknown beforehand whether traffic is in free flow or congestion, the ASM simply performs both independently and interpolates between the two as will be explained below.

To obtain the weight \( \phi \) that a measurement at location \((t_0, x_0)\) should have for the estimation of the state at location \((t, x)\), a coordinate translation is applied as in equation (3.1), where \( \Delta x = x_0 - x \) and \( \Delta t = t_0 - t \), i.e. the distance and time difference between the measurement and the coordinate of interest. Equation (3.1) is used when presuming free flow. To determine \( \phi_{\text{cong}} \) presuming congestion one uses equation (3.1) with \( c_{\text{cong}} \) instead of \( c_{\text{free}} \). Both \( \sigma \) and \( \tau \) are parameters which describe how fast weights reduce as \( \Delta x \) and \( \Delta t \) respectively become larger.

\[
\phi_{\text{free}}(\Delta t, \Delta x) = \exp \left( -\frac{|\Delta x|}{\sigma} - \frac{|\Delta t| - \Delta x/c_{\text{free}}}{\tau} \right) \tag{3.1}
\]

The spatiotemporal pattern of these weights is shown for both free flow and congestion in figure 3.2, where the dashed lines indicate the speed \( c_{\text{free}} \) and \( c_{\text{cong}} \) through space and time. The weights are largest around these lines.

Given that quantity \( z \) (e.g. speed, flow) needs to be known, and given \( I \) available measurements \( z_i \) with \( i \in \{1...I\} \), equation (3.2) is used with the presumption of free flow.

\[
z_{\text{free}}(t, x) = \frac{1}{N_{\text{free}}(t, x)} \sum_{i=1}^{I} \phi_{\text{free}}(t_i - t, x_i - x) z_i \tag{3.2}
\]

\(^1\)This way of determining the spatial precision has little to do with the ASM, but stems from the possibility of predicting the traffic state using a macroscopic model. These models are only valid if traffic cannot transverse more than a single cell during a time step. Hence, given a time step of \( \Delta t' \) and a maximum driven speed \( v_{\text{max}} \) the minimum distance of a cell is \( \Delta t' \cdot v_{\text{max}} \). However, since a filter approach has been selected in this thesis, only the resulting distance (i.e. cell size) is important.
Figure 3.2: Weights of the ASM in space-time for free flow and congestion. With $c_{\text{free}} = 85 \text{ km/h}$, $c_{\text{cong}} = -18 \text{ km/h}$, $\sigma = 300 \text{m}$ and $\tau = 20 \text{s}$. 

$N_{\text{free}}$ is used to normalize the weights $\phi_{\text{free}}$ since they do not add up to 1, and is given by equation (3.3).

$$N_{\text{free}}(t,x) = \sum_{i=1} z_{\text{free}}(t_i, x_i - x)$$  \hspace{1cm} (3.3)

For the presumption of congestion, equations similar to (3.2) and (3.3) are applied, which we omit as ‘free’ should simply be replaced by ‘cong’. With the two presumptions of free flow and congestion, there are two estimates of the traffic state at $(t,x)$. These are interpolated using equation (3.4), where $w(t,x)$ is a weight in the range $[0...1]$ indicating the level of congestion.

$$z(t,x) = w(t,x) \cdot z_{\text{cong}}(t,x) + (1 - w(t,x)) \cdot z_{\text{free}}(t,x)$$  \hspace{1cm} (3.4)

To determine $w(t,x)$, suppose that $z$ is speed data, i.e $z(t,x) = u(t,x)$. Since congestion is usually persistent it is safe to assume that if either $u_{\text{free}}$ or $u_{\text{cong}}$ gives a low speed, the traffic state at $(t,x)$ is congested and $w(t,x)$ should be close to 1. This idea is captured in equation (3.5), where $V_c$ is a flip-over speed between congestion and free flow, and where $\Delta V$ indicates the width of the transition region from congestion to free flow around $V_c$.

$$w(t,x) = w(u_{\text{free}}(t,x), u_{\text{cong}}(t,x)) = \frac{1}{2} \left[ 1 + \tanh \left( \frac{V_c - V^*}{\Delta V} \right) \right]$$  \hspace{1cm} (3.5)

with,

$$V^* = \min \left( u_{\text{free}}(t,x), u_{\text{cong}}(t,x) \right)$$

Note that if $z$ is not speed data, $w(t,x)$ still has to be determined. When multiple quantities are determined, e.g. speed and flow, one can simply first determine speed and $w(t,x)$, after which $w(t,x)$ can also be used to determine flow.

With equation (3.4), several quantities $z$ can be determined based on a single data source. The next section will elaborate on how different data sources are combined.
3.2.4 Prediction filter – combining data sources

The way in which data sources are combined is equal to the EGTF, except for how speed dependent data source reliability is defined. In this approach, each data source gets two weights which reflect i) the speed dependent reliability of the data source, and ii) the number and proximity of available measurements from the data source. Estimates for $z_j$ from data sources $j$ are combined with equation (3.6), where $\alpha$ reflects reliability and where the summation over $\beta$ reflects the number and proximity of available measurements.

$$z(t,x) = \frac{1}{N^j(t,x)} \sum_j \alpha^j(t,x) \sum_i \beta^j_i(t,x) z^j(t,x)$$  \hspace{1cm} (3.6)

with normalization factor $N^j$,

$$N^j(t,x) = \sum_j \alpha^j(t,x) \sum_i \beta^j_i(t,x)$$

The determination of $\beta(t,x)$ is based on $\phi_{free}(t,x)$ and $\phi_{cong}(t,x)$, which are the weights for a single measurements presuming either free flow or congestion, i.e. they indicate the proximity of a measurement. They are interpolated accordingly by $w(t,x)$. The total spatiotemporal and proximity weight for $z^j(t,x)$ of data source $j$ is thus the sum of state dependent spatiotemporal weights per measurement $i$ as in equation (3.7).

$$\beta^j_i(t,x) = w(t,x)^i \cdot \phi^j_{cong}(t,x) + (1 - w(t,x)^i) \cdot \phi^j_{free}(t,x)$$  \hspace{1cm} (3.7)

In the EGTF, it is assumed that the reliability of a data source depends on the traffic state. More specifically, for each data source two error variances are assumed, one for congestion $\Theta^j_{cong}$, and one for free flow $\Theta^j_{free}$. Since the reciprocal of error variance can be considered an indication of the data reliability, the state interpolation weight $w(t,x)$ can be used to determine the state specific reliability of a data source at $(t,x)$ as in equation (3.8). Note that this definition of $\alpha$ is slightly different from the original definition by Van Lint and Hoogendoorn, but allows a more intuitive determination of the values for $\Theta$.

$$a^j_i(t,x) = \frac{w^j(t,x)}{\Theta^j_{cong}} + \frac{1 - w^j(t,x)}{\Theta^j_{free}}$$  \hspace{1cm} (3.8)

At this point, any number of data sources can be used to obtain an estimate of a quantity which describes the traffic state at any location. However, not all data sources can supply an estimate of all desired quantities. In the advisory system of this thesis, we have loop detectors providing both flow and speed data, and floating car data which only provides speed data. Consequently, through an increasing penetration rate (i.e. floating car data availability) only the estimate for speed can be improved. This also means that the combination of speed and flow data at a specific location may be unrealistic. For example, suppose traffic breaks down in the middle of two loop detectors, and suppose there is so much floating car data that the speed data from the loop-detectors can be ignored. In that case, the flow will be interpolated between high flow values, resulting in a high flow value, while the floating car data results in low speeds. Especially for derived quantities, such as density, this creates a large unreliability. To deal with this problem, one could for example derive flow from floating car data by projecting the speed on the congested branch of a fundamental diagram as is done by Hegyi et al. (2013). With appropriate estimates of $\Theta$, balancing unreliability due to this approach,
especially for free flow conditions, but also reflecting that the flow measurements from detector data may not be appropriate, this may result in reasonable estimates. However, the advisory system does not require flow and speed data to be jointly realistic, so long as triggers for advice are appropriately determined. Furthermore, the above approach introduces additional assumptions and parameters that are not necessary. The determination of appropriate triggers is part of the advisory algorithm which is discussed in the next section.

### 3.3 Advice algorithm

The role of the advice algorithm is to determine which advices should be given based on the predicted traffic state. Advices that can be given are:

- Change lane to the left-hand or the right-hand lane
- Keep lane
- Drive with given speed
- Adapt speed to the left-hand or right-hand lane (i.e. synchronize speed)
- Yield for merging traffic from the left-hand or right-hand lane (i.e. create a gap)
- Maintain a short but safe headway

Note that the formulation as given to the driver is up to the HMI (Human Machine Interface), which is not considered in this thesis. The latter three of the above advices are considered qualitative advices. For headway advice, qualitative advice is preferred as research has shown that drivers are not capable to maintain a quantitative headway (Risto and Martens, 2011). Furthermore, qualitative advice may be more understandable to drivers.

The advice algorithm is a four-step procedure:

1. **Infrastructural properties;** Assign infrastructural properties to the sections for which the traffic state is determined. These properties can be used to determine which advices should be given for as far as this depends on infrastructure. The assignment of infrastructural properties is explained in section 3.3.1.

2. **Advice principles;** Run a set of advice principles, where each advice principle independently determines a set of advice regions. Advice regions are later used to determine which drivers should receive which advices. Three advice principles are explained in sections 3.3.2-4. In different sections throughout this thesis, the set of advice principles may be a subset of these three. Which advice principles are used is explicitly mentioned. The advice principles are based on different solutions to improve traffic flow, by implementing the solutions from section 2.1.2.

3. **Advice filter;** Since the various advice principles operate independently to determine a set of advice regions, there may be overlap between different regions. Overlapping advice regions are filtered making sure no overlap remains. The filtration of advices is explained in section 3.3.5.

4. **User selection;** The final step is to select users to which individual advices should be sent. This is explained in section 3.3.6.

As part of the advice algorithm, advice regions are determined and advices are only assigned to individual drivers in the final step. To clarify the difference between an advice region and an individual advice, table 3.1 shows which information is present in an advice region and which information is present in an individual advice. The lane change fraction $f_{lc}$ is a fraction of all traffic on a lane which should change lane. It is derived by an advice principle and used
to get the appropriate number of users to receive the lane change advice in the user selection. For this, the local penetration rate $p$ of the system is also required. This is further explained in section 3.3.6.

From table 3.1 it can also be seen that applicability of advice is not only determined in space and time, but also by destination and speed. The considered destination is at the next split, which on freeways usually means either the freeway or the off ramp. It is also possible that no applicable destination is assigned, in which case all destinations are applicable. The speed range determines at what speeds the advice should be given. When determining whether different advice regions overlap in the advice filter step (step 3), advices are only considered to overlap if they do so in all four applicability dimensions. If advices do not overlap in at least one dimension, there is no chance of multiple advices being valid at any one time.

Table 3.1: Contents of advice regions and individual advice.

<table>
<thead>
<tr>
<th>Content</th>
<th>Advice region</th>
<th>Individual advice</th>
</tr>
</thead>
<tbody>
<tr>
<td>Users which should receive the advice</td>
<td></td>
<td>✓</td>
</tr>
<tr>
<td><strong>Applicability</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- Section and lane</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>- Time</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>- Destination (if any)</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>- Speed range</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td><strong>Advice</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- Advised lane (if any)</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>- Advised speed (if any)</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>- Qualitative advice (if any)</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Fraction of traffic that should change lane ($f_{lc}$)</td>
<td>✓</td>
<td></td>
</tr>
<tr>
<td>Estimation of the local penetration rate ($p$)</td>
<td></td>
<td>✓</td>
</tr>
</tbody>
</table>

One more difference between an advice region and individual advice is that an advice region may contain multiple advices, whereas an individual advice should only contain one. In case of multiple advices in an advice region, the user selection step will assign different users to different individual advices. A typical example is that some fraction of drivers should receive lane change advice, while the remaining drivers receive advice to yield for merging traffic.

### 3.3.1 Infrastructural properties

The first step of the advice algorithm is to assign infrastructural properties to the individual sections and lanes for which the traffic state prediction has predicted the traffic state. These properties may be used by the advice principles and some examples are presented in figure 3.3. The following properties are assigned:

- **End lane;** This indicates whether the lane will end in a distance of $x_{end}$ (e.g. lane-drop or onramp).
- **End section;** This indicates that any lane in the section will end in a distance of $x_{end}$. It is also included whether the end lane is on the left-hand or right-hand side of the road.
- **Split section;** Whether there is a split of the road within a distance of $x_{split}$ (e.g. off ramp or weaving section). In a split section, the number of required lane changes to both splits is also included for all lanes.
- **Merge lane;** If within a split section two roads also merge (i.e. weaving sections shorter than $x_{split}$), the inner lanes of the two merging roads (i.e. the right-hand lane of...
the left-hand road and the left-hand lane of the right-hand road) are marked throughout the split section as merge lane.

Note that sections may overlap, i.e. a portion of the road may be within both an end section and a split section.

Figure 3.3: Examples of infrastructural properties assigned by the advice algorithm.

3.3.2 Acceleration advice principle
The second step of the advice algorithm is the determination of advice regions by a number of advice principles. This section elaborates on the acceleration advice principle. The aim of this principle is to reduce the capacity drop, which is one of the solutions to improve traffic flow as discussed in section 2.1.2. Several causes for the capacity drop were discussed: lane changes, bounded acceleration, reaction time, increased headways in congestion or the fact that drivers need a stimulus to accelerate. In line with the discussion of section 3.2.1 it is assumed that although lane changes may contribute to the capacity drop, the combined influence of other sources is considerable, as empirical evidence in the form of small velocity differences and small headways during lane changes conflicts with the notion of lane changes being the only major cause of the capacity drop. Bounded acceleration is considered an important cause of the capacity drop as it explains that the longer the acceleration, the larger the resulting headway, the larger the capacity drop. Therefore SPECIALIST is able to reduce the capacity drop by shortening the duration of acceleration by increasing the speed of traffic inside a moving jam. However, the basis of the bounded acceleration theory is a reaction time, or a time delay between the acceleration of one vehicle and its follower. Remaining causes of the capacity drop are thus a reaction time, increased headways and a required stimulus (larger than desired headway). Treiber and Helbing (2003) report that empirical evidence shows that net time headways are larger in congestion, which they call the memory effect, suggesting that desired headways are larger in congestion. Without attributing any level of contribution from the remaining causes, it can be noted that these causes all relate to human factors. In fact, it is reasonable to assume that if a driver is more activated, counteracting the memory effect, their reaction time is shorter, their desired headway is reduced, and their sensitivity to a larger than desired headway is larger. All these changes will therefore reduce the capacity drop, or, increasing driver activation will. Tampère (2004) investigated these behaviors related to an activation level using macroscopic simulation, and found that these indeed influence the capacity drop. It has been empirically shown that notifying drivers about the end of congestion (i.e. downstream front) reduces the capacity drop by Sato et al. (2009), where the saturation flow (or queue discharge rate) increased between 1.6 and 7.0% at different bottlenecks. The acceleration advice principle will advise drivers near the end of congestion to ‘maintain a short but safe headway’. Note that although the aim is to increase acceleration,
advice is not on acceleration itself. From the predicted traffic state, the end of congestion is recognized with the below criteria, which are visualized in figure 3.4.

- The lane is not an end lane (not ending within \( x_{\text{end}} \)). This prevents that this advice is given at a location where drivers should focus on changing lane.
- The predicted speed in the cell is below \( v_{\text{cong}} \), which is a threshold speed below which the traffic state is considered congested.
- The minimum predicted speed over a downstream distance of \( x_{\text{anti}} \) is above \( v_{\text{cong}} \). This prevents that the advice is given with nearby congestion. On the one hand this could potentially be frustrating to drivers while on the other hand one could argue that this advice will only reduce the length of the upstream congestion by increasing the length of the downstream congestion.

The cells which meet with the above criteria are the triggers for the acceleration advice. The spatial region of the advice is in an area from \( x_{\uparrow} \) upstream of the trigger to \( x_{\downarrow} \) downstream of the trigger. This region should be defined such that i) the advice is given around the actual location of the end of congestion, which might not be perfectly predicted in the traffic state prediction, and ii) to give the advice during the acceleration, which clearly requires space in the downstream direction. The validity for acceleration advice is for all destinations and only for speeds below \( v_{\text{free}} \). Speeds above the threshold \( v_{\text{free}} \) are considered to be free flow, at which point the advice is no longer required (as in figure 3.4 left). Furthermore, it may prevent these advices from being given if the traffic state prediction wrongfully predicts congestion. Note that considering the delay in detector data, the traffic state prediction may predict congestion for up to 3 minutes after it has been solved. Logically, we have \( v_{\text{cong}} \leq v_{\text{free}} \), where for speeds \( v \) for which \( v_{\text{cong}} < v < v_{\text{free}} \) holds, we assume neither congestion nor free flow.

![Figure 3.4: Overview of the acceleration advice principle.](image)

3.3.3 Distribution advice principle
This advice principle uses two solutions from section 2.1.2: reducing inflow (at lane level) and reducing the extent of disturbances. Reducing the inflow at the busiest lane may be beneficial as research has shown that not all lanes are fully utilized when traffic breaks down (Knoop et al., 2010). The principle will first notice high lane inflow, and then accordingly advise lane changes away from that lane as well as facilitate smoother lane changes that occur towards the busy lane. Lane changes towards the busy lane may be required due to infrastructure (e.g. at a lane-drop), making this advice principle strongly linked to the infrastructure. Potential triggers for advice are found in a cell if the following criteria are met:
- The flow in the cell is highest of all cells in the same cross-section (it is thus the lane with the highest inflow).
- The flow in the cell is above $q_{end}$ (inside an end section), or above $q_{split}$ (inside a split section), or above $q_{norm}$ (outside of end and split sections).

These criteria may hold for several consecutive cells. It is assumed that the busy lane is usually busy because of infrastructure, and that lane changes upstream of the busy location are required to lower the inflow. This means that only the most upstream cell for which the above criteria hold is of interest. Several advices will be given over a distance of $x_{adv}$ upstream of this location. Furthermore, to prevent overlap between different advice regions within this advice principle, cells are also considered ‘consecutive’ in case the above criteria do not hold for cells over a distance shorter than $x_{adv}$ between two cells that do meet the criteria. This is illustrated in figure 3.5.

![Figure 3.5: Overview of the distribution advice principle.](image)

Given that there is a trigger for distribution advices, multiple advices may result. As can be seen in figure 3.5, the resulting advice area covers multiple lanes. The busy lane is denoted with $l_{busy}$ and follows directly from the trigger. Since we assume that the lane is usually busy because of infrastructure, a lane from which traffic has to merge onto the busy lane, denoted with $l_{merge}$, might be found:

- The trigger is inside an end section:
  - If an adjacent lane is an end lane, that lane is $l_{merge}$.
  - If the end lane is on the right-hand side (one of the infrastructural properties) and $l_{busy}$ has no right-hand adjacent lane (i.e. on the right lane of the freeway upstream of an onramp on the right side), the ‘right-hand’ lane is $l_{merge}$. Note that although $l_{busy}$ has no right-hand lane, there is obviously a lane leading towards the onramp.
  - The same as the previous, but regarding the left-hand side.
- The trigger is on a merge lane:
  - The other merge lane is $l_{merge}$. 
Note that no \( l_{\text{merge}} \) may be found if the trigger is not in an end section or on a merge lane. A third lane \( l_{\text{adj}} \) is the lane where traffic from \( l_{\text{busy}} \) has to change lanes to. If there is an \( l_{\text{merge}} \), it is the other adjacent lane, otherwise it is the adjacent lane with lower flow. The flow on both \( l_{\text{busy}} (q_{\text{busy}}) \) and on \( l_{\text{adj}} (q_{\text{adj}}) \) is the maximum flow as estimated over a distance \( x_{\text{anti}} \) downstream of the trigger. Examples of these lanes in different infrastructural settings, as well as the advices that are given, are presented in figure 3.6.

\[
q_{\text{target}} = \begin{cases} q_{\text{thresh}}^*, & q_{\text{busy}} + q_{\text{adj}} \leq 2 \cdot q_{\text{thresh}} \\ \frac{1}{2}(q_{\text{busy}} + q_{\text{adj}}), & q_{\text{busy}} + q_{\text{adj}} > 2 \cdot q_{\text{thresh}} \end{cases}
\]

Figure 3.6: Examples of distribution advices.

The advices in figure 3.6 are determined as:

- Users from \( l_{\text{busy}} \) should change to \( l_{\text{adj}} \) where the lane change fraction of all traffic \( f_{\text{lc}} \) is such that the level of flow on \( l_{\text{busy}} \) is returned to some target value \( q_{\text{target}} \) as in equation (3.9). Usually the target flow is equal to the applicable threshold value \( q_{\text{thresh}} \in \{q_{\text{end}}, q_{\text{split}}, q_{\text{norm}}\} \). This would yield the minimum number of lane changes required to get the flow on \( l_{\text{busy}} \) below the threshold value. If however the flow on \( l_{\text{adj}} \) is sufficiently high, this would create a flow on \( l_{\text{adj}} \) above the threshold value. As a result the problem is simply moved to the adjacent lane. To prevent this, flow on both lanes is then equalized as in equation (3.10).

\[
f_{\text{lc}} = \frac{q_{\text{busy}} - q_{\text{target}}}{q_{\text{busy}}} \quad (3.9)
\]

- Users on \( l_{\text{busy}} \) that will not receive a lane change advice should yield for traffic from \( l_{\text{merge}} \). If there is no \( l_{\text{merge}} \), these drivers get an advice to reduce their speed to at most \( d\nu \) faster than the adjacent lanes, where all speeds are considered at the cross-section of the trigger. The latter is only given if \( l_{\text{busy}} \) has a speed larger than that (often occurs with asymmetrical traffic rules). The purpose of this advice is to stabilize traffic through homogenizing speeds.
- Users on \( l_{\text{adj}} \) are advised to keep to their lane.
- Users on \( l_{\text{merge}} \) (if any) are advised to synchronize their speed with \( l_{\text{busy}} \).
All of the above advices, except for the advice on $l_{adj}$, are only valid above a speed of $v_{cong}$. Advising lane changes or speed synchronization below this speed, which is in congestion, has a counterproductive effect. Furthermore, lane change and lane keep advices are only valid if this does not conflict with the destination of users, if the trigger is within a split section and so long as the destination of a driver is known. More specifically, if drivers could reduce their required number of lane changes, they will not receive advice to keep lane, and lane change advice is not given if that would increase the required number of lane changes.

### 3.3.4 Spillback advice principle

The spillback advice principle, as the name suggests, is aimed at reducing spillback, which is one of the solutions described in section 2.1.2. Given a queue on an off ramp, spillback appears an inevitable aspect of traffic flow dynamics. However, for the spillback to affect the freeway it is required that i) a vehicle has to slow down in order to take the off ramp and ii) there is sufficient traffic behind this vehicle to cause congestion. By diverting traffic from the right-hand lane (assuming an off ramp on the right-hand side) it is possible to delay the moment of traffic breakdown due to the spillback, but only for as long as the remaining lanes have spare capacity.

Potential spillback is recognized if within a distance of $x_{spill,\text{down}}$ downstream and $x_{spill,\text{up}}$ upstream of the diverge point a speed on the off ramp below $v_{spill}$ is estimated, as illustrated in figure 3.7. In that case the following advices are given:

- Users on the right-hand lane are advised to change to their left-hand lane. The lane change fraction of all traffic that should change lane ($f_{lc}$) is such that the flow in the right-hand lane $q_{right}$ is reduced as much as possible, without the flow on the left-hand lane $q_{left}$ exceeding $q_{split}$. This is expressed in equation (3.11). Flow is given by the maximum predicted flow over the advised region which has a length of $x_{spill}$ upstream of the diverge point.

$$f_{lc} = \begin{cases} 
1, & q_{right} < q_{split} - q_{left} \\
\frac{q_{split} - q_{left}}{q_{right}}, & q_{right} \geq q_{split} - q_{left} \text{ and } q_{left} \leq q_{split} \\
0, & q_{left} > q_{split} \end{cases}$$

(3.11)

- Users on the left-hand lane are advised to keep to their lane within the same section.

Similarly to distribution advices, these advices are only valid if they do not conflict with the destination of drivers. In this case advices are only given to traffic that does not use the off ramp (if their destination is known).
Figure 3.7: Overview of the spillback advice principle.

3.3.5 Advice filter

The third step of the advice algorithm is filtering overlapping advice regions, which may have been produced as the discussed advice principles determine advice regions independently. Two advice regions are said to overlap if they overlap in all four applicability dimensions: spatial range, temporal range, destination and speed range. The basic principle of the advice filter is to prioritize one advice region over another, where the priority level is given by the advice of each region. The priority order is determined based on expected positive impact on traffic flow as: short headway, lane change/keep, yield/synchronize and speed advice. Given a set of regions $R$, the filter algorithm is performed as:

1. Loop over all advice regions from $R$ and determine the maximum number of regions overlapping with a single region $n_{\text{max}}$.
2. Stop if $n_{\text{max}} = 0$.
3. Loop over all advice regions $r \in R$ and treat those with $n_{\text{max}}$ overlapping regions.
   a. If the priority of $r$ is larger than the priority of all overlapping regions of $r$ individually, remove all overlapping regions from $R$.
   b. Else, if an overlapping region of $r$ has a higher priority, or, if multiple overlapping regions of $r$ have equal priority to $r$, remove $r$ from $R$.
   c. Else, if only a single overlapping region of $r$ has equal priority to $r$, remove both from $R$.
4. Go to step 1 using the now smaller set $R$.

Only treating regions with $n_{\text{max}}$ overlapping regions makes sure that a minimum number of regions is removed in order to remove all overlap. For example, suppose that regions $A$ and $B$ have overlap, that region $B$ and $C$ have overlap, and that regions $A$, $B$ and $C$ have equal priority. By only removing region $B$, all overlap is removed as $A$ and $C$ do not overlap.

The advice filter does not check for conflicting advices, e.g. on left-hand lane change right and on right-hand lane change left. However, the presented advice principles do not create this.
3.3.6 User selection

The fourth and final step of the advice algorithm is to generate individual advices from the remaining advice regions. For this, users are selected for the (possibly multiple) advices defined in an advice region. Before this selection is explained, it is explained how the advice algorithm maintains its set of users. Since every user provides its position through floating car data, a recent position and speed of each user is known. For each user, a speed \( v_{user} \) is maintained with equation (3.12), where \( t' \) is the time when a user sends its data, \( \Delta t' \) is the time since the last data was received before that, \( v(t') \) is the reported speed of the user at \( t' \) and \( \tau_v \) is a parameter which influences the speed at which \( v_{user} \) updates to \( v \). The purpose of \( v_{user} \) is both to estimate the current position and to rank drivers for their desired speed.

\[
v_{user}(t') = v_{user}(t' - \Delta t') + \left[ v(t') - v_{user}(t' - \Delta t') \right] \frac{\Delta t'}{\tau_v}
\]

(3.12)

The position \( x_{user} \) at current time \( t \) of each user is estimated with equation (3.13), where \( x_{user}(t') \) is the last reported position.

\[
x_{user}(t) = x_{user}(t') + v_{user}(t') \cdot (t - t')
\]

(3.13)

Any user that did not transmit any data during the last \( t_{out} \) is removed from the set of users. Selecting users for an advice region occurs from two different sets. The first set of users is all users for which the currently estimated position \( x_{user}(t) \) is within the advice region or within a distance of \( x_{pre} \) upstream of it, all in the lane of the advice region. The distance \( x_{pre} \) is used as drivers upstream of the advice region may enter the region while it is still valid. This user set is denoted by \( A \). The second set of users consists of all users on the same road section but from the other lanes, denoted by \( A' \). These users may also enter the region through lane changes. A single advice region may have multiple advices and users are selected in a priority order following a few criteria:

- **Lane change/keep;** Only for given destination (if any). First, users are selected of whom the destination is known and matches. Next, users are selected of whom the destination is unknown. Users who changed in the opposite direction within the last \( t_{change} \) are excluded.
  - To left: Fastest \( n \) users from \( A \) (based on \( v_{user} \)), random \( n \) users from \( A' \).
  - To right: Slowest \( n \) users from \( A \) (based on \( v_{user} \)), random \( n \) users from \( A' \).
  - Keep lane: All users.
- **Yield/synchronize;** All remaining users.
- **Speed;** All remaining users.
- **Short headway;** All remaining users.

The selection criteria are in place to increase user-friendliness as advices are not given if they are not logical for an individual user, e.g. change left when the drivers needs to go to a near off ramp. Based on the criteria several advices may be sent to a single user. However, for any given combination of location, time, speed and destination these do not overlap. It is up to the in-car device to show the correct advice to the driver.

The number \( n \) is given by equation (3.14) where \( n_A \) is the number of remaining users in the appropriate set, \( f_{lc} \) is a lane change fraction as given in the advice region and \( p \) is an estimation of the local penetration rate.
The local penetration rate is calculated as \( p = \frac{n_A}{n'} \), where \( n' \) is an estimation of the total number of vehicles in the advice region and within a distance of \( x_{pre} \) upstream, which can be derived from the predicted traffic state.

### 3.4 Conclusions

This chapter has presented a design of an in-car advisory system. It uses a traffic state prediction filter which is efficient, robust, and able to fuse different data sources. Using the predicted traffic state, the presented advice algorithm determines a set of advices of which it is guaranteed that there is no overlap. A set of three advice principles is used which use four solutions to improve traffic flow as presented in section 2.1.2. The acceleration advice principle aims to reduce the capacity drop, the distribution advice principle aims to reduce peak lane inflow and to facilitate smoother lane changes, and the spillback advice principle aims to delay the effect of spillback on the freeway.

The remainder of this thesis will evaluate the effectiveness of the presented system. The next three chapters discuss the models and simulation tools that are used for this, after which the evaluation itself is discussed.
4 Modeling regular driver behavior

In this chapter a model for the driver behavior of unadvised drivers is discussed. It is required as a benchmark and for the evaluation of mixed traffic scenarios (with advised and with unadvised traffic). First, the requirements for a model describing this traffic are discussed. The car-following and lane change model are presented next, followed by an evaluation of the requirements. Calibration and validation of the model is discussed in the next chapter.

4.1 Requirements

Given the intentions of the advisory system under research in this thesis, a number of requirements for a model describing regular driver behavior can be made. These requirements stem from the concept that the model should be a reasonable approximation of current (i.e. unadvised) traffic with a focus on problems that advices are aimed to reduce. Also, for implementation there are some requirements. Before the requirements are discussed, four definitions are explained which are used in the requirements.

Car-following (model)
Car-following is the task of adjusting the throttle and brake pedals while following the car in front (i.e. the leader or predecessor). Adjusting the throttle and brake pedals results in a certain acceleration (deceleration if negative), determining the longitudinal movement of the vehicle. Models that describe car-following usually determine an acceleration value. If the leading vehicle is very far, or if there is no leading vehicle, one speaks of free driving. This entails accelerating to, or driving at, a desired speed. Car-following models often also describe free driving. Both are shown in figure 4.1.
Lane change (model)
Lane changing is moving laterally from one lane to another as in figure 4.2. Lane change models at the least determine in which circumstances drivers change lane. The lane change itself (i.e. duration and lateral position) may also be modelled. If not, the lane change is instantaneous. In order to perform safe lane changes, vehicles in the target lane need to be considered. A gap between two vehicles may or may not be acceptable to change into. This is usually determined by gap-acceptance models, a sub-model of lane change models.

Integrated model
An integrated model constitutes a combination of a car-following and lane change model, where the two have some correlation and/or dependency. This can be anything from a shared parameter to a full dependency where for instance the acceleration from the car-following model is used for gap-acceptance in the lane change model. The latter is shown in figure 4.3. The benefit of an integrated model is that interactions between the longitudinal and lateral driving tasks can be included in the modelled behavior. Also, it increases the intra-driver consistency, e.g. being more aggressive in both car-following and lane changing.

Synchronization
Synchronization is (in this context) the adjustment of speed and relative location with traffic in an adjacent lane, in order to facilitate a lane change. This holds for the potential lane changer itself, as well as the potential follower. In the latter case, synchronization is also referred to as courtesy yielding, gap creation or cooperation. Although speeds become similar in both lanes, synchronization in this context should not be confused with synchronization from a macro point of view, where traffic in all lanes has roughly the same speed. In this case, it may only involve a few vehicles and has lane changing as purpose, rather than being a traffic flow property. Note that it may be that synchronization for lane changing is a cause for synchronization from the macro point of view, but this is out of context.
The requirements for the driver model are given below. For each it is indicated whether it is a hard requirement (required) or a desired requirement (desired), i.e. the effectiveness of the advisory system can also be determined without, but presumably less accurately. It is also indicated whether the requirement stems from the need for realism (realism) or to enable/improve implementation (implementation).

- **Traffic phenomena**
  - Distribution of traffic over the different lanes for different levels of traffic volume and different locations [required, realism] – Realistic traffic distribution is required to evaluate whether advising drivers to change lane can have beneficial impacts.
  - Aggregate speeds on the different lanes for different levels of traffic volume and different locations [required, realism] – Realistic speed on the different lanes is required to assess the impact of speed advice. Also, drivers need an appropriate incentive in simulation to comply or not comply with a given speed or lane change advice.
  - Traffic breakdown [required, realism] – This is a difficult subject as causes and mechanisms of traffic breakdown are subject of scientific debate. However, since the advisory system aims to delay or prevent traffic breakdown, it is important to approximate reality regarding this aspect. From empirical investigations we conclude the following:
    - Lane changes can be an initial disturbance which leads to traffic breakdown (Ahn and Cassidy, 2007).
    - Lane changes may occur with headways significantly shorter than regular situations (Daamen et al., 2010; Sultan et al., 2002). These headways are relaxed to a regular size over some time after the lane change. This is known as the relaxation phenomenon (Laval and Leclercq, 2008; Cohen, 2004). Relaxation is a strong example of integration between car-following and lane changing. Relaxation may result in a capacity funnel, an empirically found phenomenon where congestion starts some distance downstream of onramps (Tampère et al., 2005b)
    - Before a lane change, drivers may adjust their speed to the speed in the target lane (Wang et al., 2005; Hidas, 2002; Yeo et al., 2008). This behavior is part of the tactical stage of lane changing, which lane change models often exclude (Kesting et al., 2007). This will be referred to as speed synchronization, or simply synchronization. Synchronization is another strong example of integration between car-following and lane changing.
    - Other drivers may yield out of courtesy in order to create sufficient space for a lane change in front of them (Wang et al., 2005; Hidas, 2002; Yeo et al., 2008). We also refer to this with synchronization since both entail adjusting the speed and alignment with a vehicle in the adjacent lane. This behavior is also known as courtesy yielding, gap-creation or cooperation.
  - Instability with regard to upstream vehicles [desired, realism] – This has been discussed in chapter 2 where it was referred to as string stability. It concerns the average growth of a disturbance as it moves from one vehicle to the next within a vehicle platoon. Ultimately this results in stop-and-go traffic.
o **Acceleration levels** [desired, realism] – The acceleration (and deceleration) values that result from a model should lie within a reasonable range. This range is roughly between $-3$ and $2\text{m/s}^2$. Furthermore, the acceleration should reduce for increasing speeds simply because of vehicle capabilities (or the extent into which drivers are willing to use their vehicle’s capabilities). Moreover, this affects saturation flow and traffic flow stability (i.e. a higher saturation flow may allow a small disturbance to dissolve before the next platoon arrives).

- **Conceptual**
  o **Integrated driver model** [required, realism] – The driver model needs to be integrated in order to properly capture traffic breakdown as discussed above (i.e. synchronization and relaxation).
  o **Non-hierarchical evaluation of lane change incentives** [desired, realism] – Many lane change models use a hierarchy between Mandatory Lane Changes (MLC) and Discretionary Lane Changes (DLC). It is clear that this simplification ignores any trade-offs between different incentives that drivers make. A clear example is whether to overtake slow traffic (or not) upstream of an off-ramp that needs to be taken. Moreover, the existence of MLC situations cannot be observed and have never been estimated (Toledo et al., 2003).
  o **Anticipative lane changes** [desired, realism] – Drivers have a level of anticipation when deciding to change lane. Typical examples are i) not changing to the right-hand lane as there is slow traffic ahead, and ii) starting an overtake maneuver before one has to decelerate considerably.

- **Implementation and calibration**
  o **Parsimony** [required, implementation] – The number of parameters should be as small as possible, while still being able to represent the above traffic phenomena. A larger number of parameters, i.e. more complex models, may potentially provide a more powerful explanation, but their predictive power is less and gives overfitting problems. Also, a lower number of parameters reduces the required computational effort for the calibration process, a process which typically requires a lot of computational effort.
  o **Fast implementation** [desired, implementation] – This is desired for the same reasons as the above requirement. Basically, model implementations that are faster are preferred over slower models.

Little direct empirical evidence of synchronization, both from the potential lane changer and potential new follower, is available; the above mentioned studies are based on simulation models. However, in the empirical study of Daamen et al. (2010) these behaviors are also visible. The short headway associated with the relaxation phenomenon also dictates well-adjusted speeds. Finally, though not empirically shown from measurements, it is common practice.

Continuing on the subject of traffic breakdown, the mentioned empirical facts seem somewhat contradicting. Lane changes are mentioned as a possible cause for traffic breakdown, while relaxation and synchronization smooth the lane change process. That is, lane changes occur with smaller speed differences than with a simpler model without these phenomena. However, smooth traffic does not contradict unstable traffic. For example, relaxation will result in increasing headways. In order to achieve this, speeds may drop. Given a realistic representation of car-following behavior (with string instability), this drop in speed may result in traffic breakdown. Consequently, we consider the mentioned phenomena important as they
make lane changes smoother and more realistic, whereas a simple approach to model lane changes may make lane changes too disruptive.

The above list of requirements is generic. A summary of specific points that car-following and lane change models will be judged on is given below.

1. The longitudinal movement should include free conditions (i.e. free driving).
2. The longitudinal movement should only have accelerations within reasonable bounds, that satisfy vehicle acceleration and deceleration limitations.
3. The lateral movement should be influenced by the route or infrastructure for both merges and diverges.
4. The lateral movement should be influenced by desired speed.
5. The lateral movement should be influenced by the rule to keep right.
6. The lateral movement should result from non-hierarchical incentives.
7. The lateral movement should be anticipative.
8. The longitudinal/lateral interactions should include relaxation.
9. The longitudinal/lateral interactions should include synchronization.
10. The longitudinal/lateral interactions should include stop-and-go traffic.
11. The number of parameters for calibration should be reasonably small and parameters should be meaningful.

Requirement 10 is mostly related to the desired string stability which has mostly to do with longitudinal movement. However, lateral movement (lane changes) may form an initial or additional disturbance creating stop-and-go traffic. To model both longitudinal and lateral behavior, a car-following model and lane change model are usually used. These are discussed in the next two sections. The level of interaction between car-following models and lane change models has a wide range. In our case, requirements 8 and 9 form strong interactions. The interactions will be discussed in conjunction with the lane-change model, which is dependent on the car-following model. Besides these interactions, the car-following and lane change model also share parameters.

### 4.2 Car-following model

Many car-following models are reported in literature. Many of these are extensions of other car-following models. In order to select a car-following model, only some well-known and often extended car-following models are reviewed here. The selected models are the linear stimulus-response model by Helly (1961), the safe-distance models by Gipps (1981), the Optimal Velocity Model (OVM) (Bando et al., 1995) and the Intelligent Driver Model (IDM) (Treiber et al., 2000), and finally the action-point model by Wiedemann (1974). We will not elaborate on the details of all car-following models but limit our analysis to the main properties of the different car-following models. Requirements 1, 2 and 8–11 pertain to car-following, and table 4.1 shows whether the car-following models meet these requirements.

The Helly model (Helly, 1961), and many other linear stimulus-response models, only consider stimuli from the leading vehicle, and therefore omit free driving (requirement 1). Tampère (2004) did include a term for free driving in this family of models. However, the term is only appropriate for speeds near the desired speed. Tampère uses a relaxation time regarding the desired speed of $\tau_w = 2.5s$. For lower speeds, this would result in very large acceleration, so the value is limited with a fixed maximum acceleration. This ignores the fact that vehicles do not have a fixed maximum acceleration while accelerating (requirement 2).
The model can reproduce unstable car-following resulting in stop-and-go traffic (requirement 10).

The linear stimulus-response model does not implement any tactic or intelligence in the behavior of the follower. The three discussed safe-distance models do implement basic behavioral concepts, including for free driving. The model by Gipps (1981) follows a simple rule, which is that for the case the leader \( n-1 \) should decelerate to full stop with deceleration \( b' \), the following vehicle \( n \) maintains a headway such that deceleration stays below \( b_n \) while stopping with a small safety margin before the leading vehicle. With \( b_{n-1} < b' \) this constitutes an over-reaction and hence unstable traffic leading to stop-and-go traffic (requirement 10). Wilson (2001) shows that choosing parameters that result in physically feasible and desired traffic patterns is difficult. Treiber et al. (2000) draw similar conclusions, stating that the model shows no traffic instabilities or hysteresis effects. Finally, the model calculates the obtained speed at time \( t + \tau \) based on the situation at time \( t \). This approach puts no bounds on the acceleration which may obtain unreasonable values (requirement 2).

The Optimal Velocity Model (OVM) (Bando et al., 1995) uses in essence a similar approach as the linear stimulus-response model; drivers respond with a certain sensitivity (or relaxation time) to a stimulus. In case of the OVM, the stimulus is the difference between the current speed, and a headway dependent desired speed \( V(h) \). For large headways \( h \gg 0 \) we have \( V(h) = v_0 \), i.e. the desired speed, while for very small headways \( V(h) \) approaches 0. In order for the model to be collision free, for the relaxation time it should hold that \( \tau < 0.9s \) (Treiber et al., 2000). Similarly as with the Helly model, this results in very high accelerations from standstill. Although the function of \( V(h) \) appears to follow a plausible car-following tactic, the lack of sensitivity to speed differences causes this problem. Furthermore, the OVM has been shown to have a worse fit to trajectory data than the IDM (Kesting and Treiber, 2007).

The Intelligent Driver Model (IDM) (Treiber et al., 2000) overcomes the problems of the model by Gipps and the OVM by implementing an ‘intelligent’ car-following tactic. The intelligent behavior is an assumption, similar as in the other safe-distance models, but in the case of the IDM desired properties are found regarding the requirements. This will be discussed further on when the IDM (which is the chosen car-following model) is explained in detail. Even though the IDM has only a few parameters, requirement 11 is not fully met as the interpretation of the ‘desired’ headway parameter \( T \) is difficult, i.e. we have \( \frac{dv}{dt} < 0 \) when the leading vehicle is followed at a headway of \( T \). This is only a small issue that will be solved with an adaptation to the IDM.

Finally, we discuss the action-point model by Wiedemann (1974). Action-point models try to implement shortcomings in human perception. The acceleration of vehicles is assumed constant between action points, while at the action points drivers perceive a change in the situation which requires an adaptation of the acceleration. Another type of action-point models defines the action points simply by the time in between, drawn from an exponential distribution (Wagner, 2006). Action-point models are generally perceived as a realistic concept and one can indeed derive action-points from trajectories with constant acceleration in between (Hoogendoorn et al., 2011). However, these action points are very scattered and often counter intuitive (e.g. an increase in acceleration while approaching a slower leader). Moreover, contrary to the assumption in the Wiedemann model, at most of the derived action points the sign of acceleration does not change. Instead, only the level of acceleration (or deceleration) is adjusted. Furthermore, the perception thresholds on which the action points are assumed to lie are defined with many parameters. These parameters are required next to
the parameters that actually determine the acceleration at an action-point. The total number of parameters therefore fails to meet with requirement 11.

Table 4.1: Overview of car-following models.

<table>
<thead>
<tr>
<th>Requirement</th>
<th>Helly</th>
<th>Gipps</th>
<th>OVM</th>
<th>IDM</th>
<th>Wiedemann</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 (free)</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>2 (accelerations)</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>8 (relaxation)</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>9 (synchronization)</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>10 (stop-and-go)</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>11 (parameters)</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
</tbody>
</table>

None of the car-following models meets requirement 8 or 9, i.e. relaxation or synchronization. This is not surprising as these two phenomena have to do with interactions with vehicles in other lanes (and also in the same lane), while car-following usually only focuses on single-lane dynamics. Still, we do require that car-following is affected by these interactions. The solution can be found in the formulation of a meta-model which uses the car-following model as a black-box (i.e. the exact formulation is not important) of which the input and output is known. Input consists of all the relevant stimuli (current headway, speed difference) pertaining to any appropriate leading vehicle, and a context-dependent desired headway. Output is simply the resulting acceleration. In our case, this meta-model is actually part of the lane change model. The integration between the car-following model and the lane change model will be discussed in conjunction with the lane change model.

Requirement 2 (reasonable acceleration bounds) is not met by the models by Helly and Gipps nor by the OVM. This is intrinsic to the models and cannot be alleviated. The IDM and model by Wiedemann both do not meet with requirement 11 (small number of meaningful parameters). However, for the IDM this only concerns the meaningfulness of the ‘desired’ headway $T$, which is at least not equal to the headway at which equilibrium conditions ($\Delta v = 0$ and $dv/dt = 0$) are found. As mentioned before, this can be alleviated by adjusting the IDM. With the above considerations, the IDM has been selected as the car-following model. First, the IDM will now be discussed in detail, after which the adaptation to the IDM is presented.

The ‘intelligent’ behavior of the IDM can be shown by deriving a formulation of the IDM for the case when a slower vehicle is approached, as done by Treiber et al. (2000), which will be shown next. The formula of the IDM is given in equation (4.1).

$$\frac{dv}{dt} = a \left( 1 - \left( \frac{v}{v_0} \right)^{\delta} - \left( \frac{s^*}{s} \right)^2 \right)$$

(4.1)

Here $v$ is the current speed, $v_0$ is the desired speed (further discussed with the lane change model), $a$ is the maximum acceleration, $\delta$ describes the rate at which acceleration decreases as one approaches the desired speed, $s$ is the net distance headway with the leading vehicle and $s^*$ is a dynamic desired distance headway given by equation (4.2).

$$s^* = s_0 + vT + \frac{v\Delta v}{2\sqrt{ab}}$$

(4.2)
Here $s_0$ is the stopping distance (i.e. distance between cars when stopped), $T$ is the desired time headway, $\Delta v$ is the speed difference with the leading vehicle (i.e. approaching rate) and $b$ is a maximum comfortable deceleration.

In equation (4.1) the first term $a(1-(v/v_0)^\delta)$ describes free traffic and is known as the free term while the second term $-a(s'/s)^2$ describes car-following and is known as the interaction term. The interaction term depends on the dynamic desired distance headway which itself has two components. The equilibrium component $s_0 + vT$ describes the desired distance headway under equilibrium conditions ($\Delta v = 0$ and $dv/dt = 0$) and is equal to the desired distance headway in many other car-following models. The second term $v\Delta v / 2\sqrt{ab}$ is the dynamic term. This term increases or decreases the dynamic desired distance headway which accordingly reduces or increases acceleration. The dynamic term incorporates responses in situations when $\Delta v \neq 0$. This term also includes the intelligent behavior giving the model its name. This intelligent behavior can be shown by simplifying the IDM in case of approaching a slower vehicle ($\Delta v >> 0$) while currently driving closely to the desired speed ($v \approx v_0$), as done by Treiber et al. (2000). In that case, the free term of equation (4.1) can be left out and the equilibrium component is dominated by the dynamic component in equation (4.2). The IDM can thus be simplified to equation (4.3) in this situation. Clearly, as speed drops, the free flow term is no longer negligible. However, for explanatory purposes it is left out in the following simplification. Note that parameter $a$ is cancelled out in this situation.

\[
\frac{dv}{dt} = -\frac{(v\Delta v)^2}{4bs^2} \tag{4.3}
\]

Furthermore, if the situation is simplified to approaching a stand-still leader ($v = \Delta v$) and by introducing $b_{min} = v^2 / 2s$ as the minimum constant deceleration which will avoid a collision (assuming a constant speed of the leader), equation (4.3) can be further simplified to equation (4.4).

\[
\frac{dv}{dt} = -\frac{b_{min}^2}{b} \tag{4.4}
\]

Finally, if we introduce $\beta = b_{min}/b$, we obtain equation (4.5).

\[
\frac{dv}{dt} = -\beta b_{min} \tag{4.5}
\]

Equation (4.5) is a very simple form of the IDM, as derived by Treiber et al. (2000), which conveniently shows the assumption of the IDM while approaching a slower leader, which is that drivers will react little ($b_{min} < b$) or overreact ($b_{min} > b$) depending on the ratio of $b_{min}$ and the maximum comfortable deceleration $b$, i.e. $\beta$. This is illustrated in figure 4.4. If $\beta < 1$ we have safe conditions and drivers are willing to postpone stronger deceleration, whereas in case of $\beta > 1$ we have critical situations which drivers quickly want to get out of by decelerating stronger than strictly required to avoid a collision. This over-reactive behavior makes the IDM suitable for requirement 10 (stop-and-go traffic). Note also that the overreaction explains how smooth lane changes may still result in traffic breakdown, a desired property of the car-following model given the empirical findings of smooth lane changes.
As mentioned before, the IDM does not comply with requirement 11 regarding the interpretation of the ‘desired’ headway $T$. Particularly, if a driver is at the desired velocity ($v = v_0$), at the desired headway ($s = s^* = s_0 + v \cdot T$) and at equal velocity as the leader ($\Delta v = 0$) it follows from equation (4.1) that $dv/dt = a \cdot (1–1–1) = –a$. In the IDM, equilibrium conditions are only found as the free term balances this deceleration such that $dv/dt = 0$, i.e. at lower speed and a larger time headway. Consequently, capacity that is derived from the maximum equilibrium flow is lower than expected for any given value of $T$. Contrary to Treiber et al. (2000), we assume that the minimum of the free and interaction terms can be used, rather than superimposing both terms. Consequently, we change the IDM into equation (4.6). The free and interaction term are separated and only the minimum of the two is used. Furthermore, the interaction term itself is changed by subtracting it from 1 such that it does not only result in deceleration and returns $dv/dt = 0$ in case of $s = s^*$.

$$\frac{dv}{dt} = a \cdot \min \left( 1 - \left( \frac{v}{v_0} \right)^\delta , 1 - \left( \frac{s^*}{s} \right)^2 \right)$$

(4.6)

The adapted IDM is referred to as the IDM+. By separating the free and interaction terms, the fundamental diagram of the IDM which is derived for equilibrium traffic, changes from a topped-off triangle into a triangle, as shown in figure 4.5. Note that the triangular fundamental diagram (and thus an expected interpretation of $T$) can also be achieved with the IDM by using $\delta = \infty$, as for $v$ just below $v_0$ it follows that $dv/dt = a \cdot (1–0–1) = 0$ at the desired headway. However, in doing so the free acceleration is simplified into constant acceleration until the desired speed is reached. In the IDM+ this still includes a reduction of the acceleration rate as one approaches the desired speed. This is more realistic as this is meant to include vehicle acceleration limitations and not just behavior (requirement 2). This limitation also plays an important role for traffic flow as it affects saturation flow. The IDM+ does however lose the ability of continuous differentiation, this is however not a requirement here.
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Figure 4.5: Equilibrium fundamental diagram of the IDM and IDM+. With $s_0 = 3m$, $v_0 = 120$ km/h, $T = 1.2s$, $\delta = 4$ and a vehicle length of 4m.

None of the mentioned car-following models meets requirement 9 (synchronization). From the description of the lane change model in the next section it follows that this can be achieved by ‘following’ a vehicle in an adjacent lane in particular circumstances. At this point, the exact circumstances are not important, but the car-following model should be able to deal with a wider range of input values to comply with requirement 9. Negative headways may occur for adjacent vehicles (see figure 4.6 left) and a negative dynamic desired distance headway ($s^*$) may occur for large negative values of $\Delta v$ which can occur after a lane change (see figure 4.6 right).

Figure 4.6: Situations for which the car-following model should be suitable. Occurrence of negative headway (left) and negative dynamic desired distance headway after a lane change (right) in multi-lane traffic, both for the grey vehicle.

In the IDM+ (and IDM) negative values of either $s$ or $s^*$ have the same effect as positive values because of the power of two in equation (4.6) (or equation (4.1)). This may cause two inappropriate situations:

- While being adjacent to a long vehicle, a negative headway of for example 15m may result in only mild deceleration or even acceleration, while the level of deceleration should indicate an unacceptable situation (should the two be in the same lane, e.g. when considering a lane change).
- If a much faster vehicle changes in front while allowing a normal headway, the large speed difference $\Delta v << 0$ may cause that $s^* << 0$, or even $|s^*| >> s$. In that case it follows that $1-(s^*/s)^2$ results in very strong deceleration.
We will therefore use the boundary conditions of equation (4.7). Negative headways are increased to just over zero (e.g. 1e-99 to prevent division by zero in a numerical implementation), which results in appropriate strong deceleration. The effect within the dynamic desired distance headway of drivers responding mildly to nearby leaders since the leader is much faster anyway, is limited up to the point that the equilibrium headway $s_0 + vT$ is fully compensated by the dynamic term (i.e. $s^* = 0$).

$$s > 0$$
$$s^* \geq 0$$ (4.7)

### 4.3 Lane change model

Lane change models have received less attention than car-following models, however, as discussed with the requirements of our driver model, lane changes are found to influence traffic flow and may cause breakdown. Particularly, there are very few models with relaxation or synchronization. We will discuss a number of lane change models and score these on requirements 3–9 and 11, see table 4.2. Note that requirement 10 is left out, as we assume that the lane change model alone should not be responsible for creating stop-and-go traffic, i.e. all lane change models create perturbations which the car-following model may develop into stop-and-go traffic.

Gipps (1986) was one of the first to formulate a model for lane changes that was intended to be integrated with a car-following model. In fact, the car-following model of Gipps (1981) is used to evaluate whether a gap could be accepted and the deceleration parameter from the car-following model is used as an acceptable threshold (twice its value). The lane change model has a number of considerations, but excludes the incentive to keep-right (requirement 5). Different considerations are active in three regions upstream of turns. Although the different considerations are not referred to as MLC or DLC, the considerations are hierarchical (requirement 6).

Cohen (2004) extends an existing simulation software (FRESIM) with a simple relaxation procedure. After a lane change, the desired headway is linearly increased from whatever actual headway value arises after a lane change, to the regular value over a fixed relaxation time. This simple approach produces vehicle trajectories similar to reality. However, the new model fails on many other requirements. In particular requirement 6 (non-hierarchical evaluations) as FRESIM uses MLC and DLC lane changes.

Wang et al. (2005) introduce a lane change model for merging traffic in which synchronization is implemented. This includes adjusting the speed and location as lane change preparation, by both the lane changer and potential follower (i.e. courtesy yielding). Also cooperative lane changes are included, which are lane changes performed to create a gap for another lane changer. Although these important phenomena are missing in most lane change models, the model by Wang et al. is limited to just this. It functions for a single onramp merging with a multi-lane freeway (of which only the lane adjacent to the acceleration lane is modelled), but fails to be applicable in other situations.

Kesting et al. (2007) introduce the lane change model MOBIL. It is designed around a simple principle where accelerations from the car-following model are used for both the gap-acceptance and the lane change incentive. Larger acceleration is preferred, and thus indirectly higher speed (requirement 4). They also introduce a bias towards the right (requirement 5)
and a virtual stand-still vehicle at the end of an onramp to force lane-changes towards the
freeway. This simple approach at least triggers lane changes from the on-ramp, but will not
work in general for the route incentive (e.g. an off ramp), failing requirement 3. The strength
of the model is its simplicity and the use of only 4 parameters (requirement 11), making it
easy to implement.

Toledo et al. (2007) recognize that most driver models fail in being properly integrated, i.e.
car-following being influenced by lane change considerations. They compose a decision tree
consisting of: target lane, gap-acceptance, target gap and acceleration. The acceleration model
is able to adhere to a selected gap (i.e. synchronization). Still, requirement 9 is not met as
there is no such behavior for the potential follower (i.e. courtesy yielding). Integration is
limited to gap selection and the model does not include relaxation (requirement 8). Finally,
the model is utility based and uses many parameters that are difficult to interpret (requirement
11).

Table 4.2: Overview of lane change models.

<table>
<thead>
<tr>
<th>Requirement</th>
<th>Gipps</th>
<th>Cohen</th>
<th>Wang et al.</th>
<th>MOBIL</th>
<th>Toledo et al.</th>
</tr>
</thead>
<tbody>
<tr>
<td>3 (route incentive)</td>
<td>✓</td>
<td>✓</td>
<td>×</td>
<td>×</td>
<td>✓</td>
</tr>
<tr>
<td>4 (speed incentive)</td>
<td>✓</td>
<td>✓</td>
<td>×</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>5 (keep right inc.)</td>
<td>×</td>
<td>×</td>
<td>×</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>6 (non-hierarchical)</td>
<td>×</td>
<td>×</td>
<td>–</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>7 (anticipative)</td>
<td>✓</td>
<td>×</td>
<td>×</td>
<td>×</td>
<td>×</td>
</tr>
<tr>
<td>8 (relaxation)</td>
<td>×</td>
<td>✓</td>
<td>×</td>
<td>×</td>
<td>×</td>
</tr>
<tr>
<td>9 (synchronization)</td>
<td>×</td>
<td>×</td>
<td>✓</td>
<td>×</td>
<td>×</td>
</tr>
<tr>
<td>11 (parameters)</td>
<td>✓</td>
<td>×</td>
<td>×</td>
<td>✓</td>
<td>×</td>
</tr>
</tbody>
</table>

The overall impression from table 4.2 is that no lane change model comes close to meeting all
requirements. Only the model by Gipps has a form of anticipation in considering the speed on
a lane, while all other models look to direct leaders only. For both relaxation and
synchronization only one model meets the requirement. These are models specifically
designed to implement these phenomena, but fail in most other aspects.

At this point we can either extend a current lane change model or propose a new model. The
basic principles of the above models prevent us from extending them in order to meet all
requirements. For example, making MOBIL anticipative would lead to determining
accelerations to vehicles that, in the context of the car-following model, are rather far away.
Or, reducing the number of parameters in the model by Toledo et al. would require a complete
redefinition. Instead a new lane change model named Lane change Model with Relaxation
and Synchronization (LMRS) is proposed which allows a general approach to include
relaxation and synchronization in many contexts (i.e. for whatever reasons drivers change
lane). To accomplish this it is hypothesized that drivers have underlying lane change desire,
but there is currently no direct evidence with which this can be proven. The occurrence of
synchronization or relaxation is based on the level of desire. Consequently, lane changes are
not classified by the reasons for which they are performed (i.e. MLC or DLC) but rather the
way in which they are performed, i.e. with or without synchronization and/or cooperation. We
call this a lane change process.
The LMRS is integrated with the car-following model IDM+. Note however that the lane change model can be integrated with any car-following model that calculates acceleration and uses a desired headway parameter. The integration is formed by:

- There are some shared parameters. These are considered 'car-following' parameters (i.e. they do not count in the number of parameters required for LMRS). In case the lane change model is integrated with another car-following model that does not have an appropriate parameter (e.g. if it has no maximum comfortable deceleration \( b \)), the parameter should be included as a lane change parameter.
- The acceleration from the car-following model is used as a measure whether a gap in an adjacent lane can be accepted for a lane change. The applicable headway depends on the level of lane change desire.
- After a lane change, the desired headway is set to the value as used for gap-acceptance. After this, it will be relaxed to a regular value.
- In certain circumstances (defined by lane change desire), synchronization may occur. This is implemented by following a leader in an adjacent lane using the car-following model.

In the remainder of this chapter ‘desire’ refers to lane change desire and ‘process’ refers to lane change process.

### 4.3.1 Lane change desire and process

This section will introduce the main mechanism of LMRS which is structured around lane change desire. The concept of lane change desire allows a flexible lane change model where various incentives to change lane result in a number of observed behaviors. There is however no evidence that drivers indeed have underlying lane change desire mechanisms similar to the description below. The desire \( d_{ij} \) to change from lane \( i \) to lane \( j \) that arises from the different incentives is combined into a single desire using equation (4.8).

\[
d_{ij} = d_{ij}^r + \theta v \cdot \left( d_{ij}^s + d_{ij}^b \right)
\]

We have a desire to follow a route \( (d_r) \), to gain speed \( (d_s) \) and to keep right \( (d_b) \), where the subscript \( b \) stands for bias to a particular side. The latter two are included with \( \theta v \) which is the level at which voluntary (discretionary) incentives are included. In the next section it is explained how these quantities are determined. Desire is meaningful between -1 and 1 where negative values indicate that a lane change is not desired (i.e. to stay or to change in the other direction). Values outside of the meaningful range may exist as incentives are added, but at a value of \(-1\) a lane change is considered fully (un)desired.

The total desire determines the behavior of drivers. Classification of lane changes is based on this behavior. We distinguish: Free Lane Changes (FLC), Synchronized Lane Changes (SLC) and Cooperative Lane Changes (CLC). To this end we split the desire range into four sub-ranges using three thresholds relating to the processes:

\[
0 < d_{\text{free}} < d_{\text{sync}} < d_{\text{coop}} < 1
\]
changing with higher desire. For little desire, no lane change will be performed. For a somewhat larger desire, FLC is performed requiring no preparation whatsoever. In SLC and CLC a potential lane changer is willing to synchronize speed with the target lane. This is achieved by following a vehicle in that lane. Concurrently this will align the vehicle with a gap (if there is a gap); this is thus a simple gap-searching model. In CLC, the potential follower will additionally start to create a gap by following the potential lane changer. This behavior is also called synchronization and may be triggered for several reasons such as the use of a turn indicator or the lateral in-lane position. An important reason is however the synchronization of the potential lane changer itself. From this behavior a driver may deduce that an adjacent driver wants to change lane. Throughout this thesis we assume that drivers are able to note whether the lane change desire of another driver is smaller or larger than $d_{coop}$.

Empirical evidence that drivers are willing to create a gap, at least at an on-ramp, was found by Daamen et al. (2010) where no merging vehicle is overtaken by multiple vehicles while on the acceleration lane. Note that although this concept shows observed behaviors, there is no proof that drivers indeed show these behaviors in relation to their lane change desire as hypothesized in the model. On the other hand, the occurrence of synchronization and cooperation may contribute to the noise in car-following models and changes in acceleration for which it is impossible to explain them purely from a car-following perspective, e.g. the noise in action points (Hoogendoorn et al., 2011). Note that these behaviors are assumed to exists depending on varying and different sources of lane change desire. These different sources show different dynamics, i.e. the route incentive slowly increases as one approaches a split, while the speed incentive may change abruptly when being overtaken or as traffic experiences a speed fluctuation. In other words, the different incentives show different action point frequencies which affect both lateral and longitudinal movement.

![Figure 4.7: Overview of LMRS. Lane change desire is based on three incentives. Lane change behavior, including the accepted headway and deceleration for a lane change, varies depending on the level of lane change desire.](image)

Besides the synchronization there are also desire dependent differences in the accepted headway and deceleration that would arise if a lane change is initiated. For higher desire drivers are willing to accept smaller headways and to decelerate more. Note however that the maximum deceleration will be smaller in our model than in most existing lane change models such as for example MOBIL (Kesting et al., 2007) where a value of $4 \text{ m/s}^2$ is used, which is rather high. This is achieved by allowing for relaxation and synchronization.

Before the details of driver behavior are presented, figure 4.8 shows the steps a driver undertakes each simulation time step. During a lane change, the only step is to follow both the
new and the old leader. Many of the steps while not changing lane are performed serial. Therefore, the figure mostly elaborates on the different decisions to initiate a lane change, synchronize for an own lane change, trigger cooperation for an own lane change, or to synchronize for another driver’s lane change. It should be noted that the latter (i.e. gap-creation) is only triggered concerning the direct leader in an adjacent lane and if a driver itself is also the direct follower. This is shown in figure 4.9 where vehicle B is creating a gap for its left-hand leader C. Vehicle A is not creating a gap for C since A is not the right-hand follower of C, although C is the left-hand leader of A. B is not creating a gap for D since D is not the left-hand leader, although B is the right-hand follower of D.

The derivation of lane change desire from the different lane change incentives will now be discussed.

Figure 4.8: Overview of steps in the driver model with references to the appropriate equations.
Figure 4.9: Occurrence of cooperation. Only direct leaders are considered.

4.3.2 Lane change incentives
This section will elaborate on the quantities of equation (4.8) in detail. In this section we assume asymmetric traffic rules, where drivers have to keep right and may only overtake on the left. Consequently a speed advantage is only considered to the left lane and in certain circumstances there may be a bias to the right. In our model we will not explicitly prevent vehicles from overtaking on the right, as this often happens in reality despite the prohibition. Note however that a speed advantage is not actively considered in the right-hand lane. Our model can be easily adapted for symmetric or left-hand traffic rules. Several parameters will be introduced in this and the next section. For an overview of all parameters the reader is referred to table 5.1.

Anticipation speed
The voluntary incentives as described in the following sub-sections use anticipation speed. This section will first elaborate on how this quantity is determined using the following definitions. Here, $v_{\text{lim}}$, $v_{\text{max}}$ and $v_{\text{lead}}$ are parameters of the model.

$$v_{\text{ant}} \quad \text{Anticipation speed, or the considered speed at a lane}$$
$$v_{\text{lim}} \quad \text{The speed limit}$$
$$v_{\text{max}} \quad \text{Maximum vehicle speed}$$
$$v_{\text{lead}} \quad \text{The actual speed of an (adjacent) leader}$$
$$\bar{v}_{\text{lead}} \quad \text{The considered speed of an (adjacent) leader given the headway}$$
$$x_0 \quad \text{Anticipation distance}$$
$$\theta \quad \text{Speed limit adherence factor}$$

The anticipation speed is intended to represent to which extent drivers take account of downstream vehicles. The further away the vehicle is, the less influence the vehicle has. The slower a vehicle is, the more it may reduce the anticipation speed. The anticipation speed $v_{\text{ant}}$ on a lane is a function of $v_{\text{lim}}$, $v_{\text{max}}$ and $v_{\text{lead}}$ where $v_{\text{lead}}$ is considered for several leading vehicles (potentially) on the assessed lane. The quantities $v_{\text{lim}}$ and $v_{\text{max}}$ are combined into a desired speed $v_0^k$ for lane $k$ as in equation (4.10). This expression includes a level of adherence $\theta$ with regard to the speed limit. For $\theta > 1$ this results in speeding and for $\theta < 1$ this results in the opposite. The desired speed from equation (4.10) is also part of the car-following model.

$$v_0^k = \min (\theta \cdot v_{\text{lim}}^k, v_{\text{max}}) \quad (4.10)$$

The speed of any leading vehicle $v_{\text{lead}}$ may be of influence on the anticipation speed. Clearly, a slow leader lowers the anticipation speed. However, if this leader is very far away, the vehicle is not considered at all. For this we use the anticipation distance $x_0$ which is also a parameter for the route incentive as described in a next sub-section. In line with equation
(4.11) we have two extremes. For \( s = 0 \) the vehicle is fully considered and for \( s = x_0 \) the vehicle is completely ignored.

\[
\tilde{v}_{\text{lead}}(s = 0) = v_{\text{lead}} \quad \text{(4.11)}
\]

\[
\tilde{v}_{\text{lead}}(s = x_0) = v_0
\]

For intermediate headways we interpolate linearly giving:

\[
\tilde{v}_{\text{lead}} = \left(1 - \frac{s}{x_0}\right) v_{\text{lead}} + \frac{s}{x_0} v_0 \quad \text{(4.12)}
\]

The anticipated speed on lane \( k \) is given by:

\[
v_{\text{ant}}^k = \min\left(v_{h}^{k}, \min_{m \in M_k} \tilde{v}_{\text{lead}}^m\right) \quad \text{(4.13)}
\]

where all leading vehicles from the set \( M_k \) are taken into account. This set is lane dependent and entails vehicles with a distance headway shorter than \( x_0 \). The set \( M_k \) by definition entails all vehicles on lane \( k \), all vehicles on lane \( k-1 \) (left) with \( d_{k-1,k} \geq d_{\text{coop}} \) and all vehicles on lane \( k+1 \) (right) with \( d_{k+1,k} \geq d_{\text{coop}} \). Vehicles with \( d_{k,j} \geq d_{\text{coop}} \) if \( k = i \) (\( i \) being the current and \( j \) being the considered lane) are however never considered. In other words; all vehicles on, or potentially on, a certain lane are considered for the anticipation speed on that lane. When assessing the anticipation speed on an adjacent lane, potential lane changers from the current lane are excluded. This exclusion is put in place to prevent situations where large speed differences between lanes are persistently maintained as drivers anticipate a slow speed on the faster lane due to other slow vehicles with a desire towards that lane.

**Speed incentive**

We assume that drivers may desire to change lane in order to increase their speed. We also assume that drivers are particularly anticipative when assessing the speed on a lane, i.e. if possible flying takeovers are performed where no speed is actually lost. Hence, to assess the desire we use the anticipation speed. Regarding the speed incentive the following assumptions are made:

- A full desire is experienced for a speed gain of \( v_{\text{gain}} \)
- Desire is linearly related to speed gain
- Drivers ignore a possible speed gain towards the right lane at high speeds (\( v_{\text{ant}} > v_{\text{crit}} \))
- Desire to change lane is reduced while accelerating

For the latter assumption we introduce \( a_{\text{gain}} \) as a reduction factor on desire. It is defined as:

\[
a_{\text{gain}} = a - \max(\dot{v}, 0) \quad \text{(4.14)}
\]

where \( a \) is the maximum acceleration from the car-following model. We also have \( \Delta_s \) which defines whether a lane change is possible and allowed (\( \Delta_s = 1 \)) or not (\( \Delta_s = 0 \)). Desire from the speed incentive is now defined as:
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\[ d_{ij-1} = \begin{cases} \frac{a_{\text{gain}}}{v_{\text{gain}}} (v_{\text{inter}}^j - v_{\text{inter}}^i), & \Delta_{ij-1} = 1 \\ 0, & \Delta_{ij-1} = 0 \end{cases} \]
\[ d_{ij+1} = \begin{cases} \frac{a_{\text{gain}}}{v_{\text{gain}}} \min\left(v_{\text{inter}}^j - v_{\text{inter}}^i, 0\right), & \Delta_{ij+1} = 1 \text{ and } v_{\text{inter}}^i > v_{\text{crit}} \\ \frac{a_{\text{gain}}}{v_{\text{gain}}} (v_{\text{inter}}^j - v_{\text{inter}}^i), & \Delta_{ij+1} = 1 \text{ and } v_{\text{inter}}^i \leq v_{\text{crit}} \\ 0, & \Delta_{ij+1} = 0 \end{cases} \] (4.15)

where \(k-1\) and \(k+1\) are the left and right adjacent lanes respectively. Note that a speed loss is always considered towards the right-hand lane to be balanced with other incentives.

As the speed incentive is based on anticipation speed, it is also based on adjacent vehicles that have \(d > d_{\text{coop}}\). In case these vehicles lower the anticipation speed, a driver may be triggered to perform a courtesy lane change. These are lane changes that are performed to create a gap for another vehicle.

**Route incentive**

If the current lane will not allow a route to be followed, lane change desire arises. This may be because the lane ends or because the lane will turn into another direction. For these situations we make the following assumptions:

- At relatively high speeds, the remaining time per required lane change determines desire. This is different from existing models such as Gipps (1986) and the lane change model in FOSIM (Dijker and Knoppers, 2004) where desire is based on distance. Desire starts at a remaining time of \(t_0\) per lane change.
- At relatively low speeds, the remaining distance becomes dominant in determining desire. Desire starts at a remaining distance of \(x_0\) per lane change.
- Desire increases linearly towards full desire for decreasing time or distance.
- Desire from the route incentive exists even if the lane change is (currently) not possible.

The latter assumption may trigger synchronization upstream of an actual merge location, which is common practice at merge locations. In order to determine desire for the route incentive we define \(x_r^k\) as the remaining distance, \(t_r^k = x_r^k/v\) as the remaining time given current speed \(v\) and \(n_r^k\) as the number of required lane changes, all for lane \(k\). Desire is now determined as:

\[ d_r^k = \max\left\{1 - \frac{x_r^k}{n_r^k \cdot x_0}, 1 - \frac{t_r^k}{n_r^k \cdot t_0}, 0\right\} \] (4.16)

which defines the desire to leave lane \(k\). To derive the desire to either the left or right lane we compare the desire on the adjacent and current lane. If the desire to leave the adjacent lane is smaller than the desire to leave the current lane, we use the desire to leave the current lane. The other way around we use the negative value of the desire to leave the adjacent lane, i.e. the lane change is undesired with the amount to leave the adjacent lane. This is defined as:
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\[ d^j_r = \begin{cases} 
  d^j_r, & \Delta^j_r = 1 \text{ and } d^j_r > d^j_r \\
  0, & \Delta^j_r = 1 \text{ and } d^j_r = d^j_r \\
 -d^j_r, & \Delta^j_r = 1 \text{ and } d^j_r < d^j_r \\
 -\infty, & \Delta^j_r = 0
\end{cases} \quad (4.17) \]

where \( \Delta_r = 1 \) indicates that the route can still be followed on the adjacent lane.

Keep right incentive

A simple incentive in accordance with the ‘keep right if possible’ traffic rule that is implemented in many models is a constant bias to the right lane, such as for example in MOBIL (Kesting et al., 2007). Indeed drivers will be inclined to change to the right. However, the phrase ‘if possible’ is stretched if drivers are forced to drive somewhat slower than their desired speed. In fact, the slugs and rabbits theory of Daganzo (2002) predicts more traffic on the left lane for typical percentages of slow traffic. However, if there is no slow traffic on the right lane for some considerable distance, a driver would at some point change right. Here, we only need to compensate the lane change threshold \( d_{free} \) whenever a vehicle anticipates an unhindered speed on the right lane.

Another influence on right-keeping behavior is a downstream turn. Drivers are not willing to change right if that lane will turn into a wrong direction, even in light traffic conditions. If a driver is within the region defined by \( t_0 \), it may experience a slight negative desire to change right. In that case we assume that drivers do not obey the traffic rule. In short, drivers will obey the keep-right rule only if the situation on the right lane is not worse with respect to speed and route. This is expressed as:

\[ d_{b,i}^{t,i} = 0 \]

\[ d_{b,i}^{t,i+1} = \begin{cases} 
  d_{free}, & v_{i+1}^{t+i} = v_0 \text{ and } d_{r,i+1}^{t,i+1} \geq 0 \\
  0, & \text{otherwise}
\end{cases} \quad (4.18) \]

Consideration of incentives

Depending on the urgency of mandatory lane changes, drivers may (partially) ignore voluntary lane change incentives. We therefore use \( \theta_v \), which is the level at which voluntary desire is included in the decision. It depends on the level of (negative) mandatory desire, as this may become dominant. For sake of argument we will use total voluntary desire \( d_v = d_r + d_b \). If both voluntary and mandatory desire are either negative or positive (\( d_r + d_v \geq 0 \)), voluntary desire is fully included as it coincides with mandatory desire. However, if voluntary desire is conflicting with mandatory desire (\( d_r + d_v < 0 \)), the voluntary desire is only partially included. For strong mandatory desire, negative or positive (\( |d_r| > d_{coop} \)), voluntary desire is ignored. For mild mandatory desire (\( |d_r| < d_{sync} \)), voluntary desire is fully included. In between, the consideration of voluntary desire is linearly interpolated. This is expressed as:
\[
\theta_i^j = \begin{cases} 
0, & d_i^j \cdot d_y^j < 0 \quad \text{and} \quad \left|d_i^j\right| \geq d_{coop} \\
\frac{d_{coop} - |d_i^j|}{d_{coop} - d_{sync}}, & d_i^j \cdot d_y^j < 0 \quad \text{and} \quad d_{sync} < |d_i^j| < d_{coop} \\
1, & d_i^j \cdot d_y^j \geq 0 \quad \text{or} \quad |d_i^j| \leq d_{sync} 
\end{cases}
\quad (4.19)
\]

At this point, all quantities in equation (4.8) have been explained and lane change initiation can be determined. What remains is the definition of relaxation and synchronization which will be discussed next.

### 4.3.3 Integration with a car-following model

**Gap-acceptance and relaxation**

A gap is accepted or rejected based on the deceleration that follows from the car-following model. Gaps that result in deceleration that is too large, are rejected as they are unsafe, uncomfortable or impolite. This is similar as in MOBIL (Kesting et al., 2007) and many other lane change models, except that the applicable headway is changed. The gap is accepted if both the lane changer \(c\) and the new follower \(f\) will have an acceleration that is larger than some safe desire dependent deceleration threshold as in:

\[
\dot{v}^g \geq -b^f \cdot d_i^{j,c}
\quad (4.20)
\]

with \(g \in \{c, f\}\). For clarity we explicitly mention to which driver the parameters pertain. The applicable headway for both the lane changer and the new follower is given by:

\[
T^g(d_i^{j,c}) = \min\left(T^g(t), \langle d_i^{j,c} \rangle, T_{min}^g + \left(1 - \langle d_i^{j,c} \rangle\right) \cdot T_{max}^g\right)
\quad (4.21)
\]

where,

- \(T^g(t)\) Current following time headway of vehicle \(g\) including previous relaxation
- \(T_{max}^g\) Regular (without influence of lane changes) following time headway of vehicle \(g\)
- \(T_{min}^g\) Minimum following time headway at maximum desire of vehicle \(g\)
- \(\langle d_i^{j,c} \rangle\) Lane change desire of vehicle \(c\) limited between 0 and 1

From equations (4.20) and (4.21) one can see that for larger desire, larger decelerations and shorter headways are accepted. If the lane change is actually initiated, both vehicle \(c\) and \(f\) should update the value for \(T^g(t)\) to the value of \(T^g(d_i^{j,c})\). The relaxation of the headway value is assumed exponential with relaxation time \(r\). In a numerical update scheme with time step \(\Delta t\) we can use:

\[
T(t) = T(t - \Delta t) + \left(T_{max} - T(t - \Delta t)\right) \frac{\Delta t}{\tau}
\quad (4.22)
\]

The assumption of an exponential relaxation is convenient for implementation as the increase in desired headway is solely dependent on the current value of the desired headway, i.e. no bookkeeping is required. From a behavioral perspective this also makes sense, as the rate of
increase of the desired headway is related to the urgency imposed by the extent into which the headway is shorter than sustainable.

**Synchronization and gap-creation**

When lane change desire is above the synchronization threshold, drivers will start to synchronize their speed with the leader on the target lane by applying the car-following model resulting in \( \dot{v}_{\text{sync}} \). Drivers will apply a maximum deceleration of \( b \) which is considered a both comfortable and safe deceleration. The maximum deceleration for speed synchronization is given by:

\[
\dot{v}^{\text{sync}} > -b
\]  

(4.23)

If an adjacent leader wishes to change lane with a desire above the cooperation threshold, a gap will be created. Gap creation is very similar to synchronization and we again apply the car-following model with a limited deceleration as in equation (4.23).

### 4.4 Evaluation of requirements

The requirements for the driver model are:

1. The longitudinal movement should include free conditions (i.e. free driving).
2. The longitudinal movement should only have accelerations within reasonable bounds, that satisfy vehicle acceleration and deceleration limitations.
3. The lateral movement should be influenced by the route or infrastructure for both merges and diverges.
4. The lateral movement should be influenced by desired speed.
5. The lateral movement should be influenced by the rule to keep right.
6. The lateral movement should result from non-hierarchical incentives.
7. The lateral movement should be anticipative.
8. The longitudinal/lateral interactions should include relaxation.
9. The longitudinal/lateral interactions should include synchronization.
10. The longitudinal/lateral interactions should include stop-and-go traffic.
11. The number of parameters for calibration should be reasonably small and parameters should be meaningful.

Requirements 1 and 2 are met by the IDM+. The LMRS (integrated with the IDM+) has been designed to include requirements 3–11. To show that these requirements are indeed met, three simple simulations are performed in a single scenario. In this scenario we have a freeway stretch of 2.5km with 2 lanes and an off ramp between 2.25km and 2.5km as in figure 4.10. On the right-hand lane there is a platoon of 5 trucks, all driving at their desired speed of 80km/h, at their desired headway and with a length of 15m. The 5 trucks are generated starting at \( t = 0 \)s. At \( t = 25 \)s a car is generated on the right-hand lane, at a desired speed of 130km/h and with a length of 4m. The car needs to take the off ramp. Other parameter values as used in these simulations are: \( a_{\text{car}} = 1.25 \text{m/s}^2, a_{\text{truck}} = 0.4 \text{m/s}^2, b = 2 \text{m/s}^2, T_{\text{max}} = 1.2 \text{s}, T_{\text{min}} = 0.3 \text{s}, s_0 = 3 \text{m}, x_0 = 300 \text{m}, v_{\text{gain}} = 50 \text{km/h}, d_{\text{free}} = 0.25, d_{\text{sync}} = 0.5, d_{\text{coop}} = 0.75 \) and \( \tau = 25 \)s. Three simulations are performed where the value for \( t_0 \) is 30s, 50s or 70s.
Results are shown in figure 4.11. Requirements 3-9 are met for the following reasons:

3. Figures 4.11a-c show that the car moves towards the off ramp (similar behavior for merges is trivial).
4. Figures 4.11a & 4.11b show that the car overtakes a number of trucks before slowing down for the off ramp.
5. This is convoluted in the figures with lane changes to the right-hand lane towards the off ramp, but this is obvious from equation (4.18).
6. The differences between figures 4.11a-c show that a balance is made between keeping left for speed, or keeping right in order to move towards the off ramp. In 4.11a all 5 trucks are overtaken, in 4.11b 4 truck are overtaken, and in 4.11c no trucks are overtaken. Figure 4.11e shows that in case of $t_0 = 50s$, the car first slows down to about 105km/h. Then, with the trucks being much closer, overtaking is still initiated as the incentive to stay right for the route is compensated. After overtaking 4 trucks, the incentive to change back has become strong enough such that synchronization is initiated, causing a drop in speed around $t = 70s$.
7. Figure 4.11d shows that in case of $t_0 = 30s$, the car hardly slows down before the decision is made to overtake. Thus, the lane change model is anticipative to such an extent that the car-following model has hardly responded to the slower trucks ahead. The lane change decision is made around 0.5km, or about 55s before the end of the off ramp. This causes that for $t_0 = 50s$ there is a stronger tendency to keep right (note that from the left-hand lane 2 lane changes are required, i.e. the route incentive is effective over $2 \cdot t_0$). For $t_0 = 50s$ the decision to change left and overtake is made later as the speed has dropped (increasing the remaining time till the off ramp slightly) and because the trucks are closer, lowering $v_{an}$ in the right-hand lane further.
8. Figure 4.11b shows that the car merges in between two trucks. The headway in front of the car is shown in figure 4.11f. The headway starts at 0.75s (at the end of a 3s lane change) and slowly increases to about 1s, i.e. we see relaxation. The next drop of the headway has to do with a lane change onto the off ramp itself.
9. Figure 4.11b shows that before the car changes to the right-hand lane, the slopes (i.e. vehicles speeds) become similar. Figure 4.11e shows that around $t = 70s$ the car slows down from about 125km/h to about 75km/h. The deceleration is in line with the maximum deceleration for synchronization $b$ (see equation (4.23)) as a drop of 50km/h over about 7s gives about $-2m/s^2$. The lowest speed is slightly below 80km/h, the speed of the trucks, as the driver is aligning with a gap behind a truck.
The calibration in the next chapter shows that the driver model meets requirement 10 and 11, completing the full set of requirements.

Figure 4.11: Simple off ramp scenario with truck platoon. Vehicle trajectories (a-c), speed of car (d-e) and headway of car (f) for different values of $t_0$ in the same scenario.
4.5 Conclusions

This chapter has presented a car-following and lane change model that together model freeway driver behavior. The car-following model is the IDM+ which adapts the IDM by separating the free and interaction terms such that capacity better matches the headway parameter.

A new lane change model called LMRS has been proposed that is based on a lane change desire that follows from a combination of the route, speed and keep-right incentives. Within the combination of incentives there is a trade-off in which the route incentive becomes increasingly dominant. For an increasing level of lane change desire drivers become more assertive. For little desire, no lane change will be performed. For slightly more desire lane changes are only performed in a free fashion. For medium desire drivers will start to synchronize with the target lane and for high desire, the potential follower on the target lane is assumed to create a gap as it notices the lane change desire. The relaxation phenomenon is implemented as drivers accept smaller headways for larger desire.

The concept of lane change desire is based on the hypothesis that drivers have such an unobservable mechanism. This means that no direct evidence is available to proof this concept. However, it does provide a model structure in which all the requirements (various incentives and various observed behaviors) are combined.

The calibration in the next chapter shows that the use of the IDM+ and LMRS complies with the requirements to evaluate in-car advice on speed, headway and lane. The models reasonably resemble regular traffic, especially regarding those aspects of traffic that the in-car advice will influence. Furthermore, the models easily allow advices to be incorporated, which is discussed in chapter 6. Chapter 6 will furthermore focus the impacts that in-car advice has on traffic. First, the next chapter will discuss the simulation framework in which the driver models are implemented.
5 Development of a microscopic simulation framework

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In order to evaluate the effects of Intelligent Transportation Systems (ITS), simulation is often used. Microscopic simulation is the simulation of individual vehicles, which is suitable for many ITS. For the in-car advisory system, it was decided to develop a new simulation framework, as existing simulation tools did not meet the requirements of openness, flexibility, adaptability and extendibility. In this chapter the design of the microscopic simulation framework which has been used to develop and investigate the effects of the advisory system is discussed. This framework has been designed for the development and evaluation of ITS in general, i.e. it is designed such that other ITS, such as for example (C)ACC or ramp metering from the state-of-the-art, can also be implemented. First, the requirements for such a framework are discussed after which the framework itself is presented. Included are descriptions of provided features such as vehicle generation. Note that the term ‘framework’ is meant as a software term, rather than a scheme describing a simulation method. Finally, the calibration and validation of the driver model from the previous chapter is discussed, including a sensitivity analysis of the model parameters.

5.1 Requirements

With the rise of Intelligent Transportation Systems (ITS), there is an increasing need to simulate such systems not only for the evaluation of systems before they are implemented, but also for the development itself. This poses a problem as existing simulation software cannot always be tailored towards the various ITS applications, requiring software development for each ITS application as depicted in figure 5.1.
The software development for simulation of ITS is a required step. Therefore, researchers need programming skills and time to develop their ITS application in simulation. There are two main approaches that can be used for the software development:

1. Development of a plug-in into an existing simulation framework.
2. Development of a simulation framework from scratch.

**Figure 5.1: General steps for software development and usage regarding simulation of ITS.**

The strengths and weaknesses of these two approaches become apparent if one considers the requirements of a simulation framework to develop and research ITS, which are:

1. **Open**: Open-source software allows full insight into the underlying simulation framework including possible consequences on model outcome and validity, which are vital for scientific research. Additionally, commands that are given to the simulation framework need to be fully understood to actually know what will happen. For example, when giving the command to start a lane change, will the framework perform additional checks on whether this is possible or not?
2. **Flexible**: Flexibility concerns the interaction between objects. The framework needs to be flexible to allow many different approaches of simulation. For example, it should be possible to implement a different method of vehicle generation or to change the way in which lane-changes are included (i.e. instantaneous, using temporary ghost vehicles, using an explicit lateral position, etc.).
3. **Adaptable**: Adaptability concerns the behavior of individual objects. It should be possible to change how objects behave. For example, the car-following model can be changed such that different acceleration values result. To clarify the difference with flexibility, adaptability in this case means that the driver determines a different acceleration value which other object rely on (i.e. to propagate the vehicle), while flexibility means that it should be possible to change the framework such that the car-following model provides a new speed instead of acceleration, which thus also requires a change in the vehicle propagation.
4. **Extendable**: Regarding ITS this is probably the most important requirement of a simulation framework. It should be extendable with new features, new objects, new types of in-car and road-side units, etc.
5. **Featured**: The framework should provide:
a. Network representation.

b. Vehicle generation.

c. Default driver models. For our application (in-car advice on freeways) required models are a car-following model, a lane-change model and a response to information from an on-board unit. Generally, responses to road-side units may also be required.

d. Facilities for controllers, on-board units and road-side units.

e. An (ever increasing) set of typical sensors, actuators and controllers such as loop-detectors and traffic light controllers.

Both development options have important drawbacks that need to be considered. The first approach, a plug-in into an existing simulation framework, has the drawbacks of reduced influence and insight into the underlying simulation framework (requirements 1-4). The influence an ITS can have on the simulation is governed by what a particular simulation framework allows. What is often desired is low-level influence such as specifics in vehicle performance or driver behavior. Commercially available simulation tools such as VISSIM and Paramics only partially allow for this. The reduced insight follows from parts of the simulation framework being shielded off, i.e. they are a black-box to the researcher. Open-source simulation frameworks are also available, such as SUMO (Behrisch et al., 2011) and the simulator by Treiber and Kesting (2010). These tools are therefore much more suitable for research, but still many choices are made about the structure and relation between objects such as lanes, vehicles and drivers within the framework. Partially this comes down to a matter of preferences, but available open-source simulation frameworks are not designed to facilitate the implementation of ITS systems (requirement 5.d). They for example have no easy manner in which a new type of road-side unit, including a response by drivers, can be implemented. Instead, many aspects of the simulation framework have to be adapted. Because of this, still a significant investment in the simulation software development for each ITS application is required.

Clearly, the second method of developing a simulation framework from scratch usually requires even more investment as one needs to consider all the relevant aspects of simulation including network representation, vehicle generation, vehicle-driver classes etc., while many of these aspects might not be of interest to the specific research. Consequently, this method is usually only used for small-scale applications, such as single-lane or single on-ramp networks using straight-forward vehicle generation. The resulting code is usually ad-hoc, not very well commented, not documented, and therefore not re-usable.

At the basis of the research performed in this thesis, a new simulation framework has been developed with the aim of i) implementing the advisory system, and ii) meeting the 5 requirements such that other researchers can use it for their ITS applications. Requirement 5.e has however not been a priority as the development of a set of feature rich controllers and units requires a lot of time while not being required for the research at hand.

5.2 Overview of the microscopic simulation framework

This section will elaborate on the framework which has been designed to meet the above requirements. First, an overview is provided in which the first four requirements are elaborated on. In the next sections, various aspects of the framework are discussed which are: the network, vehicle generation, drivers and vehicles and finally controllers and units, which partially meet with requirement five.
In order to meet the design requirements, a programming language has been selected and a class structure has been designed. The next sections elaborate on this. To meet the requirement of openness, it has been decided that the simulation framework is open-source, meaning that the non-compiled code is available.

5.2.1 Choice of programming language
Given the requirements as presented in the previous section, it is obvious that any programming language based on the paradigm of Object Oriented Programming (OOP) is a logical choice for the development of a simulation framework. Such languages are based on interacting objects where objects have different attributes and behaviors. Together, these objects simulate a complex system. Objects are of different classes which define which attributes and behaviors an object has. Objects are an instantiation of a class and multiple objects may exist of one class\(^2\). The OOP paradigm is often used in software with significant complexity and size, as it prevents cluttered code as software is being developed. An example description of OOP as used in a traffic simulator for heterogeneous traffic is developed by Venkatesan et al. (2008), where various aspects of OOP are also explained.

Throughout this section, the word *class* refers to a class in the OOP paradigm, unless explicitly stated otherwise. This may be particularly confusing when the phrase ‘driver class’ is used, as this is commonly used to indicate different groups of drivers such as for example aggressive and passive drivers. In this section ‘driver class’ refers to a class definition of a driver in OOP terms.

One particular aspect of OOP makes it suitable for building a simulation framework, which is called inheritance. If a class \(B\) inherits from \(A\), all attributes and behaviors in \(A\) are also present in \(B\). Furthermore, class \(B\) can have additional attributes and behaviors as well as redefine the inner-workings of behaviors of \(A\). Practically this also means that wherever software expects an object of class \(A\), an object of class \(B\) may also be used. These principles of OOP directly relate to the requirements of adaptability and extendibility. For example, a new driver class can be defined which extends the default driver class. Within the new driver class, the car-following model can for instance be redefined.

Inheritance may also be used to inherit from abstract classes. Of these classes there can be no instances (objects). Abstract classes are useful in defining a shell which contains functionality that is generally expected in the context, but the contents of which are by no means standard. In the context of traffic, a road-side unit is a clear example. It is desirable for the framework to define an abstract road-side unit class with the common functionality of being connected to the network, being able to run autonomous functionality, to register vehicles when they pass by and to be noticed by drivers. An object of such a shell makes no sense, but actual road-side units can extend the abstract class. As such, different types of road-side units can be implemented in the framework, as the framework only expects what is provided in the abstract class. What makes road-side units of different classes different is the behavior they define as autonomous functionality and when registering a vehicle, as well as the driver behavior when responding to different types of road-side units.

Many OOP languages exist, but their efficiency and user friendliness are by no means similar. Efficient and well known OOP languages are for example C++ and Java. We have chosen Java for a few reasons:

\(^2\) Some languages allow classes to limit the number of objects instances to 1, i.e. a singleton class.
- Efficiency, which is highly desirable for microscopic traffic simulation.
- Relatively user friendly and approachable.
- Automated memory management with the garbage collector.
- Easy integration in the Matlab environment which is often used by traffic scientists for scripting and data analysis.

5.2.2 Class structure

The class structure determines how objects are connected to one another. These connections are formed through attributes, e.g., an object (or objects) of one class are a property of another class. The class structure is used for interactions between different classes, such as invoking methods of other objects, requesting information from other objects, etc. The number of connections between objects should however be small. This increases maintainability of code, reduces possibilities of bugs, and generally keeps the structure more simple and understandable. For this reason, the class structure for the simulation framework is hierarchical. Each class in this structure has one parent, and one or more children. A parent-child connection in this context means ‘is connected to’, ‘is within’ or ‘is part of’. By linking up through the parents, and down through the children, from each class any other class can be reached.

As an example connection, the driver is a property of the vehicle. Strictly this is of course not true, as vehicle properties are the size, mass, engine power, etc. and most vehicles have no driver in them for most of the time. These sort of design issues quickly end in a discussion at the fundamentals of OOP: what is a class?, what is a property?, etc. In the simulation framework a hierarchical class structure has been chosen in which properties may also function as a ‘is connected to’, ‘is within’ or ‘is part of’ relation.

The hierarchical structure is presented in figure 5.2. At the top we have a model class, which functions to house global information such as the simulation time and a random number generator, as well as being the interface between the model and software which uses the model (e.g., a simulation script). Connected to the model object are a number of aspects which the next sections elaborate on. Some notes to clarify the overview at this point are:

- The abstract classes ‘Road-side unit’, ‘On-board unit’ and ‘Controller’ are empty shells of which derived classes provide actual functionality. For example the classes ‘Detector’ and ‘Traffic light’ provide functionality to a road-side unit. The abstract classes provide an easy integration of actual functionality within the simulation framework. For example, the ‘Controller’ class defines that controllers may have autonomous functionality that needs to be invoked.
- The ‘LcVehicle’ class is a type of vehicle which is in place at the target lane during a lane change such that two lanes are occupied. Common functionality in regular and lane-change vehicles is located in the ‘Movable’ class.
5.3 Network

This section discusses the representation of the network and how lane change information is embedded within this representation such that lane changes can be performed in accordance with the infrastructure.

5.3.1 Representation

For microscopic simulation, there are several general representations one can use for the network. Regarding the requirements for the simulation framework, flexibility is obtained if the network representation minimizes the dependencies between behavioral models and the network, while being able to provide input for the models. Other than these requirements, the network should provide the required information to driver models. This is however possible for any chosen network representation and it will be discussed further on how this is included in the chosen network representation. Some network representations are:

- **Continuous**: Space is two or three-dimensional and continuous, with bounds which represent the passable area. This representation is not commonly used for vehicular traffic as it requires complex models that are not fast to calculate. It is however used for pedestrian models, such as the model by Hoogendoorn and Bovy (2003).
- **Lane-based**: Space is divided in a set of lines along which objects can move, possibly with an explicit lateral deviation from the line. For vehicular microscopic models, this is the usual choice. It simplifies the lateral dimension but maintains a high degree of precision in the longitudinal dimension. Effectively it prevents the use of expensive spatial calculations regarding curvature and not colliding with other objects or moving off the road.
- **Cellular**: Space is divided in cells which usually have a size such that a single object may occupy the cell. This is the representation of many pedestrian models such as the model by Blue and Adler (2001), where one pedestrian fits in one cell. The downside of a cellular representation is the loss of precision inherent to spatial discretization as well as the simplifying assumptions of movement that have to be made. Flexibility is not provided by this network representation as it dictates the use of cellular models.

Figure 5.2: Hierarchical class structure of the simulation framework.
There are more types of representation, including hybrid forms. For example, vehicular Cellular Automata (CA) models are lane based, where the longitudinal direction is divided in cells. The most well-known CA model is the Nagel-Schreckenberg Model (Nagel and Schreckenberg, 1992), which is defined for a single lane. But CA models for more complex networks also exists, e.g. for a two-lane bi-directional road (Simon and Gutowitz, 1998).

Both continuous and lane-based network representation meet with the requirements for the simulation framework, while the cellular representations fail the requirement of flexibility. We choose the lane-based network representation as it is expected that this reduces the required computational effort. Regarding the driver model of the previous chapter, the network representation needs to provide the following information:

- Drivers need to be aware of surrounding vehicles in the same lane, in adjacent lanes, but also on a merging road upstream of merging sections, i.e. some distance upstream of where the roads become adjacent. Being aware entails knowing the speed, position and length of these vehicles.
- A transfer from one section to the next should occur without limitations by the section boundary itself. For example, a driver should be able to ‘see’ a vehicle on the downstream section and be able to determine a distance towards that vehicle.
- Drivers need to be able to change lane, but should also know when a lane change is not allowed due to lane markings.
- Drivers should be aware of the prevailing infrastructure, i.e. how many lane changes need to be performed (regarding lane-drops, taking off ramps, etc.) and within what distance? This is subject of the next subsection.
- Drivers should be aware of the speed limit.

In order to include such information, the following network representation is designed. The network is represented as a grid of lane objects that are both longitudinally and laterally connected. An example of such a grid is shown in figure 5.3. As drivers progress longitudinally, they are automatically transferred to downstream lanes. The same applies for lateral movement as soon as lane changes are finished. Vehicles on connected lanes are connected to each other such that longitudinal and lateral vehicle interactions can be determined. Connected vehicles are the upstream and downstream vehicle on the own and both adjacent lanes. Further vehicles can be found by secondary or higher order vehicle connections, i.e. neighbors of neighbors. However, the 6 possible direct neighbors are sufficient for most models regarding following the predecessor and changing lane safely.

Each lane has properties which are infrastructure based such as length, connected lanes, speed limit and lane change possibilities. Lane change possibilities are included as it is not always possible (or allowed) to change to an adjacent lane, such as for example at an on-ramp where lane changes are only allowed from, but not towards. Even both lane changes can be forbidden, for example due to a single or double continuous line.
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Figure 5.3: Network representation as a grid of lane objects. Each set of adjacent lane objects starts and ends at the same cross section. Arrows indicate the possible lane change direction(s) from each lane.

This representation of the network can also be used to allow traffic upstream of for example an onramp to react to each other. In many simulation frameworks this is a problem as vehicles can only ‘see’ each other at the acceleration lane. In reality, drivers will adjust their speed or create gaps before the acceleration lane. Therefore, these sections can be connected while lane changes in both directions are impossible, as indicated with the grey triangle in figure 5.3. This creates a 3-lane section upstream of the acceleration lane.

A merge taper (i.e. a lane as in figure 5.4 left indicated in grey) can also be represented as a dead-end lane in between two others. After the merging taper, the two adjacent lanes are longitudinally continued and laterally connected, i.e. there is a shift in the grid. This is shown in figure 5.4 for a merge taper, but a mirrored situation can be used to represent a diverge taper. Visually, the lanes can of course be as the actual situation without a sudden shift.

Figure 5.4: Representation of a taper merge using a shift in the lanes.

5.3.2 Lane change information

For lane change models to perform infrastructure based lane changes (also known as mandatory lane changes), information is required such as how many lane changes need to be performed and in what distance. The simulation framework provides an algorithm which couples this information to each lane object for the available (sub-)destinations. This prevents that different implementations of lane change models need complex algorithms to determine such information. Each lane has a ‘destination’ property which is simply a number. Zero means that the lane is not a destination while any number above zero means that the end of the lane is a destination. For a set of adjacent lanes, all lanes have the same destination number if appropriate.

The algorithm basically moves upstream from each destination and keeps track of the distance it covered and the lane changes it performed along the way. The current algorithm does not allow loops (i.e. a network where one can drive back to the same location), which is ok for the research at hand as only freeway sections are simulated. The formal description of the algorithm is given in appendix B. This algorithm results in information such as presented in figure 5.5, where for the two possible destinations of the small example network the lane
change information is provided. Note that no information is provided if a destination cannot be reached from a specific lane.

![Figure 5.5: Lane change information. With number of required lane changes \( n \) and distance within which these have to be performed \( x \) that results from the algorithm that determines this for two destinations.](image)

The algorithm only provides information for the nearest cause of required lane changes. Usually this is what drivers respond to, but there may be situations in which a further cause is more critical. Here, critical is defined as ‘remaining distance per required lane change’. For example, a driver might need to perform 1 lane change due to a lane drop in 1000m (i.e. 1000m per lane change) while the driver needs to take an off ramp requiring 3 lane changes in 2400m (i.e. 800m per lane change). If desired, the algorithm could be adjusted to only provide the most critical information rather than the information of the nearest cause. This is however a matter of choice relating to driver behavior. Also, depending on the lane change model, the most critical information in terms of distance per lane change might not result in lane changes being performed in time at for example a lane drop.

### 5.4 Vehicle generation

Following requirement 5.b in section 5.1, a microscopic simulation tool requires the generation of vehicles on the network through vehicle generators. Vehicle generators create traffic and function as an origin of traffic. This can be regarding an area or cross-section, here we only consider the latter. The main difficulty of a vehicle generator is to represent traffic as it would enter a network, while simultaneously being consistent with the models used to describe vehicle movement (e.g. the car-following model). Detailed descriptions of vehicle generators are not readily available in literature, though much literature about headway distributions is available (some of which will be discussed further on); however this is only a single aspect of vehicle generation. Many of these headway distributions try to cope with the fact that the arrival of vehicles is a composite of i) stochastically independent vehicle arrivals and ii) interactions between vehicles that influence the headway and therefore the exact time when vehicles cross a given cross-section.

Cowan (1975) was one of the first to mention distributions in relation to headways in traffic. Cowan mentions that independent arrival of vehicles at light volumes can be described with a Poisson process, which describes the time when random and independent events occur. The time between consecutive events in a Poisson process has an exponential distribution. Yang and Koutsopoulos (1996) for example use the exponential distribution in case of low demand, they do not describe how headways are determined in case of high demand. To cope with
vehicle interaction, often parameterized headway distributions are used, which still do not guarantee consistency with the models. Cowan for example also mentions the shifted exponential distribution, denoted by M2, where the exponential distribution (denoted by M1) is shifted by a minimum headway $h_{\text{min}}$, making sure the average arrival rate remains the same. This is for example used in TSIS/CORSIM. A third model (M3) extends this by introducing a fraction $\theta$ of vehicles that are in following mode, following at a headway of $h_{\text{min}}$, while the remaining traffic is in free mode and follows a shifted exponential distribution. The difference between these distributions, for an equal demand level, is given in figure 5.6. A fourth model (M4) is also introduced by Cowan, which basically adds a random distribution to the value of $h_{\text{min}}$.

![Cumulative distribution function](image)

**Figure 5.6:** Gross headway distributions for $q = 1800$ veh/h. With $h_{\text{min}} = 1$ s in M2 and M3 and $\theta = 0.3$ in M3.

Besides these headway distributions that are based on the exponential distribution, many other distributions are reported in literature, with different success in terms of their fit to empirical headway data. Riccardo and Massimiliano (2012) for instance mention the exponential, lognormal, gamma, Erlang, inverse Gaussian, inverse Weibull, log-logistic, Pearson 5 and Pearson 6 distributions, although their analysis uses even more. They found the inverse Weibull distribution to fit best to their data from rural roads. Zhang et al. (2007) on the other hand found the double displaced negative exponential distribution to fit best on both regular and HOV (High Occupancy Vehicle) lanes.

All of the above headway distribution functions have significant drawbacks. The simple headway distribution functions such as the M1 model introduce unrealistically small headways and ignore the fact that vehicles interact. More complex headway distribution functions have the drawback of being parameterized, requiring calibration and introducing parameters to the already large parameter set required for microscopic simulation in general. Whether simple or complex, all mentioned headway distribution functions do not guarantee in any way that generated vehicles are positioned on the network at a time and location and with a speed that is consistent with the used models for vehicle movement. For instance, in the M2 model, the use of $h_{\text{min}}$ is not consistent with car-following models. When approaching a much slower vehicle, a value of e.g. $h_{\text{min}} = 2$ s (a large value allowing only a maximum demand of 1800 veh/h) is not sufficient.
To overcome these drawbacks, a new vehicle generator has been designed which strictly separates independent vehicle arrivals from model-dependent vehicle interactions. In-fact, the car-following model is used to incorporate vehicle interactions. The vehicle generator is appropriate for freeways, as used in this thesis, but might be less appropriate for urban settings. Note however that one could easily extend the vehicle generator by replacing the distribution of independent vehicle arrivals with a distribution which includes the influence of intersections and traffic lights. The model-dependent vehicle interactions can still be separately applied following the method described in the next section.

5.4.1 Demand and headway
If we, for the moment, ignore vehicle interaction, the exponential distribution can be used to describe vehicle arrivals. Note that for this we also need to ignore other influences which make vehicle arrivals dependent, such as traffic lights. This distribution has a single parameter $\lambda$, which is the reciprocal of the mean time between events $h^*$, as in equation (5.1).

$$\lambda = h^{*-1} \tag{5.1}$$

The mean time between events, which for traffic is the same as the mean gross headway between vehicles, depends on the current demand level $q(t)$ as in equation (5.2).

$$h^* = q(t)^{*-1} \tag{5.2}$$

Substituting (5.2) in (5.1) we obtain equation (5.3), i.e. parameter $\lambda$ is equal to the current demand level (where demand should be in veh/s to obtain headways in seconds).

$$\lambda = q(t) \tag{5.3}$$

In our vehicle generator, demand can be set as a multi-linear function where demand levels $Q$ at specific times $T$ are provided and linearly interpolated for intermediate moments. Given that a vehicle is generated at time $t$, the next vehicle should be generated at time $t + h$, where $h$ is a randomly drawn gross headway following the exponential distribution. The cumulative distribution function (cdf) of the exponential distribution is:

$$F_h = 1 - e^{-\lambda h} \tag{5.4}$$

To draw random values in simulation, one can rewrite equation (5.4) into the inverse cumulative distribution function:

$$h = -\ln \left(1 - F_h \right) \quad \frac{1}{\lambda} \tag{5.5}$$

Next, a value for $F_h$ can be determined as a random number drawn from a uniform distribution in the range $[0, 1]$, denoted by $R$. Recognizing that $R$ is equally distributed as $1 - R$, equation (5.6) can finally be used to draw random headways with an exponential distribution.

$$h = -\ln \left(R \right) \quad \frac{1}{\lambda} \tag{5.6}$$
Still ignoring vehicle interaction, equation (5.6) can be used to determine all vehicle arrivals. The exponential distribution does however not guarantee that the current demand is actually obtained. The resulting demand may be somewhat smaller or larger. When using empirical data to define demand, this is undesired. Therefore, the vehicle generator also provides another mode of operation, which changes two aspects of the process described above:

- The current demand $q(t)$ is not linearly interpolated, but equal to the last value of $Q$ for which it holds that $T \leq t$. For example, demand can be equal to 1-minute aggregated detector measurements.
- The gross headway $h$ is not drawn from the exponential distribution, but is simply equal to $h^*$, i.e. vehicles arrive uniformly. This ensures that, for example, during one minute, the number of generated vehicles is exactly equal to the number of vehicles counted in the data.

The method using uniform demand should be used with care, as it may generate a rather flattened demand, omitting peaks in demand that may for instance cause traffic breakdown. It can however be used if:

- Demand $(Q, T)$ can be provided in sufficient detail. For instance, 1-minute aggregated data might be ok, but hourly demand data is most probably not.
- Upstream of locations on the network where traffic might breakdown (i.e. potentially active bottlenecks), there should be sufficient space such that traffic can form platoons as faster vehicles catch up with slower vehicles.

The two above requirements are connected since more detailed data may lead to less space being required for platoons to form.

So far, we have ignored vehicle interactions. However, especially in case of the exponential distribution, values for $h$ can be very small and even approach 0. Clearly, this results in unrealistically small headways. Moreover, the speed of the previous vehicle may be considerably lower than a generated vehicle, which would either require the speed of the generated vehicle to be lower, or the headway to be larger. This is where consistency with the models describing vehicle movement needs to be guaranteed. Only these models can tell us what a reasonable headway for vehicle generation in simulation is. To overcome this problem, the vehicle generator in the simulation framework can create vehicles in two distinct manners. It can create free vehicles or it can create queue (also including free flow car-following, i.e. platoon) vehicles. For each vehicle, the moment of independent arrival is determined using $h$, relative to the previous moment of independent arrival. This is thus a pure Poisson process if the exponential distribution is used. The generation of free and queue vehicles is defined as:

- Free vehicles are generated at the minimum of the speed of the first downstream vehicle (if any) and their desired speed, and at the moment determined by $h$. This moment lies somewhere during the previous time step of simulation, and the location where the vehicle is generated is as if the remainder of the previous time step has been covered at the set speed. The car-following model is invoked to determine the acceleration. If this is negative, the free vehicle generation has failed. Note that using the speed of the first downstream vehicle is necessary, even for far away vehicles, as these might otherwise trigger slight deceleration which causes the vehicle to be generated as a queue vehicle. That is, at a considerable distance on the network
directly following the first downstream vehicle. The considerable distance would then effectively create a generation time before the moment determined with $h$.

- A queue vehicle is generated at the speed of the first downstream vehicle and at the desired headway behind this vehicle. The desired headway should be provided by the car-following model. If insufficient space for this headway is available (i.e. the vehicle would be generated upstream of the generator), the queue vehicle generation has failed and the vehicle will be generated in a later time step.

Using these two methods of generation and a queue counter, the algorithm of vehicle generation works as depicted in figure 5.7. It starts by generating queue vehicles for a present waiting queue, so long as these vehicles can be generated. Next, for as long as new vehicle arrivals are determined to be in the previous time step, new vehicles are either generated or added to the queue if this fails.

**Figure 5.7: Vehicle generation algorithm using two methods of vehicle generation.**

Effectively, headways $h$ that are too short for a next vehicle will result in the next vehicle being in car-following mode and slightly delayed. In this manner, a pure Poisson arrival process is translated partially into platoons, incorporating vehicle interaction consistent with the models describing vehicle movement.

This could also be viewed from the perspective of queuing theory as an M/G/1 queue (Zhang et al., 2007). Here, M stands for Markovian arrival (i.e. a Poisson process), the ‘1’ stands for a single server (i.e. a single lane) and G stands for a general service time distribution. Service time of a vehicle should be regarded as the gross time headway it requires, including the leader’s vehicle length. Even for a simple car-following model in which the desired time headway is deterministic, the leader’s vehicle length and a usual additional stopping distance create a speed dependent gross time headway (i.e. service time). The distribution function of G is thus not trivial even for simple car-following models. Moreover, the vehicle generation is
unaware of how desired headway is defined. Nonetheless, it is able to request the resulting desired distance headway of a given vehicle with given speed to implement G in the queue.

If the service time is simplified into a (known) deterministic process, obtaining an M/D/1 queue, time in the queue (i.e. delay by being in a platoon without the occurrence of congestion at the vehicle generator) can be analytically derived. With equation (5.3) the arrival rate $\lambda$ of the Poisson process for arrivals can be calculated from flow $q$. For the service time $t_s$ (i.e. gross time headway) we use a simple model of a desired headway as in equation (5.7) where $T$ is the desired net time headway, $s_0$ is a stopping distance, $l$ is the vehicle length and $v$ is vehicle speed.

$$t_s = T + \frac{s_0 + l}{v} \quad (5.7)$$

We obtain a maximum service rate as $\mu = 1/t_s$. In queuing theory the utilization $\rho$ is the ratio between arrival rate and service rate, i.e. $\rho = \lambda/\mu$. With the deterministic service time we have an M/D/1 queue for which equation (5.8) can be used to determine the average time in queue $t_q$.

$$t_q = \frac{\rho}{2\mu(1-\rho)} \quad (5.8)$$

To show the relation between flow and average time in queue, we assume homogeneous traffic with $T = 1.2s$, $s_0 = 3m$ and $l = 4m$. For the speed we assume a linear relation with flow, where $v = 120\text{km/h}$ for $q = 0$ and $v = 90 \text{ km/h}$ for $q = 2400 \text{ veh/h}$. Note that the simple model for the desired headway as used in equation (5.7) gives a maximum flow of just over 2400 veh/h at 90 km/h given the assumed values for $T$, $s_0$ and $l$. Figure 5.8 shows that the time in queue is small for flows up to about 2000 veh/h, but steeply increases as the flow approaches the maximum flow. Note that $t_q$ represents the average time by which the arrival of a certain vehicle is delayed for vehicle generation (given the assumed model for desired headway) and is only valid for as long as congestion does not spill back to the location of a vehicle generator. In case of congestion, service time $t_s$ depends on downstream traffic conditions and would become larger, also resulting in larger $t_q$.

![Figure 5.8: Relation between flow and average time in the vehicle generation queue.](image)
5.4.2 Classes
In traffic, no two vehicles and no two drivers are exactly the same. Differences between vehicles and drivers are often incorporated in simulation by defining a set of vehicle-driver classes. This is a simplification of reality as one for instance uses one class for trucks and one for cars, where all trucks and all cars are equal. However, within a single class one can define differences. For instance, the desired speed of drivers in cars can be drawn from a random distribution.

The previous section has described the arrival process of vehicles, and how this is demand dependent. Similarly to the arrival process, the class of a vehicle and driver that arrives is also a random process. In fact, for each class a separate arrival process could be used, where the mean headway $h^*$ (and thus also demand) could be made class dependent. However, if one would define demand of one class to be a percentage of the total demand, one can simply use that percentage as a probability that the next vehicle is of a given class, where all vehicle arrivals are based on a single process.

The main model object in the simulation framework contains a set of vehicle-driver classes, which are defined by a default vehicle (including the driver and possibly an on-board unit) for each class. For each vehicle generator, probabilities are provided for each of the vehicle-driver classes. Every time a new vehicle is to be generated, these probabilities are used to randomly select a vehicle-driver class for the new vehicle. In the current simulation framework these class probabilities are static, but one could easily implement them dynamically.

5.5 Drivers and vehicles
A vehicle and the driver inside are basic elements in any microscopic traffic simulation, and are sometimes combined in a single object. We have chosen to keep the driver and vehicle (and on-board unit) separate as this better structures functionality. The requirements of vehicles and drivers are:

- Allowing longitudinal movement. Drivers should be able to perform a car-following model, where headways between vehicles should be available.
- Allowing lateral movement. Drivers should be able to perform a lane-change model while being aware of surrounding vehicles, including vehicles that are merging into a potential gap where the considered driver also might want to merge into.

The simulation framework invokes a method of the driver to determine both acceleration and lateral movement (i.e. lane change speed). The content of this method is flexible and may utilize a number of other methods. In this way, the car-following and lane change model can be integrated into any desired extent. To determine acceleration and lateral movement, information from many objects may be required. By default, road-side units within a certain range may be noticed, affecting parameters (e.g. dynamic speed limit) or setting acceleration (e.g. traffic light). Next, surrounding vehicles are used to evaluate lane changes and to set a (lower) acceleration. The default driver behavior is described in chapter 4; behavior for urban situations is briefly discussed in chapter 8. Information from the on-board unit may be incorporated within this behavior. The set acceleration and lateral movement are used by the framework to move vehicles and to start or end lane changes.
Vehicles contain a driver and are located at a certain coordinate on a lane. Each vehicle is connected with up to six surrounding vehicles, the upstream and downstream vehicle on the current and both adjacent lanes. These connections allow vehicle interactions such as car-following and gap-acceptance for lane changing, and are automatically updated by the framework. They actually point to Movable objects, which represents either an actual vehicle or a virtual vehicle that is located at the target lane during a lane-change, i.e. an LcVehicle in figure 5.2. Simulating lane changes in this way is one of the few design choices in the framework that may influence, or limit, the underlying models, though the framework could be changed to deal with lane changes in a different manner. The use of temporary vehicles has been selected as it is a convenient way to allow proper vehicle interaction. It prevents that multiple vehicles change into the same gap, which may not only lead to unrealistic situations, but presents the simulation framework with very complex situations regarding which vehicle is the (for example) left upstream vehicle. Another design choice is that vehicles that do not change lane in time in order to follow their route (or at a lane drop or onramp) are deleted from simulation. This is considered more realistic than forcing the vehicle on an adjacent lane, which may cause collisions and is essentially unnecessary interference of the framework with respect to the lane change model. A message is however provided such that users may adapt their lane change model if this occurs. Headways between two movable objects can be supplied by the framework, which is useful for driver models.

5.6 Controllers and units

Part of any ITS application is some form of control or autonomous functionality of system components. Three types of main system components exist: road-side units, on-board units and controllers, as can be learned from the ITS in the state-of-the-art of chapter 2. The framework provides empty shells for these system components such that development of new components only has to focus on the component functionality itself. Autonomous functionality and component interactions are automatically facilitated by the framework. The following sections will elaborate on the three different kinds of system components. Note that these system components need not be part of what is referred to as ITS, but conventional systems as well.

5.6.1 Road-side units

Road-side units (RSUs) are units that are, as the name suggests, at the road side. Strictly, they can also be above or underneath the road. Examples of RSUs are traffic signs, cameras, loop detectors, traffic lights, etc. The main aspect distinguishing RSUs from other types of units is that RSUs are location based. They are located at a specific location on the network and are noticed by drivers around that location or they register vehicles at that location. The simulation framework can have a number of RSUs connected to a lane, each with a specific longitudinal coordinate at that lane. RSUs are not necessarily an actual road-side object, but may also be used to incorporate infrastructural information not provided by the lane objects, such as for example bends for which drivers need to slow down. RSUs may have autonomous functionality which is invoked by the framework.

The framework by default provides a dual-loop detector which aggregates vehicle counts and speeds over a predetermined period and a traffic light with a simple fixed-time controller for a single light.

5.6.2 On-board units

On-board units (OBUs) are devices within vehicles, which have autonomous functionality and may communicate either to road-side or centralized units or servers. These communications
are used in ITS to obtain data for road-side or centralized traffic control, and to provide information to the driver or tasks for the vehicle. Currently available examples of RSUs are navigation devices (with or without live traffic information) or for example an adaptive cruise control (ACC). One might argue that an ACC controller is part of the vehicle, and not a separate device, but OBUs in the simulation framework are intended to contain non-human intelligence of the vehicle-driver unit.

Interaction between the driver, vehicle and OBU is provided in a very flexible manner. The simulation framework requests the driver to set the acceleration and lateral movement of the vehicle. The implementation of this request is free to use methods of the OBU or vehicle in order to achieve this. For example in case of ACC, the driver may request the OBU to set the vehicle acceleration. Autonomous functionality of the OBU is invoked by the framework automatically.

5.6.3 Controllers
Controllers in simulation can represent anything from a centralized traffic management center to a local traffic light or ramp metering controller. The simulation framework will invoke the traffic control automatically. Connecting controllers to appropriate RSUs (e.g. traffic light controller to the traffic lights and detectors) occurs at model setup. OBUs can connect to a controller as soon as a vehicle is generated. The framework does not provide default controllers, but an empty shell. This allows any form of traffic optimization algorithms, both locally and centralized, to be created.

5.7 Calibration, validation and sensitivity analysis
In this section we describe the model calibration and validation. We discuss the model implementation, the calibration setup and the data. At the end the results are shown.

5.7.1 Numerical implementation
Although the IDM+ and LMRS have been presented in minute detail, the precise implementation can still have influence on model results. In this section we briefly present our implementation. The procedure from figure 4.8 should be performed for each driver at each time step. The minimum acceleration based on all applicable leaders $g_{\text{min}}$ should be used. In order to prevent negative speeds, the acceleration of vehicles is limited as in equation (5.9).

$$\dot{v} = \max \left( g_{\text{min}}, -\frac{v}{\Delta t} \right)$$  \hspace{1cm} (5.9)

During a time step, accelerations are assumed constant. The update scheme for speed and position is provided in equation (5.10).

$$v(t + \Delta t) = v(t) + \dot{v}\Delta t$$  
$$x(t + \Delta t) = x(t) + v(t)\Delta t + \frac{1}{2} \dot{v}\Delta t^2$$  \hspace{1cm} (5.10)

We have used a lane change duration of 3s taken from FOSIM (Dijker and Knoppers, 2004). The value also complies with empirical findings (Thiemann et al., 2008). During a lane change a virtual and temporary vehicle is placed on the target lane to prevent other lane
changes towards the same location. Over the first 100m of the network, lane changes are never performed as upstream vehicles that influence such a lane change may not yet be generated. We have used $\Delta t = 0.5s$ (from FOSIM) as a balance between short running times and modeling precision. On a 2.8 GHz CPU this results in running times in the order of 10-50 seconds per modeled hour depending on the level of congestion (i.e. number of vehicles ranging from 150 to 600). Note that the time step influences both car-following and lane changing, however, if the time step is sufficiently small, overall properties of the models are maintained without numerical errors such as overshooting when stopping. Although single-lane trajectories may show only small differences in space, speed and acceleration if one follower is considered and when varying $\Delta t$ from very small values to 0.5s, this may not be true for platoons as any difference will influence a number of followers. However, the small difference of a single follower shows that important properties, e.g. the “intelligent” approaching, are maintained. The lane change model, however, has a more binary result, especially the lane changes themselves. If a gap is available during less time than $\Delta t$, it may be missed and a lane change is postponed or not executed. However, for lane changing $\Delta t$ has a clear behavioral interpretation since $1/\Delta t$ can be regarded as a screening frequency. In fact, it is reasonable to assume that drivers do not continuously consider changing lane. In conclusion, the value of $\Delta t$ influences outcome, but if sufficiently small, does not devalue it.

5.7.2 Calibration setup
To calibrate the driver model we take a similar approach as Ossen and Hoogendoorn (2009), which is to calibrate a subset of the parameters to free flow traffic, and the remaining parameters to congestion traffic. This is shown in figure 5.9. Both the free flow and congestion scenarios will involve an iterative process to determine the calibrated parameter values. Such iterative processes may take a lot of time and as such the use of two scenarios has three benefits: the lower degree of freedom per scenario reduces the total number of simulation runs, convergence is reached in less iterations, and finally the free flow simulation runs involve less time due to the lower number of vehicles. This approach can only work if the parameters that are calibrated in free flow are not sensitive to the values of the remaining parameters. Since the free flow scenario is calibrated with the initial values for the remaining parameters, this would lead to different values for the free flow parameters. The sensitivity analysis however shows that using two scenarios is appropriate.

![Figure 5.9: Overview of calibration scenarios and parameters.](image_url)

To further reduce the time required for the calibration process, not all of the in total 20 parameters are calibrated. An overview of all model parameters is given in table 5.1. Which parameters are calibrated in free flow, in congestion, or not calibrated can be seen in figure
5.9 and table 5.1. For the parameters that are calibrated, it is assumed that these are sensitive in their respective scenario, and not sensitive in the other scenario. This is confirmed by the sensitivity analysis. For parameters that are not calibrated it is assumed that they are fairly well known, or can be derived otherwise. These evaluations are presented in the last column in table 5.1. Finally, \( d_{\text{sync}} \) and \( d_{\text{coop}} \) are related to the value of \( d_{\text{free}} \) as in equation (5.11), where the range from \( d_{\text{free}} \) to 1 is equally divided. This not only gives us a reduction of 2 parameters to calibrate, it also ensures that \( d_{\text{free}} < d_{\text{sync}} < d_{\text{coop}} \) is satisfied.

\[
d_{\text{sync}} = d_{\text{free}} + \sqrt{1-d_{\text{free}}}
\]
\[
d_{\text{coop}} = d_{\text{free}} + \sqrt{1-d_{\text{free}}}
\]

We apply two classes being passenger cars and trucks. Most parameters are equal between classes except for the maximum acceleration (\( a \)), vehicle length (\( l \)) and desired speed. For cars we assume the desired speed is given by driver preference \( \theta_{\text{car}} = \mathcal{N}(v_{\text{des},\text{car}}, \sigma_{\text{car}})/v_{\text{lim}} \) where \( \mathcal{N}(v_{\text{des},\text{car}}, \sigma_{\text{car}}) \) is a Gaussian distribution with mean \( v_{\text{des},\text{car}} \) and standard deviation \( \sigma_{\text{car}} \). For trucks we assume the desired speed is given by the maximum vehicle speed \( v_{\text{max,\text{truck}}} = \mathcal{N}(v_{\text{des,\text{truck}}}, \sigma_{\text{truck}}) \).

The error measure \( \varepsilon \) which should be minimized is based on a comparison of real and virtual detector data at lane level. In free flow we use:

\[
\varepsilon_{\text{free}} = \sqrt{\frac{\sum_{n=1}^{N} \left( \sum_{t=1}^{H} q_{n,t}^{\text{real}} - \sum_{t=1}^{H} q_{n,t}^{\text{sim}} \right)^2}{N}} + 25 \cdot \sqrt{\frac{\sum_{n=1}^{N} \left( \frac{H}{\sum_{t=1}^{H} v_{n,t}^{\text{real}}} - \frac{H}{\sum_{t=1}^{H} v_{n,t}^{\text{sim}}} \right)^2}{N}} + m \tag{5.12}
\]

where \( t = 1 \ldots H \) is the considered time period, \( n = 1 \ldots N \) are the considered detectors on individual lanes, \( q \) is a 1-minute flow count, \( v \) is the arithmetic mean speed of all vehicles within a minute and \( m \) is the number of deleted vehicles in simulation. The first part of equation (5.12) is the root mean squared error (RMSE) of hourly flow (as \( H = 60 \)) of all detectors. By aggregating flow we suspect that the solution space is more smooth, leading to more reliably calibrated parameter values. Note that in free flow, generated traffic will essentially pass over the network unhindered, i.e. parameter values within reasonable bound do not influence this. However, the distribution of traffic over the lanes at different cross-sections is influenced. Thus, the calibration will fit the model to the distribution of traffic over the lanes, a required phenomenon for the driver model and for evaluating lane advice. The second part of equation (5.12) is the RMSE of the harmonic mean of speed measurements. We include the RMSE relating to speed with a factor of 25 meaning that an error of 25 veh/h is weighed equally to an error of 1 km/h. Finally we include the number of deleted vehicles as, depending on the parameter values, drivers in the model may not be able to change lane before they have to. This is included to keep the number of deleted vehicles small.
Table 5.1: Overview of model parameters.

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Initial or assumed value</th>
<th>Calibration(^a)</th>
<th>Calibrated value</th>
<th>Remarks(^b)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(a_{truck})</td>
<td>0.4 m/s(^2)</td>
<td>fixed</td>
<td></td>
<td>Taken from FOSIM (Dijker and Knoppers, 2004).</td>
</tr>
<tr>
<td>(a_{car})</td>
<td>1.0 m/s(^2)</td>
<td>congestion</td>
<td>1.25 m/s(^2)</td>
<td>Treiber et al. (2000) found a value of 0.73. This however pertains to mixed traffic. For cars we start somewhat higher.</td>
</tr>
<tr>
<td>(b)</td>
<td>1.67 m/s(^2)</td>
<td>congestion</td>
<td>2.09 m/s(^2)</td>
<td>Treiber et al. (2000) found a value of 1.67 which we will use.</td>
</tr>
<tr>
<td>(T_{max})</td>
<td>1.2 s</td>
<td>congestion</td>
<td>1.2 s</td>
<td>On the left lane of the two-lane section of our network we find maintainable flows around 2400 veh/h. From this we calculate a value of 1.2s at 90 km/h.</td>
</tr>
<tr>
<td>(s_0)</td>
<td>3 m</td>
<td>fixed</td>
<td></td>
<td>This value is based on the length of cars and a jam density of about 140 pce/km.</td>
</tr>
<tr>
<td>(v_{des,car})</td>
<td>123.7 km/h</td>
<td>free flow</td>
<td>123.7 km/h</td>
<td>We fitted a cumulative Gaussian distribution to the average speeds in free flow on the middle and the left lane using the fractions of traffic on these lanes. We added 5% to the resulting fit as this approach gives a lower limit to desired speed.</td>
</tr>
<tr>
<td>(\sigma_{car})</td>
<td>8.3 km/h</td>
<td>free flow</td>
<td>12.0 km/h</td>
<td>See (v_{des,car}).</td>
</tr>
<tr>
<td>(v_{des,truck})</td>
<td>85 km/h</td>
<td>fixed</td>
<td></td>
<td>Taken from FOSIM (Dijker and Knoppers, 2004).</td>
</tr>
<tr>
<td>(\sigma_{truck})</td>
<td>2.5 km/h</td>
<td>fixed</td>
<td></td>
<td>It is assumed that the majority of trucks has a desired speed between 80 and 90 km/h.</td>
</tr>
<tr>
<td>(l_{car})</td>
<td>4 m</td>
<td>fixed</td>
<td></td>
<td>Estimated using helicopter data (Hoogendoorn et al., 2003).</td>
</tr>
<tr>
<td>(l_{truck})</td>
<td>15 m</td>
<td>fixed</td>
<td></td>
<td>Estimated using helicopter data (Hoogendoorn et al., 2003).</td>
</tr>
<tr>
<td>(T_{min})</td>
<td>0.7 s</td>
<td>congestion</td>
<td>0.56 s</td>
<td>Based on Daamen et al. (2010) we assume an average minimum headway of 0.7s. Some studies (Laval and Leclercq, 2008; Sultan et al., 2002; Cohen, 2004) estimate values between 20-30s. Due to our exponential relaxation we assume a value at the lower end.</td>
</tr>
<tr>
<td>(r)</td>
<td>20 s</td>
<td>congestion</td>
<td>25 s</td>
<td></td>
</tr>
<tr>
<td>(x_0)</td>
<td>300 m</td>
<td>free flow</td>
<td>295 m</td>
<td>Based on the last traffic signs indicating a lane-drop.</td>
</tr>
<tr>
<td>(t_0)</td>
<td>67 s</td>
<td>free flow</td>
<td>43 s</td>
<td>Gipps (1986) found a value of 50s to resemble driver behavior. We set this equal to (t_0·(1-d_{free})), where lane changes start.</td>
</tr>
<tr>
<td>(d_{free})</td>
<td>0.25</td>
<td>free flow</td>
<td>0.365</td>
<td>We start with four equal desire ranges.</td>
</tr>
<tr>
<td>(d_{sync})</td>
<td>0.50</td>
<td>related</td>
<td>0.577</td>
<td>The range beyond (d_{free}) is equally divided, (d_{sync} = d_{free} + \frac{1}{2}(1-d_{free})).</td>
</tr>
<tr>
<td>(d_{coop})</td>
<td>0.75</td>
<td>related</td>
<td>0.788</td>
<td>The range beyond (d_{free}) is equally divided, (d_{coop} = d_{free} + \frac{1}{2}(1-d_{free})).</td>
</tr>
<tr>
<td>(v_{gain})</td>
<td>70 km/h</td>
<td>free flow</td>
<td>69.6 km/h</td>
<td>Based on (d_{free}) and speed differences between lanes in the order of 15-20 km/h on our road stretch we start with 70 km/h.</td>
</tr>
<tr>
<td>(v_{crit})</td>
<td>60 km/h</td>
<td>fixed</td>
<td></td>
<td>Estimated on plots of speed vs. lane fraction where in the range around 60 km/h, fractions tend to become more equal.</td>
</tr>
</tbody>
</table>

\(^a\) Whether a value is fixed, related to another parameter or calibrated in a scenario.
\(^b\) Describes how initial or assumed values have been determined. Values were additionally determined with a few initial runs of the model.
For the congestion scenario we will use:

\[
\varepsilon_{\text{cong}} = \sqrt{\sum_{n=1}^{N} \sum_{t=1}^{H} \left( 60 \cdot (q_{n,t}^{\text{real}} - q_{n,t}^{\text{sim}}) \right)^2 / N \cdot H} + 25 \cdot \sqrt{\sum_{n=1}^{N} \sum_{t=1}^{H} \left( v_{n,t}^{\text{real}} - v_{n,t}^{\text{sim}} \right)^2 / N \cdot H} + m
\] (5.13)

which is similar to (5.12). Minute measurements are however not aggregated in order to capture the dynamics of congestion. For an equal comparison between flow and speed, the minute flows are calculated to hourly flows.

Both error measures are based on detector measurements from individual lanes. As such, these error measures indicate in both free flow and congestion how well the model reproduces the distribution of traffic over the different lanes at different locations, as well as the speeds on the different lanes at different locations. Both are requirements for the model.

To find the optimal parameter values, we will use the calibration algorithm as presented below. We start with a large search space which is incrementally reduced in the second step. As soon as the search space is smaller than 0.1% of the parameter values, an arbitrary small value, the algorithm stops. This method is unable to change the sign of a parameter, which is not a problem for our parameters.

**Optimization algorithm**

0. Start with \( \mathbf{x} \) as the set of initial values. Set \( f_1 = 0.8 \) and \( f_2 = 1.25 \).

1. For each individual parameter in \( \mathbf{x} \), determine the error at two new points with a value which is a factor of \( f_1 \) and \( f_2 \) of the value in \( \mathbf{x} \).
   a. If a lower error is found, set \( \mathbf{x} \) where the lowest is found, i.e. one parameter is changed by a factor of \( f_1 \) or \( f_2 \). Redo step 1.
   b. If no lower error is found, go to step 2.

2. Reduce the search space by \( \frac{2}{3} \); \( f_2 := 1 + \frac{2}{3} (f_2 - 1) \) and \( f_1 := 1 / f_2 \).
   a. If \( f_2 > 1.001 \), redo step 1.
   b. If \( f_2 \leq 1.001 \), stop.

To cope with the stochastic nature of the model, each error is an average error of 5 model runs with different random seeds. A higher number of runs would give more certainty, but would also increase running times. Each simulation starts 10 minutes before the applicable period in order to fill the network.

### 5.7.3 Calibration and validation data

We calibrate and validate our model using detector data on a section of the A20 freeway near Rotterdam in the Netherlands as in figure 5.10. The speed limit is 120 km/h. This section has a few on- and off-ramps and a lane drop, furthermore it has closely spaced detectors (300-500m). This data is too widely spaced to detect actual lane changes. However, the main purpose of our model is to accurately represent lane distributions, lane specific speeds and the onset and progression of congestion. These phenomena can be found in detector data, and the calibration is successful if these characteristics can be reproduced in simulation.
Congestion on the A20 towards Gouda is often initiated by spillback from off-ramp Moordrecht. For calibration we require that the traffic state on the network is not influenced by external phenomena, except for the demand pattern. A detector on off-ramp Moordrecht (not shown in figure 5.10) was used to find days where congestion started due to the lane-drop and on-ramp Nieuwekerk a/d IJssel and remained unaffected by the off-ramp for a considerable period. Two days with comparable weather (e.g. no rain) were selected; Monday June 8th 2009 and Thursday June 25th 2009. The first day was used for calibration for free flow (5:15 – 6:15 AM) and congestion (6:00 – 7:00 AM) while the latter day was used for validation for free flow (5:30 – 6:30 AM) and congestion (6:15 – 7:15 AM). Truck percentages were very similar at 11.0% and 10.6% respectively.

Inflow into our model is based on detector data aggregated over one minute. During each minute, the vehicles are uniformly distributed. The number of vehicles to be generated on the on-ramps has been determined by subtracting the downstream flow from the upstream flow. This method may result in negative flows, which are solved by moving some vehicles earlier in time as this maintains the peaks in traffic demand. Detector data was also used to estimate an origin-destination pattern, assuming a constant pattern over the simulated period. For each off-ramp, split fractions were determined. These were then used to assign probabilities of traffic from each origin towards the destinations taking consecutive split fractions into account. As the gas station is rather close to the beginning of the network, traffic towards the gas-station is only generated on the right-hand and middle lane. Trucks are only generated on the right-hand lane and on-ramps. The percentage of trucks was estimated using class specific traffic counts on the A20 upstream of our network. These traffic counts were aggregated per month, but separated per weekday.

Only detectors from \( x = 1400 \)m till \( x = 7400 \)m are considered for the error measure to allow traffic to settle and as downstream of on-ramp Moordrecht speeds may be influenced by a narrow bridge and road curvature.

5.7.4 Calibration and validation results

In table 5.1 the calibrated parameter values are given. Some parameters have not or hardly changed from the initial value. In general, these parameters have a range that may result in a more or less equal fit to data for as long as other parameters also change within such a range. Substantial changes from the initial values are found for \( a_{\text{car}}, b, \sigma_{\text{car}}, T_{\text{min}}, \tau, t_0 \) and \( d_{\text{free}} \). However, once these parameters received a few course adjustments at the beginning of the calibration, again a range of values can result in a more or less equal fit.

One remarkable observation from the parameter values is that drivers are apparently willing to change lane for a speed gain of \( d_{\text{free}} v_{\text{gain}} \approx 25 \) km/h or higher. We suspect that this rather large value is not only a minimum speed gain, but simultaneously an adjustment of speed at both the origin and target lane. For instance, a bounded driver on the right lane driving at 80 km/h, with a desired speed of 95 km/h, is willing to overtake its leader by temporarily driving 105...
km/h in order not to holdup traffic on the left lane. The interpretation for $v_{des}$ is thus a combination of desired speed and the speed at which drivers are willing to overtake. Such speed adaptation is however not explicitly modeled.

Another observation is that drivers look about 300m ($x_0$) ahead on the right-hand lane and will not keep right if there is any slower vehicle within this range. This may appear to be a rather long range. The value may however result from the 3-lane section, where traffic on the middle lane will not feel inclined to keep-right as they can still be overtaken. Also, some drivers may have little to no attention for the keep-right rule.

In figure 5.11 calibrated lane fractions of the first run are shown related to the density at a cross-section with detectors. Lane fraction is the flow on a lane divided by the flow over all lanes. The density $k_{road}$ is calculated as the flow over all lanes divided by the harmonic mean of the speeds on all lanes. The model is able to represent the relation between the density and the amount of traffic that can be found at different lanes. Furthermore we can see that between $x = 2400m$ and $x = 3500m$ the amount of traffic on the left lane reduces as it will we dropped at $x = 3751m$. Consequently the amount of traffic on the middle lane increases while the amount of traffic on the right lane hardly changes. At $x = 5200m$ there is more traffic on the right-hand lane than at $x = 3751m$. This is due to off-ramp Moordrecht as well as traffic moving away from the busy left lane due to the upstream lane drop.

Calibrated speeds of the first run are shown at a 3-lane cross-section and a 2-lane cross-section. There are clear differences between lanes, and speeds appear to drop linearly for increasing density (in free flow). The model is able to represent both phenomena. Runs 2 till 5 show similar results as run 1 with regard to lane fractions and lane speeds.

The model has been validated by running the model with data from June 25th 2009. It is difficult to compare the model fit based on the error as with more traffic the RMSE of flow will also increase for an equal error in terms of percentage. On June 25th there was 26% more traffic in the free flow scenario resulting in larger values of the RMSE of flow, as can be seen in table 5.2. This growth causes most of the increase of the total error in free flow. Traffic demand in the congestion scenario differs by only 1.2% between both days, but still the underlying demand pattern can strongly influence the amount of congestion.

The results of the congestion scenario are presented in space-time-speed plots as these allow for good recognition of congestion patterns. These figures were created using the Adaptive Smoothing Method (Treiber and Helbing, 2002). In figure 5.12 we can see that the calibration runs are able to produce comparable congestion with reality. There are however differences between congestion patterns, showing the influence of stochastic input. Similar plots were created for the validation day. Although there was mild congestion in reality, none of the 5 model runs showed congestion, although there are a lot of drops in speed, none of which actually trigger congestion. These drops in speed indicate that congestion could arise with only little changes in input or parameter values. Note that with only mild congestion in reality and the binary character of the occurrence of congestion (and following capacity drop making it likely that congestion remains once created), the model is not considered to be far off. Moreover, the validation is only a single draw from reality, which may show relatively much congestion given the inflow. The fact that the error measure is still smaller than for calibration, indicates that the error value of different time periods cannot be directly compared.
Figure 5.11: Free flow calibration results. Lane fractions (run 1) at $x = 2400$ m (a), $x = 3500$ m (b), $x = 3751$ m (c) and $x = 5200$ m (d). Lane speeds (run 1) at $x = 2400$ m (e) and $x = 4700$ m (f). Each dot represents a 1-minute measurement.
Figure 5.12: Congestion calibration results. Speed pattern for the calibration day June 8\textsuperscript{th} 2009 in the congestion scenario. Real data (a) and five model runs (b)-(f).

Besides comparing the model performance quantitatively, face-validity is found for lane distributions in free flow and speeds on the lanes in free flow as these are similar between validation and calibration. Also, the congestion from the calibration runs show valid properties: upstream moving waves, location and time of traffic break-down and overall extent of congestion.
Table 5.2: Calibration and validation errors of the free flow and congestion scenario.

<table>
<thead>
<tr>
<th>Day</th>
<th>Error measure</th>
<th>Error value</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Free flow scenario</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Monday June 8th 2009</td>
<td>RMSE flow [veh/h]</td>
<td>33.6</td>
</tr>
<tr>
<td>(calibration day)</td>
<td>RMSE speed [km/h]</td>
<td>4.70</td>
</tr>
<tr>
<td></td>
<td>Total ($\varepsilon_{\text{free}}$)</td>
<td>154.8</td>
</tr>
<tr>
<td>Thursday June 25th 2009</td>
<td>RMSE flow [veh/h]</td>
<td>61.4</td>
</tr>
<tr>
<td></td>
<td>RMSE speed [km/h]</td>
<td>5.35</td>
</tr>
<tr>
<td></td>
<td>Total ($\varepsilon_{\text{free}}$)</td>
<td>202.4</td>
</tr>
<tr>
<td><strong>Congestion scenario</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Monday June 8th 2009</td>
<td>RMSE flow [veh/h]</td>
<td>440</td>
</tr>
<tr>
<td>(calibration day)</td>
<td>RMSE speed [km/h]</td>
<td>22.6</td>
</tr>
<tr>
<td></td>
<td>Total ($\varepsilon_{\text{cong}}$)</td>
<td>1011.6</td>
</tr>
<tr>
<td>Thursday June 25th 2009</td>
<td>RMSE flow [veh/h]</td>
<td>373</td>
</tr>
<tr>
<td></td>
<td>RMSE speed [km/h]</td>
<td>19.8</td>
</tr>
<tr>
<td></td>
<td>Total ($\varepsilon_{\text{cong}}$)</td>
<td>877.5</td>
</tr>
</tbody>
</table>

5.7.5 Sensitivity analysis

A sensitivity analysis is performed on the ‘free flow’ parameters $v_{\text{des,car}}, \sigma_{\text{car}}, x_0, t_0, d_{\text{free}}$ and $v_{\text{gain}}$, the ‘congestion’ parameters $a_{\text{car}}, b, T_{\text{max}}, T_{\text{min}}$ and $\tau$, as well as on $v_{\text{crit}}$ in order to confirm or reject the following hypotheses:

1. The free flow parameters are sensitive in the free flow scenario.
2. The free flow parameters are not sensitive in the congestion scenario.
3. The congestion parameters are sensitive in the congestion scenario.
4. The congestion parameters are not sensitive in the free flow scenario.
5. Parameter $v_{\text{crit}}$ is sensitive in neither scenario.

If all these hypotheses are confirmed, the calibration method of using two scenarios while not calibrating $v_{\text{crit}}$ is appropriate. The sensitivity analysis is performed by recalculating the error values in the same way as during calibration for various parameter settings where one of the parameters is changed in the range of 50% to 150% of the calibrated value. For all 6 free flow parameters, 5 congestion parameters and $v_{\text{crit}}$ this was done in both the free flow and congestion scenario.
Figure 5.13 shows the results of the free flow scenario. Hypothesis 1 is confirmed as the free flow parameters show significantly larger errors ($\varepsilon_{\text{free}}$) when deviating from the calibrated values. Hypothesis 4 is also confirmed as the congestion parameters do not result in considerably larger error values throughout the tested range. Only for $T_{\text{max}}$ a considerable error increase is visible, but only for values much larger than the calibrated value of $T_{\text{max}}$. These large values probably trigger congestion in the free flow scenario as capacity is related to $1/T_{\text{max}}$. From this it can be concluded that the use of the initial values rather than the calibrated values of the congestion parameters in the free flow scenario does not influence the error value considerably. Hypothesis 5 is partially confirmed as parameter $v_{\text{crit}}$ is not sensitive in the free flow scenario.

Figure 5.13: Sensitivity in free flow. (Error = $\varepsilon_{\text{free}}$, ‘o’ is the calibrated value). Boxed parameters were calibrated in free flow. Note that the scales on the y-axis are different.
Figure 5.14 shows the results of the congestion scenario. Hypothesis 2 is confirmed as the free flow parameters are either not sensitive or only result in a considerable increase of the error value ($\varepsilon_{\text{cong}}$) for large deviations from the calibrated value. Note that in the congestion scenario the calibrated values of the free flow parameters were used. Hypothesis 3 is also confirmed for all congestion parameters except for $\tau$. Apparently, this parameter is sensitive in neither scenario which means that its value is not very important. This does not devaluate the relaxation which is implemented with $\tau$ as it is important to return from small to normal headways after a lane change during some time. It does however indicate that the value for $\tau$ has a wide distribution for different situations or different drivers. Finally, hypothesis 5 can now be fully confirmed as $v_{\text{crit}}$ is also not sensitive in the congestion scenario.

Figure 5.14: Sensitivity in congestion. (Error = $\varepsilon_{\text{cong}}$, ‘o’ is the calibrated value). Boxed parameters were calibrated in congestion. Note that the scales on the y-axis are different.
5.8 Conclusions

In order to simulate an ITS system, it has to be implemented in a simulation framework, as every new ITS works differently. In this chapter a simulation framework has been discussed which is aimed at meeting a set of five requirements for ITS development in simulation: openness, flexibility, adaptability, extendibility and features, though the last requirement is not fully met. The structure of the simulation framework, as well as a number of algorithms and approaches, have been discussed and show that the simulation framework is suitable for the implementation of various ITS applications, including the in-car advisory system from this thesis.

The driver model has been calibrated and validated in both free flow and congested traffic. In free flow, we get a good fit to lane distributions for different levels of density on a particular cross-section of the road. Speeds on the different lanes for different levels of density are also realistic. The fit in congestion is less clear as this highly depends on the stochastic input. For some runs we however find good fit on the location and moment of breakdown and the following progression of congestion. A sensitivity analysis shows that the approach of two calibration scenarios, one for free flow and one for congestion, is appropriate.
6 Evaluation of the effects on freeway efficiency

Parts of this chapter have been published in: Schakel, W.J., B. van Arem (2014) “Improving Traffic Flow Efficiency by In-Car Advice on Lane, Speed, and Headway”, IEEE Transactions on Intelligent Transportation Systems, Vol. 15, Issue 4, pp. 1597-1606.

This chapter uses the results of chapter 3, 4 and 5 to perform an evaluation of the in-car advisory system in simulation. It will discuss the assumed responses of drivers and how these are modeled, the evaluation setup and finally the results of the evaluation. The evaluation will assess the effects of the different advice principles on (average) travel time delay.

6.1 Modeling advised driver behavior

This section will elaborate on how the model for regular driver behavior (LMRS and IDM+) is adapted to include responses to in-car advice. The advices as given by the system (see chapter 3) are:

- Speed advices
  - Maintain a certain speed.
  - Synchronize speed to adjacent lane.
- Headway advices
  - Create gap for merging traffic.
  - Maintain a short but safe headway.
- Lane advices
  - Drive in a certain lane (current or adjacent lane).

Throughout this section, important equations that describe behavior of advised drivers are boxed to distinguish them from equations describing regular drivers. Regular driver behavior as discussed in chapter 4, modeled with the IDM+ and LMRS, is the basis of advised driver behavior. This means that behavior is equal if a driver with the in-car advisory system does not have an active advice, or has zero compliance. If there is an active advice this may result
in a number of changes to the regular driver behavior which will be discussed in the following sections. Common in all responses is a general compliance rate \( \omega \) with a value from 0 (no compliance) to 1 (full compliance). By changing this value the effects of in-car advice can be investigated for different compliance rates. The use of a single compliance rate per scenario for all advices and in all situations simplifies the expected complexity of driver responses. However, this is required to obtain a manageable number of simulations and parameters to research the overall effect of compliance.

Similar to the concept of lane change desire in the model for regular drivers, there is no evidence on how drivers will respond to advice. Therefore, the changes in driver behavior are hypotheses based on literature where possible, and assumptions otherwise. Even if literature is available, it usually involves a similar, but not equal, situation.

### 6.1.1 Speed advice

Speed advice can be quantitative (e.g. drive 90 km/h) and qualitative (e.g. synchronize speed with the right-hand lane). These are implemented in different ways which are discussed next.

**Quantitative Speed Advice**

Quantitative speed advice affects the desired speed of drivers which is given by equation (6.1) for regular drivers.

\[
v_0 = \min\left(v_{\text{max}}, \theta \cdot v_{\text{lim}}\right)
\]  

(6.1)

Here, \( v_{\text{max}} \) is the maximum speed of the vehicle which is unaffected by advice. The intended speed is given by a factor \( \theta \) of the local speed limit \( v_{\text{lim}} \). It is assumed that drivers are willing to deviate from their intended speed linearly with the compliance rate towards an advised speed \( v_{\text{adv}} \). This behavior is implemented with equation (6.2).

\[
v_0 = \begin{cases} 
\min\left(v_{\text{max}}, (1 - \omega) \cdot \theta \cdot v_{\text{lim}} + \omega \cdot v_{\text{adv}}\right), & \text{advice} \\
\min\left(v_{\text{max}}, \theta \cdot v_{\text{lim}}\right), & \text{no advice}
\end{cases}
\]  

(6.2)

This form of partial speed limit compliance has been empirically observed by Hegyi and Hoogendoorn (2010) with road-side dynamic speed limits. The level of compliance to speed limits, let alone to speed advice, however depends on many factors such as the location of the information and the frequency (Hoogendoorn et al., 2012).

If the advised speed is below the current speed it may occur that \( v > v_0 \), where \( v \) is the current speed. The car-following model for regular drivers as given in equation (6.3) is not designed for this situation.

\[
\frac{dv}{dt} = a \cdot \min\left(1 - \left(\frac{v}{v_0}\right)^\delta, 1 - \left(\frac{s^*}{s}\right)^2\right)
\]  

(6.3)

where,

\[
s^* = s_0 + vT + \frac{v \Delta v}{2 \sqrt{ab}}
\]  

(6.4)

This can easily be seen if we take \( v = 30 \text{m/s}, v_0 = 20 \text{m/s}, \delta = 4 \) and \( a = 1 \). The free flow term as in equation (6.5) would then result in a value of \(-4.06\text{m/s}^2\), which is an unreasonably strong deceleration if one is only lowering the speed to a lower desired speed.
\[ a \cdot \left( 1 - \left( \frac{v}{v_0} \right)^g \right) \] (6.5)

Therefore, the free flow term from equation (6.5) is limited to a maximum deceleration of \( b_0 \). This changes the free flow term to equation (6.6),

\[ a \cdot \max \left( 1 - \left( \frac{v}{v_0} \right)^g, -\frac{b_0}{a} \right) \] (6.6)

which changes the car-following model for advised drivers into equation (6.7).

\[ \frac{dv}{dt} = a \cdot \min \left( \max \left( 1 - \left( \frac{v}{v_0} \right)^g, -\frac{b_0}{a} \right), 1 - \left( \frac{s}{s^*} \right)^2 \right) \] (6.7)

For \( b_0 \) a value of 0.5m/s\(^2\) is assumed, which allows a speed reduction of 20km/h during 11.1s over a distance in the order of 300m depending on the initial speed. It is not expected that the level of deceleration towards a lower speed is important, so long as strong disturbances are avoided.

**Qualitative Speed Advice**

The response to qualitative speed advice (i.e. synchronize speed to adjacent lane) is incorporated by setting an appropriate value for \( v_{adv} \) in equation (6.2). The value for \( v_{adv} \) should reflect the speed a driver perceives at the adjacent lane. In the previous chapter such a quantity is given by the anticipation speed \( v_{ant} \). It is determined with equations (6.8) and (6.9) for lane \( k \), which reflects that near and slow vehicles lower the anticipation speed.

\[ v_{ant}^k = \min \left( v_0^k, \min_{m \in M_k} \left( \bar{v}_{lead}^m \right) \right) \] (6.8)

with,

\[ \bar{v}_{lead} = \left( 1 - \frac{s}{x_0} \right) \cdot v_{lead} + \frac{s}{x_0} \cdot v_0 \] (6.9)

where,

- \( v_0 \) desired speed
- \( M \) set of considered leaders
- \( v_{lead} \) actual speed of leader
- \( s \) headway towards leader
- \( x_0 \) anticipation distance

Using \( v_{ant} \), in case of qualitative speed advice we assume:

\[ v_{adv} = v_{ant}^k \] (6.10)

where \( k \) is the lane to which the speed should be synchronized.
6.1.2 Headway advice
Headway advice is only given as qualitative advice. There are two types of qualitative headway advice which are i) creating a gap for merging traffic and ii) maintaining a short but safe headway. These two are modeled in different manners which are discussed next.

Gap creation advice
Creating gaps for merging traffic, or cooperation, is a behavior which is modeled in LMRS. It is triggered if a driver notices that the leader in an adjacent lane has a lane change desire towards its lane larger than the desire threshold $d_{coop}$. For advised drivers the following is assumed:

- When advised to create a gap for merging traffic this behavior will occur for a lower desire threshold depending on the compliance rate.
- At full compliance, the desire threshold equals zero.

The trigger to create a gap is therefore redefined as in equation (6.11), where $d_{ji}$ is the desire of the leader in adjacent lane $j$ towards the current lane $i$.

\[
\begin{align*}
    d_{ji} &\geq d_{coop} \cdot (1-\omega), \quad \text{advice} \\
    d_{ji} &\geq d_{coop}, \quad \text{no advice}
\end{align*}
\]  

Short headway advice
Maintaining a short but safe headway is modeled in a different way where the desired headway is not affected. Instead it is assumed that drivers have a stronger response to any headway deviation resulting in larger accelerations as the leading vehicle accelerates away. Tampère et al. (2005a) found that changing the maximum acceleration influences the capacity drop. They assumed that activation levels reduce at low speeds in congestion, and that maximum acceleration is linearly reduced in relation to the activation level. This resulted in a more pronounced capacity drop. Similar results were obtained by relating the lower activation level to larger desired headways, indicating that affecting either one is a suitable tool to reflect changes in the capacity drop. Sensitivity to a deviating dynamic headway (i.e. also affected by speed difference) in the IDM+ is given by the maximum acceleration parameter $a$. This can be shown by simplifying the IDM+ for an acceleration situation. In this situation either the free or interaction term is critical. For the free term as in equation (6.6) it can easily be seen that larger acceleration results for larger values of $a$ if $v < v_0$, which is the case during acceleration. The interaction term can also be critical as the leading vehicle may limit acceleration below the free acceleration. During acceleration the headway is usually larger than the desired headway while speed differences are usually small. For explanatory purposes, we can leave out the dynamic part of the dynamic desired distance headway of equation (6.4). Equation (6.7), the car-following model for advised drivers, can now be simplified into equation (6.12). From this equation it can again easily be seen that acceleration is larger for larger values of $a$ if $s_0 + vT < s$, i.e. if the equilibrium desired distance headway is smaller than the current distance headway, which is usually true for an accelerating leading vehicle.

\[
\frac{dv}{dt} = a \left( 1 - \left( \frac{s_0 + vT}{s} \right)^2 \right) 
\]  

(6.12)
Given that the regular maximum acceleration is calibrated to reflect the capacity drop, the value of \( a \) in equation (6.7) is made dynamic to reflect an increase in activation. It is assumed that if there is no advice, the parameter is equal to the regular value denoted with \( a_0 \). For the case of short headway advice the following assumptions are made:

- Fully compliant drivers increase their maximum acceleration by a factor of \( \chi_a > 1 \), reflecting a higher activation level.
- At intermediate levels of compliance the maximum acceleration increases linearly.
- Drivers ignore short headway advice if \( s_0 + vT > s \), i.e. if the distance headway is smaller than desired. In these situations it is assumed that drivers show regular collision avoidance behavior.

This is all captured in equation (6.13).

\[
a = \begin{cases} 
  a_0 \cdot (1 - \omega) + a_0 \cdot \chi_a \cdot \omega, & \text{advice and } s_0 + vT < s \\
  a_0, & \text{otherwise}
\end{cases}
\]  

(6.13)

In order to estimate the value for \( \chi_a \) we assume that fully compliant drivers are as efficient as drivers at traffic lights. A saturation flow of 1800 veh/h is generally considered at traffic lights in perfect circumstances (i.e. no reduction factors such as turning, parking vehicles, etc.). So, we need to find a value for \( \chi_a \) such that the IDM+ produces a saturation flow of about 1800 veh/h. For this a simple scenario is setup in which a stand still queue of cars starts accelerating at \( t = 0 \). The parameter values are as calibrated in the previous chapter, except for \( a_{car} \) which is varied. The saturation flow is measured at the initial position of the first vehicle at every moment a vehicle passes this location. Two flows are calculated:

**Aggregated:** This is the total flow measured up to any given time. It is calculated with equation (6.14) where \( n \) is the vehicle number (i.e. the number of vehicles that has passed the measurement location) and \( t_n \) is the time when the vehicle passes the measurement location.

\[
q_{agg}(t_n) = n / t_n
\]  

(6.14)

**Instantaneous:** This is the flow as measured by the time difference between two consecutive vehicles passing the measurement location (strictly, this is not instantaneous). It is given in equation (6.15) where \( n-1 \) is the previous vehicle and \( t_{n-1} \) is the time when that vehicle passed the measurement location.

\[
q_{ins}(t_n) = \frac{1}{t_n - t_{n-1}}, \quad n > 1
\]  

(6.15)

The aggregated saturation flow is for comparison with saturation flow at traffic lights, while the instantaneous saturation flow is for comparison with reported saturation flow in literature.

With \( \chi_a = 1.6 \) (\( a = a_0 \chi_a = 2m/s^2 \)) we get the results as shown in figure 6.1. The aggregated saturation flow has a value of about 1800 veh/h around \( t = 45s \), which is a reasonable green time period. The instantaneous saturation flow is similar to the empirical flows reported by Fing-Bor and Thomas (2005). They find that saturation flow quickly grows from 1559 veh/h for the first 4 vehicles, to 1990 veh/h for vehicles 17 through 20. With the 5th vehicle resulting in an instantaneous saturation flow of about 1600 veh/h, and with vehicles 15 through 20
resulting in about 2000 veh/h, we consider that $\chi_a = 1.6$ is an appropriate value. Also, the resulting acceleration value of $a_0\chi_a = 2m/s^2$ (as $a_0$ was calibrated at 1.25m/s$^2$ for cars) complies with empirical findings for acceleration at traffic lights (Wilmink et al., 2007).

The impact of a short headway advice during the acceleration process can be shown by simulating a similar scenario. Between $t = 30s$ and $t = 60s$ a short headway advice is active. The advice is only valid for speeds below $v_{free} = 80km/h$. In this case we measure instantaneous saturation flow at $x = 1000m$ to capture the full acceleration of vehicles. The resulting trajectories and instantaneous saturation flow are presented in figure 6.2. The trajectories that are indicated with continuous lines (those that are substantially influenced by advice) clearly boost the instantaneous saturation flow when they pass $x = 1000m$. The difference is roughly 300 veh/h.

![Figure 6.1: Saturation flow over stop line of an initial standing queue. Simulated with the IDM+ with calibrated parameters, a time step of 0.1s and $a = 2 m/s^2$.](image1)

![Figure 6.2: Trajectories and instantaneous saturation flow. With 30s short headway advice during the acceleration process. Trajectories indicated with continuous lines have at one point an acceleration > $1m/s^2$ while advice is active, i.e. their acceleration can be considered substantially influenced by advice. Trajectories indicated with discontinuous lines either have no active advice at all, or only during small acceleration < $1m/s^2$.](image2)
6.1.3 Lane advice
In LMRS lane change behavior is based on lane change desire \( d \) as in equation (6.16) where \( d_r \) is mandatory desire from the route and infrastructure, \( d_s \) is desire from speed, \( d_b \) is desire to keep right and \( \theta_v \) is the level in to which voluntary desire is considered, which is a function of mandatory and total voluntary desire given by \( d_v = d_s + d_b \).

\[
d = d_r + \theta_v \cdot (d_s + d_b)
\]  
(6.16)

To include the influence of lane change advice an extra lane change incentive \( d_a \) can simply be added to this equation resulting in equation (6.17).

\[
d = d_r + \theta_v \cdot (d_s + d_b + d_a)
\]
(6.17)

The value of \( \theta_v \) remains a function of mandatory desire \( d_r \) and total voluntary desire which is now determined as \( d_v = d_s + d_b + d_a \). The value of \( d_a \) should be in the range \([-1...1]\), where a value of 1 means that a lane change is fully desired and a value of -1 means fully undesired.

For advised drivers we assume the following:

- Lane change advice is only considered if it does not increase the number of lane changes that have to be performed due to the route and infrastructure (i.e. mandatory lane changes) regardless of the distance within which these have to be performed.
- Similarly, lane keep advice is only considered if the number of lane changes that have to be performed due to the route and infrastructure cannot be reduced by changing lane.
- In case of lane keep advice, lane change desire to adjacent lanes equals \(-\omega\).
- For lane change advice, lane change desire grows linearly over a time of \( \tau_a \) after the advice is given to a maximum value of \( \omega \). This causes even very compliant drivers to take some time to perform the lane change if not immediately possible without forcing cooperation.

These assumptions are implemented in equation (6.18) where \( \Delta_n \) is the potential number of mandatory lane changes that a driver could reduce by not adhering to the advice and \( T_a \) is the time since advice was given.

\[
d_a = \begin{cases} 
-\omega, & \Delta_n \leq 0 \text{ and advice (keep)} \\
\omega \frac{\min(T_a, \tau_a)}{\tau_a}, & \Delta_n \leq 0 \text{ and advice (change)} \\
0, & \Delta_n > 0 \text{ or no advice}
\end{cases}
\]  
(6.18)

The value for \( \tau_a \) is assumed to be 30s, which is in line with driver simulator tests in which drivers changed lane within 1km (30s at 120 km/h) after receiving the advice.
6.2 Evaluation setup

The potential effectiveness of the system is investigated by implementing the in-car advisory system in the simulation framework of chapter 5. The prediction and advice algorithm are implemented as described in chapter 3 and appendix A. Driver responses to the advices are as described in the previous section. To refresh the readers memory, the system is shortly summarized in the following steps.

- Data is gathered from detectors and equipped vehicles (floating car data).
- A lane-level traffic state prediction is performed using the ASM, where different data sources get a weight depending on the estimated speed (due to e.g. detectors being less accurate with low vehicle speeds) and depending on the availability of data from one data source (number of measurements and proximity).
- The estimated traffic state is used to derive advices in 4 steps.
  - Assigning infrastructural properties to various locations (e.g. lane drop section).
  - Different advice principles are operated independently. The used advice principles are: acceleration (at end of congestion), distribution (avoiding peak lane intensities) and spillback (removing traffic from right-hand lane).
  - Advice filtering for overlap based on priorities.
  - User selection by estimating which users may enter the region and by selecting the faster or slower users for left or right lane change advice.
- Advices are sent to on-board units. At any one time the validity of the various advices results in no or one advice being valid. If one advice is valid, it is presented to the driver.

For all system settings a value has been determined as shown in table 6.1. Settings concerning the prediction filter were roughly based on Van Lint and Hoogendoorn (2010) and Treiber and Helbing (2002). For $c_{free}$ a slightly larger value was assumed in line with the average speed of trucks in the LMRS/IDM+ calibration. The value of $c_{cong}$ was chosen at -18 km/h which is in accordance with rough visual estimations based on space-time-speed plots (see figure 6.4b). Note however that the filter is very robust to these settings (Treiber and Helbing, 2002). The standard deviation of measurement errors ($\Theta$) for speed are taken from Van Lint and Hoogendoorn (2010). For flow measurements from detectors it is assumed that 25 veh/h is a reasonable estimate of $\Theta$, which is increased to 50 veh/h in congestion as detectors are less reliable for low speeds. The advice algorithm settings are all based on engineering judgment since no literature is available for these.

Within simulations no delay due to calculation time is simulated as the prediction method is very efficient and because the advice algorithm is light-weight, at least for the considered section. In our simulations, floating car data is sampled every 4s. Every 20s a set of measurements is communicated to the traffic management center. For the communication delay 5s is assumed. The same delay applies on communication of advices back to the in-car device. The delay of detector data is 75s based on the observed delay of the actual system.

The used network, data and scenarios are discussed in the next two sub section.
Table 6.1: Overview of settings in the traffic state prediction and advice algorithms.

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Value</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta t$</td>
<td>3s</td>
<td>Time step determining the spatial precision. In our case this gives 107.10m per cell.</td>
</tr>
<tr>
<td>$c_{\text{free}}$</td>
<td>85 km/h</td>
<td>Propagation speed of free flow traffic states.</td>
</tr>
<tr>
<td>$c_{\text{cong}}$</td>
<td>-18 km/h</td>
<td>Propagation speed of congestion traffic states.</td>
</tr>
<tr>
<td>$\tau$</td>
<td>30s</td>
<td>Temporal size of area with important measurements (kernel size).</td>
</tr>
<tr>
<td>$\sigma$</td>
<td>300m</td>
<td>Spatial size of area with important measurements (kernel size).</td>
</tr>
<tr>
<td>$\Delta t_{\max}$</td>
<td>300s</td>
<td>Maximum temporal range of considered measurements.</td>
</tr>
<tr>
<td>$\Delta l_{\max}$</td>
<td>1500m</td>
<td>Maximum spatial range of considered measurements.</td>
</tr>
<tr>
<td>$V_c$</td>
<td>80 km/h</td>
<td>Flip-over speed between free flow and congestion.</td>
</tr>
<tr>
<td>$\Delta V$</td>
<td>10 km/h</td>
<td>Flip-over range between free flow and congestion.</td>
</tr>
<tr>
<td>$\Theta_{\text{det,v,free}}$</td>
<td>12 km/h</td>
<td>Standard deviation of measurement error of speed by detectors in free flow.</td>
</tr>
<tr>
<td>$\Theta_{\text{det,v,cong}}$</td>
<td>4 km/h</td>
<td>id. of speed by detectors in congestion.</td>
</tr>
<tr>
<td>$\Theta_{\text{fcd,v,free}}$</td>
<td>4 km/h</td>
<td>id. of speed from floating car data in free flow.</td>
</tr>
<tr>
<td>$\Theta_{\text{fcd,v,cong}}$</td>
<td>1 km/h</td>
<td>id. of speed from floating car data in congestion.</td>
</tr>
<tr>
<td>$\Theta_{\text{det,q,free}}$</td>
<td>25 veh/h</td>
<td>id. of flow by detectors in free flow.</td>
</tr>
<tr>
<td>$\Theta_{\text{det,q,cong}}$</td>
<td>50 veh/h</td>
<td>id. of flow by detectors in congestion.</td>
</tr>
<tr>
<td>$x_{\text{end}}$</td>
<td>2 km</td>
<td>Length of end sections.</td>
</tr>
<tr>
<td>$x_{\text{split}}$</td>
<td>2 km</td>
<td>Length of split sections.</td>
</tr>
<tr>
<td>$V_{\text{cong}}$</td>
<td>60 km/h</td>
<td>Threshold for ‘end of congestion’ detection.</td>
</tr>
<tr>
<td>$x_{\text{up}}$</td>
<td>2 km</td>
<td>Length of section which should have no congestion to be the ‘end of congestion’.</td>
</tr>
<tr>
<td>$x_{\text{down}}$</td>
<td>1.5km</td>
<td>Advice range downstream of ‘end of congestion’.</td>
</tr>
<tr>
<td>$V_{\text{free}}$</td>
<td>80 km/h</td>
<td>Speed below which acceleration advice is valid.</td>
</tr>
<tr>
<td>$q_x$</td>
<td>2200 veh/h</td>
<td>Flow trigger for distribution advices in different sections $y \in {\text{end, split, norm}}$.</td>
</tr>
<tr>
<td>$x_{\text{adj}}$</td>
<td>2 km</td>
<td>Advice range upstream of distribution trigger for distribution advice.</td>
</tr>
<tr>
<td>$dV$</td>
<td>20 km/h</td>
<td>Maximum speed difference between lanes in case of speed advice.</td>
</tr>
<tr>
<td>$x_{\text{spill,down}}$</td>
<td>0.1 km</td>
<td>Trigger area for spillback advice downstream of diverge point.</td>
</tr>
<tr>
<td>$x_{\text{spill,up}}$</td>
<td>0.5 km</td>
<td>Trigger area for spillback advice upstream of diverge point.</td>
</tr>
<tr>
<td>$V_{\text{spill}}$</td>
<td>70 km/h</td>
<td>Speed threshold for spillback detection.</td>
</tr>
<tr>
<td>$x_{\text{spill}}$</td>
<td>2 km</td>
<td>Advice range upstream of diverge point for spillback advice.</td>
</tr>
<tr>
<td>$t_{\text{out}}$</td>
<td>300s</td>
<td>Time since last user information after which users are removed from the user set.</td>
</tr>
<tr>
<td>$\tau_v$</td>
<td>30s</td>
<td>Relaxation time of user speed to new speed information.</td>
</tr>
<tr>
<td>$x_{\text{pre}}$</td>
<td>2km</td>
<td>Distance upstream of advice area in which drivers also receive advice.</td>
</tr>
</tbody>
</table>

6.2.1 Network and data

For the network, the same network as for the regular driver model calibration is used, which is the A20 near Rotterdam in the Netherlands. For the advisory system the section needs to be extended at the upstream end as more distance upstream of the lane drop is required. 2km is required for the length of an advice region, 2km to find vehicles upstream of an advice region which may enter the region in the next minute, and additional length as the highest flow may be found some distance upstream of the lane-drop. Upstream of the lane drop a length of just over 6km is available, as at that location the A16 connects with the A20. The entire network is shown in figure 6.3.

Figure 6.3: A20 network for evaluation. Distances and detector locations in meters.
Detector data from the A20 is used to determine demand, including split fractions. This is performed similarly as for the calibration in chapter 5, with the exception that split fractions are determined for every 15 minutes instead of the entire simulation period, as longer simulation periods are applied. Data of two morning rush hours is selected where one day shows mild congestion while the other shows heavy congestion. Days were chosen on which a number of different congestion sources are active being i) lane-drop, ii) on-ramp Nieuwerkerk a/d IJssel, iii) spillback from off ramp Moordrecht and iv) spillback from the A12. The selected days are Monday the 8th of June 2009 (5h45–7h45) for mild congestion, referred to as day 1, and Tuesday the 24th of March 2009 (6h00–8h30) for heavy congestion, referred to as day 2. Furthermore, congestion on the first day is initiated by congestion sources i and ii whereas congestion on the second day is initiated by source iii and iv. Congestion patterns are shown in figure 6.4a and 6.4b in the results section. Truck percentages are 11.0% and 9.8% respectively. The simulation time step is 0.5s.

As the spillback from off ramp Moordrecht and the A12 generates moving jams it is required that spillback is simulated. For this, virtual road-side units (objects at a specific location in the network) are used at the detector locations at the end of the section and off ramp Moordrecht. In our simulation framework drivers may notice road-side units and respond appropriately depending on the type of road-side unit. Drivers within 300m will decelerate to a speed \( v_s = \gamma_{spill} v_{det} \) where \( v_{det} \) is the real measured speed at the detector and \( \gamma_{spill} < 1 \) is a factor which increases the spillback severity required to match the actual moving jam size. The acceleration is given in equation (6.19) where \( v \) is the current speed, \( s \) is the distance up to the virtual road-side unit and \( b \) is the maximum desired deceleration which is a parameter of the car-following model. Note that a similar principle as in the IDM is applied where drivers apply a factor \( \beta = b_{mid}/b \) on the current minimum required constant deceleration \( b_{min} \), which makes them slowly increase the deceleration up to \( b \). Decelerations are limited to not be larger than \( b \) to prevent large decelerations when \( v_{det} \) drops to a lower value.

\[
\frac{dv}{dt} = -\frac{b_{min}^2}{b} \cdot v - \frac{v^2 - v_s^2}{2 \cdot s}
\]  

(6.19)

In order to match the congestion pattern from simulation with the data, three settings are used which are \( \gamma_T \) which is a factor on \( T_{\min} \) and \( T_{\max} \) as calibrated in chapter 5, \( \gamma_{spill,ramp} \) which is the factor on speed for spillback on off ramp Moordrecht and \( \gamma_{spill,main} \) which is for the end of the section. For the first day we have \( \gamma_T = 1 \) as the LMRS has been calibrated on this day and spillback is excluded. For the second day \( \gamma_T = 0.65 \), \( \gamma_{spill,ramp} = 0.4 \) and \( \gamma_{spill,main} = 0.5 \) produce reasonable results. Apparently, as \( \gamma_T < 1 \), the calibrated values for \( T_{\min} \) and \( T_{\max} \) produce too much congestion for the second day.

### 6.2.2 Scenarios

The effectiveness of the system depends for a large part on the penetration rate \( \lambda \) (as a fraction of cars, i.e. excluding trucks) and the compliance rate \( \omega \). Different scenarios for different combinations are defined where both \( \lambda \) and \( \omega \) will obtain the values 0, 2, 10, 40 and 100%. For each scenario 10 runs are performed to average results. The scenarios with \( \lambda = \omega \) are also evaluated for each of the three advice principles individually to evaluate their effect. The spillback advice for the first day is omitted as there is no spillback. Throughout all these scenarios the route availability \( \rho \) is 100%. The scenario with \( \lambda = \omega = 10\% \) is also evaluated with varying route availability \( \rho = 0, 2, 10 \) and 40%. This will cause that less drivers follow lane-change advice as we assume that drivers ignore such advice in case it increases their required number of lane changes. The extent into which this affects overall results can be
derived from this. As results are the same if either $\lambda = 0\%$ or $\omega = 0\%$ this gives a total of 62 scenarios and 620 runs.

### 6.3 Results

A number of indicators is derived to evaluate the performance of the system. These indicators are determined for the analysis area which is the entire network minus 1km at the upstream and downstream side and excluding ramps. Here, congestion is defined as speeds below 60 km/h.

- Congestion duration at the lane drop ($x = 6319m$).
- Congestion duration at off ramp Moordrecht ($x = 8606m$).
- Saturation flow; maximum 5-min flow at cross section $x = 10847m$ during minutes where at least one detector is congested, normalized per lane.
- Maximum lane intensity; max. 5-min intensity at any detector.
- Maximum cross section intensity; maximum 5-min intensity at any cross section, normalized per lane. Includes lane distribution.
- (Mean) travel time delay which is equal to the travel time minus the free flow travel time, which is equal to the travel time at the desired free speed of a driver.

Space-time-speed/flow plots have been created based on virtual detectors which are presented in figure 6.4 for one run. Acceleration advices are given at the downstream end of congestion. Depending on the local presence of floating-car-data, these advices can be given quickly after a (mild) traffic breakdown. The distribution advices are not as closely related to the traffic pattern shown. This can be partially explained as these advices may originate from conditions on an adjacent lane, but as the second lane from the right is shown (which should usually be the busiest) it appears that these advices suffer from data delay. Contrary to speeds in congestion which trigger acceleration advices, high flow measurements appear less reliable considering the data delay to trigger distribution advices. Many advices are visible around position 8km, upstream of off ramp Moordrecht, on the second day, which are spillback related advices.

The resulting mean travel time delay of the various scenarios is given table 6.2, and visualized in figures 6.5a and 6.5b, for both days. For day one there is a small but steep decline in delay for low rates. Beyond rates of 10% the reduction is gradual with a maximum travel time delay reduction of 49% as seen in table 6.3. However, for $\lambda = 10\%$ the net effects are close to zero, despite positive effects for $\lambda = 2\%$. A similar pattern can be found for day two, although the net effects for mainly low $\lambda$ are slightly negative. The worst scenario is with $\lambda = \omega = 10\%$ with an increase of 14% in travel time delay. These results are however much better than results without the spillback advices, showing that the distribution advices have a potentially significant negative side effect relating to spillback without the spillback advices. On day two the maximum travel time delay reduction is similar with 43%.
Figure 6.4: Overview of traffic pattern and advices. Day 1 (a, c & e) and day 2 (b, d & f). Actual speeds (a & b). Ex-post traffic state estimation for the scenario $\lambda = \omega = 2\%$ showing speed data on the 2nd lane from the right with acceleration advices superimposed (vertical dotted lines), horizontal lines indicate the lane drop and off ramp Moordrecht (c & d) and the same but showing flow data and advices from the distribution and spillback principles (e & f).
Figure 6.5: Overview of indicators. Day 1 (a, c & e) and day 2 (b, d & f). Mean travel time delay for different combinations of $\lambda$ and $\omega$ (a & b). Travel time delay on diagonal ($\lambda = \omega$) for individual advice principles (c & d). Other indicators on diagonal (e & f). For a, b, e & f all advice principles are used. For all, the route availability $\rho$ is 100%.
Table 6.2: Mean travel time delays in the various scenarios. Compliance rate $\omega$ increases from right to left in accordance with figure 6.5.

<table>
<thead>
<tr>
<th>$\lambda \setminus \omega$</th>
<th>Day 1 (June 8th 2009)</th>
<th></th>
<th>Day 2 (March 24th 2009)</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Base scenario ($\tau = 0$ and/or $\lambda = 0$)</td>
<td>365s</td>
<td>Base scenario ($\tau = 0$ and/or $\lambda = 0$)</td>
<td>363s</td>
</tr>
<tr>
<td>2%</td>
<td>310s</td>
<td>296s</td>
<td>325s</td>
<td>312s</td>
</tr>
<tr>
<td>10%</td>
<td>355s</td>
<td>368s</td>
<td>331s</td>
<td>358s</td>
</tr>
<tr>
<td>50%</td>
<td>265s</td>
<td>283s</td>
<td>305s</td>
<td>328s</td>
</tr>
<tr>
<td>100%</td>
<td>185s</td>
<td>260s</td>
<td>318s</td>
<td>329s</td>
</tr>
</tbody>
</table>

Table 6.3: Changes in mean travel time delay in the various scenarios. Compliance rate $\omega$ increases from right to left in accordance with figure 6.5.

<table>
<thead>
<tr>
<th>$\lambda \setminus \omega$</th>
<th>Day 1 (June 8th 2009)</th>
<th></th>
<th>Day 2 (March 24th 2009)</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>100%</td>
<td>50%</td>
<td>10%</td>
<td>2%</td>
</tr>
<tr>
<td>2%</td>
<td>-15,1%</td>
<td>-18,7%</td>
<td>-10,7%</td>
<td>-11,9%</td>
</tr>
<tr>
<td>10%</td>
<td>-2,6%</td>
<td>+1,0%</td>
<td>-9,3%</td>
<td>-1,9%</td>
</tr>
<tr>
<td>50%</td>
<td>-27,2%</td>
<td>-22,3%</td>
<td>-16,4%</td>
<td>-10,0%</td>
</tr>
<tr>
<td>100%</td>
<td>-49,2%</td>
<td>-28,6%</td>
<td>-12,7%</td>
<td>-9,9%</td>
</tr>
</tbody>
</table>

Based on the results, the following hypotheses, with varying certainty, can be made as to the underlying mechanisms. More in-depth analysis is required to (dis)proof these hypotheses. Looking at figures 6.5c and 6.5d it becomes apparent that the results from the different advice principles cannot be superimposed. For instance in 6.5d at $\lambda = \omega = 10\%$ we see that the individual advice principles all show a minor decrease of delay, whereas the total shows a slight increase in delay. At 100% the differences are even much larger, especially between the spillback advices and all advices. One explanation for this could be that the spillback advices alone create a disturbance on the left-hand lane for large compliance and penetration, whereas the acceleration advices increase the stability of the left-hand lane such that it can handle the additional flow from the right-hand lane. The distribution advices show a slight decrease in delay for small rates and a slight increase for large rates on day two. The small effects are logical as the main source of congestion is spillback and not the lane drop. The pattern of a small decrease followed with a small increase is coherent with the negative side effect of the distribution advices and spillback. For day one (6.5c) the distribution advices show a less clear pattern. Possibly that for 10% the increased flow on the right-hand lane interferes with flow from the nearby onramp, whereas for 40% the flow on the left-hand lane is reduced to an extent that (unadvised) drivers are able to make compensating lane changes to the left-hand lane. Remarkably, the acceleration advices alone show almost exclusively positive results on both days which are better than, or close to, the results of all advices.

In figure 6.5e the other indicators for day one are shown. Both the maximum intensities and saturation flow grow in the order of 100 veh/h. The shape of the saturation flow increase is different than for example found by Kesting et al. (2010), where an exponential increase was found due to more blocking by leaders for low rates. The scenarios are however not comparable and here the shape appears close to linear. The duration of congestion at the off ramp is always close to zero as on day one there is no spillback. The duration of congestion at the lane drop is only reduced for rates of 100%. As the travel time delay is reduced it is likely that the length of congestion is reduced at smaller rates, but the exact congestion pattern is highly demand related. On day two (6.5f) the congestion at both locations is reduced, after a small increase at the lane drop at low rates which coincides with figure 6.5b. The fact that the duration of congestion at off ramp Moordrecht is reduced shows that the spillback advices
work as intended. The maximum intensities and saturation flow show a chaotic pattern in a range of about 100 veh/h. This is probably due to a number of interactions between sources of congestion and advice principles.

No substantial differences between cars with and without advice are found in the travel time delay distribution of individual scenarios (e.g. as in figure 6.6) and the average delay for drivers with or without advice per scenario. One scenario shows a mean delay difference of 22.5s, but most differences are much smaller. This indicates that advice is neither beneficial nor detrimental for individual drivers with advice, other than the overall effect. The hypothesis that advice does not influence the distribution of travel time delay is confirmed by the statistical Kolmogorov-Smirnov test in all but 5 scenarios. From figure 6.6 it can be seen that trucks suffer less travel time delay, which is logical considering their lower free speed.

Figure 6.6: Travel time delay distribution. Day 1 (a) and day 2 (b) from the scenario with $\lambda = 40\%$ and $\omega = 100\%$ over all runs combined (adv. is advised).
On both days the level of route availability $\rho$ appears to have little influence on results, as can be seen from figure 6.7. For day 1 this is not surprising as this day has the lane drop as source of congestion. At the lane drop advices will be given towards the right-hand lane which is never a problem for the route, resulting in hardly visible differences. On day 2 some differences can be seen, but these are still small, indicating that route availability is not important for the results. This statement can however not be generalized to all networks. In our case most (effective) advices are independent of the route or comply with the route of most traffic. This may very well not hold for instance at a weaving section.

Figure 6.7: Overview of indicators with varying route availability. Indicators for day 1 (a) and day 2 (b) for the scenario $\lambda = \omega = 10\%$. 
6.4 Conclusions

This chapter has evaluated the effect of three advice principles (acceleration advice, distribution advice and spillback advice) on (average) travel time delay. The following important insights have been obtained:

1. In-car advice can reduce travel time delay up to about 40-50% with all advice principles combined.
   a. There is no monotonic relation between penetration rate and travel time delay as there is a deterioration between 2% and 10% penetration rate on both days. This is caused by interactions between sources of congestion and different advices. These include:
      i. Lane change advice towards the right-hand lane which increases disturbances with busy onramps and off ramps with spillback.
      ii. Lane advice which brings intensity up to a level which may or may not cause traffic flow breakdown depending on whether acceleration advice is given. Note that acceleration advice may solve local drops in speed before they cause full traffic break-down.
   b. Drivers with advice suffer no significant higher delay than unadvised drivers, which indicates a small gap between individual and system benefits. Nonetheless, this may not be perceived as such by drivers.
   c. Route availability is not important for the investigated network. This can be explained by the fact that lane changes are usually given towards the right-hand lane, i.e. the number of lane changes required to follow the route does not increase.

2. Acceleration advice has strongest positive effects. It reduces the capacity drop which strongly improves travel time delay as congestion does not only occur during a smaller time period, but is is also shorter (i.e. drivers still affected experience less delay).
   a. Maximum intensity and saturation flow are shown to increase with about 100 veh/h. The lane distributions at maximum intensity are all about 55% (left) and 45% (right), with or without advice. Since headways are not affected, this indicates increased traffic flow stability, or in other words, when traffic breaks down, acceleration advice increases the probability that congestion is quickly solved. Therefore, large congestion is delayed.
   b. Since acceleration advice only relies on speed data this shows that in-car advice can be similarly effective in parts of the freeway network without detectors.

3. Distribution advices are found to have negative side effects that may be larger than the related positive effects. Positive effects arise from spare capacity on the right-hand lane being utilized. Negative effects have to do with increased disturbances from onramps and off ramps in case of an increased flow on the right-hand lane, as discussed at observation 1.a.i.

4. Spillback advice may reduce (or delay) spillback from off ramps by diverting traffic from the right-hand lane. A negative side effect found is oversaturation of the left-hand lane, depending on what the left-hand lane can handle as discussed at observation 1.a.ii.
The negative side effects of distribution advices show that these should be given with care. Besides the mentioned interactions with onramps and off ramps with spillback in case distribution advices are given towards the right-hand lane, other causes of negative effects are related to:

- Coarseness of the underlying data. The data is aggregated with 1 minute intervals and delayed for 75s. During this time, the situation may have changed such that advices are no longer required.

- Distribution advices have been designed in a pro-active manner, i.e. current high flows, assumed to exist mainly due to infrastructure related lane changes, are assumed to be indicative of high flow in the next minute at the same location. Consequently, lane changes are given upstream of estimated high flow such that this may be prevented. It may be more effective to advice lane changes in a reactive manner (at high flows), rather than a pro-active manner (upstream of high flows). Given fluctuations in inflow, perhaps that the pro-active approach tends to give advice in low flow traffic upstream of high flow traffic.

This chapter has drawn the most important conclusions of this thesis, which explain what the effects of in-car advice are on traffic flow. An important remark at this point is that these results depend on the assumed driver responses, while no investigation into the sensitivity of these responses (other than compliance rate) has been performed. More research is required to better understand how drivers respond to in-car advice. The conclusions have been drawn based on simulations. The next chapter will investigate whether the system operates as expected in the actual pilot system, and will derive the empirical validity of the different advices.
7 Empirical evaluation of the advisory system

Parts of this chapter have been published in: Schakel W.J., B. van Arem, J.W.C. van Lint (2014) “Empirical Analysis of an In-car Speed, Headway and Lane Use Advisory System”, Proceedings of the TRAIL Congress 2014, November 13, Delft, the Netherlands.

Whereas the previous chapter has evaluated the effects on freeway efficiency using simulation, this chapter evaluates the actual operations of the system. This is done to check whether the system produces advices as expected (advice validity) and whether these advices can be expected to be credible to drivers (advice credibility). For any traffic system, this is a useful step between evaluations using simulation, and actual implementation, where the most significant difference is real instead of simulated traffic. In our case, the algorithms are running with real and delayed data and advices are being produced. However, no equipped vehicles are driving on the road. Advice credibility as such is thus not determined empirically, i.e. as reported by drivers, but it is estimated based on empirical detector and advice data from the system. This chapter will first elaborate on the importance of this evaluation, then describe the methodology of this analysis. After a discussion concerning advice frequency and driver workload, the results are presented. This chapter ends with conclusions.

7.1 Empirical evaluation

The empirical evaluation in this chapter is performed as an indication whether the system as evaluated in simulation, will also be effective in reality, which always presents more complexity. This complexity arises from the unpredictable nature of driver behavior and the variability in traffic patterns. The empirical evaluation will attempt to take away these uncertainties, for as far as possible without a large-scale implementation of the system. To this end, the system ran on real and delayed traffic data, but without any equipped vehicles on the road. The system ran without the spillback advice principle\(^3\). Three aspects will be evaluated which are:

\(^3\)The spillback advice principle was developed after the system ran for the empirical evaluation.
advice validity; Advices are valid if they are consistent with the design considerations from chapter 3, regarding their location, time and the traffic state. Also, if the system does not give advices where it should, this is considered as a failure regarding advice validity. If the system has advice validity, it both operates as expected and the used settings are appropriate for real traffic.

• Advice credibility; Advices are credible if drivers are (most) willing and able to comply to advices. Assumptions are made concerning what drivers consider credible or not, which are operationalized in a number of indicators discussed later in this chapter.

• Advice frequency; Drivers should be able to receive and act upon advices safely. This touches upon the subject of human factors, which is a complex research field. A simple approach is undertaken, assuming that having a small number of advices during a limited period of time is acceptable. The limitations and possible repercussions of this assumption will be discussed further on in this chapter.

For both advice validity and advice credibility, it is important that the system can cope with the data delay. It may be that certain traffic circumstances are poorly predicted, which reduces both advice validity and credibility as the advice does not comply with the actual traffic state. Furthermore, the empirical evaluation allows the system to be evaluated for both advice validity and credibility over a considerable time period, providing more certainty about the possible effects in reality.

This form of empirical evaluation may provide a number of leads for system improvement before actual implementation. As we will show in the methodology in the next section, this is possible provided that traffic data and system data is available. Using a readily available traffic state estimation technique, the advices can be compared to the traffic state. With the use of a novel trajectory estimation technique, evaluations from the vehicle as frame of references are also performed.

### 7.2 Methodology of empirical evaluation

The general concept of the empirical evaluation is depicted in figure 7.1. The system logs its operations, including the detector data and the generated advice regions. From the detector data, the traffic state is estimated. This estimation is ex-post, i.e. all available data is used (rather than delayed data only in the live system). Next, the traffic state is used to derive virtual trajectories. The trajectories are compared with the advice regions, and a number of indicators for advice validity and advice credibility is derived concerning the advices a vehicle following the trajectory would have received.

![Figure 7.1: Overview of the methodology for the empirical evaluation.](image-url)
Chapter 7 - Empirical evaluation of the advisory system

The system ran for two weeks from February the 11th till the 24th of 2013, during which no exceptional circumstances such as incidents or bad weather were present. Although operations under such circumstances are interesting, the focus in this chapter is on regular circumstances. Advices were generated for a 10km stretch on the A20 freeway, from Prins Alexander (Rotterdam) to Gouda, see also figure 7.2. Other than in the simulated system, the flow threshold for distribution advices was set at 2000 veh/h in this case.

Figure 7.2: A20 network for empirical evaluation. Distances and detector locations in meters.

The following subsections will describe the available log data, the ex-post traffic state estimation, the estimation of vehicle trajectories and how these are compared with the advice regions, and finally how indicators for validity and credibility of advices are determined and derived from the vehicle trajectories.

7.2.1 Available log data
Among information about the state of the advisory system, the log files contain the incoming data and the generated advice regions. Since the system ran without equipped vehicles on the road, no floating car data is available. Dual loop detector data is available and contains 1 minute aggregated flow and arithmetic mean speed, including location and time. Detector locations can be seen in figure 7.2.

The advice data concerns advice regions rather than individual advices (as no vehicles with the system were on the road) which includes the following information:

- Valid range, including the lane and valid time span.
- Which qualitative advices were active (synchronization, yielding, short headway).
- Advised speed (if any).
- Advised lane (if any), which may or may not be equal to the current lane.

7.2.2 Ex-post traffic state estimation
Using the detector data from the log files, the traffic state on the freeway stretch can be estimated. Similarly as for the prediction method of the advisory system itself, we used the EGTF, or Extended Generalized Treiber-Helbing Filter (van Lint and Hoogendoorn, 2010), which is based on the ASM, or Adaptive Smoothing Method (Treiber and Helbing, 2002), at lane level to derive the traffic state. Just as with the actual system, this ignores lane changes, especially influencing flow. However, with closely spaced detectors and by the use of all data, this error is expected to be small enough for the empirical evaluation. The used cells have a length of $\Delta x = 100m$ and a time span of $\Delta t = 10s$. Other parameters are the free flow propagation speed $c_{free} = 85km/h$, the congestion propagation speed $c_{cong} = -18km/h$, flip-over speed between congestion and free flow $V_c = 80km/h$, flip-over region width $\Delta V = 10km/h$.

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4 The simulations were performed later, and a higher value was preferred then. Note that system settings were only manually optimized.
spatial kernel size $\sigma = 300\text{m}$ and temporal kernel size $\tau = 30\text{s}$. Within each cell, the traffic state is assumed homogeneous and equal to the state as derived with the EGTF for the center of the cell. Similarly, the middle of the aggregation period of the detector data was used.

7.2.3 Virtual trajectories

Virtual lane-level trajectories are required since no equipped vehicles were on the road, while the driver perspective is vital for determining advice credibility. Methods to derive trajectories from detector data are readily available in literature (Ni and Wang, 2008; van Lint, 2010), and are often used for travel time estimation. In our case there is no need for very high travel time accuracy as trajectories merely function as a representative sampling of when and where advice credibility is evaluated. Moreover, for each individual advice encountered, advice validity is independent of the travel time.

Ni and Wang (2008) compare a number of trajectory estimation methods. They compare very simple methods, where trajectories are assumed to obtain a speed instantaneously when entering a new section, with more complex methods where speeds are assumed to change linearly over space, and possibly also over time. Sections are defined between detector locations, and the speed within a section is a simple average of the detectors at both ends for the instantaneous methods, or the result of linear interpolation of these speeds for the linear methods. In the latter approach, the speed at a given location $x$, is used to derive the travel time over some small distance $\Delta x$. At $x + \Delta x$ the speed is determined again for the next $\Delta x$. In this manner a trajectory is sequentially determined. They find that the more complex methods perform better, especially in congested traffic. Van Lint (2010) performs a similar comparison, but extends the set of trajectory estimation methods with methods which first filter the detector data. This filtering is essentially the EGTF traffic state estimation method (van Lint and Hoogendoorn, 2010), which provides speed information consistent with general traffic patterns at a finer grid than the detector locations. Travel times as derived with the filter method are more accurate than other methods.

Since the traffic state from the traffic state estimation using the EGTF is already available in the empirical analysis, the use of the filtered trajectory estimation method is straightforward, and the used method is essentially equal to the method described by Van Lint (2010). The algorithm to describe how trajectories are derived using the EGTF speed field will be described next. An important difference with the description of Van Lint is that each cell has a representative speed derived at its center in space and time. The comparison by Van Lint considers cells (i.e. sections) in between measured (or in this case estimated) locations, which is equal to earlier methods dealing with detector data. Consequently, in our case no interpolation of any sort is required within a single cell, and speeds are assumed to be obtained instantaneously when entering the next cell.

For each considered day and for each lane, the first coordinate of the $m$th trajectory has $x_0 = 0$ (the start of the network) and $t_0 = (m-1)\cdot\Delta T$, where $\Delta T$ is the time difference between trajectories which is set at 5 minutes. The algorithm to find the next coordinate $(x_{n+1}, t_{n+1})$ based on the current coordinate $(x_n, t_n)$ is given in equation (7.1) and visualized in figure 7.3. It describes that the next coordinate is restricted by the next cell boundary in either space or time. Lane changes are not considered.

$$
(x_{n+1}, t_{n+1}) = \begin{cases} 
(x'_n, t_n + \Delta t), & t_s < t_i \\
(x_n + v \cdot t'_s, t'_n), & t_s \geq t_i 
\end{cases}
$$ (7.1)
In equation (7.1), \( x'_n \) is the location of the first cell boundary downstream of \( x_n \) and \( t'_n \) is the time of the first cell boundary after \( t_n \). With the speed \( v \) inside the cell, two times are derived being the time until \( x' \) is reached, given by \( t_x = (x' - x)/v \) and the time until \( t'_n \) is reached, given by \( t_t = t'_n - t_n \). Depending on which time is shortest, either boundary defines the next trajectory coordinate. This is displayed in figure 7.3 for two different values of \( v \) leading to two different next boundaries from the same point \((x_n, t_n)\). Figure 7.5 shows some example trajectories with the actual data.

![Figure 7.3: Determination of the next coordinate in a trajectory. This depends on the speed of the cell that is passed.](image)

### 7.2.4 Virtual trajectories and advice regions

With the virtual trajectories, statistics can be gathered concerning the advice validity and credibility. These statistics concern the advice regions, which are available from the system log, that a trajectory encounters. A region is considered to be encountered when a single section of a trajectory, i.e. from \((x_n, t_n)\) to \((x_{n+1}, t_{n+1})\), crosses an entering boundary of an advice region in either space (upstream edge) or time (start time). Two aspects of the advisory system should be explained before statistics are gathered. These are user selection, which assigns the advices of an advice region to individual users, and in-car filtering, which may filter some of the received advices and not show them to the user. These aspects will now be explained.

**User selection**

The advice regions describe a region over time and space within which certain advice(s) may be active. An advice region is different from an individual advice. The main difference is that a region describes one or more advices that can be given, for which the system then selects individual users, resulting in individual advice. Typically, this is the case if a percentage of users gets the advice to change lane, with the remaining users receiving some other advice. In other cases, an advice region contains only a single advice for all users. Generally, it holds that each user will receive an advice when entering an advice region. Thus, the number of advice regions encountered is equal to the total number of advices received. However, when counting different types of advice, it is unclear in the empirical analysis which advice will be given to a specific user if an advice region contains multiple advices. Consequently, a count of a specific type of advice yields the maximum number of advices of this type that could have been given. This is illustrated in figure 7.4 with the advice regions that contain both...
‘change left’ and ‘yield right’ advice. Drivers will either receive one of the two advices twice, or each advice a single time, depending on the user selection.

![Diagram of space and time with virtual trajectory, short headway, 15% change left, 85% yield right, and number of advices table]

<table>
<thead>
<tr>
<th>Number of advices</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gross: 4</td>
</tr>
<tr>
<td>Net: 3(^a)</td>
</tr>
<tr>
<td>- per type -</td>
</tr>
<tr>
<td>All (= net): 3</td>
</tr>
<tr>
<td>Short headway: 1(^a)</td>
</tr>
<tr>
<td>Change left: 2 or less(^b)</td>
</tr>
<tr>
<td>Yield right: 2 or less(^b)</td>
</tr>
</tbody>
</table>

\(^a\) in-car filtering; the adjacent short headway advices are merged
\(^b\) user selection; together these account for 2 net advices

**Figure 7.4: Effects of user selection and in-car filtering on advice counts.**

**In-car filtering**

The second aspect, in-car filtering, may filter advices that are received and not show them to the user. This filtering is intended to lower the number of advices that are given if this is appropriate. Circumstances in which advices may be filtered are:

- An active advice being equal to the currently active advice, which means that two advices can be merged into one and only the duration of the advice should be increased.
- An advice only being valid for little remaining time or distance, for instance when an advice region is entered as the start time boundary is crossed, while being in the last 50m of the valid spatial region.
- An advice being conflicting with other information, such as changing left while the route requires a lane change to the right, or advising about the head of congestion while the speed is (already) high.

In our case, we do not want to fully resemble in-car filtering, as statistics about otherwise filtered advices are also interesting concerning advice validity and credibility. For instance, it is interesting to find out how often it occurs that an advice about the head of congestion is received while the speed is high. Therefore, the third bullet is not implemented here. The second bullet introduces some complexity and requires settings of which it is unknown what values are optimal for user credibility, e.g. is 100m remaining distance acceptable? Consequently we also do not implement this form of in-car filtering. However, it does mean that the number of advices that the empirical analysis finds is an upper boundary. Finally, the first bullet is implemented, as merging equal advices is important in lowering the number of advices a user receives.
In the remainder of this chapter, a distinction is made between the number of encountered advice regions, denoted as the gross number of advices, and the number of advice regions that are not filtered by the simulated in-car filtering, denoted as the net number of advices. This is illustrated in figure 7.4 with the advice regions with ‘short headway’ advice which are merged into a single advice towards the driver. Advice validity and credibility will only be derived for the advices that are not filtered, as these are presented to the driver (the other advices are merged). The effect of this in-car filtering in the actual system is visualized in figure 7.5, where the net advices are indicated.

Finally, for each trajectory the travel time is also determined in order to evaluate the correlation between travel time and the (maximum) number of advices given of different types, since certain advices are often given in free flow while other advices are typically given in congestion.

![Figure 7.5: Example trajectories (white lines) on February 12th 2013. These go through the speed field [km/h]. Dashed regions are from the acceleration advice principle and continuous regions are from the distribution advice principle. The continuous arrows indicate the location and time when advices are given and for which advice validity and credibility is determined. The dashed arrows indicate advices that are merged with the previous advice. Note that given the traffic state estimation grid of \( \Delta x = 100\text{m} \) and \( \Delta t = 10\text{s} \) the trajectories appear continuous at this scale, but they are piece-wise linear.](image)

### 7.2.5 Indicators of advice validity and credibility
Advice validity and credibility is evaluated for six different advice categories, which are: synchronize, yield, short headway, speed, change lane and keep lane. Given that the acceleration advice principle and the distribution advice principle are used (see chapter 3), we can be sure that short headway advices originate from the acceleration advice principle while the remaining advices originate from the distribution advice principle. The six advice categories cover the complete set of advices that result from the system. For the indicators that are defined for advice credibility, assumptions are made about what drivers would and would not consider as credible in terms of the traffic circumstances they encounter when and shortly after they receive advice.
Part of advice validity is that advices are given in line with the advice principles. In order to gain insight into this, both the spatial and temporal distributions of the various advice categories are derived. The spatial and temporal distributions are given per lane in order not to obscure effects on individual lanes. The spatial distribution is based on the gross advice regions, whereas the temporal distribution only concerns the net advices encountered with the trajectories. The latter allows the number of advices during different times of the day to be considered.

While the spatial and temporal distributions are important indicators to check whether the advices are in line with the advice principles, and whether the system does not overload drivers with information, other indicators are required to check that the traffic state around an advice is also in line with the advice principles (for advice validity) and does not present the user with a situation in which a given advice is not credible (for advice credibility). From the perspective of both advice validity and credibility, each of the six categories will use one or more indicators. In total 12 indicators will be used, a) though l). An overview of these indicators, and for which advice category or perspective they are used, is shown in table 7.1.

Table 7.1: Overview of indicators for advice validity and credibility.

<table>
<thead>
<tr>
<th>Advice category</th>
<th>Advice validity</th>
<th>Advice credibility</th>
</tr>
</thead>
<tbody>
<tr>
<td>Change lane</td>
<td>a) Maximum flow in next 2km</td>
<td>c) Current density</td>
</tr>
<tr>
<td></td>
<td></td>
<td>d) Density difference with target lane</td>
</tr>
<tr>
<td></td>
<td></td>
<td>e) Current speed</td>
</tr>
<tr>
<td></td>
<td></td>
<td>f) Speed difference with target lane</td>
</tr>
<tr>
<td>Keep lane</td>
<td>Equal to ‘change lane’ validity</td>
<td>Equal to ‘change lane’ credibility</td>
</tr>
<tr>
<td>Synchronize</td>
<td>Equal to ‘change lane’ validity</td>
<td>g) Distance to lane drop</td>
</tr>
<tr>
<td>Yield</td>
<td>Equal to ‘change lane’ validity</td>
<td>h) Distance to lane drop</td>
</tr>
<tr>
<td>Short headway</td>
<td>b) Distance to end of congestion</td>
<td>i) Current speed</td>
</tr>
<tr>
<td></td>
<td></td>
<td>j) Time until next slowdown</td>
</tr>
<tr>
<td>Speed</td>
<td>Equal to ‘change lane’ validity</td>
<td>k) Current density</td>
</tr>
<tr>
<td></td>
<td></td>
<td>l) Speed difference with advice</td>
</tr>
</tbody>
</table>

Many of the advice categories stem from the distribution advice principle, and consequently have common advice validity. Essentially all these advices are valid if one lane indeed has a high flow for which advices are required. This validity will only be evaluated for the ‘change lane’ category, but applies to other advice categories as well, as shown in table 7.1. Similarly, indicators of advice credibility for ‘change lane’ and ‘keep lane’ advice are equal, as the latter is given on the target lane of the first (according to the distribution advice principle), i.e. there is one single traffic circumstance for which the target lane is credible to drive on. These indicators are also only evaluated for the ‘change lane’ category. All indicators are derived at the time and location where and when an advice region is encountered by a virtual trajectory. Also, the advice should not be filtered. The indicators, and why they are used, will be discussed next per category.

**Change lane advice**

The advice validity of this advice, as well as a number of other advice categories which are related as they all stem from the distribution advice principle, depends on whether there indeed is a peak flow in the lane where drivers receive advice to change lane. These advices are triggered by an estimated high flow, but due to data delay and other sources of estimation...
As drivers are unable to perceive the maximum flow in the next 2km, advice credibility is assumed to rely on the traffic state around the driver on both the current and the target lane. Specifically, advice is assumed credible if the current speed is low or the current density is high, especially if the target lane has higher speed or lower density. Consequently the following four indicators are used: “c) current density”, “d) density difference with target lane”, “e) current speed” and “f) speed difference with target lane”. Both indicators d) and f) are calculated as $y_{tar} - y_{cur}$, where $y_{tar}$ is the density or speed on the target lane and $y_{cur}$ is the density or speed on the current lane. Thus positive values advice a lane change towards a lane with higher speed or density.

Lane change advice may or may not be given in correlation with the lane-drop. Clearly drivers may find lane change advice credible if they can link the advice with the lane-drop, for which the distance to the lane drop is assumed important. This aspect of advice credibility is however not evaluated for lane change advice, as this advice can also be given elsewhere and may have nothing to do with the lane drop. However, the credibility of synchronize and yield advice perfectly represents the cases in which lane change advice is given in relation to the lane-drop, as the distribution advice principle will then also give synchronize and yield advice in exactly the same region (to those drivers that will not receive lane change advice).

**Keep lane advice**
Advice validity is equal to the ‘change lane’ validity. Advice credibility is equal to the ‘change lane’ credibility. Both for reasons discussed earlier.

**Synchronize advice**
Advice validity is equal to the ‘change lane’ validity. Advice credibility concerns the perspective of the driver. For this we need to make assumptions about what is, and what is not credible to users. For synchronize advice it is assumed that the distance to the lane drop (the only infrastructural change leading to these advices in the used network) is important, as drivers may understand the reason for the advice if the lane drop is near. It is difficult to state what is near at this point, but the system defines infrastructural areas with lengths of 2km. Thus, preferably distances should not be much larger than this. For synchronize advice indicator “g) distance to lane drop” is used to indicate advice credibility.

**Yield advice**
This is similar to advice validity and credibility of synchronize advice. In this case indicator “h) distance to lane drop” is used to indicate advice credibility. Note that indicators g) and h) are technically equal, but g) is evaluated if synchronize advice is encountered while h) is evaluated when yield advice is encountered. Consequently they describe the validity of the two advice categories independently.

**Short headway advice**
Short headway advice (from the acceleration advice principle) is only valid if indeed the end of congestion is within a reasonable distance downstream. In other cases, there apparently is
Development, Simulation and Evaluation of In-car Advice on Headway, Speed and Lane

no end of congestion to give this advice for. Short headway advice is given from 0.5km upstream until 1.5km downstream of the estimated location of the end of congestion, for which a flip-over speed of 60km/h is used. However, this assumes backward propagating congestion, which does not hold for standing congestion for instance at an onramp (which is one of the reasons why the advice is given in an area around this location). Consequently, a distance up to 2km is reasonable. Short headway validity is indicated with indicator “b) distance to end of congestion”. This is derived instantaneously at the moment a virtual trajectory enters an advice region, and from the entering location. The location of the end of congestion is derived from the ex-post traffic state estimation using a flip-over speed of 60km/h as well. If no downstream congestion is found, the distance is infinite. Indicator b) is also appropriate for headway advice credibility, as a driver would expect such advice only near the end of congestion. A second indicator is “i) current speed”, which in itself is an indicator of whether the driver is in congestion or not. It may be assumed that if drivers are still in free flow, this advice is experienced as not credible. This situation may however occur in case of short congestion for which the driver has yet to decelerate, while the end of congestion is also already near. In other cases, a high speed indicates an error in the traffic state estimation. Note that these problems can easily be solved with in-car filtering by not giving the advice at high speeds, but in the current analysis it is interesting to evaluate how often this occurs. Finally, it is expected that if drivers are notified about the end of congestion, while they will enter other congestion quickly thereafter, this brings about some annoyance which lowers the advice credibility. In fact, for this reason these advices are not given if congestion is estimated within 2km downstream of the end of congestion. To this end, indicator “j) time until next slowdown” is used. This is derived from the virtual trajectory itself. Up to four phases are considered:

- **Phase 1:** The driver receives the advice while driving >60km/h. This can occur if the congestion is short and the driver has yet to decelerate for the congestion for which the advice is given. If the speed is <60km/h, this phase is skipped.
- **Phase 2:** The speed is <60km/h, in congestion for which the advice is given.
- **Phase 3:** The speed is >80km/h, the driver is in free flow.
- **Phase 4:** The speed is <60km/h, the driver is again in congestion.

The start of phase four is used as ‘next slowdown’. If there is no phase four, i.e. no next congestion, the value is infinite. The threshold values of 60km/h and 80km/h are assumed to coincide with drivers’ perception of congestion and free flow.

**Speed advice**

Advice validity is equal to the ‘change lane’ validity. For advice credibility it is assumed that drivers would consider speed advice credible if the advised speed is slightly lower than the current speed, if they are in traffic near the critical density (which they would call busy traffic). Some drivers may already show this behavior if they perceive busy traffic ahead, a behavior which this advice may enhance, especially if the driver is not able to evaluate the traffic state ahead due to visual blocking. Reversely, advice to a slightly higher speed is only credible if the density is low. To evaluate the combination of density and the speed difference between the current speed and the advised speed, two indicators will be used: “k) current density” and “l) speed difference with advice”. The latter is calculated as $v_{adv} - v_{cur}$, where $v_{adv}$ is the advised speed and $v_{cur}$ is the current speed. Thus positive values result from an advised speed which is higher than the current speed.
Summarizing, the methodology gives the following indicators for advice validity and credibility:

- Temporal distribution of (net) advices and travel time, given per lane.
- Spatial distribution of (gross) advices, given per lane.
- Indicators a) through l).

### 7.3 Advice frequency, driver workload and safety

We defined advice credibility as drivers being (most) willing and able to comply to advices. To comply to advice also concerns safety, which should not deteriorate. For this it is assumed that aiming for a low number of advices is suitable, as to not overload the driver with information. Indeed this empirical analysis shows that the largest expected number of advices on a 10km stretch of road is about 2 in the evening rush hour (see the results section).

Concerning the willingness of drivers to comply with advice, credibility entails that drivers are as compliant as they can be by providing the advice only (e.g. rewards are not considered). For this a number of assumptions of what is credible advice is captured in the credibility indicators. The ability of drivers to comply with advice in a safe manner will now be discussed, and a number of possible safety reducing or compensating effects may be hypothesized or found in literature. The compensating effects may also have influence on the effectiveness of the system. Since both safety reducing and compensating effects may be present, it is unclear into what extent advice is still safe. However, a thorough analysis is out of the context of this thesis. The following effects are of interest concerning driver workload.

- Risto and Martens (2011) show that drivers are unable to properly maintain quantitative headway advice (e.g. keep 2s distance, or keep 40m distance). For this reason, the advisory system was designed to only provide qualitative headway advice (e.g. yield for merging vehicles).
- Advices are given on the tactical, or maneuvering, scale. Kaber et al. (2012) show that drivers experience a higher workload during such maneuvers. Advices may increase or decrease the number of tactical maneuvers, and ideally advice is not given during a tactical maneuver. This may however occur. Even if we consider that advices should lead to, rather than be given during, tactical maneuvers, Kaber et al. also show that cognitive distraction increases driver workload. Since advices do concern the tactical scale, and since the tactical scale requires cognitive effort (Michon, 1979), processing in-car advice thus increases the workload. If advice happens to be given during a tactical maneuver, the workload is further increased.
- Additionally, Kaber et al. show that in case of an increased workload, drivers may compensate for this by increasing their headway to reduce the workload. This however only occurs in their tests in case of visual distraction. Cognitive distractions did not show the same effect. It is thus probably best to not provide tactical advice visually, as increased headways are counterproductive for traffic flow efficiency. The cognitive processing of advice however does not seem to affect the headway negatively, as distance keeping to the lead vehicle is an operational rather than tactical skill. Tönnros and Bolling (2006) show that reducing speed may also be a means to lower workload. They found that an increased workload due to a mobile phone conversation was compensated with lower speeds, but only in certain environments associated with high workload (90km/h urban and complex rural environment).
- Tönnros and Bolling show that the workload depends on the environment, or more precisely, the complexity of traffic. Teh et al. (2014) find that workload increases
linearly with increasing traffic density up to moderate (i.e. sub-critical) levels. Furthermore, an increasing number of lane changes in the field of view increases the workload. This effect is stronger for nearer lane changes. These ‘high workload’ situations are exactly the situations in which triggers for in-car advice are likely, which is unfortunate. However, advices are intended to be given upstream of triggers such that the workload is not yet at its highest and drivers have time to process and act upon the advice.

- Mueller and Trick (2012) show with driver simulator tests that in case of fog, experienced and inexperienced drivers have similar speeds, though the compensation behavior is larger for experienced drivers as these drive faster in clear conditions. Despite similar speeds in fog, inexperienced drivers performed worse and were involved in accidents, while experienced drivers were not. This result is in line with literature mentioned by Mueller and Trick, giving rise to the idea that inexperienced drivers have more difficulty in coping with both operational and cognitive requirements for traffic. Consequently, an increased workload due to advice is more likely to present a dangerous situation for inexperienced drivers, than for experienced drivers. Besides the relatively high workload itself, inexperienced drivers may be prone to unsafe attention division.

The above considerations make a strong case for keeping the number of advices low in order not to deteriorate safety. There might however be a credibility paradox, which is that too few advices might render the advisory system as a whole less credible, e.g. if drivers would like or even expect advice but none is given. Also, advices should probably not be given visually. Finally it may be safer to drive with in-car advice only with sufficient driving experience.

7.4 Results

This section will elaborate on the results of the log analysis by presenting the temporal and spatial distribution, as well as the indicators a) through l) of advice validity and advice credibility.

7.4.1 Temporal distribution of advices and number of advices per vehicle

In figure 7.6 the average number of advices of different types throughout the day (as an average of the full analysis period) is presented, together with the average travel time. A clear evening peak can be seen from the travel time, though the morning peak is much less evident. The drop in travel time at 20h is due to missing data caused by an error in the logging system, which occurred on every day at 20h when log files were sent. Generally, the travel time is strongly correlated to the number of advices that is given, especially regarding the short headway advices. Other advices are also given before congestion occurs. This is as expected as the short headway advices are given at the end of congestion while the remaining advices originate from the distribution advice principle which aims to prevent congestion.

There are also lane specific observations. The left lane predominantly has synchronization advices. The middle lane has many lane change advices, but also yield, short headway and some speed advices. The right lane mainly has keep lane and short headway advices. All of this complies with expectations from the advice principles as the left lane is dropped (therefore little short headway advices) and as the middle lane is the busiest.
Figure 7.6: Number of advices and average travel time. Average number of net advices given on the left (a), middle (b) and right (c) lane over the full two week period, per time-of-day.

From figure 7.6 it can also be seen that the expected average number of advices per vehicle is quite low, with the highest expected number of advices in the evening peak being about 2 on a 10km stretch. The low number of advices per vehicle is confirmed by table 7.2, where it can be seen that only few drivers experience more than 3 (net) advices, and no driver experiences
more than 6 (net) advices over the entire two week period. Furthermore, table 7.2 shows the importance of in-car filtering as the number of advices is strongly reduced between the gross and the net counts. In fact, the in-car filter implemented in this thesis is able to merge about 3 advices into 1, except for the first advice (as for the first advice, there is no other advice to merge with). For example, the 75 trajectories with 7 gross advices have an average of 3.09 net advices, see the 4th column. Only for \( n_{\text{gross}} = 10 \) this is not true, but this is due to the fact that only two trajectories had 10 gross advices.

**Table 7.2: Number of gross and net advices encountered. The arrows indicate a shift in the advice distribution to fewer advices due to the in-car filtering.**

<table>
<thead>
<tr>
<th>Number of advices ((n))</th>
<th>Trajectories with (n) gross advices</th>
<th>Trajectories with (n) net advices</th>
<th>Average number of net advices for (n) gross advices</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>9728</td>
<td>9728</td>
<td>0</td>
</tr>
<tr>
<td>1</td>
<td>684</td>
<td>1345</td>
<td>1</td>
</tr>
<tr>
<td>2</td>
<td>461</td>
<td>691</td>
<td>1.31</td>
</tr>
<tr>
<td>3</td>
<td>396</td>
<td>300</td>
<td>1.59</td>
</tr>
<tr>
<td>4</td>
<td>321</td>
<td>61</td>
<td>1.93</td>
</tr>
<tr>
<td>5</td>
<td>276</td>
<td>11</td>
<td>2.28</td>
</tr>
<tr>
<td>6</td>
<td>163</td>
<td>2</td>
<td>2.59</td>
</tr>
<tr>
<td>7</td>
<td>75</td>
<td>0</td>
<td>3.09</td>
</tr>
<tr>
<td>8</td>
<td>24</td>
<td>0</td>
<td>3.29</td>
</tr>
<tr>
<td>9</td>
<td>8</td>
<td>0</td>
<td>3.88</td>
</tr>
<tr>
<td>10</td>
<td>2</td>
<td>0</td>
<td>2.5</td>
</tr>
</tbody>
</table>

The distribution of gross and net advices is also shown in figure 7.7 (for \( n \geq 1 \)). It clearly shows that the net distribution lies at a lower number of advices, showing higher probability for up to 2 advices (i.e. the in-car filter reduces a higher number of gross advices to a lower number of net advices).

**Figure 7.7: Distribution of gross and net number of advices.**

The temporal distribution of advices shows that advices are given as expected from the advice principles, indicating advice validity. Also the number of advices per vehicle is generally low.
7.4.2 Spatial distribution of advices

The temporal distribution of advices shows that the differences between lanes are as expected given the advice principles. The spatial distribution of different advices is presented in figure 7.8. As to the differences between lanes this is similar as in figure 7.6, the temporal distribution. There are however some additional observations to be made concerning the longitudinal (i.e., driving direction) distribution. Short headway advices are almost all given between the lane drop and the next off ramp. This is in accordance with the known sources of congestion which are spillback from the off ramp and the lane-drop with a busy onramp (see chapter 6). Furthermore, lane change advices are usually accompanied by a lane keep advice and by yield advices for about 33% and synchronize advices for about 40%. This strongly depends on whether the trigger for distribution advices is upstream or downstream of the lane-drop, as yield and synchronize advices are only given upstream of the lane-drop. Remaining differences can be explained by the overlap filter (step 3 of the advice algorithm). The spatial distribution of advices is thus in accordance with expectations from the advice principles, which indicates advice validity.

![Figure 7.8: Spatial distribution of advices of the full two week period.](image)

7.4.3 Indicators for advice validity and credibility

The advice validity and credibility indicators of different advice categories will now be discussed.

Change lane and keep lane advice

Validity and credibility of lane change and keep advice is derived from the indicators presented in figure 7.9. The validity concerns the distribution advice principle and therefore also synchronize, yield and speed advice.

Most lane change advices are given for densities below 25 veh/h and speeds above 80 km/h, which is as intended as lane changes are advised to prevent congestion. Since lane change advices are usually given from the middle to the right lane (in the considered network), it is not surprising that the target lane has densities which are usually 0 to 12 veh/km lower than in the current lane. Similarly, it is not surprising that speeds on the target lane are 0 to 25 km/h lower, because of trucks. Concerning advice credibility, the lower density is favorable but the lower speed is not. The maximum flow within 2 km is higher than 2000 veh/h, the trigger value for distribution advices, for 25.8% of lane change advices. This indicates that advices from the distribution advice principle are often not valid. This is also in line with speed...
advices often being given at low densities (presented further down). Summarizing, advices from the distribution advice principle have limited validity regarding the flow levels found. Lane change and lane keep advice also have limited credibility due to the lower speeds on the target lane. On the other hand, densities are usually lower, which is considered credible.

Figure 7.9: Indicators for distribution advice.

**Synchronize and yield advice**

In figure 7.10, the distance towards the lane drop for synchronize and yield advices is shown. These are in the range between 1 and 4 kilometers upstream of the lane drop. The larger distances may be rather early for some drivers, possibly delaying the moment when drivers become compliant. However, they do allow sufficient time to perform smooth lane changes. Advice credibility may not be optimal for all synchronize and yield advices.

Figure 7.10: Indicators for synchronize and yield advice.

Advice validity for synchronize and yield advice is discussed with lane change and lane keep advice, as these stem from the distribution advice principle.
Short headway advice

Figure 7.11 shows the indicators that are concerned with short headway advices. The majority of the advices is given between 0.7km and 1.7km upstream of the end of congestion, which is reasonable as drivers need some time to become more active. For 16.7% of these advices, no congestion is encountered from which to accelerate (hence the cumulative probability of indicator b) up to 0.833). This can be (partially) explained by the delay in the detector data which causes the algorithm to assume congestion for about 3 minutes after it actually has been solved, including very small traffic breakdowns that are quickly solved. Note however that short headway advices can be filtered in-car as they should only be given if the vehicle has a speed below e.g. 80km/h. For 6.4%, the advice is given while the end of congestion is more than 2km downstream.

For 63.8% of all drivers the speed indicates that the driver is in congestion when receiving short headway advice. For 19.2% of short headway advices the speed of the vehicle when the advice is first given is above 80km/h, which can be (partially) explained by the lack of actual congestion. For the remaining 16.9% the speed is between 60km/h and 80km/h, whereas congestion is recognized below 60km/h. This may be partially due to short congestion for which the driver is decelerating when the short headway advice is first given. In fact closer examination of the trajectories reveals that 39.2% of drivers that get short headway advice while driving above 60km/h do find the end of congestion within 2km. For speeds above 60km/h but below 80km/h this is 58.0%. Some of these drivers might not encounter congestion at all. Of the drivers that do encounter congestion, 71.3% experience the end of the congestion within 2km. For speeds above 60km/h but below 80km/h this is 79.7%.

Figure 7.11: Indicators for short headway advice.

Although the distance to end of congestion is assumed to reflect how valid short headway advice is for drivers, it may also be argued that the time until the end of congestion is important. If the end of congestion is reached a considerable time after the advice was first given, attention may have dropped. As speeds in congestion are low, this could occur. Analysis of the trajectories reveals that for those drivers that encounter congestion, 50% reach the end of congestion (defined as reaching 60km/h) within 97.5s, whereas 92.7% reaches the end of congestion within 180s. Note that during this time, the advice remains active.

Finally, the time until next slowdown shows that in practically all cases (indicator “j”) lies just above the x-axis, but too little to be visible) there is no next slowdown, i.e. drivers do not
have to slow down shortly after receiving the advice to maintain a short headway while accelerating out of congestion. However, there may be drops in speed before 80km/h is reached, which drivers may consider ‘new’ congestion.

Closer examination of the trajectories, starting from the moment that short headway advice was given, reveals that indeed such drops in speed are present. Between the moment that the minimum speed during advice is reached, and the moment that 80km/h is reached, for instance 21.3% experience a drop of 5km/h or larger. The percentage decreases to 10.3% for a drop of 10km/h or larger, and 2.2% for a drop of 20km/h or larger. It is however unknown what drop in speed may be considered as new congestion, and the absolute speed from which the drop starts may also be important.

Overall, short headway advices are valid and credible, though credibility may be improved by obtaining a better understanding of what drivers consider a drop in speed which is conflicting with such advice. Furthermore, for 36.2% the speed when receiving this advice indicates that deceleration for short congestion is first applied, after which drivers indeed encounter the end of congestion. Although the end of congestion is indeed near in 71.3% of these cases, advice may be less credible if drivers are still approaching the congestion.

Figure 7.12: Indicators for speed advice.
**Speed advice**

Figure 7.12 shows the indicators for speed advice. The cumulative distribution (figure 7.12a) shows that the current density is usually below 20 veh/km when speed advice is given. This is expected as the advice is intended to be given in free flow. However, speed advice should only be given in near critical traffic, while clearly this advice is often given in low density traffic. This discrepancy is further discussed with the advice validity of lane change and keep advice (i.e. the distribution advice principle). The advised speed is higher than the current speed for 28.3% of the advices. Here, the traffic state estimation makes an error as speed advice should only be given if the current speed in a section is larger than the target speed.

Speed advice is assumed credible if a slightly lower speed is advised at a density near the critical density. Or, to a higher speed in low density. This can only be evaluated with a combination of both indicators, which is shown in figure 7.12b. It shows the opposite of what is assumed credible; lower speeds are advised at lower densities. The cause of this may be the fundamental relation between density and speed, i.e. at lower densities the speed is higher and consequently a lower advised speed is further from the current speed. Summarizing, speed advice seems not credible. This may be partially explained by the advice not being valid (i.e. being given in unintended circumstances), which is evaluated for lane change and keep advice.

### 7.5 Discussion

Advices from the distribution advice principle have limited validity with 25.8%. This is probably an important cause of the little effectiveness of lane change advices that was found in chapter 6, besides negative side effects that have to do with increased flow on the right-hand lane causing more interference with a busy onramp and off ramp with spillback. These advices were intended to advise drivers to change from the busy middle lane in case of high inflow. It however appears that inflow is fluctuating to such an extent, that giving such advices *upstream* of a trigger results in giving advices in areas where the flow can be considerably lower, as shown by indicator a) in figure 7.9. Besides the lane change advice, this also explains the low validity of speed advice. Therefore it is probably better to give lane change advices *around* the trigger, whereas advices were originally intended to be given upstream of the trigger (i.e. pro-active). On the other hand, the discussion on workload shows that typical trigger situations are associated with high workload, for which it would be desirable to give advice upstream where the workload is lower.

The data delay and coarseness (1 minute aggregation) may contribute to mismatches between distribution advice triggers and actual flow, since critical platoons that exist due to the lane drop, may become non-critical if only a few vehicles move from the platoon to another lane. With a delay of 2-3 minutes there is sufficient time for this to occur. More detailed and less delayed detector data, or possibly full trajectory data using cameras at critical locations, may allow for a significant improvement regarding the validity of lane change advices.

Credibility is different between advice categories. Short headway advice is credible in 76.9% of the cases (end of congestion within 2km). A large proportion of the remaining 23.1% may be easily filtered in-car by only providing this advice at speeds that indicate congestion. Furthermore, if the traffic state prediction is enhanced e.g. with floating car-data, acceleration advice credibility can be expected to improve. Synchronize and yield advices are now given as early as 4km upstream of an infrastructural cause, which is a combination of a 2km section being defined as a lane-drop section (or some other infrastructural change) and a 2km section...
upstream of a trigger in which advices are given. Combined, this may be too long for drivers to mentally link an advice with the infrastructure. In order to allow drivers about 1 minute (i.e. 2km at 120km/h), the advice region has to stay 2km in length, but the infrastructural section length could be reduced to for example 1km.

To assess the willingness to comply with advice, a number of assumptions has been made concerning what drivers would find a credible circumstance for the advice. The analysis shows that this is not always present. This is however to be expected as the basic principle of advice on the tactical scale is that drivers have an opportunity to perform maneuvers concerning a (potential) problem which is about 1-2km downstream and which drivers cannot yet perceive. The circumstance in which drivers get advice is thus structurally different from the circumstance for which the advice is given. To enhance advice credibility, a motivation for the advice may also be provided to the driver. In fact, as can be seen in appendix A, supplying a motivation is part of the advisory system. A possible downside of this could be an increase in workload and the net effect could be an interesting topic for future research.

7.6 Conclusions

This section presents the main findings from the empirical analysis into advice validity, credibility and frequency.

- The system operates as expected and designed, with advices from different advice principles showing the expected temporal and spatial distribution.
  - In-car filtering is important to reduce the number of advices given to drivers.
  - Advice frequency is low with a maximum expected number of advices of about 2 during the evening peak on a 10km road stretch.
- Short headway advice (from the acceleration advice principle) is valid and credible in 76.9% of the cases with the end of congestion being within 2km.
  - Credibility can be improved with in-car filtering.
  - Considering that acceleration advice is both credible and effective (see chapter 6), these advices alone show the strong potential of in-car advice on a tactical scale.
- Advices from the distribution advice principle have limited validity, as flows are indeed high for 25.8% of the cases. This is caused by a combination of data coarseness and a poor correlation between estimated high flows and upstream (i.e. pro-active) advices.
  - Synchronize and yield advice is given up to 4km upstream of the lane drop, which is probably not credible to all drivers.
  - Credibility of speed advice is low because the validity is low and as relatively lower speeds are advised at lower densities.

Given the limited validity of advices from the distribution advice principle, future work should focus on improving this by a combination of more, or more detailed, and less delayed data, as well as by different approaches for the distribution advices.
8 Conclusions and recommendations

This chapter summarizes the conclusions from the previous chapters in the next section. In the process of this research, many issues and opportunities have been found. From these, recommendations are given in the second section of this chapter.

8.1 Conclusions

This thesis has investigated the potential of in-car advice on headway, speed and lane to improve the efficiency of traffic flow, and found that:

- Travel time delay may be reduced up to about 40-50%.
- Both maximum intensity and saturation flow can increase with over 100 veh/h (5.4% and 7.0% respectively).

To this end, drivers are advised for their tactical maneuvers, i.e. on the tactical scale. According to the state-of-the-art, the tactical scale is not used in many current systems that try to optimize traffic flow efficiency. Additionally, most systems target a limited set of aspects of traffic flow dynamics which may be improved. Tactical advice can cover many aspects of traffic flow dynamics, with human limitations as main boundary condition. Aspects of traffic flow dynamics that may improve are: reducing inflow at lane level, reducing disturbances, reducing the capacity drop, and reducing spillback. The first two aspects are targeted by the distribution advice principle (diverting traffic from the busiest lane while enabling smoother lane changes), while the latter two aspects are target by the acceleration advice principle (increasing driver efficiency out of congestion) and spillback advice principle (diverting traffic from the right-hand lane) respectively.

The system is implemented in a newly developed microscopic traffic simulation framework, which is tailored to the implementation of new traffic systems. An enhanced car-following model (IMD+) and new lane-change model (LMRS) form the default (unadvised) driver behavior. The new lane change model includes both relaxation, where drivers accept small
headways during and shortly after lane changes, and synchronization, where drivers adapt speed and position before a lane change to the target lane in order to improve their changes for a safe lane change. Both relaxation and synchronization are not present in current lane change models, while they in our view are important to represent interactions between longitudinal and lateral driver behavior, and the resulting traffic flow dynamics.

The combination of LMRS with the IDM+ has been calibrated using a novel automated procedure. The results show that the model can represent lane distributions and the speeds on different lanes, all at different locations relative to infrastructural changes (e.g. lane drop or ramp), remarkably well. The level and location of congestion also resembles the calibration data, though the fit on validation data is less.

With assumptions on how drivers respond to in-car advice, while using a variable compliance rate, the potential of in-car advice has been investigated using simulation. This shows the potential to reduce travel time delay up to about 40-50%. Significant improvements are also found at low levels of compliance and/or penetration rate. However, in some cases the travel time delay deteriorates due to negative side effects. This may however be improved by applying the insights from this thesis in future advisory systems. Furthermore, the results show that advising short but safe headways at the end of congestion is a robust and effective approach to reduce travel time delay.

An empirical analysis of the system running with real detector data shows that the system does not present the driver with frequent advices and that many advices are valid (given in circumstances as expected) and credible (reasonable to drivers). Advices from the distribution advice principle show validity for 25.8%, caused by a combination of data coarseness (e.g. delay) and a flow mismatch resulting from the chosen pro-active approach. Both validity and credibility are probably improved when additional data sources such as floating car data are used. It should be mentioned that further research is required on human factors in order to prevent undesired effects from a possibly increased workload.

8.2 Recommendations

This section discusses a set of recommendations for further research and possible improvements in both the in-car advisory system and the simulation tools and models that have been used to evaluate this system. The next subsections will discuss recommendations regarding the traffic state prediction, the advice algorithm, the lane change model (LMRS) and the simulation framework.

8.2.1 Traffic state prediction

For the traffic state prediction of 1 minute into the future and a data delay of 75s (detector data) the Extended Generalized Treiber-Helbing Filter, or EGTF (van Lint and Hoogendoorn, 2010), which is based on the Adaptive Smoothing Method, or ASM (Treiber and Helbing, 2002), has been used on lane level, which essentially propagates traffic states with an expected speed. This is a simple and robust approach, but assumes no influence from lane changes or infrastructural inhomogeneity (e.g. lane-drop, onramp). The ASM is designed to cope with the latter by interpolation, i.e. later data corrects this. For traffic state prediction this is not possible and errors arising from the following causes may be larger:

- The tail of a queue may move slower due to low inflow. The tail may also move faster due to flow near capacity, but this error is never large as the backwards propagation speed assumes an inflow equal to saturation flow.
• The head of the queue may be (or become) stationary at a bottleneck.
• New congestion may arise.
• Lane changes cause the traffic state on individual lanes to change.

Accuracy of the predicted traffic state and advice region size
The empirical evaluation has shown that advices have limited validity and credibility. Through in-car advice filtering, the system aims to make advices as valid and credible as possible. By using sufficiently large advice regions, validity is further enhanced (e.g. the advice region around the estimated location of the end of congestion, such that indeed the end of congestion will usually be within the region). No benchmarking has taken place to compare the predicted traffic state with the actual (ex-post estimated) traffic state, or other methods of traffic state prediction. With such a benchmark it may be possible to reduce the size of advice regions, enabling a better understanding and compliance with drivers as they can mentally couple the advice better to what they experience. Even more, a different approach may produce more reliable results. Further research should thus be aimed at a fast and robust prediction method at lane level.

Estimation of local penetration rate
For the determination of the current and local penetration rate, which is used to decide how many drivers receive lane change advice given that a certain percentage of all traffic should change lane, the densities from the traffic state estimation and the estimated positions of equipped vehicles are used. There are two sources of inaccuracy for this estimation, which should be improved in future systems. These sources are:

• The estimated traffic state is determined 1 minute in to the future, and consequently this density was compared to the estimated current positions of equipped vehicles. Rather, current densities should be estimated, but this doubles the traffic state estimation calculation time, which may provide difficulties for large scale implementation.
• Densities are derived as the ratio of flow over speed. In the current system, only detector data is available for the estimation of flow. For the estimation of speed, both detector data and floating car data is available. This can result in an inconsistent traffic state as congestion that arises in between detectors may result in low speeds through floating car data, while high flow is derived from the detector data, that is until congestion reaches a detector. As explained by Hegyi et al. (2013), a better approach to estimate flow and density in congestion is to use the fundamental diagram with accurate speeds from floating car data, if that is available, to determine density (and flow), rather than using flow from detectors somewhat upstream and downstream.

Inclusion of estimation reliability
Besides the fact that the traffic state estimation relies on the reliability of the data, which includes the data delay, there are two sources of unreliability in the current traffic state prediction method which may produce an unreliable traffic state at some locations. In case of an unreliable traffic state, it could benefit advice credibility to not give advice even if the estimated traffic state meets the requirements to otherwise trigger advice. Credibility may improve as false-positives are reduced. The sources of unreliability are:

• The ASM propagates traffic states along the line of $c_{\text{free}}$ (85km/h) or $c_{\text{cong}}$ (-18km/h). In case no data is available in those (general) directions, the ASM will estimate the traffic state with data from other directions (which are otherwise overruled as these...
have low weight). There is no underlying traffic flow theory to support the movement of a traffic state in those directions. Consequently, the resulting traffic state is unreliable (regarding its location and time).

- In case of prediction, when the ASM can only extrapolate data rather than interpolate, the ASM is unable to reliably estimate the traffic state directly downstream of congestion. The problem is that this state is essentially a new state generated by accelerating and then free-flowing traffic. In a considerable area, which extends the acceleration area if data is substantially delayed, the estimated traffic state is propagated along $c_{\text{cong}}$, although traffic is in free flow. Any trigger found in this area is thus improperly positioned in space and time, and should not trigger advice.

It is recommended that these sources of unreliability are included in a measure of reliability. Next, triggers for advice should be defined carefully including reliability.

*Additional data sources*

In chapter 6 the effectiveness of the advisory system has been assessed in simulation using both detector and floating car data (of the equipped vehicles only), whereas chapter 7 has performed an empirical evaluation on advice validity and credibility of the system running only on real detector data. In both cases, results will improve if better data is available. For instance, with floating car data it may be possible to detect the formation and solvation of congestion more accurately and quickly. This will lower the number of both false-negative and false-positive advices, increasing advice validity and credibility. Some (but not all) additional data sources that could improve the effectiveness, advice validity and advice credibility are:

- Floating car data, either from vehicles equipped with the in-car advice itself, or from other in-car systems. Note that effectiveness was already assessed using floating car data of equipped vehicles.
- Trajectory data derived by road-side systems such as cameras with image processing algorithms. Such systems could for instance be placed on locations where traffic is likely to breakdown, or where the end of congestion might settle (i.e. effective locations depend on the used advice principles).
- Wifi-p data, which is data transferred between vehicles and road-side systems, may enrich the system by either supplying more data to the centralized traffic state estimation, or by use for in-car advice filtering. In the latter case, for instance slow speeds of vehicles some distance ahead may be used to filter advice meant to be given at the end of congestion, in case the traffic state prediction is (apparently) inaccurate.

It is recommended that if available, additional data sources are included in the traffic state prediction. The EGTF method used in the described system is able to deal with additional data sources. In case data sources only supply speed data, it should be used carefully to improve the estimation of flow and density in congestion, as well as to provide a consistent traffic state (as discussed with the estimation of local penetration rate above).

### 8.2.2 Advice algorithm

This thesis has shown that in-car advice on the tactical scale has considerable potential, though the validity and credibility of advices is limited (varying between advices). This sections recommends some ways in which advice validity and credibility may be improved through the advice algorithm. Furthermore, some recommendations are made on how the system can be made more robust for implementation.
Self-calibrating system
In chapter 6 (table 6.1) many system settings as discussed in chapter 3 were given a value. These values have not been optimized. The most important settings are the trigger thresholds that help in recognizing (potential) problems. Optimization could be performed, for instance in simulation, on a few different networks and locations. However, it may be expected that it is impossible to find values that are near-optimal on every location. Therefore, a self-calibrating extension of the system could evaluate itself and adjust location specific settings accordingly. Simultaneously, this allows the system to adapt to changing traffic flow dynamics. As found in chapter 6, it seems that with a higher penetration rate, more traffic can be advised to a certain lane without oversaturating that lane. The optimal setting for the maximum flow on a lane that the system could accept, is thus dependent on the penetration rate. A self-calibrating system could adapt to a slowly changing penetration rate (i.e. not daily fluctuations, but rather monthly trends in penetration rate). Self-calibration could even include aspects that influence driver behavior, such as weather, and adapt system settings accordingly.

Conflicting advices
The described advice algorithm in chapter 3 uses independently operating advice principles, the result of which is filtered to deal with overlap of different advice regions. There is no check on conflicting advices, such as two lane change advices with the other lane as target lane. With the current advice principles, this is not a problem, but to assure a well-functioning and extendable system, conflicting advices also need to be filtered.

Pro-active versus reactive
The advisory system has been designed as a pro-active system. Specifically, when high flows are found at a lane drop, lane change advices upstream of the lane drop are given to prevent high flows produced by traffic that will merge but is currently upstream of the lane-drop. The validity of lane change advices from chapter 7 shows that the actual flows that result when these advices are given (without any equipped vehicles on the road) are often (74.2%) lower. Thus, it appears that peaks in inflow often trigger advices during the subsequent drop in inflow. Therefore, it is recommended that such advices are given in a reactive manner, i.e. when high flows are found, lane change advices should be given where these flows are found. This location should possibly be dynamic as such high flow traffic states may be expected to move downstream with speeds of about 80-90km/h.

It should be mentioned that a pro-active advisory approach may still contribute in a pro-active system if the traffic state prediction is pro-active as well. The use of a model with a robust prediction of lane changes and consequent peak flows may form such a prediction method.

8.2.3 Lane change model
In chapter 5, the LMRS has been discussed, which shows the ability to resemble the distribution of traffic over the lanes at various locations, as well as the speeds on individual lanes. The LMRS combines three incentives, being route/infrastructure, speed and to keep right, into a single lane change desire. The resulting level of lane change desire may fall in any of 4 desire regions divided by threshold values. In the two regions with largest desire, the potential lane changer is assumed to synchronize with the target lane, i.e. adjust speed and position to a target gap. In the desire region with largest desire, the potential follower is assumed willing to yield in order to create a gap for the potential lane changer. Additionally, the accepted headway when changing lanes reduces for increasing lane change desire. After the lane change, the headway is then slowly relaxed to normal values. This phenomena is known as relaxation. There are a few leads for possible improvements.
**Desired speed and desire lane**

The calibrated threshold to change lane for speed is a speed gain of $d_{\text{free}} \cdot v_{\text{gain}} \approx 25\text{km/h}$. In practice, one observes lane changes that initially allow a negligible speed gain. Although $25\text{km/h}$ may be reasonable on average with some drivers having much lower thresholds, it appears that the model tries to capture behavioral aspects that are not explicitly modelled. Such aspects may be:

- (Temporarily) accepting a lower speed then desired in order not to hinder traffic in the left lane.
- (Temporarily) driving faster than the desired speed while overtaking in order to allow followers with a higher desired speed to drive faster.
- Changing lane based on past experience and expecting that one will be better off on average, i.e. a tactical decision under little influence of current speeds of nearby traffic.

Including these aspects of lane changing and car-following (desired speed) may further improve the model. These improvements are mostly expected on the level of individual lane changes, i.e. when comparing lane changes from trajectory data with the model. On the other hand, probably additional parameters are required which makes calibration more difficult.

**Courtesy lane changes**

Some lane changes are performed out of courtesy for other drivers (Wang et al., 2005). The LMRS shows courtesy lane changes, but only if the speed of a vehicle in an adjacent lane is much lower and if the driver of this vehicle has a considerable lane change desire ($d > d_{\text{coop}}$) towards the own lane. Courtesy lane changes could be a more explicit part of the LRMS, e.g. as an additional incentive contributing to the set of voluntary lane change incentives. As such, the model could include:

- Lane changes which allow another driver to change lane, e.g. moving to the left lane at an onramp.
- Lane changes which allow followers to overtake.

The latter type of lane change has overlap with the earlier discussion on desired speed and desired lane. The whole constitutes complex tactical interactions between drivers, for which game-theory may even be suitable. For instance an approach as conducted in the Nomad pedestrian model (Campanella et al., 2014) may be suitable, where a set of interaction components are superimposed resulting in a single directed acceleration. Clearly, the interaction components themselves are different between pedestrians and drivers, though similar approaches (e.g. using an influence zone) can be used. Again, the model may improve, particularly on the level of individual lane changes, but the complexity increases and additional parameters are required. Whether such extensions of the lane-change model are worthwhile depends on the application, and more research into this is recommended.

### 8.2.4 Simulation framework

The microscopic simulation framework which has been developed for the research in this thesis, has been specifically developed for implementation of new ITS with a focus on freeways. This section generally describes two recommendations to improve the framework.
Urban traffic
The driver model from chapter 4 allows simulation of freeways. To also simulate urban networks, additional network elements and behavioral models are required. In this sense, urban traffic is much more complex and its simulation takes more effort. Effort has been spent in defining models to include some important aspects of urban traffic. This will be briefly discussed here. Details, which are out of the scope of this thesis, are discussed by Schakel and van Arem (2012). The following features are defined:

- Adaptation of driver behavior near intersections, capturing increased attention levels and slowing down before bends.
- An additional lane change incentive in the lane change model near intersections, reflecting drivers’ preference for the shortest queue allowing their route. This creates a balance with the route incentive.
- Inclusion of traffic light as road-side units, to which drivers respond using an adapted (i.e. parameter values) version of the car-following model.
- Inclusion of conflict area’s as road-side units, to which drivers respond with a large number of rules. The basis of these rules is formed by traffic anticipation, where the short-term future trajectory of relevant vehicles is predicted assuming various levels of constant acceleration. Based on the predicted order of events such as ‘vehicle x leaving conflict area’ and ‘vehicle y entering conflict area’ a gap is accepted or rejected. The set of rules includes:
  - Stopping if no priority and gap-rejected.
  - Stopping if priority but a collision may occur.
  - Assessment of a series of conflicts, i.e. keeping part of intersections clear.
  - Yielding with priority, as a courtesy to conflicting traffic, in case a driver cannot pass the conflict area due to congestion.
  - A safety factor on event times.

The above short overview of urban driver behavior does not reflect the complexity involved. Many details have been left out, especially regarding conflict areas. A persistent difficulty is the occurrence of dead-lock, where different directions of traffic block each other in such a way that none move, nor will ever move. A few ways to reduce this problem are also discussed by Schakel and van Arem (2012). It is recommended that these efforts for urban simulation are continued to make accessible and open microscopic simulation for urban ITS available to researchers.

Modular driver behavior modeling
The microscopic simulation framework as discussed in chapter 5 has been designed to be flexible, such that new systems and behaviors can be modelled. However, regarding driver behavior the structure has been found to fall short as all driver behavior is placed at a single place. The lack of structure makes it difficult to understand how a change affects the driver behavior. For instance, the car-following equation may be changed to reflect an Adaptive Cruise Control (ACC) system. Then, as the lane change model uses the car-following model, the lane change decision all of a sudden relies on acceleration from the ACC, which is not correct as lane changing is still up to the driver. For both an easier implementation of driver behavior relating to new ITS, as for scientific research into different models, it is desirable if the various subtasks of the driving task are structured. This would allow addition of behavior, or replacement of behavior (e.g. replacing the car-following model alone). Defining a structure for the various tasks is not trivial, as the tasks need to be as independent as possible, while driver behavior presents many interactions between the different models. Details of a
newly designed structure for driver models are presented by Schakel et al. (2013). It contains the following driving task categories.

- Desired headway model
- Desired velocity model
- Car-following model
- Lane change model
- Route choice model
- Responses (to road-side units)
- Behaviors (generic, to implement some behavior)

The driver model framework allows three different kinds of interactions.

- Using default functions of the driving task models.
- Using parameters, which are packages of information shared among different models.
- Using explicit dependencies, where the implementation of one driving task explicitly requires some functionality to be present at another driving task.

These three methods vary in the level in which models for subtasks remain exchangeable, and the guarantee that the models properly interact (e.g. one model may assume that another model uses a certain parameter, which it actually might not). Note that the more flexible methods allow more room for error, but should still result in correct behavior and full exchangeability of models if implemented and used correctly.

It is recommended that this driver model structure is used in microscopic simulation software to allow the use and development of models regarding certain subtasks of the driving task. Furthermore, the structure allows new behavior, for example regarding a new ITS, to be implemented in simulation. This is possible without affecting parts of the driving task that are not affected by a given model or ITS.
Appendix A  Real world implementation

In this appendix the systematic context of the software for the traffic state prediction and advice algorithm of the advisory system is described. These algorithms are used both in simulation and the actual system, which creates some unique requirements. Parts of the advisory system that are specific to the real-world application, as well as their relation with parts used in both the actual and simulated system, will be discussed in this appendix.

Since the algorithms need to run in both simulation and the actual system, and since these were developed with time constraints by multiple people, the software that runs these algorithms has the following requirements:

1. It should be possible for different parts of the software to be developed in parallel, i.e. independently.
2. In order to optimize algorithms, some parts need to be developed iteratively, without requiring the entire software to be changed.
3. The software should allow as much flexibility in the development of separate parts as possible.
4. The traffic state prediction and advice algorithm need to be able to run in simulation and on the actual server.
5. The traffic state prediction algorithm and advice algorithm need to run in synchronization with the arrival of detector data, such that the delay of detector data at the moment when these algorithms run is minimized.
6. The traffic state prediction and advice algorithm need to keep functioning in case, for whatever reason, no detector data is received.
7. The interactions between different parts of the software should be fast, i.e. one function should not have to wait for a considerable time on another function before proceeding.
In order to comply with requirements 1 through 4, it has been decided to take a modular approach for the software development, where each module has a specific role with defined input and output. Requirements 1, 2 and 3 are best met if the interaction between modules is minimal. Therefore, modules were defined such that clear and simple data could be transferred from one module to another. The next section will present the general structure of the different modules, focusing on their interactions. After that there are a few sections covering different aspects which are: data, specifics of the real-world prediction module, and finally a detailed description of the interfaces of the different modules. In the description of the real-world prediction module it is mentioned how the software deals with requirements 5, 6 and 7.

A.1 Modularity

Three modules were defined; the server module, the prediction module, and the advice module. An overview of these modules, and how these interact, is given in figure A.1. The server module is the connection between the server and the rest of the advisory system, i.e. the on-board units and other data sources. As data becomes available on the server, it is forwarded to the appropriate module. Loop detector data and floating car data (from the on-board units) are forwarded to the prediction module while user data is forwarded to the advice module. The server module will also request the traffic state prediction algorithm to start, which will then run in synchronization with the arrival of detector data. The prediction module will predict the traffic state using the available data at time of running, and forward the traffic state to the advice module. The advice module will derive appropriate advices to be given and forward these to the server module which will communicate them to the appropriate drivers.

The server module differs strongly between the real-world and the simulation implementation. In simulation it is rather easy to transfer data between objects, but the real-world implementation has to gather and sent data using various communication protocols and techniques. Section A.1 will elaborate on this.

The implementation of the prediction module is also different between simulation and the real-world. This is mainly for two reasons being: i) the macroscopic prediction network is derived from either a microscopic simulation network or a digital road map and ii) timing of when the module should run is either based on simulated time or real-time. This has led to the choice of not adhering to the prediction module interface in simulation, though much functionally is common and defined in the common prediction module. Note that the server module in simulation is aware of this bypass and relies on the simulation prediction module, i.e. the simulation server module cannot work with the real-world prediction module. The modules on the actual server do adhere to the interfaces. The common functionality is the algorithm as described in chapter 3.

Finally, the advice module has only one implementation which is used both in simulation and the real-world.
Figure A.1: Overview of modules for the server functionality. A triangle of three modules shows the interaction between modules, which is defined in the interfaces. Each interface has an implementation. The dotted boxes show that the actual implementation of the prediction module differs between the real-world and simulation, though they have a lot of common functionality.

A.1 Data
This section describes how the server receives data from both loop detectors and on-board units.

A.1.1 Loop detector data
In the Netherlands the National Data Warehouse (NDW) provides live traffic data from the freeways, provincial roads and many important urban roads. Clients of the NDW can obtain this information over the internet where the received data is usually a sub-set of all available data based on filters such as a geographical filter. For the advisory system, live loop detector data from the freeways is obtained. This data is aggregated over one minute and distributed within 75s after the aggregation minute (Felici and Vroom, 2012). On average, this makes the loop detector data 105s old.

A.1.2 Floating car data
The in-car unit of the pilot system is equipped with a GPS receiver and a digital map and is able to determine its position (both GPS location and road location including the lane number) and speed. This data, both position and speed, is sent to the server using 2/3.5G cellular communications, which is also used to receive advices. The frequency of floating car-data can be set, as well as the aggregation period. Although the delay in 2/3.5G cellular communications is variable, the data was received in a matter of seconds during the field tests.
A.2 Real-world prediction module

This section describes the aspects of the prediction module which are specific to the real world implementation.

A.2.1 General functionality

When the real-world prediction module is initialized, parameter values and settings are read from an ini-file. The parameters can either be for the prediction module itself (e.g., prediction method), or for the used traffic prediction algorithm.

The traffic state prediction is performed every minute, in line with detector data which are aggregated over a minute. Ideally, the traffic state prediction is performed just after detector data has been received (requirement 5), as this minimizes the data delay. To this end, a dynamic array of data is implemented into which data is put and retrieved using two different processing threads. Each thread runs in parallel with the other threads such that one thread does not have to wait for another thread. One thread from the server module puts the data into the array while a second thread from the prediction module reads from it. While the prediction module is running, the server module thread can still operate parallel to add data without waiting (requirement 7).

Through the use of two different threads which put and get data from a dynamic array, and by carefully determining how long the thread to get data should wait for as long as no data in the array is present (i.e., timeout), requirement 6 can be met. This concept is presented in figure A.2. The prediction module thread will continuously request data from the dynamic array. When no data is available, this will wait for data with a given timeout. If data is found, it is added to the macroscopic network of the prediction algorithm and data from the dynamic array is requested again. The timeout for requesting data from the dynamic array is such that the traffic state prediction is performed 1s after detector data is received. Note that when a batch of detector data is processed this 1s is continuously shifted until the batch is depleted. Each batch is detector data of one aggregation period of 60s, which results in the traffic state prediction being performed every 60s. In case detector data is not received for some unknown reason, the traffic state prediction is performed at most 65s after the previous run. This is presented schematically in figure A.2 where in a) it is shown that the next time to run the traffic state prediction (\(t_{\text{run}}\)) is changed as detector data is received or when the traffic state prediction runs and in b) the effect of this synchronization is shown.
Figure A.2: Synchronization of estimator with detector data. (a) Data request loop in which the timeout is dynamically set such that the traffic state prediction is run at the appropriate time. (b) Synchronization between arrival of detector data and runs of the traffic state prediction algorithm. This is independent of when floating car data arrives.

One more important function of the real-world prediction module is to return a section id and distance along this section of a point on the network closest to a given GPS coordinate. This is used by the server module to assign a network location to floating car data. The reason that the prediction module has this functionality is that the network details are only known at the prediction module, see also the following section.

A.2.2 Network import

Upon initialization of the real-world prediction module, the macroscopic network is derived from a digital road map. This network is a set of connected cells per lane with a length in the order of 100m. The digital road map has an interface which supplies the required information. This section describes the algorithm to derive the macroscopic network from this map interface. The map interface supplies the following:

- Link id of the first (most upstream) link of the applicable road section
- Link id of the last (most downstream) link of the applicable road section
- Link properties
  - Section id
  - Road type
  - Number of lanes
  - Length
  - Speed limit
  - Upstream link ids
  - Downstream link ids
With this information the network is created with the following algorithm.

1. Start at the first link and move downstream until the last link is reached. Store the corridor of links with properties for the links. For every link encountered:
   a. Derive properties which can be directly obtained from the map interface.
   b. If the number of upstream links is 2, define the link as an onramp section.
   c. If the number of downstream links is 2, define the link as off ramp section. (Note that for this network import more than 2 upstream or downstream links is not supported as it cannot be derived what the exact layout is. Also weaving sections are not supported.)
   d. The number of lanes on ramps might not be defined (i.e. be 0), in that case set it to 1. Also include this in the number of lanes on the link as acceleration and deceleration lanes are not included in the number of lanes of a link.
   e. Determine the next link, using the road type to distinguish ramps from the freeway in case of two downstream links.

2. As multiple links may be defined in the digital map for a section with an acceleration lane or deceleration lane due to other property changes (e.g. speed limit), extend the ramp by defining further sections as ramp as well (further downstream for onramps, further upstream for off ramp). This process is only performed for as long as further sections have an equal number of lanes. Note that this usually has no effect as acceleration and deceleration lanes are thus usually of the length of a single section which may or may not be in accordance with reality. Acceleration and deceleration lanes are thus usually of the length of a single section which may or may not be in accordance with reality.

3. Now that the corridor is defined, create the cells. Assume that ramps are on the right and that in case of a change in the number of lanes without a ramp that the additional lane starts or ends on the left (e.g. lane-drop). The number of cells per link and lane is the length of the link divided by the cell length which depends on the speed limit. The number of cells is rounded.

A.3 Module Interfaces

This section elaborates on the technical details of the interfaces between the different modules as described in section A.1.

A.3.1 Server Module Interface

The server module has a central role in the system but performs most of its tasks autonomously or as data arrives. In regards of the interaction with the other modules, it only has to be able to receive advices from the advice module in order to send them to the appropriate on-board units. The interface is defined as:

- **Server module interface**
  - Process an array of advices as given by the advice module and send them to the appropriate on-board units.

The attributes of the advices that are received from the advice module are also defined. The attributes define advice applicability (users, range, time span, speed and destination) and the actual advice itself. The list of attributes is:
• **Advice**
  - *Array of user id’s*; Id’s of users for which the advices are meant. The server module will send the advices to these users.
  - *Lane number*; The applicable lane where the left lane is 1.
  - *Section id*; Id of the section at the start of the applicable region. This id comes from the digital map.
  - *Start coordinate*; Location within the section of the start of the applicable region.
  - *Length*; Length of the applicable region.
  - *Start time*; Absolute start time of the applicable time span.
  - *Duration*; Time after the start time during which the advice stays valid.
  - *Minimum speed*; Speed below which the advice should not be given.
  - *Maximum speed*; Speed above which the advice should not be given.
  - *Destination*; Section id of the first section after the next split. Traffic towards this section should receive the advice. This may be empty which means that the advice is valid for all destinations.
  - *Advised speed*; Advised speed. Empty if no speed is advised.
  - *Advised headway*; Advised time headway. Empty if no headway is advised.
  - *Advised lane*; Number of advised lane to drive at where the left lane is 1. Empty if no lane is advised.
  - *Qualitative advice*; See below.
  - *Motivation*; See below.

The latter two attributes may have a value from a fixed list. The qualitative advice describes advices that the system can give which are qualitative in their formulation. There are two qualitative speed advices and three qualitative headway advices. The exact formulation as given to the driver is determined by the HMI. Here, merely a technical explanation is provided. The qualitative advices are:

• **Qualitative advice**
  - Synchronize speed with the left lane.
  - Synchronize speed with the right lane.
  - Yield for merging traffic from the left lane.
  - Yield for merging traffic from the right lane.
  - Maintain a short but safe headway.

A motivation is also included in the advices which may provide some information to the driver as to why an advice is given. The exact formulation as given to the driver is determined by the HMI. Here, merely a technical explanation is provided. The list constitutes:

• **Motivation**
  - *Weaving section*; A busy lane at or near a weaving section.
  - *Lane-drop*; A busy lane in a section where the left lane ends.
  - *Onramp*; A busy lane in a section where the right lane ends.
  - *Off ramp*; A busy lane upstream of an off ramp.
  - *Shockwave*; Busy lane in a section without infrastructural change.
  - *End of queue*; End of queue.

In case the trigger for an advice is given in a section where multiple motivations are applicable (e.g. there is a nearby lane-drop and a nearby onramp), a priority scheme is used,
which depends on the specific advice principle which is part of the advice module (see also chapter 3).

A.3.2 Prediction Module Interface
The prediction module has a higher level of interaction with other modules and operates for a large part from the initiative of the server module. The functions that the prediction module should have are:

- Prediction module interface
  - Initialize by importing the network from a given digital map interface and loading parameter values and settings from an ini-file at a given file path.
  - Add a measurement to the underlying data where each measurement is given by: section id, lane number, coordinate at the section, time, flow (optional), speed and the data source.
  - Start running (see section A.2.1).
  - Stop running.
  - Register an advice module which should receive the predicted traffic state.
  - Return a location based on a given GPS coordinate (see section A.2.1).

The location as returned by the last function is simply defined as:

- Location
  - Section id; Number of the section id.
  - Coordinate; Location within the section.
  - Lane number; The lane where the left lane is 1.

For the data sources a list of possible sources is defined. Based on this the prediction module can determine the reliability of measurement data. The list of data sources currently is:

- Data source
  - Loop detector data.
  - Floating car data.

A.3.3 Advice Module Interface
The advice module operates completely on the command of other modules. The commands that the other modules can give are:

- Advice module interface
  - Initialize by loading parameter values and settings from an ini-file at a given file path.
  - Update user info in the underlying user set where each update gives: user id, section id, lane number, coordinate at the section, time, speed and destination (optional, if known).
  - Process an array of traffic state predictions as given by the prediction module. This generates the advices which are then forwarded to the server module.
  - Register the server module to which the advices should be forwarded.
A.4 Conclusions

In this appendix the aspects of the advisory system that enable a real-world implementation have been discussed. The software modules that run the traffic optimization algorithms are defined in interfaces, which allows independent development. Additional features of the real-world implementation are: synchronization with incoming detector data and importing a network from a digital map.
Appendix B  Lane change information algorithm

This appendix provides a detailed description of an algorithm which automatically determines lane change information regarding mandatory, i.e. infrastructure based, lane changes in microscopic simulation. This information consists of the number of lane changes that have to be performed, as well as the distance within which these have to be performed, regarding different (sub)destinations. This information is coupled to the various lane objects which make up the network. The algorithm is part of the microscopic simulation framework from chapter 5 and is used during the initialization of simulation.
**Lane change information algorithm**

1. For each destination \( d \), initialize the set of lanes \( A \) as the destination section. For these lanes, set the required number of lane changes \( n = 0 \) and the distance within which these have to be performed \( x = l_A \) (the length of the section).

2. Loop over \( a \in A \) and for each \( a \) move left:
   a. Set \( n_{\text{tmp}} = 1 \) and the current lane \( b \) to \( a \)
   b. Check for the left adjacent lane (\( b_{\text{adj}} \)), if any, whether:
      - The lane change \( b_{\text{adj}} \rightarrow b \) is possible
      - \( b_{\text{adj}} \notin A \Rightarrow b_{\text{adj}} \) is not in the current set, i.e. it is an ending lane or it will turn into another direction
   c. If this is all true:
      - Set \( n \) of \( b_{\text{adj}} \) to \( n_{\text{tmp}} \)
      - \( x \) equal to the length of \( b_{\text{adj}} \)
      - Add \( b_{\text{adj}} \) to the set \( A \)
      - Move left once more setting the current lane \( b := b_{\text{adj}} \) and \( b_{\text{adj}} := \) left lane of (the new) \( b \)
      - Set \( n_{\text{tmp}} := n_{\text{tmp}} + 1 \), go to step 2.b

3. Repeat step 2 for the right-hand direction

4. Create a temporary set of lanes \( B \), starting empty

5. Loop over \( a \in A \) and for each \( a \) move upstream:
   a. If \( a \) has an upstream lane \( a_{\text{up}} \):
      - Add \( a_{\text{up}} \) to \( B \)
      - Set \( n(a_{\text{up}}) \) equal to \( n(a) \).
      - \( x(a_{\text{up}}) \) equal to \( x(a) + l(a_{\text{up}}) \)

6. Set \( A \) equal to \( B \).
   a. Return to step 2 if \( A \) is not empty
   b. Return to step 1 (for the next destination) if \( A \) is empty


Development, Simulation and Evaluation of In-car Advice on Headway, Speed and Lane
Summary

With the use of Advanced Driver Assistance Systems (ADAS), traffic efficiency may be improved such that congestion is reduced or throughput is increased. In this thesis, an advisory ADAS is presented, which fills a few voids in between current systems. Current systems generally function on the operational scale (vehicle control) or strategic scale (routing, planning). In-car advice is on the intermediate tactical scale, or specifically on headway, speed and lane. Potential problems in the next 1-2km can as such be reduced or prevented. Advice is flexible, and allows many potential problems to be targeted. Many current systems are only aimed at improving one or two aspects of traffic flow, while in-car advice can:

- Reduce inflow on the busiest lane.
- Reduce disturbances through smoother lane changes or a more stable speed.
- Reduce the capacity drop by making drivers more attentive at the end of congestion.
- Reduce, or delay, spillback by moving traffic to less sensitive lanes.

Moreover, in-car advice prevents liability issues that automated systems are faced with, and can be achieved with current technology.

The first step in the system is to gather data from traffic (detector data and floating car data) and to estimate the traffic state. This is achieved using a data filter that extrapolates measurements while obeying two fundamental properties of traffic: free flow traffic states move forward, while congestion traffic states move backwards. This method is robust and fast, but does not create new traffic states (e.g. traffic breakdown). To provide a traffic state on individual lanes, the method is applied on lane level.

The second step of the system is to derive advices from the estimated traffic state. Three different principles are applied, that together implement the above four possibilities to improve traffic flow. The resulting advices are sent to vehicles and presented to the drivers.
The effectiveness of the system is evaluated using microscopic simulation. For this, a model of regular driver behavior is developed that includes those behaviors, and resulting traffic flow characteristics, that the system aims to improve. For example, the distribution of traffic over the lanes is achieved with a new lane change model that also includes interactions between lateral and longitudinal vehicle movement. In particular, speed synchronization as preparation for a lane change (for the driver itself, or for a driver in an adjacent lane) and relaxation are included. Relaxation is the fact that drivers accept small headways for lane changes, that are slowly increased after a lane change. Both synchronization and relaxation are considered important aspects of traffic flow, as they influence traffic stability and capacity.

The behavioral model is implemented in a new microscopic simulation framework, that has been specifically developed to allow the implementation of various new ADAS, or more widely, Intelligent Transportation Systems (ITS). Using this framework, the parameters for regular traffic are calibrated using data from the A20 near Rotterdam. The calibration shows a good fit on detector data, with a similar level of congestion and a similar congestion pattern. A validation with data from another day on the same network has been performed, giving a worse fit. This shows that the model is not able to include daily differences, and/or that daily differences are highly stochastic.

Next to the model for regular traffic, the advisory system is implemented in the simulation framework. For advised drivers, the regular models are adapted such that advice has influence on both lane change and car-following behavior. A number of assumptions is made on how drivers would respond given a certain level of compliance. By varying both the compliance rate, as well as the penetration rate, the influence of in-car advice is assessed. Data of two days from the same network as the calibration and validation is used. On the first day, congestion starts at the lane-drop within the network. On the second day, congestion starts outside of the network and spills back at the downstream end, as well as from an off ramp. On both days, travel time delay is reduced up to 40-50% at maximum penetration and compliance rate. Some negative side effects are however also found at lower rates, which in some cases increase travel time delay slightly. One side effect is that traffic that is moved to the right-hand lane at a lane-drop, increases spillback at an off ramp further downstream. Remarkably, providing advice at the end of congestion to make drivers more attentive, shows to be very effective on its own.

An empirical evaluation of the system is performed using advices that the system created over a two week period using real data. The evaluation suggests that the results from simulation can for some part be explained by the limited validity of lane change advices, and the high validity of advice at the end of congestion. A combination of data coarseness and delay, makes it difficult to match lane change advice with an actual potential problem (i.e. local high flow). At least at a lane-drop, the problem may disappear during the data delay. On the other hand, once congestion occurs, it is relatively predictable and advice at the end of congestion shows to be valid and effective.
Samenvatting

Door middel van Advanced Driver Assistance Systems (ADAS) is het mogelijk om de efficiëntie van verkeer te verbeteren zodat file word verminderd of de doorstroming wordt verhoogd. In dit proefschrift word een adviserend ADAS gepresenteerd dat een aantal leemtes vult tussen bestaande systemen. Over het algemeen fungeren huidige systemen op de operationele schaal (voertuig controle) of de strategische schaal (routeren, planning). Advies in het voertuig fungeert op de tussenliggende tactische schaal, of meer specifiek, betreft de afstand tot de voorligger, de snelheid, en de rijstrook. Potentiële problemen ca. 1-2km verderop kunnen als zodanig worden gereduceerd of voorkomen. Advies is flexibel en maakt het mogelijk dat verscheidene potentiële problemen worden aangepakt. Veel huidige systemen beïnvloeden slechts 1 of 2 aspecten van verkeersdoorstroming. Met advies is het mogelijk om:

- De verkeersvraag op de drukste rijstrook te reduceren.
- Verstoringen te reduceren door geleidelijke rijstrookwisselingen en stabiele snelheden.
- Capaciteitsval te reduceren door bestuurders actiever te maken aan het einde van file.
- Terugslag te reduceren/vertragen door verkeer van gevoelige rijstroken te verplaatsen.

Daarnaast voorkomt advies problemen rond aansprakelijkheid waar geautomatiseerde systemen wel mee te maken hebben, en is advies mogelijk met huidige technologie.

De eerste stap van het systeem is het verzamelen van verkeersdata (lusdata en floating car data) om daarmee de verkeerstoestand te schatten. Hiertoe word een datafilter gebruikt welke metingen extrapolereert in lijn met twee fundamentele eigenschappen van wegverkeer: toestanden van vrij verkeer bewegen voorwaarts, terwijl toestanden van file zich achterwaarts bewegen. Deze methode is robuust en snel, maar creëert geen niet verkeerstoestanden (bijvoorbeeld het ontstaan van file). De methode wordt op rijstrokkniveau toegepast zodat de verkeerstoestand op rijstrokkniveau bekend is.
De tweede stap van het systeem is om op basis van de geschatte verkeerstoestand adviezen af te leiden. Drie verschillende principes worden toegepast die gezamenlijk de vier bovenstaande mogelijkheden om de verkeersdoorstroming te verbeteren, implementeren. De resulterende adviezen worden naar de voertuigen verstuurd en aan de bestuurders getoond.

De effectiviteit van het systeem is geschat met microscopische simulatie. Een model voor regulier bestuurdersgedrag is ontwikkeld om gedragingen, en de resulterende verkeersstroom-eigenschappen, te modelleren waar het systeem invloed op uitoefent. Bijvoorbeeld, de verdeling van verkeer over de rijstroken wordt bewerkstelligd met een nieuw rijstroomwissel-model dat interactie tussen laterale en longitudinale voertuigbewegingen bevat in de vorm van synchronisatie van de snelheid ter voorbereiding van een rijstroomwisseling (van de bestuurder zelf, of een bestuurder in een naastliggende rijstrook) en relaxatie. Relaxatie beschrijft het gedrag dat bestuurders korte afstanden accepteren voor rijstroomwisselingen, die erna langzaam worden teruggebracht naar normale afstanden. Zowel synchronisatie als relaxatie zijn belangrijke aspecten van verkeersdoorstroming aangezien ze verkeersstabiliteit en capaciteit beïnvloeden.

Het gedragsmodel voor bestuurders is geïmplementeerd in een nieuw microscopisch simulatie raamwerk dat speciaal is ontwikkeld om verscheidene ADAS in te implementeren, of meer generiek, Intelligente Transport Systemen (ITS). Met dit raamwerk zijn de parameters voor regulier gedrag gekalibreerd met data van de A20 nabij Rotterdam. De kalibratie vertoont een goede fit op lusdata met een gelijkende hoeveelheid file en een gelijkend filepatroon. Validatie met data van een andere dag op hetzelfde netwerk vertoont een mindere fit. Dit geeft aan dat het model niet in staat is om dagelijkse verschillen de modelleren, en/of dat dagelijkse verschillen in grote mate stochastisch zijn.


Op basis van adviezen die het systeem heeft gecreëerd gedurende twee weken met echte data is er een empirische evaluatie uitgevoerd. De resultaten van de simulaties kunnen voor een deel worden verklaard doordat de rijstroomwisseladviezen een beperkte validiteit hebben, terwijl advies aan het einde van file een hoge validiteit heeft. Door een combinatie van datagroefheid en datavertraging is het moeilijk om rijstroomwisseladvies goed overeen te laten komen met een daadwerkelijk potentiële probleem (lokale hoge verkeersvraag). In ieder geval bij een afvallende rijstrook, kan het probleem verdwijnen gedurende de vertraging. Aan de andere kant, zodra file eenmaal plaatsvindt, is file relatief voorspelbaar en advies aan het einde van file is valide en effectief.
About the author

Wouter Schakel was born in Naarden, the Netherlands, on the 8th of November 1984. He started his BSc in Civil Engineering at the faculty of Civil Engineering and Geosciences at Delft University of Technology in 2003. A particular interest was discovered in traffic and in 2007 he started his MSc at Transport and Planning at the same faculty. He graduated in 2009 with a Master thesis on network performance degeneration in dynamic network loading models.

In 2009 he started his PhD research under the Connected Cruise Control project at Transport and Planning. The aim of this project was to develop and evaluate a first in-car advisory system on the tactical scale, including both hardware and the traffic optimization algorithms. During this research, a particular interest in microscopic models in relation to traffic flow dynamics evolved. Next to that, an interest in programming led to the development of a completely new simulation framework. This combination provided an excellent toolset to evaluate the advisory system. Other activities during his PhD included Master student supervision and contributions to several Master courses.

Wouter Schakel is currently working at Transport and Planning, continuing his efforts in follow-up projects using in-car advice, as well as other projects where both his traffic and programming expertise is utilized.
Author’s publications

Journal articles

Schakel, W.J., V.L. Knoop, B. van Arem (2012) “Integrated Lane Change Model with Relaxation and Synchronization”, *Transportation Research Record: Journal of the Transportation Research Board*, No. 2316, pp. 47-57. (Awarded with the Greenshields Prize)


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