DISSERTATION

A Microscopic Framework for Modeling and Simulating Human and Automated Driving

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to Karin

Abstract

"Self-driving cars are the natural extension of active safety and obviously something we should do." ELON MUSK

Automated driving is regarded as a potentially disruptive technology, and is expected to bring fundamental changes to our transportation systems, ranging from increased road capacities over reduced accident rates to impacts on travel behavior and car ownership. Even though partially automated driving is already possible with current factory-fresh vehicles, anticipating the long-term impacts of vehicle automation is vital for both traffic scientists and road authorities, especially when considering that there will most likely be a long gradual transition from manual to automated driving, and thus a long period of time in which both human-driven and automated vehicles share our roads. Since field experiments are scarcely feasible in this particular context, simulations have emerged as an important instrument to perform such kind of investigations. The present thesis adopts this methodology, and develops a conceptual framework to facilitate the ex-ante evaluation of automated driving and its impacts on traffic flow. The proposed framework is formulated in a rather generic way, and is intended to enable traffic scientists to systematically augment existing models for driving behavior with a variety of behavioral traits and technology-appropriate assumptions to distinguish between human-driven and automated vehicles, but also between different degrees of vehicle automation. The first part of this thesis focuses on the various factors governing the behavior of human drivers, and incorporates some of these factors into a microscopic car-following model. Thereby, a particular focus lies on aspects related to distracted driving, and a novel approach is presented to incorporate the dynamics associated therewith into traffic simulations. Furthermore, we propose a meta-model to differentiate between different degrees of vehicle automation, but also to take into account technological constraints and limitations associated with automated driving. Subsequently, the microscopic traffic simulator TraffSim is introduced, which integrates all models developed in the scope of this thesis into a single simulation framework. In the final part of this thesis, we illustrate this framework by evaluating the impacts of automated driving on the stability of traffic flow, traffic safety, and efficiency

under consideration of mixed traffic flows, that is, assuming different penetration rates of automated vehicles. For our simulations we consider a single-lane scenario comprising a platoon of vehicles following an exogenous leader as well as a large-scale scenario with multi-lane traffic and road intersections. Our findings provide evidence that automated driving may indeed result in safer and more efficient traffic operations, however, they also reveal that vehicle automation might initially even have a slight negative effect on traffic flow stability, especially at low penetration rates. With regard to traffic safety, our results indicate that even at very high penetration rates of automated vehicles and a high level of automation there still remains a residual risk of road accidents caused by distracted drivers, suggesting that a full elimination of human error seems to be a fundamental prerequisite to reach the ultimate goal of "vision zero" on our roads, i.e. to effectively avoid fatalities and serious injuries in road traffic. Overall, the findings presented in this thesis provide reasonable grounds to believe that humans might actually not be too bad at driving at all, and that considering the "human factor" is therefore indispensable when studying the potential impacts of automated driving on traffic safety and efficiency.

Kurzfassung

Automatisiertes Fahren ist nicht zuletzt durch die öffentlichkeitswirksame Arbeit namhafter Firmen wie Google oder Tesla derzeit in aller Munde und eine Technologie, die zweifelsohne das Potenzial hat, unsere Verkehrssysteme, wie wir sie heute kennen, nachhaltig zu verändern. Diese Veränderungen reichen von einer Erhöhung der Straßenkapazitäten über eine Verbesserung der Verkehrssicherheit bis hin zu noch nicht absehbaren Auswirkungen auf das Mobilitätsverhalten und die Fahrzeugnutzung. Auch wenn einige Technologien für das teilautomatisierte Fahren zum Teil schon Serienreife erlangt haben, so sind aus Sicht von Verkehrsplanern und Straßenverkehrsbehörden insbesondere die längerfristigen Auswirkungen des automatisierten Fahrens von großem Interesse, vor allem angesichts der Tatsache, dass der Übergang vom konventionellen Individualverkehr hin zum hochautomatisierten Verkehr nicht von heute auf morgen vonstatten gehen wird, sondern aller Voraussicht nach Jahre, wenn nicht Jahrzehnte in Anspruch nehmen dürfte. Um die möglichen Auswirkungen automatisierten Fahrens schon heute abschätzen zu können, hat sich in den letzten Jahren insbesondere die Methodik der Simulation etabliert, nicht zuletzt, weil experimentelle Feldversuche aus Zeit-, Kosten- oder Ressourcengründen oft schlicht nicht durchführbar sind. Auch die vorliegende Dissertation macht sich diese Methodik zu Nutze. Konkret wird im Rahmen dieser Arbeit ein Simulationsframework entwickelt, welches die Ex-ante-Evaluierung der Auswirkungen automatisierten Fahrens auf Verkehrssicherheit und -effizienz unterstützen soll. Grundsätzlich bietet dieses Framework Anwendern die Möglichkeit, mikroskopische Fahrzeugfolgemodelle um eine Reihe verhaltensspezifischer und technologiebezogener Faktoren zu erweitern, und soll so eine realitätsnähere Modellierung menschlichen und automatisierten Fahrverhaltens ermöglichen. Der erste Teil der vorliegenden Arbeit beschäftigt sich mit den unterschiedlichsten Einflussfaktoren auf das menschliche Fahrverhalten sowie der Abbildung dieser Einflüsse in einem mathematischen Modell. Ein besonderer Schwerpunkt liegt dabei auf Ablenkungen im Straßenverkehr und der Modellierung dieser im Rahmen von Verkehrssimulationen. Desweiteren wird in dieser Arbeit ein Meta-Modell vorgeschlagen, welches nicht nur eine Unterscheidung zwischen unterschiedlichen Stufen der Fahrzeugautomatisierung ermöglicht, sondern darüber hinaus auch etwaige technologische Einschränkungen und Hemmnisse im Zusammenhang mit automatisiertem Fahren berücksichtigt. Sämtliche Modelle finden im

letzten Teil der Arbeit Anwendung, in dem die Auswirkungen automatisierten Fahrens auf die Stabilität von Verkehrsflüssen sowie auf Verkehrssicherheit und -effizienz simulativ untersucht werden. Die Stabilitätsanalyse erfolgt anhand von Fahrzeugkolonnen unter dem Einfluss externer Störungen, die Auswirkungen auf Verkehrssicherheit und -effizienz werden hingegen im Zuge eines großräumigen Szenarios untersucht, welches auch mehrspurige Straßenabschnitte und Kreuzungen beinhaltet. Alle Simulationen werden unter Verwendung des mikroskopischen Verkehrssimulators TraffSim, der im Rahmen dieser Arbeit entscheidend weiterentwickelt wurde, sowie unter Berücksichtigung gemischter Verkehrsflüsse durchgeführt, das heißt unter der Annahme unterschiedlicher Durchdringungsraten automatisierter Fahrzeuge. Die Ergebnisse dieser Untersuchungen deuten zum einen darauf hin, dass automatisiertes Fahren erwartungsgemäß zu einer Erhöhung der Verkehrssicherheit und -effizienz beitragen kann, liefern jedoch auch Grund zu der Annahme, dass unter bestimmten Umständen auch negative Effekte zu Tage treten könnten, vor allem bei niedrigen Austattungsgraden. Darüber hinaus zeigen die Ergebnisse dieser Arbeit, dass selbst bei hohen Durchdringungsraten automatisierter Fahrzeuge oder hohem Automatisierungsgrad stets ein gewisses Sicherheitsrisiko bestehen bleibt, das auf menschliches Fehlverhalten zurückgeführt werden kann. Ungeachtet dessen liefern die Ergebnisse der vorliegenden Arbeit hinreichend Gründe zu der Annahme, dass der Mensch letzten Endes gar kein allzu schlechter Fahrer ist, und dass bei der Untersuchung der möglichen Auswirkungen automatisierten Fahrens im Hinblick auf Verkehrssicherheit und -effizienz daher die Berücksichtigung des Faktors Mensch unabdingbar ist.

Acknowledgments

Undertaking a PhD has been a truly life-changing experience for me, and helped me to improve myself in many directions, be it personally or in view of professional skills. This journey has indubitably been an emotional roller coaster, moments of enthusiasm followed by thoughts of surrender, flashes of inspiration followed by feelings of hopelessness. Unquestionable, ending this journey would not have been possible without the continuous support and backing of many individuals, who either contributed to this thesis, or supported me in one way or the other during the last four and a half years.

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Contents

1 Introduction

MOBILITY is an integral part of our everyday lives, an indicator for personal freedom and welfare, and vital for the functioning and prosperity of a modern, globalized society. Today's transportation systems, however, are increasingly confronted with the externalities of road traffic such as congestion, noise and exhaust pollution, safety hazards, or the consumption of energy and space, and improving the safety and efficiency of road traffic by at the same time minimizing its environmental impact has become probably one of the greatest societal challenges [1, 2]. Every year about 1.25 million people are killed on our roads, and more than 20 million suffer from non-fatal injuries due to road accidents around the globe [3]. Road crashes, however, are not just a tragic cause for the loss of human lives, they also pose a considerable financial burden for governments worldwide. Currently, the economic damage resulting from road vehicle accidents makes up for approximately 3% of the GDP of middle- and low-income nations [4]. In the US alone, the annual costs of crashes amount to about $305 billion, and are over double that of congestion [5, 6]. In addition, it is expected that the continuing population growth and the ongoing process of urbanization will lead to a further increase in traffic volume in the coming decades, and thus exacerbate the problem of traffic congestion, with detrimental effects for our economy and the environment [7]. Already today, drivers in Germany spend about 30 hours per year in traffic jams, with no end in sight to this trend [6].

In view of these numbers it is not surprising that road authorities and transport engineers are seeking solutions to make traffic operations safer and more efficient. Since the extension of existing transport infrastructure to alleviate congestion is often no longer appropriate, especially in densely populated areas, and usually involves years of planning and high investments for construction, utilizing the available road infrastructure more efficiently has become one of the biggest challenges in transport planning recently. Considerable research in that regard is performed in the interdisciplinary field of Intelligent Transportation Systems (ITSs). The term ITS is broad, and generally describes services and concepts to improve the safety, mobility, efficiency, and environmental sustainability of transportation systems by integrating information and wireless communication technology with transport infrastructure, vehicles, and road users [8]. Road-based ITS strategies for example aim to improve traffic operations on specific road sections or in entire road networks, and comprise different kinds of advanced traffic control systems such as entrance ramp metering systems [9,10], variable message signs [11–13], adaptive speed limits [14,15], or dynamic route guidance [16]. Already in the 1990s, so-called automated highway systems have been proposed as a first visionary concept of vehicle-based ITS [17–20]. Recent advances in sensing technology, data processing, and connectivity finally paved the way for making this vision become reality, and over the last few years technology industries have made significant leaps in developing systems that automate a task which has for over a century been accomplished almost exclusively by humans: driving.

Today, automated driving is considered a potentially disruptive technology, and it is widely acknowledged that this technology will bring fundamental changes to our transportation systems [21], shape the future of safety and mobility management [22], and redefine the way humans travel [23]. Remarkably, many of the problems prevalent on our roads can at least in part be attributed to improper or suboptimal behavior of human drivers. For example, it is believed that driver error is the main reason behind over 90% of motor vehicle crashes [24, 25]. Traffic congestion, in turn, is not only a result of road accidents, also the drivers' trip-making decisions and driving styles play an important role [26]. It is therefore hardly surprising that there is no lack of predictions stating that automated vehicles have the potential to deliver a significant increase in safety and driving comfort [27], but also to considerably improve traffic flow and road capacities, and thus alleviate congestion and many of its negative effects [28]. Moreover, automated driving is expected to reduce personal transportation costs in terms of time and stress [29], to mitigate the need for parking space in urban areas [30], and to enable new models of vehicle usage for cities such as car sharing, peer-to-peer rentals, or city-wide mobility-on-demand services [31]. In light of such prospects, it is not surprising that the automation of road vehicles has been on the horizon for several decades [32,33], and that road authorities, car manufacturers, and governments are striving to establish a common legal and technical framework to pave the way for this disruptive technology. Even though many barriers to implementation and mass-market penetration of automated vehicles still remain, concerning in particular issues related to liability, litigation, safety, and security [34], vehicle automation has started to find its way into production vehicles already at the turn of the century [35]. Current factory-fresh vehicles are already equipped with different assistive systems that support the driver under various aspects, with the ultimate goal of making traffic operations safer and more efficient. The scope of so-called Advanced Driver Assistance Systems (ADAS) is wide, and ranges from systems that support the driver in route planning decisions over systems capable of monitoring and evaluating the vehicle's ambient environment, to ones providing active support for lateral or longitudinal vehicle control, or both. Lane departure and forward collision warning systems, for example, inform the driver when he or she is about to leave the current lane unintentionally, or when a collision is imminent. Lane keeping assistance or cruise control systems, in turn, are designed to proactively support the driver in his or her tasks, and are able to automate certain driving operations, or even take control of the vehicle. Especially in combination with current information and communication technologies facilitating the exchange of traffic-relevant information either directly between vehicles or with road-side infrastructure, these systems hold great promise in increasing the safety, efficiency, and convenience of driving.

1.1 Problem Description

Even though ADAS have in part already found their way into mass production, they only form the start of the era of vehicle automation from vehicles that are controlled by human drivers to vehicles that are driving autonomously, that is, without human intervention [36]. Clearly, this transformation will not take place over night, and the uptake of automated vehicle technology will presumably be affected by many yet unpredictable factors, such as the technological and economic development, or regulatory incentives and barriers [36, 37]. In spite of these circumstances, it is widely recognized that it is going to take years, if not decades, until automated vehicles make up for a significant share of the vehicle fleet [36, 38, 39]. This gradual deployment will naturally result in a long transition period in which vehicles with different degrees of automation and human-driven vehicles will co-exist on our roads. Such mixed traffic flows pose a very real and demanding challenge for road authorities and network operators, especially in view of the many yet unknown traffic dynamics associated therewith, which have the potential to both aid or cripple our transportation systems [35]. In view of the undeniable opportunities of vehicle automation to improve the safety and efficiency of traffic operations, but also in light of the many uncertainties that still remain in this context, researchers in industry and academia have recently been eager to provide estimates on the potential impacts of automated driving. A large proportion of these studies focused on the expected efficiency impacts of automated vehicles, including an increase in road capacities or improved congestion mitigation [40–53], while only recently further emphasis has been put on safety-related aspects of vehicle automation [54–56]. For obvious reasons, performing these investigations in the course of field experiments or on real road networks is most often neither safe nor practical, be it due to time constraints, the costs involved, or the large number of vehicles equipped with cutting-edge technology that would be required for such kind of experiments. It is for those reasons that a majority of the work carried out within the transportation research community makes use of computer simulations, which have become an integral part of modern research [57]. Simulations provide a fast and cheap alternative to field experiments, and enable researchers to essentially control all aspects of the scenario under investigation, which would certainly not be possible in a real-world setup.

Remarkably, the mathematical description and simulation of traffic has a long history already, and, starting from the early thirties of the last century, a multiplicity of models has been developed over the years to describe the dynamics and empirical features of traffic flows at different levels of abstraction. Considerable attention has thereby been paid to microscopic traffic models, which, as the name suggests, describe traffic flows at the microscopic level, i.e. they model the dynamics of every single vehicle individually. Over the years, microscopic modeling of traffic flows has turned into a very lively research field, which manifests in the large number of models and different schools of thought that have been reported in the pertinent literature. Even though these models have successfully been applied to describe many of the phenomena observed on our roads, such as the emergence and propagation of traffic jams or the capacity drop [58–61], legitimate concerns have been raised that a majority of the models used actually lacks the ability to provide a plausible explanation of human driving behavior [62–64]. In fact, the paradox is that although most traffic models have been designed to reproduce phenomena that are essentially a result of human (mis)behavior, the behavior mimicked by those models in its nature corresponds more to the dynamics of automated vehicles than to the behavior of human drivers [35]. Since we are currently at the start of a major transition from today's conventional traffic towards higher levels of vehicle automation [36–38], there is now a stronger need than ever to consider the various factors governing the way humans drive in those traffic models, and to realistically predict not only safe traffic operations, but also potentially unsafe situations [65]. Moreover, and contrary to the many in industry and science focusing on the utopic future of vehicle automation [35], that is, assuming either a high degree of automation or market penetration, particular attention should be paid to the early deployment stages, where automated vehicles will presumably make up only for a small proportion of the vehicle fleet. In fact, considering also lower levels of automation when investigating the impacts of automated vehicles is something that deserves further consideration, not least since it is widely recognized that we are still far from ready to deploy highly or even fully automated vehicles on public roads [66]. From the traffic scientist's point of view, in turn, there is hence an increasing need for models that reasonably mimic the behavior of human drivers, but notably also for models that are able to distinguish between different degrees of vehicle automation.

1.2 Objective, Scope and Boundaries

Based on those deliberations, the primary objective of the research presented in this thesis is to obtain a better understanding of, and new insights into the possible impacts of automated vehicles on our transportation systems, especially under consideration of mixed traffic flows. Fundamentally, this thesis is aimed at answering the following overarching research question:

> "To what extent can traffic flow efficiency and safety be improved by automated vehicles, and what penetration rates are required to achieve significant improvements?"

The present thesis addresses this particular question by means of simulations, and therefore develops a comprehensive modeling framework to describe the behavior of human drivers as well as the dynamics of automated vehicles at the microscopic level. The proposed framework builds upon widely recognized models for driving behavior, and incorporates various aspects associated with human driving behavior as well as a number of technology-appropriate assumptions in the context of automated driving into those models. In this manner, the framework is not only able to differentiate between manual and automated driving, but also to distinguish between different degrees of vehicle automation, including partially automated vehicles as well as autonomous and connected vehicles which utilize advanced communication technologies to interact with their environment.

The framework developed in the scope of this thesis is embedded in the microscopic traffic simulator TraffSim, which has been substantially developed further as part of this research, and which forms the basis for investigating the potential impacts of vehicle automation on traffic safety and efficiency. Those investigations are performed in the final part of this thesis, and aim to give both quantitative and qualitative estimates of the possible safety and efficiency impacts of automated driving. Adhering to the general consensus that it will presumably take years, if not decades, until the deployment of automated vehicles reaches significant dimensions [36–38], a particular focus thereby lies on evaluating those impacts for different penetration scenarios and traffic compositions, that is, under consideration of a varying share of automated vehicles and different degrees of automation.

1.2.1 Contributions

The research that was performed in the scope of this thesis has a number of scientific contributions that are either of a theoretical or a methodological nature, but which may also have some practical relevance. The main contributions of the present work are highlighted in the following.

Microscopic Simulation Framework. As part of this research, a new microscopic simulation framework has been developed jointly with Christian Backfrieder. The functional scope of the framework goes far beyond what is required for this thesis, and can be used for the ex-ante evaluation of different ITS applications. The main benefit over existing simulation tools are inherent flexibility and the extensive support for parallelization. This thesis provides an overview of the requirements for developing such a framework, and discusses those functions which are most relevant for the present work.

Models. This thesis uses microscopic simulations to evaluate the impacts of automated vehicles on traffic safety and efficiency. To this end, a number of models has been developed as part of this research to describe the behavior of human drivers as well as the dynamics of automated vehicles. These models are formulated in a rather generic way, which makes them applicable to a wide range of traffic simulation models.

- A meta-model is proposed which incorporates several aspects and behavioral traits related to human driving behavior into existing traffic models. The model is inspired by the everyday and scientific understanding of human driving behavior, and the assumptions it rests on are justified based on the pertinent literature.
- A novel approach is presented which aims to bridge the gap between the rich body of literature available on distracted driving and traffic simulation. Particularly, the proposed model can be used to mimic the drivers' engagement in potentially distracting activities, and in a sense provides the temporal frame for the drivers' behavioral adaptations as a result of distraction. The soundness of the modeling approach is verified based on the findings of a naturalistic driving study from literature.
- A meta-model is proposed which integrates a number of technology-related assumptions and constraints related to automated driving with microscopic traffic models. These include, for example, sensor and actuator delays, sensor ranges, or imperfect communication capabilities.

Conceptual Framework for Human and Automated Driving. The models developed in the scope of this thesis together form an overarching conceptual framework which combines well recognized traffic models with reasonable behavioral and technology-appropriate assumptions. The framework distinguishes not just between human and automated driving, but also between different levels of vehicle automation, and allows analysts to mix a variety of traffic models with an even wider range of assumptions and hypotheses, without necessitating the development of new driver behavior models.

Impacts of Vehicle Automation on Traffic Flow Dynamics. This thesis provides insights and new perspectives regarding the potential impacts of vehicle automation on traffic safety and efficiency. The findings presented in this work are to some extent also of a more practical relevance, not only because they add a societal value, but also because they pinpoint that considering the human factor when investigating the impacts of automated driving is an important topic in its own right, and undoubtedly deserves further consideration on the part of the scientific community. For an in-depth discussion on the results of this research it is referred to the final chapter of this thesis.

1.2.2 Limitations

Given the breadth of the research question addressed by this thesis, it is important to understand the scope and limitations of the present work. With reference to the primary objective and the contributions set out above, the work presented in this thesis is subject to the following limitations.

- The modeling framework developed in this thesis focuses on describing the longitudinal aspects of manual and automated driving, that is, car-following behavior. Extending the framework to include also the lateral traffic dynamics, i.e. lane changes, is beyond the scope of this work and subject of future research activities.
- Though the framework presented in this work is formulated in a rather generic way, its primary application is on modeling the dynamics of passenger cars. Other vehicle types such as trucks or two-wheelers, for example, are not taken into consideration.
- The models proposed in this thesis consider a number of behavioral aspects and technology-appropriate assumptions to describe manual and automated driving. Behavioral adaptations on the part of the driver or potential rebound effects of automation such as reduced vigilance, mental overload, or fatigue [67–70], however, are not considered in the scope of this work.
- The framework developed in this thesis distinguishes between different levels of vehicle automation, ranging from partially over highly automated to connected vehicles which make use of advanced communication technologies to interact with their environment. In the context of the latter, only Vehicle-to-Vehicle (V2V) communication, that is, the exchange of (traffic-relevant) information directly between vehicles, is considered, while infrastructure-based V2I communication is left aside.
- The framework presented in this work is based on the current scientific understanding of human driving behavior and automated driving, but has in parts not been verified using empirical data. It is important to notice, however, that in the scope of this

research the framework is applied to traffic models which have previously been found to be in good agreement with empirical observations.

- Although the automation of road traffic is widely expected to bring fundamental changes to our transportation systems and to make traffic operations both safer and more efficient, it might also have some unfavorable consequences such as increased urban sprawl [71], or people becoming more willing to undertake more and longer trips [72], ultimately resulting in a significant rise in traffic volumes [73, 74]. These short- and long-term effects of vehicle automation are heavily debated in the field of transportation planning, and are not further discussed in the scope of this thesis.

1.3 Thesis Organization

A general overview of the structure of this thesis is given in Figure 1.1. It consists of seven chapters which can be divided over four sections in accordance to their thematic focus. Note that some of the contents discussed in the scope of this work have been published prior to the writing of this final thesis, and certain passages out of those papers and articles have been quoted verbatim throughout this document. The remainder of this thesis is organized as follows.

Chapter 2 provides the theoretical foundation for the contents discussed in this thesis, and gives a general overview of automated and assisted driving, with a specific focus on its potential impacts on our transportation systems and possible deployment paths. Moreover, a brief introduction into the topic of traffic simulation is given, followed by a comprehensive review of recent developments in the field of driver behavior modeling. The focus thereby lies on models describing the car-following dynamics of human-driven and automated vehicles, and on the various factors that govern the way humans drive.

In **Chapter 3** a conceptual framework is presented which aims for incorporating various traits and aspects related to human driving behavior into car-following models. The framework builds upon an existing meta-model, and addresses two aspects which have largely been ignored in the car-following model literature, namely context sensitivity and distracted driving. Moreover, a novel approach is presented to model the frequency and duration of distractions in the scope of microscopic traffic simulations, which is verified with the aid of a naturalistic driving study from literature.

Chapter 4 focuses on the microscopic modeling of automated vehicles, and presents a conceptual framework which incorporates different technology-appropriate assumptions into existing car-following models. Moreover, the framework provides an intuitive means for traffic analysts to distinguish between different levels of vehicle automation by specifying operational design domains representing the functional limits of automation.

In **Chapter 5** the microscopic simulator TraffSim is introduced, which has been substantially developed further as part of this research, and which combines all models developed in the scope of this thesis into a common simulation tool. The presented framework forms the basis for all simulations conducted in the scope of this work.

Chapter 6 investigates the impacts of human and automated driving on traffic flow stability, traffic safety, and efficiency under consideration of various penetration scenarios and traffic compositions by means of simulations.

Finally, **Chapter 7** summarizes and discusses the main findings of this thesis, and provides recommendations and suggestions for future research directions.

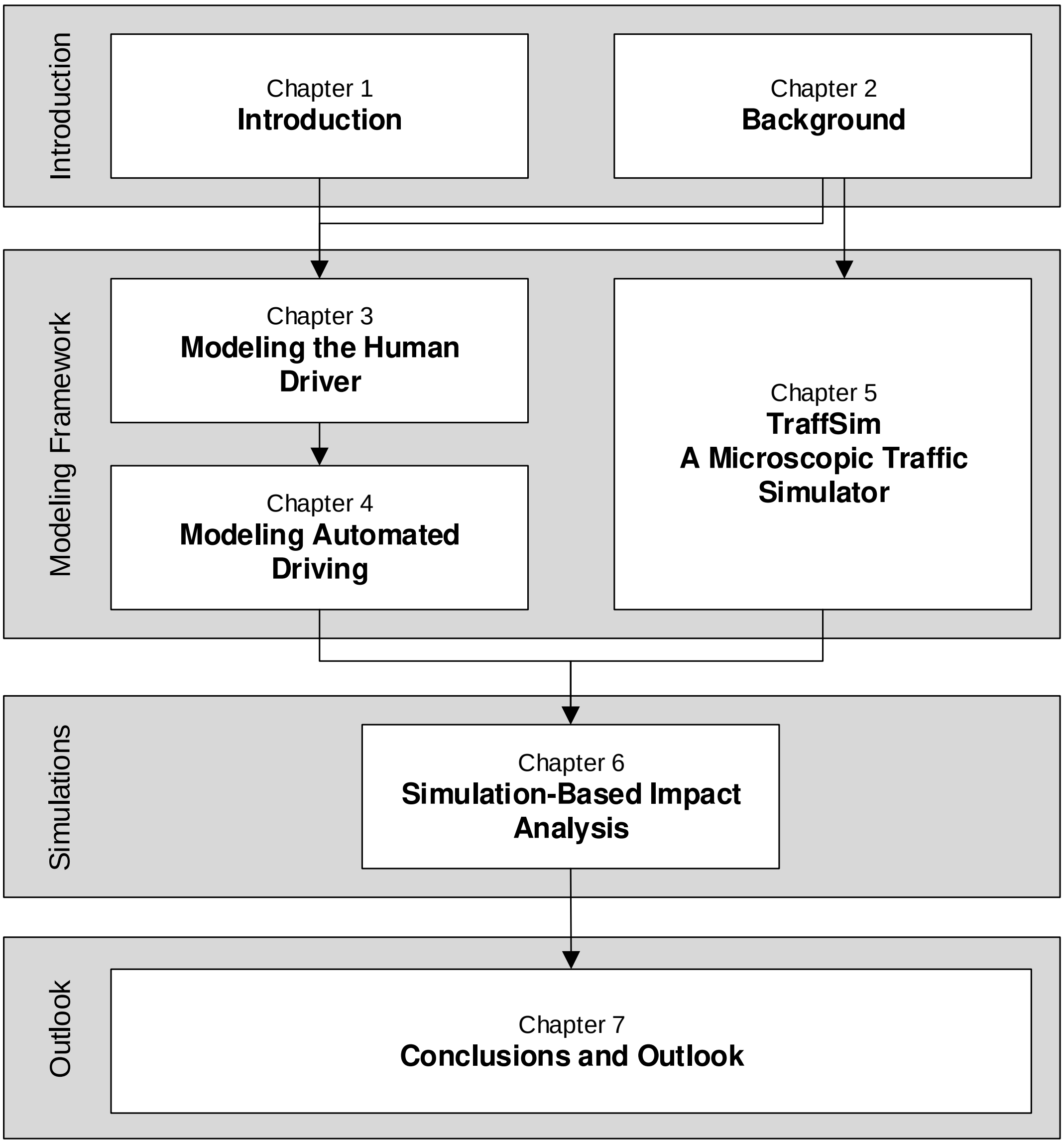


Figure 1.1: Overview of the thesis structure.

2

Background

AUTOMATED driving has been the focus of research for several decades already, and it is widely recognized that this technology has the potential to bring disruptive yet beneficial changes to our transportation systems. Anticipating these changes is vital, not only for policy makers and transport planners, but also for governments and road authorities, and it is therefore no surprise that investigating the possible impacts of vehicle automation has received increased attention within the scientific community recently. While before and after studies based on empirical field data or actual incident statistics are the most preferable way to perform such kind of investigations, real-world experiments have only limited applicability to evaluate the impacts of automated vehicles, or are most often even intractable, for both practical and financial reasons. Such kind of experiments require not only a proper test environment, but also a sufficiently large number of vehicles equipped with the technology or system under evaluation [57, 75]. It is therefore no surprise that simulations have become an integral part of transport-related studies, and much of the research performed in the context of automated driving or ITS in general is carried out using computer simulations. Since the investigations conducted in the scope of this thesis are also based on simulations, this chapter gives a brief introduction into traffic simulation, the models used in such simulations, and the assumptions underlying these models. The first part of this chapter, however, focuses on automated and assisted driving and its potential impacts on our transportation systems, and reveals certain aspects which have to be considered when evaluating those impacts.

2.1 Automated and Assisted Driving

According to the definitions of Gasser and Westhoff [76] and the Society of Automotive Engineers (SAE) [77], the term automated driving is used for vehicles which are, at least to some extent, able to drive themselves. Apparently, automated driving is not a matter of all or nothing, and ranges from assistive systems that support the driver in operating the vehicle to the fully autonomous vehicle, which is capable of handling all driving situations without any human intervention. The following sections present a classification of different levels of automated driving following internationally established standards, provide a brief introduction into ADAS, and discuss some of the potential impacts automated vehicles might have on our transportation systems.

2.1.1 Levels of Automation

Over the last years, several standards for describing levels of automated driving have been proposed by both government institutions and the industry, see Table 2.1. All these definitions are similar insofar as they differentiate between different levels of automation in which an automated system gradually takes over control of the vehicle, i.e. the driver hands over more responsibility to the system as the degree of automation increases. Perhaps the most commonly used standard is the one by the SAE [77], which distinguishes between six levels of automation based on how much human intervention and monitoring are required, and in which situations. Unless stated otherwise, the terminology of automation levels as defined in the following will be used throughout this thesis.

Level 0 - No automation. The driver is in charge of all operational and tactical aspects of the driving task at all times, such as steering, braking, accelerating, or deciding when to change lanes. At this level, the driver is in complete and sole control of the vehicle, even though he or she might be supported by warning or intervention systems.

Level 1 - Driver assistance. An automated system supports the driver by taking over either longitudinal or lateral control of the vehicle using information about the driving environment. The driver carries out all remaining aspects of the driving task, engages and disengages the system, and is expected to monitor the system at all times, and to intervene if necessary in order to ensure safe operation.

Level 2 - Partial automation. At this stage, the division of roles between the driver and the automated system is essentially the same as in the previous level, with the exception that the latter is now able to provide support for both longitudinal and lateral motion control. However, the driver is still responsible for supervising the system the whole time and for independently taking control of the vehicle if required.

Level	0	1	2	3	4	5
SAE	No automation	Driver assistance	Partial automation	Conditional automation	High automation	Full automation
BASt	Driver only	Assisted	Partial automation	High automation	Full automation	-
NHTSA	No automation	Function specific automation	Combined function automation	Limited self-driving automation	Full self-driving automation	-

Table 2.1: Levels of driving automation as defined by the SAE [77], the German Federal Highway Research Institute (BASt) [76], and the National Highway Traffic Safety Administration (NHTSA) [78].

Level 3 - Conditional automation. The automated driving system carries out all aspects of the driving task and monitors its execution. The system is able to independently determine whether its operational limits are exceeded or whether there is a relevant failure, and prompts the driver to resume control if this is the case. At this level, the driver does not have to monitor the system at all times, but is expected to serve as fallback, and to appropriately respond in case of a system limitation in order to bring the system to a risk minimal state.

Level 4 - High automation. The system is capable of handling all aspects of the driving task, is responsible for monitoring its execution, and for establishing a risk minimal state in case of a failure, even if the driver does not respond appropriately to a request to intervene. What differentiates highly automated driving from full automation is that the system usually operates only within a specific domain, for example in a certain speed range, a geographically-defined area, or a particular driving scenario such as expressway merging, high speed cruising, or stop-and-go traffic.

Level 5 - Full automation. The sixth and last level of automation refers to the full-time performance of an automated driving system. A fully automated driving system is able to perform all aspects of the driving task under all roadway and environmental conditions that can be managed by a human driver. At this level, no human intervention or monitoring are required, and the driver is not expected to take control of the vehicle at any time.

2.1.2 Advanced Driver Assistance Systems

The term ADAS embraces virtually any system in a vehicle that gives support to various aspects of the driving task in order to enhance driving comfort, mitigate driving errors, and ultimately to enable safer and more efficient traffic operations [79]. Since ADAS include very different types of functions, several attempts have been made to categorize such systems depending on their enabling technology [75], their functional scope [80], or the potential system impacts [81]. According to a more general definition by Knapp et al. [79], an ADAS is a system capable of

- supporting the driver in the primary driving task,
- providing active support for lateral and/or longitudinal vehicle control with or without warnings,
- detecting and evaluating the vehicle's environment,
- enabling the direct interaction between the driver and the system,
- and using complex signal processing and sensing technology.

Early ADAS such as the anti-lock braking system [82] brought up by Bosch or electronic stability control [83] found their way into automobiles already in the 80s and 90s of the last century, and were primarily based on proprioceptive sensors measuring the internal status of the vehicle, such as wheel velocity or acceleration [84]. Current driver assistance systems instead make use of exteroceptive sensors such as radar, lidar, ultrasonic, or video sensors to continuously acquire information from outside the vehicle and to monitor their environment. Examples for, if you like, this second generation of ADAS include parking assistance systems [85], lane departure warning and lane keeping assistance systems [86], or the meanwhile widespread adaptive cruise control [87]. Nowadays, many of these systems have already reached serial maturity, and some of them are even mandatory in production cars by law [84]. More recently, the rapid advances in information and communication technology have opened up a new era of ADAS. Some of these systems require the exchange of data either directly between vehicles or with road-side infrastructure, and are a promising approach towards an extension of the current systems' boundaries in terms of increased information availability [88]. Such inter-vehicle communication technologies are considered an integral part of ITS [57], and pave the way for the expansion of current ADAS functions to an entire collective of vehicles and, thus, for cooperative maneuvering [89]. Today, this next generation ADAS is widely expected to unlock the true potential of automated driving, and is considered as the next big leap towards safer and more efficient traffic operations [90, 91].

As mentioned in the introduction, the range of ADAS is wide, and providing a complete overview of the systems already available and those currently under development would definitively go beyond the scope of this thesis. Hereinafter, we thus elaborate only on two systems which have probably attracted most attention within the transportation research community in more detail: Adaptive Cruise Control (ACC) and its more sophisticated variant Cooperative Adaptive Cruise Control (CACC). For further reading on ADAS we recommend the recent reviews by Bengler et al. [84] and Ziebinski et al. [92].

Adaptive Cruise Control

Cruise Control (CC) systems are already available in a wide range of commercial passenger cars, and primarily aim for increasing the comfort of driving by maintaining the vehicle's speed at a preset value [93]. Such a system must usually be activated intentionally by the driver, and can be turned off both explicitly or automatically when the driver applies the vehicle's brakes. Even though the driver does not have to use the pedals all of the time, it is still up to him or her to decelerate in case a slower vehicle is in front. ACC extends the functionality of a regular cruise control system and automatically adjusts the vehicle's speed to maintain a safe distance from the vehicle ahead by controlling the throttle and/or the brake [94]. As such, an ACC system is capable of taking over the longitudinal driving task. An important part of an ACC system is the range sensor which measures the distance and the relative velocity to the vehicle in front, usually using radar or lidar [95]. In the absence of a preceding vehicle, ACC maintains the speed preset by the driver, much like a regular CC system [87]. Though intended to increase driving comfort, ACC systems are also able to improve the efficiency of traffic operations. For example, they allow for a more accurate control of speed and distance compared to human drivers, and are therefore able to reduce disturbances in traffic flow by mitigating over-reactive decelerations and unintentional fluctuations in speed [96]. Other potential benefits of ACC include an overall increase in road capacity [97] and a reduction in travel times [98], and will be further discussed in Section 2.1.4.

Cooperative Adaptive Cruise Control

ACC systems make use of a range sensor to measure the distance and the relative velocity to the vehicle in front, and are thus only aware of the leading vehicle, i.e. they have a limited reach in perception. CACC is an extension of ACC, and makes use of vehicular communication technologies to provide the system with more and better information about its environment [99]. For matters of illustration, a schematic comparison between ACC and CACC is presented in Figure 2.1. While an ACC system has to rely solely on the distance and speed information obtained from the preceding vehicle, CACC uses additional information also from vehicles further ahead, including their current speed and acceleration, or regarding unequipped vehicles in between [95]. Even though CACC is not yet commercially available, it is expected to further enhance the benefits of conventional ACC systems. The main advantage over ACC is that CACC-equipped vehicles can operate at significantly shorter headways, i.e. they can drive closer behind each other, which allows for an even better utilization of the available road infrastructure [100]. Moreover,

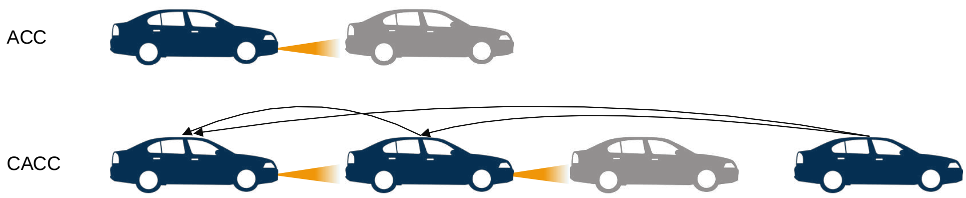


Figure 2.1: Schematic illustration of ACC and CACC. Vehicles equipped with the respective technology are highlighted in blue, vehicles without ACC/CACC support are grayed out.

the information shared between traffic participants can be used to further optimize vehicle movements, and enables a safer, smoother, and more "natural" control of the vehicle [50].

2.1.3 Advancement of Automated Driving

While the theoretical opportunities of automated vehicles to enable safer and more efficient traffic operations are undeniable, it is generally presumed that it will take years, if not decades, until we can expect a perceptible impact on our roads [38, 39]. The deployment of automated vehicles thereby depends not only on the technological, economic, and regulatory developments in the automotive industry in the upcoming years [36, 37], but also on how fast the market adopts and the current vehicle fleet phases out once the required technology is available [101]. In the meantime, our transportation systems will undergo a slow transition from vehicles operated by human drivers to (partially) automated ones. Even though predictions on the possible uptake of automated vehicles are – from today's point of view – extremely difficult to make, many attempts have been made to estimate the potential deployment horizon for automated vehicle technology [37, 38, 102–105].

The exemplary timeline given in Figure 2.2 is based on a recent estimate by Motamedidehkordi et al. [105] on the expected share of automated vehicles in the German passenger car fleet. This illustration is by no means meant to be definitive, but is intended to give a rough indication of the duration of the transition phase and the deployment paths of different automated vehicle technologies. Based on this estimate, the share of automated vehicles will start to increase significantly from 2020 onwards, but may still be below 25% of the entire vehicle fleet by 2030. Various estimations from governments, industry, and academia are in a similar order of magnitude [35], and a strong indication that the transitional phase from conventional to automated vehicles will indeed last for many decades [101]. The same holds true for the deployment and share of vehicles which are able to drive cooperatively (e.g., CACC), which is expected to pick up from 2025 onwards as a result of vehicles becoming increasingly connected, but which is also assumed to lag behind due to "early" automated vehicles remaining uncooperative [106].

Even though the actual deployment of automated vehicle technology will be influenced by many yet unpredictable factors, the recent estimates reported in the literature draw

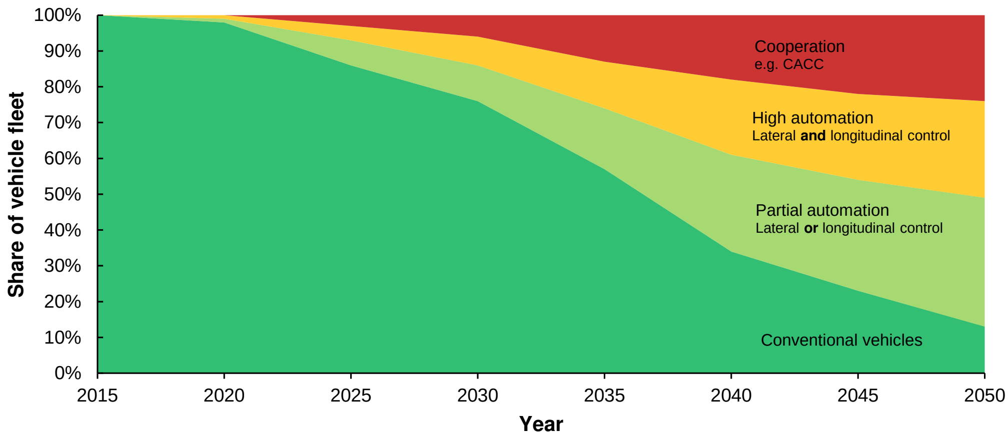


Figure 2.2: Estimated share of automated vehicles in the German passenger car fleet [105].

a clear picture: It will take decades until automated vehicles make up for a significant portion of the vehicle fleet, and there will be a long transitional period in which traffic will be characterized by a varying share of conventional and automated vehicles with a different degree of automation [106]. It is therefore no surprise that carefully considering such mixed traffic flows is incredibly important when drawing inferences about the potential impacts of automated vehicles on our transportation systems.

2.1.4 Traffic Flow Effects of Automated Vehicles

Though the proliferation of automated vehicles, and especially that of highly or even fully automated ones, is far from guaranteed, anticipating the potential impacts of vehicle automation has attracted researchers in both industry and academia for several years, and many studies have been conducted to investigate the possible effects of automated driving on the dynamics of traffic flow. This section tries to summarize the main rationale of these studies, and discusses some of the possible implications vehicle automation might have on our transportation systems. The following review thereby focuses specifically on these aspects which are also addressed by the present thesis, that are, those related to traffic safety and efficiency.

Impacts on Traffic Efficiency. The influence of vehicle automation on traffic flow efficiency has widely been investigated in recent years, with a majority of the studies reported in the literature focusing on the impact of automation on the longitudinal traffic dynamics [107]. Thereby, particular attention has been paid to the impacts of automation on road capacities and the stability of traffic flows, which have emerged as important performance indicators in the context of automated driving [108]. The former corresponds to the maximum flow of traffic that a road or a single lane can facilitate [95], while traffic stability refers to the way disturbances in traffic affect traffic flow along an entire corridor or network, and has a direct influence on the formation and propagation of congestion [35]. Using computer simulations, several studies showed that ACC and CACC have the potential to improve both traffic stability as well as road capacities considerably, mainly due to the more exact and constant vehicle control and, in case of CACC, significantly shorter headways [40–49]. Other studies reported in the literature, however, are less optimistic. For instance, van Arem et al. [50] and Shladover et al. [51] found that the increase in capacity will be marginal unless the market penetration rate of automated vehicles exceeds about 60%. Moreover, Ploeg [52] and Zwaneveld et al. [53] even argue that ACC will only have a limited contribution to traffic flow stability at all. In summary, one can conclude that in the literature there is no real consensus with respect to the effects of vehicle automation on traffic efficiency, and varying estimates and evidence exist in regard of what impacts can be expected, and at which penetration rates. Moreover, and even though automated vehicles are generally expected to improve traffic flow efficiency, especially on the long run, there are also some indications that the initial effects of automation might be limited, since relatively high penetration rates are required to have a substantial effect [35].

Impacts on Road Safety. As mentioned in the introduction, it is believed that in more than 90% of all accidents some element of human error is involved [24, 25], and that for more than three-quarter of motor vehicle crashes the driver is solely to blame [109]. Since automated vehicles gradually reduce driver burden and provide assistance to the driver, it is expected that the benefits for road safety could be substantial. For example, Fagnant and Kockelman [34] and Hayes [110] analyzed historical crash data, and concluded that a reduction in crash rates in the order of 90% or even more can be achieved by a near elimination of human error, ultimately reaching a similar level of safety as in aviation or rail transport. Recently, real-world data captured in testbeds in California has been used for assessing the safety impact of vehicle automation [111–114], concluding that automated vehicles might not only have the potential to reduce crash rates, but also to lower the overall crash severity. Moreover, several studies have investigated the impact of vehicle automation using computer simulations. For instance, Li et al. [54] showed that automated driving might be able to reduce the risk for rear-end collisions on freeways considerably, while Morando et al. [55] estimated a reduction of traffic conflicts at signalized intersections in the order of 65% assuming a full market penetration of automated vehicles. A recent study by Validi et al. [56] comes to a similar conclusion, stating that ACC in combination with V2V communication might be able to successfully mitigate collisions at intersections even at moderate penetration rates of just about 40%.

2.2 Introduction to Traffic Simulation

The modeling and simulation of traffic flows is a broadly diversified topic, and has received considerable attention over the last decades. Today, simulations are an indispensable and often the only feasible method to investigate complex traffic scenarios or to evaluate ex-ante emerging technologies or new measures in the area of ITS, as in many cases real-world experiments are simply impractical to perform, be it because of the large number of involved vehicles or limitations in terms of time and costs. Remarkably, the origins of traffic simulation go back as far as to the pioneering work of Greenshields [115, 116] on the fundamental relations of traffic flow, density and velocity in the 1930s, and the first mathematical descriptions of traffic by Lighthill, Whitham and Richards [117–119] in the mid-fifties. From then on, modeling and understanding the behavior of drivers and the physical propagation of traffic flows have evolved into very lively research fields, and scientists developed a multiplicity of models to describe the dynamics of traffic at different levels of abstraction. Over the years, these models have been applied successfully to reproduce and study different traffic phenomena such as the propagation of stop-and-go-waves, the capacity drop, or traffic hysteresis [58–61]. Fundamentally, traffic flow models can be categorized according to different criteria, including their level of detail, the scale of their variables, their mathematical structure, or conceptional aspects [120, 121]. The most common classification of models, however, is with respect to their aggregation level. In general, one can distinguish between two major approaches to describe the spatiotemporal dynamics of traffic flows. Macroscopic models describe traffic as if it was a continuum flow, and are often compared to continuum models for compressible fluids or gases. Rather than modeling individual vehicles, the collective traffic dynamics are described in terms of locally aggregated quantities such as average flows, densities or velocities [122, 123]. As these quantities vary across space and time, macroscopic models are capable of describing collective phenomena such as the propagation velocity of traffic waves or the formation and disaggregation of traffic jams [120, 124–126]. By contrast, microscopic traffic models describe the motion of each vehicle individually, and usually do so by modeling the driver's behavior as a response to the surrounding traffic. This high level of detail makes such models particularly suited for studying heterogeneous traffic streams consisting of different vehicle types, or drivers with different preferences and skills [127]. Over the years, microscopic modeling of traffic flows has shown to be a fruitful research direction, which is supported by the large number of models available in the literature, and the many different schools of thought that have emerged in view of the models' underlying behavioral assumptions. This section provides a review of the current state-of-the-art on microscopic traffic models, highlights different modeling approaches, and is intended as a motivation and underpinning for the conceptual framework developed in the remainder of this thesis. Thereby, we confine ourselves to models describing the behavior of vehicles in the longitudinal sense, commonly referred to as car-following models. For reviews on models describing the lateral traffic dynamics, i.e. lane change models, we refer to the pertinent literature [128–137].

2.2.1 Car-Following Theory: The Historical Perspective

Generally speaking, car-following models describe the longitudinal interactions of vehicles on the road, i.e. they describe how drivers follow the vehicle(s) in front of them, and how they adjust their behavior to that of their leader(s). Since the first car-following models have been developed in the early fifties of the last century, their mathematical formulation has been that of a dynamic system: the driver is presumed to continuously respond to a given traffic situation by adjusting the vehicle's speed, which in turn results in a new situation that calls for a new response [138]. Generally, the driver's response to a given situation is modeled by outputting a suitable acceleration for a given configuration of different variables such as the vehicle's speed, the distance to the leading vehicle, or the speed of the vehicle in front. Up until now, a multiplicity of car-following models has been reported in the literature, which differ in terms of complexity and their behavioral assumptions on how drivers respond to their surrounding, and to which stimuli they respond. In the following, different types of car-following models will be discussed, including safe-distance models [139–147], stimulus-response models [148–154], and action point models [155–158]. Note that this list is certainly not exhaustive, but merely identifies some of the fundamental modeling approaches. For a more comprehensive overview of car-following models we recommend the following works [97, 159, 160].

Safe-Distance Models

The earliest car-following models are based on the intuitive assumption that drivers tend to keep a large enough distance to their direct leader, within which a collision would be unavoidable if the driver of the vehicle in front were to brake suddenly. The first safe-distance models were developed as early as the 1950s, when Reuschel [139] and Pipes [140] proposed that the minimal safe distance to the leading vehicle should be proportional to the vehicle's speed. This relation can be expressed equivalently by requiring that the time gap between two vehicles should not be below a certain safe time gap. Despite their simplicity, these early models were found to show good compliance with empirical observations [161], and several models based on similar concepts have been developed to this day, e.g. [141–147]. One of the most widely used safe-distance models is the one by Gipps [144], which correspondingly assumes that "the driver travels as fast as safety and the limitations of the vehicle permit" [162]. Unlike previous models, the model by Gipps introduces two regimes into the underlying mathematical description: the car-following regime, in which the driver is presumed to control the vehicle's speed such that he or she is able to keep a certain minimum distance at standstill in case the vehicle in front brakes at the maximum deceleration rate, and the free-flow regime, where the driver is not constrained in its longitudinal driving behavior, and thus tends to drive at his or her desired speed. Apart from its fundamental Newtonian equations of motion, the model by Gipps already contains basic behavioral parameters such as the driver's desired acceleration or a desired speed, and has been used in several traffic simulation models [163].

Stimulus-Response Models

A very diversified class of car-following models are those belonging to the branch of so-called stimulus-response models. Generally speaking, such models make assumptions on how drivers adapt their response (i.e., their acceleration) to a range of different stimuli, such as the vehicle's own velocity, the distance to the leading vehicle, or the relative velocity with respect to the vehicle in front [160]. The development of stimulus-response models started in the late 1950s with the models by Chandler [148], Herman et al. [149] and Helly [151], and ultimately consolidated in the now popular GHR model named after Gazis, Herman and Rothery [150]. After these initial developments, considerable efforts have been put into the calibration and validation of these models, and several attempts have been made to mitigate limitations in their original formulations [164–169]. In fact, in early models such as the GHR or the Helly model the driver's response is based solely on stimuli from the direct leader, and they are thus not particularly suited to describe free driving [120]. Later offshoots of the branch of stimulus-response models overcome this limitation. The Optimal Velocity Model (OVM) by Bando et al. [170, 171], for example, was one of the first models covering both free-flow and car-following conditions while at the same time exhibiting plausible traffic patterns. In essence, the model's underlying assumption is that drivers tend to choose a speed that fits best to the actual distance to the vehicle in front. In free-flow conditions, i.e. at large distances, this "optimal velocity" is close to the driver's desired speed, while for shorter distances, e.g. in car-following scenarios, it decreases likewise. Some years later, the Intelligent Driver Model (IDM) by Treiber et al. [152] redefined the optimal velocity concept: the driver's response now depends not only on the following distance with respect to the vehicle in front, but also on the speed difference between both vehicles. Over the years, the IDM has become one of the most widely used stimulus-response models, which can probably be explained by its small number of intuitive parameters, which all have reasonable value ranges, its ability to reproduce different traffic states, and its easy calibration [121, 126, 172]. More recent models such as those by Kerner and Klenov [153, 154] go even a step further, and take into account three traffic regimes as proposed in the three-phase traffic theory, i.e. they distinguish between free driving, synchronized, and jammed traffic [173]. Apart from the models mentioned here, researchers have proposed a variety of stimulus-response models over the last one or two decades [160]. This goes so far that Wilson and Ward [174] even conclude that there are actually too many models, and that one should focus just on a smaller set of models with good qualitative properties.

Action Point Models

The third branch of car-following models are the so-called action point or psycho-physical models, which were first introduced by Wiedemann [156] in the 1970s. These models are grounded on the findings by Michaels [175] and Todosiev [176], who discussed the underlying concept that drivers would only react if they actually recognize that they are approaching or drifting away from the vehicle in front. In other words, the stimuli to which a driver responds, for example the deviation in speed or distance with respect to the vehicle in front, must be large enough to be perceived. This stands in contradiction to the models discussed so far, where drivers are assumed to react to changes in their environment in a continuous way, and no matter how small these changes are. Action point models such as the one by Wiedemann [156] as well as the adaptations thereof [157, 158] thus aim for implementing shortcomings in human perception, and do so by making use of so-called perception thresholds. These thresholds define the minimum value of a stimulus a driver can perceive, and hence will react to, and are expressed as a function of the relative speed and the distance to the vehicle in front. Each of these thresholds separates a different driving regime, and in each regime the driver is presumed to adapt his behavior accordingly. While being generally regarded as a meaningful concept, an inherent limitation of action point models is the inevitably large number of parameters required to determine both the perceptual thresholds as well as the driver's behavior in the individual regimes, which poses a challenge particularly with regards to model calibration [177]. Nevertheless, it is worth mentioning that several attempts have been made to estimate the parameters and thresholds of such models [178–180], and that a modified version of the Wiedemann model is also implemented in the commercial simulation software VISSIM [181].

2.2.2 Car-Following Theory: The Human Perspective

Over the past decades, a large number of car-following models has been developed in an attempt to describe driving behavior under a wide range of traffic conditions. Although these models have contributed to a better understanding of many phenomena that can be observed on our roads, there have also been criticisms that they lack the ability to provide a psychologically plausible explanation of human driving behavior [62, 63]. In fact, it is quite universally accepted that most of these "classic" car-following models are not very realistic descriptions of how humans drive [64]. An inherent limitation of those models is that they are relatively straightforward servomechanisms that rely on the assumption that the driver's behavior is completely rational, and that he or she is perfectly able to observe and react to the surrounding traffic situation [182]. Recent research on the psychological aspects of driving behavior, however, draws a different picture. First of all, the human driving style is anything but perfect, and in any case not deterministic, as anticipated by most traditional car-following models. Moreover, each driver and each driving style is different, and several factors affect how drivers perceive and react to their environment [64]. These factors are collectively designated as "human factors" [183].

The models reviewed in the previous section, with few exceptions, ignore the well-acknowledged impact of human factors on driving by large, be it due to methodological limitations or data availability, and thus fail to explain the often complex dynamics behind the drivers' behavior [184]. Paradoxically, and even though intended to explain the behavior of human drivers, the usually collision-free and faultless dynamics of classic car-following models in essence correspond more to those of automated vehicles. The growing body of literature on human factors and their impacts on traffic dynamics, however, has encouraged researchers to increasingly incorporate these factors into existing car-following models, or to develop new ones. The reasons why research in this direction has accelerated lately are manifold. On the one hand, there are still many phenomena not fully understood by traffic scientists, such as traffic hysteresis, the capacity drop, or stop-and-go oscillations [64]. On the other hand, we are at the start of a major transition from today's conventional traffic towards higher levels of vehicle automation [36–38, 102], and more sophisticated models are required to facilitate the development and evaluation of ADAS and ITS applications, or to study the potential interactions between human drivers and automated vehicles. Moreover, traditional car-following models are by design collision-free, and thus limited in their ability to describe driving behavior under extreme and incident conditions [185]. To assess the efficiency of safety-related technologies and policies, be it in relation to vehicle automation or in the here and now, there is hence an increasing need to realistically model the drivers' behavior in such unsafe situations [186, 187].

Notwithstanding, there are ample reasons to increase the human factors sophistication in car-following models, and several approaches have already been proposed in this direction over the last years. The following section aims for providing an overview of these attempts, and reviews the literature along two dimensions. First, different human factors and their impacts on driving behavior are identified based on the existing body of literature [64, 121, 188], followed by a comprehensive survey of notable developments and attempts to incorporate these factors into car-following models.

Human Information Processing

To explain which factors govern the way in which drivers drive, it is worthwhile to take a quick glance at the fundamental theories on human information processing by Wickens [189] and Shinar [190]. In essence, these theories provide conceptual frameworks for

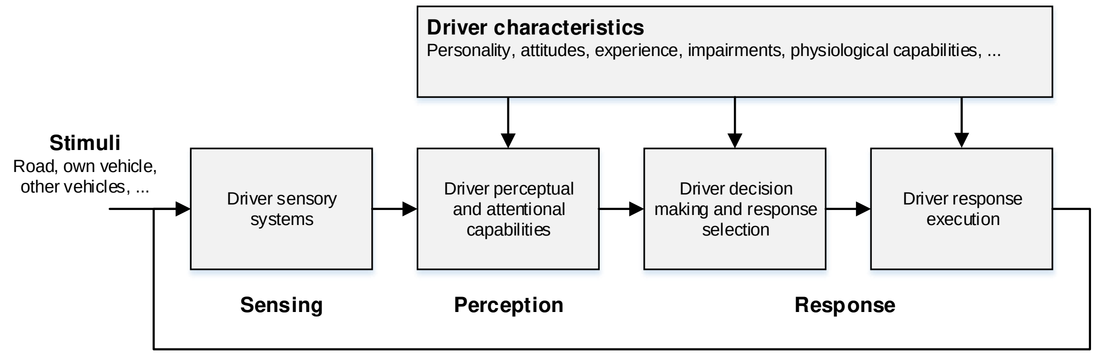


Figure 2.3: Simplified representation of Shinar's driver information processing model [190], in which the driver's ability to perceive driving-related cues, make instantaneous decisions, and acting on those decisions through physical response depends on various factors. The feedback loop indicates that the entire process is an ongoing one that is continuously modified depending on the driver's response and in accordance to new stimuli.

analyzing and understanding the sequence of psychological processes humans go through when carrying out a certain task. While the model of Wickens is a generic representation of how humans process information, and may thus be used across different domains, Shinar's limited-capacity model of information processing focuses specifically on the driving task. In this model, the driving task is separated into a sequence of processes which are affected by both external stimuli and different driver-specific characteristics, as illustrated in Figure 2.3. These processes together form a closed-loop system, indicating that the driving task is a continuous process, and that every response action carried out by the driver will in turn result in new stimuli to be perceived [190]. Generally, three overarching psychological stages are involved in the driving task: sensing, perception, and response.

Sensing. The human brain continuously receives raw information and stimuli from the ambient environment, and the sensory processing stage comprises the reception and filtering of the stimulations impinging on the driver's senses. In the context of driving, this includes primarily visual inputs from other drivers, traffic signs or signals, or the own vehicle's speedometer and mirrors, but also auditory or tactile inputs may provide relevant information [191–193]. However, these are only the stimuli which are relevant for the driving task. Additionally, there are many irrelevant stimuli which affect the driver's behavior and his allocation of attention, such as outside scenery or in-vehicle distractions originating from the use of cell phones, navigation systems or other passengers [194].

Perception. In order to perform the driving task efficiently, the driver has to recognize, interpret, and understand the raw stimuli received through his sensing organs. Put differently, the driver has to provide a meaning to the sensory information. This perceptual processing is a highly automated and rapid task, and is dictated not only by the stimulus itself, but is also driven by the driver's long-term memory and experience [195]. While the actual perception of a stimulus (i.e., becoming aware that there is "something") requires only little of the driver's attention [196], assigning a meaning to the information that was just perceived (identifying what that "something" is) is a more demanding task, and usually involves cognitive processes such as rehearsal, reasoning, or image transformation [189]. These cognitive functions can be affected by several factors such as the driver's physiology, emotions, or stress level, and are also dictated by the driver's familiarity with the environmental situation and its inherent complexity [196]. Obviously, far more cognitive resources are required if the driver faces an unfamiliar situation. This, in turn, increases the likelihood of cognitive tunneling or cognitive capture, as most of the driver's attentional resources will be allocated to handle the unknown situation [197]. During this period of cognitive capture the driver is particularly vulnerable for missing important visual cues, and has thus a higher risk of being involved in an incident [198].

Response. The understanding of a situation achieved through perceptual and cognitive processing of sensory information will often trigger an action on the part of the driver. Response selection is the stage where the driver makes use of the knowledge acquired to determine whether a response is warranted, and if so, to choose the appropriate one. This process is typically viewed separately from response execution, which generally involves the activation and coordination of muscles for controlled motion to ensure that the chosen response (e.g., steering, braking) is carried out as desired [199]. Similar to the perception and cognition stage, response selection and execution requires attentional resources for adequate performance, and their efficiency and appropriateness depend on several factors including the driver's experience, physical constraints, or mental state [194].

Attention. Arguably one of the most critical aspects in view of the driver's ability to process information, both perceptually and cognitively, and to act accordingly based on this information is attention [200]. Attention can generally be considered as a supply of mental resources a driver is able to devote to a task at any time [189]. Humans have a limited supply of such resources, and the allocation of these resources is dictated by both driver-specific characteristics as well as stimulus-driven factors [201–203]. In fact, humans are not only constrained in terms of attentional capacity, they are also limited in their ability to divide this capacity between different tasks [204]. Driving, however, is a multi-tasking skill, and requires the division of attention between a variety of tasks, including strategic ones such as route choice, tactical or maneuvering control (e.g., speed choice), and operational tasks such as steering, braking or accelerating, as illustrated in Figure 2.4 [205, 206]. The amount of attention allocated to each of these tasks varies with both environmental factors such as traffic conditions, road layout, or traffic rules, but also

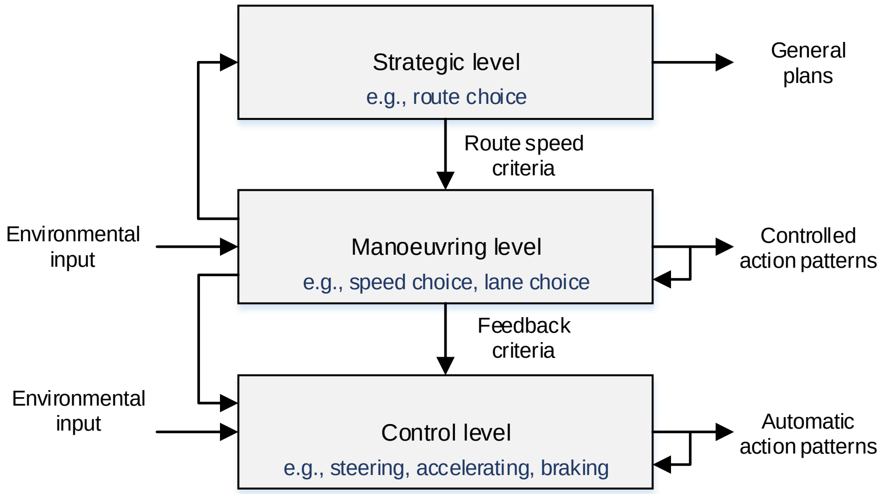


Figure 2.4: The hierarchical structure of the driving task according to Michon [205].

with the driver's experience and skills [190]. Most of the time drivers will certainly have enough attentional capacity to carry out different tasks, both driving-related and non-driving tasks, at the same time and without an incident [194]. However, they sometimes fail to allocate their attention appropriately, and there might even be situations in which increasing demands of the driving environment or a combination of tasks exceed the total amount of attentional capacity, with detrimental effects on driving performance [206, 207]. The next section elaborates on some of these effects in more detail, and explores various factors affecting the way in which drivers perceive and respond to their environment.

Modeling Human Factors in Car-Following

Notwithstanding, there are many factors influencing how drivers perceive their ambient environment, and how they react upon these perceptions. Based on the extensive review literature available [64, 65, 121, 188, 208], this section aims for identifying those factors considered to be most influential at the operational and tactical level, and structures them along the different stages of human information processing, as illustrated in Figure 2.5. The ensuing paragraphs elaborate on some of these factors and their impact on the drivers' behavior in more detail, and present notable attempts to incorporate these factors into car-following models. It is important to note, however, that the list of behavioral traits and aspects discussed hereinafter is certainly not exhaustive, but merely aims for identifying those factors considered to be most influential on the behavior of human drivers.

Socio-economic factors. This rather general term embraces virtually any sociological or economical aspects that influence the driver's personality and attitude, such as his or her age, gender, level of education, or family background [208]. Apparently, each driver

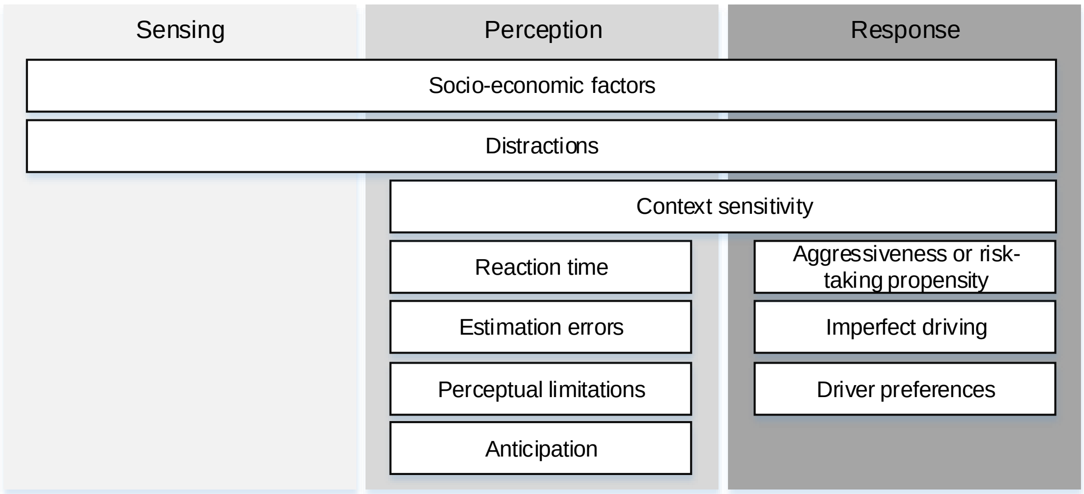


Figure 2.5: Human factors in car-following structured along the different stages of human information processing following the presentations in [65, 208].

and his or her driving style is different, and recent studies provide evidence that age and gender, for example, have a significant impact on the driver's perception of risky driving situations [209]. However, and even though the effects of socio-economic characteristics have been studied extensively in different fields such as traffic safety [210] and driver compliance research [211], these factors have, to the best of the author's knowledge, widely remained disregarded in the traffic flow modeling domain.

Reaction time. A finite reaction time is an essential feature of human driving behavior, and a result of the physiological aspects of perception, recognition, decision, and physical response [212]. Generally, the reaction time involves the physical delay between observing a stimulus and response execution as well as the delay caused by response times of the vehicle's brakes or accelerators, and depends on several factors including the driver's age, experience, or visibility conditions [121]. It is widely recognized that the reaction time of human drivers is one of the prime contributing factors to traffic instabilities and, consequently, the emergence of stop-and-go waves [213], and has therefore been considered in many car-following models [131, 144, 150, 170, 170, 214, 215].

Perceptual limitations. There is ample evidence that human drivers are not able to respond to stimuli they perceive unless the changes in this stimuli, e.g. the speed differences or distances, exceed a certain threshold [216–219]. Michaels [175] and Todosiev [176] initially discussed the underlying concept of perceptual thresholds, which essentially define the minimal rate of change of a stimulus a driver can perceive and react to [64]. Wiedemann [155] was among the first to consider such perceptual constraints in car-following models, which are typically expressed as a function of speed differences or spacings between vehicles. Other examples for such "psycho-physical" car-following models include those by Fritzsche [158] or the data-driven action point model by Hoogendorn et al. [180].

Estimation errors. Apart from being limited in their ability to perceive small changes in their ambient environment, human drivers are also ill-suited to estimate the speeds of other vehicles or the distances to those vehicles reliably [121]. In fact, several studies revealed that drivers have systematic biases in judging these parameters [220–222], and that these biases in turn depend on different factors such as the spacing to neighboring vehicles or the prevalent visibility conditions [65]. Despite the abundant evidence in the existing body of literature, estimation errors have been considered only in a handful of car-following models, and are usually modeled as auto-correlated noise processes to account for the temporal persistence of such errors [185, 215, 223].

Imperfect driving. As mentioned previously, the behavior of human drivers is anything but deterministic, nor is it completely rational [121]. Quite the contrary, drivers behave differently, even if they perceive the same stimuli at different times or locations. Such driving errors or irregularities in driving style can in the broadest sense be considered as a form of intra-driver heterogeneity[1], which has clearly been observed in real traffic [177], and which might be one possible explanation for many traffic flow phenomena such as traffic breakdowns or the capacity drop [224–226]. Nevertheless, only a few attempts have been made to incorporate imperfect driving capabilities in traffic models. A commonly used approach to do so is to introduce some form of stochasticity in the underlying model, for example by adding noise to the model's acceleration function [121].

Distractions. Arguably one of the most important aspects related to human driving are distractions. In the context of driving, distractions can be understood as any "diversion of attention away from activities critical for safe driving towards a competing task" [227]. Usually, this is the case when a secondary task is so complex or compelling that drivers are not able to allocate enough attentional resources to the driving task, or when the driving task itself is too demanding, and thus does not allow for performing additional tasks at any level [228]. The sources of distraction may take many forms, and may reside inside or outside the vehicle, be self-initiated, or imposed upon by a given situation. While the causes of driver distraction are manifold, it is typically distinguished between three main types of distraction depending on how they interfere with the driving task: visual, manual, and cognitive distraction [229]. Research on driver distractions has accelerated

[1] Intra-driver heterogeneity implies that the driver's behavior varies over space and time, while inter-driver heterogeneity illustrates that the driving styles of drivers (or groups of drivers) differ inherently from each other.

in recent years, and numerous studies have been devoted to study their effects on driving performance, ranging from an increase in reaction time over a narrower visual focus to impacts on the lateral lane position [230–240]. Apart from their adverse effects on driving performance, distractions – and visual distractions in particular – have also been identified as one of the most serious safety hazards on the roads, and a significant number of all police-reported crashes can be related to distracted driving [200, 206, 241–243]. It is therefore surprising that distractions and their impact on driving behavior have hardly been considered in car-following models, with just a few exceptions [65, 184, 244].

Anticipation. Beyond question, and especially in view of the physiological and perceptual limitations of human drivers, safe driving would not be possible most of the time if drivers were not able to compensate for some of these weaknesses to a certain extent. This compensatory behavior is commonly known as anticipation, and the literature distinguishes between two types of anticipation, usually referred to as temporal and spatial anticipation [121, 127, 215]. The former reflects the ability of (experienced) drivers to successfully predict a traffic situation for the next couple of seconds, especially when driving in a familiar environment [245, 246]. Spatial anticipation, in turn, describes the driver's ability to take into account not only the vehicle directly in front in the decision making process, but also other vehicles in his or her vicinity [127, 215]. This includes vehicles further ahead as well as vehicles on other lanes, but also the following vehicle might be taken into consideration [121]. Anticipation terms have been included in several car-following models recently [127,215,223,247–250], and generally result in more stable traffic dynamics by counter-effecting the detrimental impacts of human reaction time [65].

Aggressiveness or risk-taking propensity. It is commonly known that under certain conditions many drivers are willing to take a higher risk, or to drive more "aggressive". Aggressive driving behavior usually involves neglecting the rights or safety of other road users [251], and can have many different forms ranging from flashing lights over tailgating up to speeding or unsafe lane changes [252]. There is a rich body of literature focusing on how driver characteristics and contextual parameters affect the drivers' risk-taking propensity, and under which conditions drivers tend to apply a more aggressive driving style [253–256], and a few attempts have been made to incorporate such kind of behaviors and attitudes into car-following models [185, 254, 257, 258].

Driver preferences. As noted before, each driver and his or her driving style are different, and so is his or her response to a certain traffic situation. Apart from socio-economic characteristics (e.g., age, gender), the driver's behavior is also influenced by personal preferences, such as a preferred speed, a desired spacing to the vehicle in front, or a deceleration rate perceived as comfortable [208]. Such driving desires are an integral part of most car-following models reported in the literature, and most models contain one or more parameters describing driver preferences [65]. These parameters naturally allow for an intuitive exploration of inter-driver heterogeneity, e.g. by modeling them as distributions over drivers [250, 259].

Context sensitivity. It is widely recognized that the driver's behavior does not only depend on his or her personal preferences, skills, or physiological capabilities, but also on the surrounding traffic situation [147, 250, 260]. In fact, the driving style is influenced by both the current and the past overall traffic situation. For example, after driving in dense or congested traffic for some time, most of the drivers become less alert and their headway to the vehicle in front increases [121]. Such memory or resignation effects usually result in a less efficient driving style, and are one possible explanation for the capacity drop phenomenon [121]. Moreover, the driver's response to his or her environment may also be affected by changes in the weather or lightning conditions, but also speed limits, road signs, or changes in the infrastructure (e.g. tunnels, work zones) can play an important role. Usually, such dependencies on the local traffic context can be modeled in a straightforward and intuitive manner by adjusting one or more model parameters, either gradually or instantaneously, and many existing traffic simulators actually do this implicitly, e.g. by imposing speed limits on certain road segments. However, to the best of the author's knowledge, hardly an attempt has been made to explicitly incorporate some form of context sensitivity into car-following models.

2.3 Conclusions

In this chapter, a general introduction into the topic of automated and assisted driving was given, including the most important definitions and the common terminology used in the scope of this thesis. Summarizing, it can be concluded that automated driving has indubitably the potential to bring fundamental changes to our transportation systems, however, there is currently no real consensus on what changes can actually be expected, and on what time horizon. What seems to be clear is that it will take years, if not decades, until automated vehicles reach significant market penetration rates, resulting in a long transitional period in which both human-driven and automated vehicles share the very same roads. Anticipating the impact of such mixed traffic flows has been subject of extensive research recently, and numerous studies have been devoted to predict the potential effects of vehicle automation on traffic safety and efficiency, primarily using computer simulations. However, many of the studies reported in the literature make use of very idealistic, if not over-simplistic models to describe the dynamics of automated vehicles, but also for mimicking the behavior of human drivers. The latter in particular involves complex psychological and cognitive processes, and incorporating the various factors that govern the way drivers drive has been a very lively research field in the last years. Though several attempts have been made to integrate human factors with traffic simulation models recently, there are still certain aspects related to human driving behavior which have largely been disregarded by previous modeling attempts.

The forthcoming chapters can be regarded as an attempt to make up for some of the shortcomings identified in the existing simulation models. To this end, a comprehensive simulation framework is proposed which enables traffic analysts to incorporate various factors related to human driving behavior into microscopic simulation models. Moreover, the framework provides a plausible means to distinguish between different levels of vehicle automation, and to integrate several aspects affecting the dynamics of automated vehicles with the underlying simulation models. Chapter 3 and Chapter 4 elaborate on the proposed framework in more detail, followed by the introduction of the microscopic traffic simulator TraffSim [261] in Chapter 5, which has been substantially redeveloped as part of this research, and which combines all models discussed throughout this thesis into a single software tool. Finally, the framework is put to use in Chapter 6 in order to investigate the impacts of automated driving on traffic safety and efficiency.

3

Modeling the Human Driver

Parts of this chapter have been published in similar form in:

Lindorfer, M., Mecklenbräuker, C.F., Ostermayer. G. (2017) 'Modeling the Imperfect Driver: Incorporating Human Factors in a Microscopic Traffic Model', IEEE Transactions on Intelligent Transportation Systems, vol. 19, no. 9, pp. 2856-2870.

Lindorfer, M., Backfrieder, C., Mecklenbräuker, C.F., Ostermayer. G. (2017) 'A Stochastic Driver Distraction Model for Microscopic Traffic Simulations', Proceedings of the 31st European Simulation and Modeling Conference, Lisbon, Portugal, pp. 252-257.

THE improper and suboptimal behavior of human drivers is one of the main causes for many problems prevalent on our roads, and a prime contributing factor to a large portion of motor vehicle crashes [24,25] and traffic congestion [26]. In order to draw meaningful conclusions with respect to the potential impacts of vehicle automation based on simulations, the models used in such simulations must be able to adequately describe the dynamics of automated vehicles, but notably also the behavior of human-driven vehicles. However, many of the simulation-based studies reported in the literature often ignore the many factors that govern the way humans drive, and thus lack the ability to appropriately capture much of "real" driving behavior [35]. This chapter addresses this particular issue, and aims for developing a comprehensive framework to incorporate a whole range of human factors into microscopic traffic models[1]. The proposed framework builds upon

[1] As argued in the introduction, the focus of this thesis lies on driver behavior models capturing the longitudinal dynamics of vehicles, i.e. car-following models. Extending the framework to incorporate aspects related to lane changing is beyond the scope of this work, but further research in this direction is intended, as will be discussed in the concluding chapter.

the IDM [152] as underlying car-following model, and is intended as an extension to the well known Human Driver Model (HDM) [215]. After introducing both models, we propose two extensions to the HDM which focus on behavioral aspects related to the drivers' contextual sensitivity and distracted driving, and provide the theoretical and empirical justification for the adopted approach. Moreover, we introduce a novel attempt to integrate driver distractions with microscopic traffic simulations. The proposed model in a sense provides the temporal frame for the behavioral adaptations caused by the drivers' engagement in secondary tasks, and is verified with the aid of a naturalistic driving study from the pertinent literature.

3.1 Intelligent Driver Model

The IDM belongs to the class of stimulus-response models, and is probably one of the most widely used deterministic car-following models in the literature. In the following, we elaborate on the model's mathematical properties and detail some of its fundamental characteristics. This section is intended to provide the theoretical foundation for the conceptual framework developed in the remainder of this chapter, but also as an underpinning for selecting the IDM as baseline model for our framework.

3.1.1 Mathematical Description

Generally speaking, car-following models describe the longitudinal interactions of vehicles on the road. A basic assumption of many models reported in the literature is that the dominant influence on the driver's behavior comes from the vehicle in front. This holds also true for the IDM, which essentially describes the motion of a vehicle α by means of an acceleration function $\dot{v}_\alpha(t) = \frac{dv_\alpha}{dt}$, which is a continuous function of the vehicle's actual velocity $v_\alpha(t)$, the net distance $s_\alpha(t)$, and the velocity difference $\Delta v_\alpha(t)$ to the vehicle in front, as illustrated in Figure 3.1. More precisely, the IDM describes the acceleration of a vehicle α by the following equation:

$$\dot{v}_\alpha(s_\alpha, v_\alpha, \Delta v_\alpha) = a\left[1 - \left(\frac{v_\alpha}{v_0}\right)^\delta - \left(\frac{s^*(v_\alpha, \Delta v_\alpha)}{s_\alpha}\right)^2\right] \tag{3.1}$$

where v_0 denotes the vehicle's desired velocity, a is the vehicle's maximum acceleration, and δ describes the rate at which the vehicle's acceleration decreases as it approaches its the desired speed[2]. In principle, Equation (3.1) can be regarded as a superposition of two separate terms, namely the acceleration on a free and empty road $\dot{v}_\alpha^f$, which compares the

[2]Note that the acceleration exponent δ will be set to 4 throughout this thesis, which was found to correspond to the most realistic acceleration behavior [127, p. 18]

current speed v_α with the desired speed v_0, and an interaction term $-\dot{v}_{int}$ to maintain a dynamic desired minimum distance s^* to the vehicle in front:

$$\dot{v}_\alpha^f(v_\alpha) = a\left[1 - \left(\frac{v_\alpha}{v_0}\right)^\delta\right] \tag{3.2}$$

$$-\dot{v}_{int}(s_\alpha, v_\alpha, \Delta v_\alpha) = -a\left(\frac{s^*(v_\alpha, \Delta v_\alpha)}{s_\alpha}\right)^2 \tag{3.3}$$

with

$$s^*(v_\alpha, \Delta v_\alpha) = s_0 + v_\alpha T + \frac{v_\alpha \Delta v_\alpha}{2\sqrt{ab}} \tag{3.4}$$

where s_0 is the stopping distance (i.e., the distance between cars in standstill), T the time gap, and b the vehicle's maximum comfortable deceleration, respectively. While the stopping distance s_0 is relevant only in case of low velocities, the term $v_\alpha T$ is most influential in stationary traffic, and describes the desired distance headway under equilibrium conditions, i.e. $\Delta v_\alpha = 0$ and $dv/dt = 0$. The third component is a dynamic term, and is only active in non-stationary conditions, i.e. $\Delta v_\alpha \neq 0$. This term implements an "intelligent" braking strategy, which limits braking decelerations to the comfortable deceleration b in nearly all situations, and guarantees collision-free driving under all circumstances [121,152]. Throughout this thesis, we will consider a slightly refined version of the IDM which addresses certain weaknesses in the original formulation, and which aims for avoiding unrealistically strong decelerations in situations where the vehicle's actual velocity exceeds its desired speed, i.e. $v_\alpha > v_0$ [121]. Such situations may occur, for example, when the desired speed is decreased locally by a speed limit. Consequently, we replace the free acceleration $\dot{v}_\alpha^f$ in Equation (3.2) with the following term:

$$\dot{v}_\alpha^f(v_\alpha) = \begin{cases} a\left[1 - \left(\frac{v_\alpha}{v_0}\right)^\delta\right] & \text{if } v_\alpha \leq v_0 \\ -b\left[1 - \left(\frac{v_0}{v_\alpha}\right)^{a\delta/b}\right] & \text{otherwise} \end{cases} \tag{3.5}$$

3.1.2 Model Properties

As indicated above, the conceptual framework developed in the remainder of this chapter builds upon the IDM as basic car-following model. The reasons for selecting the IDM as baseline model are manifold, and are best illustrated taking into account some of the model's fundamental properties. Following the presentations in [121,127,152], these properties can be summarized as follows:

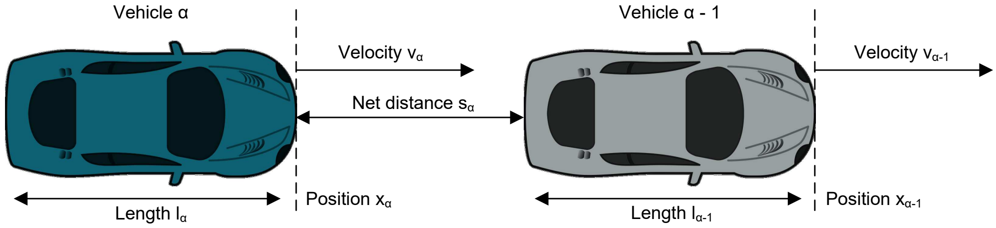


Figure 3.1: Illustration of the basic parameters of the IDM. The net (bumper-to-bumper) distance and velocity difference between the following vehicle α and the preceding vehicle $(\alpha - 1)$ are defined as $s_\alpha = x_{\alpha-1} - x_\alpha - l_{\alpha-1}$ and $\Delta v_\alpha = v_\alpha - v_{\alpha-1}$, respectively. It is worth noting that this notation will be used throughout this thesis.

Completeness. In the context car-following models, the term completeness refers to the ability of a model to "consistently describe all situations that may arise in single-lane traffic" [121]. Remarkably, the IDM is regarded as probably the simplest complete model describing both free-flow and car-following situations while at the same time resulting in plausible behavior and acceleration profiles [127]. This differentiates the IDM from many other stimulus-response models such as the GHR model [150] or the model by Helly [151], which consider only stimuli from the leading vehicle in their formulations, and which are therefore not particularly suited to model free driving [95, 262].

Parsimony. A small number of interpretable parameters is an important feature of any car-following model, especially in view of the efforts required for model calibration and validation. The IDM is parsimonious in the sense that it has only a few parameters which are all meaningful, within reasonable ranges, and empirically measurable [152]. Additionally, each model parameter describes only one aspect of driving behavior, which allows for an intuitive description of different driving styles by solely tuning a single parameter, and which facilitates the process of model calibration [127]. A list of typical parameter values for the IDM and their reasonable ranges is given in Table 3.1.

Compliance to empirical observations. The third and presumably most important aspect of a car-following model is how good it describes the behavior and phenomena observed in reality. Over the years, the IDM has been applied successfully to reproduce a variety of macroscopic traffic phenomena such as the capacity drop, traffic breakdowns, or the propagation of stop-and-go waves [152]. On a microscopic scale, several attempts have been made to calibrate the IDM on empirical trajectory data [263–265], generally concluding that it fits the data better than many other car-following models, including the OVM [170, 171], the Full Velocity Difference Model [266], or the models by Krauss [145] and Wiedemann [155].

Parameter	Typical value	Reasonable range
Desired speed v_0 [m/s]	30	12 - 55
Time gap T [s]	1.5	0.9 - 3
Stopping distance s_0 [m]	2.0	1 - 5
Desired acceleration a [m/s^2]	1.4	0.3 - 3
Comfortable deceleration b [m/s^2]	2.0	0.5 - 3

Table 3.1: Basic model parameters of the IDM with typical values and value ranges [121, 127].

3.2 Human Driver Model

Even though traditional car-following models – including the IDM – have been developed to reproduce the behavior of human drivers and the traffic phenomena resulting thereof, the driving characteristics of many of these models in essence correspond to that of automated vehicles [65, 121]. The nature of human driving behavior however differs substantially from the idealized and automated response presumed by many traditional car-following models, and encouraged researchers to develop new models or extend existing ones in order to provide a better understanding and a psychologically plausible explanation of human driving behavior. A very generic attempt in this context was made by Treiber et al. [215] and Kesting [127], who proposed the HDM as an extension to traditional car-following models. From a formal perspective, the HDM can be regarded as a meta-model capable of incorporating a variety of "human factors" into the underlying car-following model. In other words, the HDM itself is per se no car-following model, but a framework which allows to enrich existing models with different behavioral assumptions and explanatory human factor mechanisms. This framework is formulated in such a way as to be applicable to a wide class of car-following models characterized by a continuous acceleration function exhibiting the general form

$$\frac{dv_\alpha}{dt} = \dot{v}_\alpha(s_\alpha, v_\alpha, \Delta v_\alpha) \tag{3.6}$$

As a result, the HDM can be combined with essentially any car-following model in which the acceleration is a continuous function of the vehicle's current speed v_α, the net distance s_α, and the velocity difference Δv_α to the leading vehicle, such as the OVM [170, 171], the model by Gipps [144], or the IDM, for example. In the scope of this thesis, we will apply the HDM extensions to the latter, and consider this combined model as a starting point for Section 3.3, where the existing framework will be extended by additional aspects for which the original model cannot account for. Following the deliberations in [127, 215], the subsequent sections highlight the main rationale behind the HDM, discuss its underlying behavioral assumptions, and describe the modifications that are necessary to integrate it with the IDM.

3.2.1 Finite Reaction Time

A fundamental feature of human driving behavior is a considerable reaction time resulting from the physiological aspects of sensing, perception, and response [212]. The HDM incorporates such a delayed reaction into the underlying car-following model by simply evaluating the right-hand side of Equation (3.6) at a previous time $t - T'$. Mathematically speaking, this transforms the differential equations of the time-continuous car-following model into a coupled set of Delay-Differential Equations (DDEs). Generally, the resulting DDEs cannot be integrated analytically, but it is straightforward to solve them approximately by means of numerical integration [121]. Given that the reaction time is an integer multiple of the update time Δt of the numerical scheme, i.e. $T' = n\Delta t$, these equations can be solved by simply calculating all terms on the right-hand side of Equation (3.6) using the vehicles' speeds and positions n time steps earlier. Otherwise, the authors in [215] propose a linear interpolation scheme according to

$$x(t - T') = \beta x_{t-n-1} + (1 - \beta) x_{t-n} \tag{3.7}$$

where x denotes any quantity on the right-hand side of Equation (3.6), such as the vehicle's own speed v_α, the net distance s_α or speed difference Δv_α to the vehicle in front, and x_{t-n} corresponds to the same quantity n time steps in the past. Here, n represents the integer part of $T'/\Delta t$, and the weight factor of the linear interpolation β is given by $T'/\Delta t - n$.

3.2.2 Imperfect Estimation Capabilities

As discussed previously, there is abundant evidence that human drivers have systematic biases in judging distances and speeds [220–222], and that these stimuli can only be estimated with limited accuracy [65, 188]. Such estimation errors are often modeled using auto-correlated noise processes to take into account that human errors are of a certain persistence [185, 223]. For example, if a driver underestimates the distance to the vehicle in front at a given time, the probability of underestimating it at a somewhat later point in time is high as well, i.e. the errors are positively correlated for small time differences [121]. Based on the assumption that the driver is able to reliably determine the own velocity by looking at the vehicle's speedometer, the HDM considers estimation errors only with respect to the distance and speed difference to the preceding vehicle, and uses stochastic Wiener processes [267] to model the errors' finite persistence. Ultimately, this results in the following expressions for the estimated distance $s_\alpha^{est}(t)$ and velocity difference $\Delta v_\alpha^{est}(t)$ to the vehicle in front:

$$\begin{aligned} s_\alpha^{est}(t) &= s_\alpha(t) e^{V_s \omega_s(t)} \\ \Delta v_\alpha^{est}(t) &= \Delta v_\alpha(t) + s_\alpha(t) r_c \omega_{\Delta v}(t) \end{aligned} \tag{3.8}$$

where V_s is the statistical variation coefficient describing the relative standard deviation of the estimated distance s_α^{est} from the true value of s_α, and $1/r_c$ is a measure for the average estimation error of the time-to-collision, respectively. Moreover, $\omega_s(t)$ and $\omega_{\Delta v}(t)$ are stochastic variables obeying independent Wiener processes $w(t)$ of unit variance with correlation time τ, and are given by

$$\frac{dw}{dt} = -\frac{w}{\tau} + \sqrt{\frac{2}{\tau}}\xi(t) \tag{3.9}$$

Here, $\xi(t)$ denotes standardized white noise with $\langle\xi(t)\rangle = 0$ and $\langle\xi(t)\xi(t')\rangle = \delta(t-t')$. Considering a numerical integration scheme with update time Δt, as adopted in this thesis (see Section 5.2.4), the Wiener process given by Equation (3.9) is approximated as suggested in [267]:

$$\omega(t+\Delta t) = e^{-\Delta t/\tau}\omega(t) + \sqrt{\frac{2\Delta t}{\tau}}\eta_t \tag{3.10}$$

where $\{\eta_t\}$ are independent realizations of a Gaussian distributed random variable with zero mean and unit variance.

3.2.3 Anticipatory Driving

Considering the detrimental effects on driving performance originating from the perceptual limitations and the delayed reaction of human drivers, it is remarkable that humans are still able to drive safely and essentially accident-free in most situations, even in dense traffic and at time gaps that are far below the average reaction time [268–270]. This suggests that human drivers achieve additional safety by considering not only the vehicle directly in front, but also further vehicles ahead [65, 121, 127, 215]. Moreover, there is also evidence that drivers tend to predict what happens next, especially while upon familiar traffic situations [245], and also depending on their level of experience [246]. The HDM takes account of these capabilities by introducing two mechanisms which can broadly be categorized as temporal and spatial anticipation [121].

Temporal Anticipation

The temporal anticipation mechanism is based on the assumption that drivers are able to compensate for their delayed reaction to a certain extent by anticipating the future traffic situation – at least for a short period of time. The HDM incorporates such kind of foresightedness by adopting a simple form of dead-reckoning, i.e. by extrapolating the stimuli perceived by the driver over space and time [215]. More precisely, the HDM uses a constant-acceleration heuristic to predict the movement of the own vehicle, and a constant-speed heuristic to anticipate the distance and velocity difference with respect to the vehicle in front. The former is based on the assumption that the speed and acceleration of the own vehicle are known, and that the vehicle's acceleration will not change significantly during the anticipation time horizon. In case of the latter, a simpler constant-velocity heuristic is applied, since it is known that human drivers are not able to estimate the accelerations of other vehicles reliably [127]. Taking into account the combined effects of a delayed reaction and imperfect estimation capabilities, the temporal anticipation mechanism can be formulated as follows:

$$\begin{aligned} v'_\alpha &= \left[v_\alpha^{est} + T'\dot{v}_\alpha\right]_{t-T'} \\ s'_\alpha &= \left[s_\alpha^{est} - T'\Delta v_\alpha^{est}\right]_{t-T'} \\ \Delta v'_\alpha &= \left[\Delta v_\alpha^{est}\right]_{t-T'} \end{aligned} \tag{3.11}$$

where the parameters in parentheses correspond to the respective quantities delayed by the reaction time T'. Notably, the anticipation terms given by Equation (3.11) are intended to compensate particularly for the detrimental effects of human reaction time, and do not contain any additional model parameter.

Spatial Anticipation

The second anticipation mechanism takes account of the ability of human drivers to consider not only the vehicle immediately in front when carrying out the driving task, but also several vehicles ahead – whenever this is possible[3]. This ability is commonly referred to as spatial or multi-anticipation, and has been included in a number of car-following models recently [144, 170, 171, 247, 248]. The HDM expresses this kind of behavior by splitting the acceleration function given by Equation (3.6) into two separate terms using a social force approach [271, 272]:

$$\dot{v}_\alpha(s_\alpha, v_\alpha, \Delta v_\alpha) = \dot{v}_\alpha^f(v_\alpha) + \dot{v}_{\alpha\beta}^{int}(s_\alpha, v_\alpha, \Delta v_\alpha) \tag{3.12}$$

where $\dot{v}_\alpha^f$ corresponds to the free-flow acceleration reflecting the driver's desire to drive at a certain speed, which is independent of any other vehicles, and $\dot{v}_{\alpha\beta}^{int}$ is an interaction term reflecting the need to maintain a safe distance to the vehicle in front [121]. Subsequently, the reaction to several vehicles in front is modeled intuitively by simply summing up all interaction terms $\dot{v}_{\alpha\beta}^{int}$ between the subject vehicle α and the n_a next-nearest vehicles β:

$$\dot{v}_\alpha = \dot{v}_\alpha^f(v_\alpha) + \sum_{\beta=\alpha-n_a}^{\alpha-1} \dot{v}_{\alpha\beta}^{int} \tag{3.13}$$

[3] For example, it may be possible to recognize vehicles further downstream by either looking beyond the preceding vehicle on a curvy road, or through the windows of the vehicle in front.

with

$$\dot{v}_{\alpha\beta}^{int} = \dot{v}_{int}(s_{\alpha\beta}, v_\alpha, v_\alpha - v_\beta) \tag{3.14}$$

Here, $s_{\alpha\beta}$ denotes the sum of all net distances between vehicle α and vehicle β, and determines the "criticality" of the situation [215]. An inherent yet reasonable assumption of this approach is that when considering more than one leading vehicle, the driver's behavior will be most affected by the vehicle immediately in front, while the impact of vehicles further ahead becomes less influential as the distance to those vehicles increases [127].

3.2.4 Application to the Intelligent Driver Model

After providing the theoretical foundation of the HDM and elaborating on the different behavioral assumptions it builds upon, it is now time to actually apply the HDM to the IDM. As mentioned before, this combined model serves as a starting point for the developments and extensions discussed in the forthcoming sections, which essentially aim for providing an even richer description of human driving behavior. While reaction times, estimation errors and temporal anticipation capabilities can be integrated straightforwardly with the IDM under consideration of Equations (3.2) to (3.4), incorporating the spatial anticipation mechanism described in Section 3.2.3 requires additional attention. In fact, one may recognize that the summation of interaction terms given by Equation (3.13) may become negative when increasing the number of considered vehicles. This, in turn, changes the fundamental diagram, and ultimately decreases the modeled road capacity [121]. In order to overcome these unwanted consequences, the authors in [215] and [127] suggest to multiply all interaction terms in Equation (3.13) with a common prefactor c such that the following condition is satisfied for stationary and homogenous traffic conditions[4]:

$$c \sum_{j=1}^{n_a} \dot{v}_{\alpha\beta}^{int}(j s_e(v_\alpha), v_\alpha, 0) = \dot{v}_{\alpha\beta}^{int}(s_e(v_\alpha), v_\alpha, 0) \tag{3.15}$$

By setting $\dot{v}_\alpha = \Delta v_\alpha = 0$ and applying the general Equation (3.15) to the IDM interaction term given by Equation (3.3), we obtain

$$c \sum_{j=1}^{n_a} a \left(\frac{s_0 + v_\alpha T}{j s_\alpha} \right)^2 = a \left(\frac{s_0 + v_\alpha T}{s_\alpha} \right)^2 \tag{3.16}$$

From that, the renormalization factor required to satisfy Equation (3.15) follows directly by solving Equation (3.16) for c:

[4] Stationary and homogenous traffic implies that all vehicles are driving at the same speed, and that the gaps between all vehicles are equal to the equilibrium distance, i.e. all accelerations are zero.

$$c = \frac{1}{\sum_{j=1}^{n_a} \frac{1}{j^2}} \tag{3.17}$$

After inserting this term in Equation (3.16) and re-writing the left-hand side of the equation, we finally obtain the following expression:

$$\sum_{j=1}^{n_a} a \left(\frac{\sqrt{c} s_0 + v_\alpha \sqrt{c} T}{j s_\alpha} \right)^2 = a \left(\frac{s_0 + v_\alpha T}{s_\alpha} \right)^2 \tag{3.18}$$

As argued in [121], these transformations are crucial to guarantee that the fundamental diagram of the "original" IDM and its multi-anticipative counterpart are not different from each other, and thus both models can be compared. Consequently, we apply the following transformations for all simulations conducted in the scope of this thesis:

$$s_0 = \sqrt{c} s_0, \qquad T = \sqrt{c} T \tag{3.19}$$

From a mathematical perspective, these renormalizations have another advantage, that is, the sum of all interaction terms converges, even when considering an infinite number of leading vehicles [121]. In this limiting case $n_a \to \infty$ one obtains $c \approx 0.61$, which means that the immediate leader contributes to 61% of the overall interaction "forces", while the remaining 39% stem from vehicles further ahead [127].

3.3 Extending the Human Driver Model

Beyond question, the HDM [127, 215] presented in Section 3.2 can be considered as an initial attempt towards developing a generic modeling framework that allows traffic scientists to incorporate different aspects and traits associated with human driving behavior into existing car-following models. The key advantage of separating the idealized – and in general collision-free – car-following models from the models that describe the various factors characterizing the behavior of human drivers is that analysts have the possibility to mix a variety of models for driving behavior with an even wide range of behavioral assumptions and human factors, without necessitating the development of new models in addition to the already broad family of car-following models [65, 174]. On the other hand, this separation of concerns has also some more practical implications, as it facilitates the development of simulation frameworks that are modular in their design, easier to maintain, and tractable. In light of these circumstances, we consider the meta-model approach pursued by the HDM a worthwhile attempt towards augmenting existing car-following models with different explanatory human factor mechanisms. However, it is also recognized that the HDM disregards several factors affecting the behavior of human drivers. In the scope of this thesis we intend to fill some of the existing gaps in the original formulation, and propose two extensions to the original HDM. These extensions focus on two important aspects of human driving behavior which – despite their evident impacts on driving performance – have hardly been considered in existing car-following models, and the HDM in particular, namely context sensitivity and distractions. The following sections elaborate on how both aspects are included in the model, and discuss the assumptions underlying our modeling approach in more detail. For reasons of clarity, the extended model will hereinafter be referred to as HDM*.

3.3.1 Context Sensitivity

As discussed previously, the behavior of human drivers is not only governed by the drivers' preferences, skills, and capabilities, but is also influenced by the prevalent traffic situation [147, 250, 260]. In fact, there is ample evidence that drivers adapt their driving style to the surrounding traffic on time scales up to a few minutes, for example after being stuck in congested traffic for some time [273], or when driving in the dark or in tunnels [274]. Probably the easiest way to model these behavioral adaptations would be to introduce some form of stochasticity into the underlying car-following model. In the following, however, we propose a deterministic approach to describe such kind of context-sensitivity. Our approach is motivated by the findings of Green [269], indicating that the driver's reaction time does not only depend on the driver's age, gender, or cognitive load, but is also strongly influenced by his or her level of expectation under certain conditions.

Situation-Dependent Reaction Times

The human reaction time has been subject of extensive research for several decades, and has been incorporated in many car-following models over the years [131, 144, 150, 170, 214, 215]. However, an inherent limitation of these models is that they consider the driver's reaction time to be an invariable parameter, which is obviously an oversimplification compared to reality. In fact, previous research indicates that the driver's reaction time in response to unexpected events, e.g. an object moving into the driver's path, is up to twice as high as when he or she reacts to an expected signal [269]. Moreover, there are also indications that the local traffic context may affect the drivers' response, and that drivers react differently when they are queued in front of an intersection, stuck in congestion, or driving freely [275, 276]. To account for these temporal variations in reaction time, we propose a multi-regime model which dynamically adjusts the driver's reaction time in accordance to different driving regimes. More precisely, we differentiate between three regimes a driver may belong to at any point in time, namely car-following, free driving, and standing traffic, each of which is associated with a different reaction time, hereinafter designated as T'_{cf}, T'_{fd}, and T'_{st}, respectively.

Determining the Driving Regime

Since the driver's reaction time is governed by the driving regime he or she currently belongs to, a clear distinction between the different regimes is required. While the standing traffic regime is rather self-explaining, i.e. $v_\alpha(t) = 0$, we use two headway thresholds to determine whether the driver is in the car-following or the free driving regime. To be more specific, whenever the driver's time headway given by

$$h_\alpha(t) = \frac{s_\alpha(t)}{v_\alpha(t)}, \text{ with } v_\alpha(t) > 0 \tag{3.20}$$

is less than a threshold value h_t^*, the driver is assumed to be in the car-following regime and to follow its leader. Since Equation (3.20) results in rather large values when driving at low velocities, we additionally consider a space headway threshold h_s^* to distinguish between both regimes whenever h_t^* is exceeded. Consequently, when both the vehicle's time headway h_α and the distance to the vehicle in front s_α are larger than their respective thresholds, the driver is presumed to be in the free driving regime. The reason for prioritizing the time headway over the space headway, i.e. the distance between the following vehicle and its leader, is that drivers usually tend to maintain a certain time gap to the vehicle in front [277,278], and that the same space headway would essentially result in the same driving regime, even though the speeds of both vehicles may be very different. To avoid that potential short-term fluctuations in the vehicle's speed trigger several consecutive transitions between both driving regimes, the instantaneous headways are given by the Exponential Moving Average (EMA) of the past headways:

$$x(t) = \int_0^t x(t')e^{-(t-t')/\tau}dt' \tag{3.21}$$

where x denotes either the time or space headway, respectively, and τ is the relaxation time of the filter, which is set to a rather short value of $3s$.

Varying Reaction Times

Apparently, the regime a driver belongs to may vary over time, and so does the driver's reaction time. Thus, whenever a transition from one driving regime to another is invoked, the reaction time of the underlying car-following model is adjusted accordingly. From an implementation perspective, this requires some form of bookkeeping, since the state of all simulation variables which are relevant for the car-following model, such as speeds, speed differences, or distances, have to be accessed at different points in time. Therefore, a historical list of those variables is maintained in a queue, whose size naturally depends on the maximum value the driver's reaction time may be set to during simulation, as illustrated in Figure 3.2. In every simulation time step the most outdated set of variables

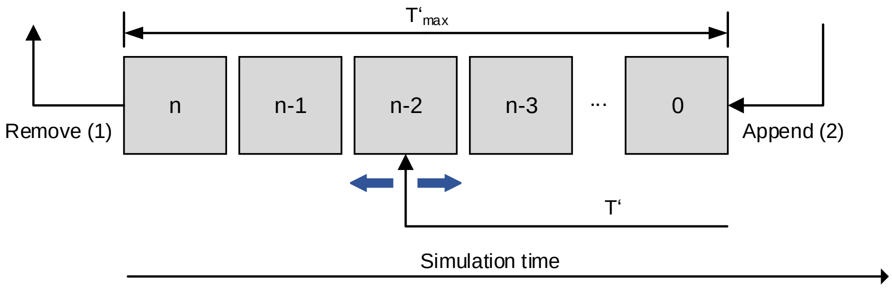


Figure 3.2: Schematic illustration of the queue data structure used for maintaining the state of simulation variables up to n time steps in the past. The pointer determining the set of variables to be considered may be moved back or forth as the driver's instantaneous reaction time T' changes.

is removed from the queue, and a new set reflecting the current state of all variables is added. Finally, a pointer determines which set of parameters has to be taken into consideration by the underlying car-following model at a certain point in time, whereby the pointers' position is dictated by the driver's instantaneous reaction time.

3.3.2 Driver Distractions

Distracted driving poses a massive safety risk on our roads, and it is widely believed that a significant number of police-reported crashes and near-crash situations is somehow a result of distraction [200, 206, 241–243]. Research on distracted driving has accelerated in the last years, and there exists a large body of literature focusing on different types of distraction and their effects on driving performance [230–240]. Until a short time ago, however, driver distraction has largely been ignored in car-following models. More recent studies partially overcome this limitation, and consider some of the impairments reported in connection with distracted driving, such as an increase in reaction time [184, 244], or impacts on the driver's situational awareness [65]. In the present thesis, distractions are integrated with the underlying car-following model in two ways, depending on their level of severity and their implications on driving behavior.

Types of Distraction

In the general literature on distracted driving it is commonly distinguished between three types of distraction depending on how they interfere with the driving task: visual, manual, and cognitive distraction [229]. Manual distraction refers to anything causing the driver to take one or both hands off the steering wheel, while cognitive distraction involves any thoughts or activities affecting the driver's ability to pay attention to the driving task. Visual distractions form the third and probably most critical type of distraction [230, 240], and usually occur when the driver focuses his or her visual attention on another object or person inside or outside the vehicle rather than looking at the road ahead. From a modeling perspective, there is a good reason to differentiate between distractions involving visual perception and ones that do not, since the former essentially utilize the same information processing channel that is required for performing the driving task. Consequently, we distinguish between two types of distraction a driver may be subjected to, namely minor and severe distractions.

Minor Distractions. The first category refers to all distractions that cause the driver's attention to divert from activities that are relevant for driving to any competing task, such as talking to other passengers or on the mobile phone. Such kind of distractions are incorporated into the underlying car-following model in two ways. First, the driver's instantaneous reaction time is assumed to increase as a result of the distraction, which is in line with empirical observations indicating a degradation in reaction time of up to thirty percent [279–281]. At the same time, we assume that the driver reduces his or her desired speed for the duration of the distraction. This speed reduction is also a commonly known phenomenon, and is often interpreted as some kind of compensatory effect, where drivers, whether consciously of unconsciously, reduce their task load in order to maintain driving performance on an acceptable level [282–285]. The magnitude of both behavioral adaptations is thereby determined by two auxiliary parameters λ_r and λ_v representing the relative increase (or decrease) in the driver's reaction time (or desired speed) for the duration of the distraction.

Severe Distractions. The second type of distraction comprises all secondary tasks that involve some form of visual perception on the part of the driver. This includes distractions originating from the use of in-vehicle devices such as navigation systems, or from other objects or persons either inside or outside the vehicle catching the driver's visual attention. It is generally recognized that such kind of distractions are particularly detrimental for the driving task [230, 240], since they usually involve a significant deterioration in the driver's sensing and perceptual abilities. Ultimately, this may result in the driver missing safety-critical information or other important visual cues such as vehicles in an adjacent lane, or changes in relative speed or distance with respect to the vehicle in front. In a sense, the diversion of visual attention makes the driver oblivious of any changes in the driving environment. A simple but plausible approach to model such kind of obliviousness is to assume that the driver does not update his or her driving status during the distracted period. From a modeling perspective, this means that all input parameters of the underlying car-following model, and thus the applied acceleration, are kept at their previous level, that is, at their state prior to the distraction[5]. After being distracted, the driver is assumed

[5]It is worth noting that similar effects have been observed in connection with lateral vehicle control, indicating that a diversion of visual attention results in periods with a fixed steering wheel angle, ultimately resulting in lane weaving, and sometimes even lane exits [284, 286].

to pay full attention to the driving task again, and thus all parameters of the car-following model are updated in their normal fashion. This instantaneous change in the state of the model parameters will naturally result in a delayed but at the same time stronger (braking) response, for which there is also ample empirical underpinning [287–289].

3.4 Modeling and Simulation of Distracted Driving

In recent years, the rich literature on distracted driving has encouraged researchers to increasingly incorporate distractions and their impacts on driving performance into microscopic traffic models [65, 184, 244]. While these models provide a plausible means to describe how drivers adapt their behavior while being preoccupied by secondary tasks, for instance in terms of increased reaction times or errors in perception, they do not sufficiently account for how often drivers engage in such tasks, or for how long. To overcome this deficiency, we propose a novel approach towards modeling the frequency and duration of distractions in the scope of microscopic traffic simulations, which in a sense provides a temporal frame for the behavioral adaptations governed by the underlying traffic models. The following sections elaborate on the general modeling approach in more detail, review its underlying assumptions, and finally discuss the calibration and validation of the model with the aid of a naturalistic driving study from literature.

3.4.1 Overview of the Modeling Approach

Given that the intention of the proposed model is to integrate driver distractions with microscopic traffic simulations, a number of requirements can be made. These requirements stem from the concept that the model should be able to provide a reasonable approximation of how often drivers engage in certain distracting activities, and for how long they typically engage in them.

- **Frequency and duration of distractive tasks.** Drivers frequently engage in a variety of potentially distractive tasks [290]. In the literature, there is ample evidence that the frequency of engagement and the amount of time drivers engage in a particular activity vary strongly among different types of secondary tasks [230, 232]. The model should take account of these differences, and provide a means to distinguish between different types of distracting activities.

- **Driver heterogeneity.** Not all drivers engage in the same activities with equal probability. In fact, there is a large body of evidence that several characteristics such as age, gender, driver experience or personality influence the driver's willingness to engage in potentially risky secondary tasks [230, 291–293]. The model should be able to reflect such inter-driver differences, albeit in a more abstracted manner.

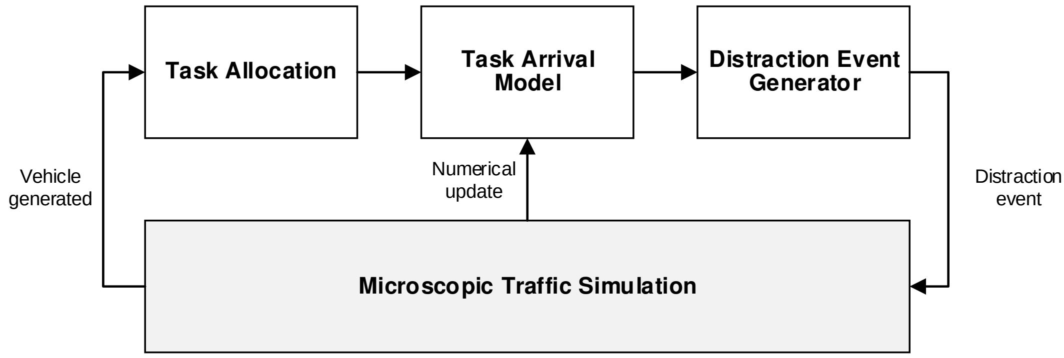


Figure 3.3: Schematic illustration of the distraction simulation framework.

- **Parsimony.** The number of model parameters should be reasonably small, and all parameters should have an intuitive meaning. A small number of parameters facilitates the process of model calibration, a process which typically requires considerable computational effort, especially for more complex models.

- **Separation of concerns.** The intention of the proposed model is to explicitly simulate the occurrence of potentially distracting tasks in a microscopic simulation environment. To which extent these tasks influence the way in which drivers adapt their behavior, or how these tasks impair driving performance, however, is entirely governed by the underlying traffic models. This strict separation between distraction simulation and traffic simulation makes the model maintainable and applicable to essentially any microscopic simulation framework.

A general overview of a framework which we believe accounts for all of the abovementioned requirements is depicted in Figure 3.3. Fundamentally, the proposed model consists of three separate components which are bi-directionally coupled with the underlying traffic simulation model. Whenever a vehicle is generated in the traffic simulation, the task allocation module is responsible for determining the driver's exposure to a given set of distracting tasks, hereinafter denoted as D. Based on this allocation, the task arrival model estimates the point in time when a driver actually engages in a particular task, and is therefore synchronized with the traffic simulation model. Finally, the distraction event generator is used to determine for how long a driver engages in a certain activity, and to update the traffic simulation model accordingly. Before discussing the different aspects of the proposed framework in more detail, we briefly review the fundamental assumptions that have been made prior to model implementation:

- The probability that drivers engage in a certain type of distracting activity varies across different tasks. In other words, it is assumed that there are particular tasks drivers are more likely to engage in than others, which is in line with recent findings reported in the literature [230].

- At all times, a driver has an equal probability of engaging in a potentially distracting task. Apparently, this is a simplification compared to reality, where several contextual variables, such as task urgency, traffic density, or the complexity of the prevalent traffic situation influence the engagement in secondary tasks [228,232,233]. However, only little evidence exists on how these variables affect driver behavior, and how they interrelate with task demands and distractions [230]. Moreover, we emphasize that considering these factors should be the task of the underlying traffic model, where the required contextual variables are typically available.

- Drivers engage in secondary tasks at random instants in time and independently from previous activities. Similar to our second assumption, this might not precisely reflect reality, however, we justify this assumption for the same reasons. Obviously, it is reasonable to presume that certain types of distractions are actually random in their nature, i.e. unpredictable. On the other hand, as mentioned earlier, the engagement in distracting tasks is certainly influenced by several contextual variables, and one may argue that these tasks may also be causally related. For the lack of evidence otherwise, however, we will leave such causal chains disregarded.

3.4.2 Drivers' Exposure to Distracting Activities

As mentioned before, it is assumed that drivers engage in different distracting tasks with different probabilities. With this in mind, we introduce the task exposure e_d which reflects the probability that drivers engage in a particular activity. The task exposure can have any value ranging from zero (i.e., no drivers engage in this task) to one (i.e., all drivers engage in this task), and is used to determine whether or not a driver is likely to engage in a secondary task. Whenever a vehicle v is generated in the simulation, an exposure vector $\vec{e}_v$ is constructed which establishes the relation between that particular vehicle and one or multiple types of distracting tasks. To this end, for each task $d \in D$ a random sample is drawn from a uniformly distributed random variable $X \sim U(0, 1)$, and compared with the task's exposure:

$$\vec{e}_v(d) = \begin{cases} 1, & \text{if } X \leq e_d(d) \\ 0, & \text{otherwise} \end{cases} \tag{3.22}$$

As indicated by Equation (3.22), the driver of vehicle v is presumed to engage only in those secondary tasks d for which the condition $\vec{e}_v(d) > 0$ is satisfied. It is worth mentioning that the probability that drivers engage in a certain distracting task could also be viewed the other way round, i.e. as the percentage of all drivers engaging in that task. This, in turn, reflects driver heterogeneity to a certain degree, as different drivers not necessarily engage in the same distracting activities.

3.4.3 Frequency of Distracting Activities

With the exposure vector $\vec{e}_v$ of a vehicle at hand, the next problem to deal with is the rate of distraction, i.e. how often a driver engages in a particular task. As discussed earlier, it is assumed that drivers engage in distracting tasks in a random fashion and independently from previous distractions. A commonly used approach to model the occurrence of seemingly random and mutually independent events are Poisson processes. Such processes have been applied successfully across various domains, including queuing theory [294], network simulation [295–297], or financial and insurance mathematics [298, 299]. Formally, a Poisson process can be considered as a special case of a counting process $\{N(t), t \geq 0\}$, a type of stochastic process representing the number of events that have occurred during the time interval from 0 up to and including time t. Such a process is called a Poisson process of rate $\lambda > 0$ if it satisfies the following conditions [300]:

- **Independent increments.** The occurrence of an event does not affect the probability that a second event will occur, i.e. events occur independently.
- **Stationary increments.** The expected number of occurrences in any time interval depends only on the length of that interval and the rate parameter λ denoting the average number of occurrences during that interval.
- **Non-simultaneity.** The probability of two or more occurrences of an event in the same narrow time interval is negligible. That is, events occur only one at a time.
- **Poissonness.** The number of occurrences in a time interval of length t is a Poisson random variable with mean λt, i.e. $E[N(t)] = \lambda t$. Put differently, the probability that the number of occurrences in that time interval is equal to n is given by:

$$P\{N(t) = n\} = e^{-\lambda t} \frac{(\lambda t)^n}{n!} \tag{3.23}$$

Taking into account these deliberations and our assumptions discussed earlier, we consider Poisson processes as an appropriate means to describe the time differences between the occurrences of distracting activities. In a Poisson process, these time differences – also known as inter-arrival times – are independent and identically distributed exponential random variables with mean $1/\lambda$ [301]. The rate parameter λ in our case represents the average number of occurrences of a particular type of distraction in a time interval of one second. For a distracting task which was found to occur a hundred times during one hour, for example, this results (on average) in a time difference of 36s between consecutive secondary task engagements. Note, however, that this rate of distraction is only appropriate when all drivers potentially engage in the respective activity, i.e. $e_d = 1$. In other words, the actual rate λ does not only depend on the number of task occurrences n_d in a given time interval t, but also on the percentage of drivers engaging in this task:

$$\lambda = \frac{n_d}{t \cdot e_d} \tag{3.24}$$

In this manner, the model determines the (average) rate of distraction for each secondary task $d \in D$ a driver potentially engages in, i.e. $\vec{e}_v(d) = 1$. Finally, for each task satisfying this condition the actual point in time a driver engages in that task is estimated by drawing a sample from an exponentially distributed random variable with mean $1/\lambda$.

3.4.4 Duration of Distracting Activities

Apart from the rate of distraction, that is, how often drivers engage in a particular task, another important aspect determining the potential risk associated with secondary tasks is the amount of time drivers engage in such tasks. Over the years, several studies have been devoted to determine the duration of secondary task engagement for different types of distracting activities [200, 230, 232, 233, 302, 303]. What a majority of these studies have in common is that the duration of secondary tasks is usually quantified in terms of descriptive statistics rather than in the form of the corresponding probability distributions, which are critical for modeling purposes. For the lack of evidence otherwise, we will thus have to rely on reasonable assumptions in view of the distribution characteristics of task durations. Generally, any continuous and non-negative distribution comes into question for modeling the duration of distracting activities. Apart from this fundamental prerequisite, another distributional assumption we make is that the durations of secondary tasks are positively skewed, that is, shorter task durations are observed more often than longer ones. This is in line with the findings in [303, 304] and the general modeling literature, where right-skewed probability distributions are commonly used to model the duration of telephone calls [305], traffic incidents [306–310], in-vehicle glances [311, 312], or lane changes [313]. However, it is important to note that there is no general consensus about what distribution should preferably be used for duration modeling, and that essentially several probability distributions may be appropriate [314, 315]. With this in mind, and rather than making even stronger distributional assumptions, we consider two different probability distributions for modeling the duration of distracting activities: the log-normal distribution and the gamma distribution. These distributions are frequently used for modeling task durations in general [304, 306, 310, 313, 316, 317], and satisfy the abovementioned requirements of non-negativity and positive skewness.

Distribution Parameter Estimation

In the literature, there exist various methods to determine the parameters of a probability distribution, such as Maximum Likelihood Estimation (MLE) [318], Bayesian inference [319], Least Squares Estimation (LSE) [320], or method of moments estimation [321]. The latter is preferably used when MLE or LSE are intractable, or when only limited knowledge about the empirical distribution is available, for example in form of descriptive statistics[6], and is generally regarded a simple and consistent approach towards estimating the parameters of a given distribution. On the other hand, method of moments estimates do not necessarily represent sufficient statistics. Put differently, they do not always take into account all relevant information in the empirical sample, and are sometimes even outside the distribution's parameter space [321]. With this in mind and for the reasons discussed above, however, we argue that the method of moments constitutes an eligible approach for estimating the parameters of the task duration distributions.

Fundamentally, the method of moments is based on matching the moments of the empirical (or sample) distribution with the corresponding counterparts of a theoretical distribution [321]. This is done by expressing the first k moments $E[X], \dots, E[X^k]$ of the sample distribution as a function of the k unknown parameters $\theta_1, \dots, \theta_k$ characterizing the theoretical distribution:

$$\begin{aligned} E[X] &= g_1(\theta_1, \dots, \theta_k), \\ E[X^2] &= g_2(\theta_1, \dots, \theta_k), \\ &\vdots \\ E[X^k] &= g_k(\theta_1, \dots, \theta_k) \end{aligned} \tag{3.25}$$

In this manner, one obtains a set of k equations in k unknowns, which are then solved for the parameters of interest. Finally, the method of moments estimator $\hat{\theta}_1, \dots, \hat{\theta}_k$ is defined as the solution (if there is one) to these equations. In the following, we apply the methods of moments to determine the parameters of the log-normal and the gamma distribution. Both distributions are characterized by two parameters, and thus the first and second central moment of an empirical distribution (i.e., the sample mean and variance) can be used to estimate the theoretical counterpart. At this point, it is worth noting that there is no guarantee that the set of equations given by Equation (3.25) can be solved, and that sometimes the equation system might even be over-identified, for example when the number of known sample moments exceeds the number of unknown distribution parameters.

[6]Note that more sophisticated types of parameter estimation such as MLE or LSE require detailed information about the empirical distribution in terms of actual data samples. To the best of the author's knowledge, however, such information is not provided in the existing body of literature on secondary tasks and distracted driving, e.g. in [230, 233, 303].

Thus, it might not be possible to unambiguously estimate the parameters $\theta_1, \ldots, \theta_k$, or to estimate them at all [322]. For those reasons, we preclude other probability distributions which are commonly used to model task durations from our further investigation, such as the exponential distribution or the Weibull distribution.

Log-normal distribution. A random variable follows the log-normal distribution with location parameter $\mu \in \mathbb{R}$ and shape parameter $\sigma > 0$ if its logarithm is normally distributed [323]. From the moment generating function given by

$$E[X^k] = \exp\left(k\mu + \frac{k^2\sigma^2}{2}\right) \tag{3.26}$$

the mean and variance of the log-normal distribution follow directly [324]:

$$E[X] = \exp\left(\mu + \frac{\sigma^2}{2}\right) \tag{3.27}$$

$$Var[X] = \exp\left(2\mu + \sigma^2\right)\left(\exp(\sigma^2) - 1\right) \tag{3.28}$$

By solving Equations (3.27) and (3.28) for μ and σ, respectively, the location and scale parameter of the log-normal distribution can be estimated straightforwardly:

$$\hat{\mu} = \ln\left(\frac{E[X]^2}{\sqrt{Var[X] + E[X]^2}}\right), \qquad \hat{\sigma} = \sqrt{\ln\left(1 + \frac{Var[X]}{E[X]^2}\right)}. \tag{3.29}$$

Gamma distribution. The gamma distribution [325] with shape parameter $k \in (0, \infty)$ and scale parameter $b \in (0, \infty)$ is a family of continuous probability distributions on the interval $(0, \infty)$. In fact, several distributions such as the exponential distribution, the Erlang distribution, or the chi-squared distribution are special cases of the gamma distribution. With the mean and variance given by $E[X] = kb$ and $Var[X] = kb^2$, respectively, the distribution parameters $\hat{k}$ and $\hat{b}$ can be estimated by simple transformations:

$$\hat{k} = \frac{E[X]^2}{Var[X]}, \qquad \hat{b} = \frac{Var[X]}{E[X]} \tag{3.30}$$

3.4.5 Numerical Implementation

As discussed earlier, the proposed model is capable of integrating driver distractions with essentially any microscopic traffic simulation model. In this section we briefly present our implementation of the model assuming a numerical update scheme, as applied in the simulation framework discussed in Chapter 5. Figure 3.4 exemplifies the basic flow of

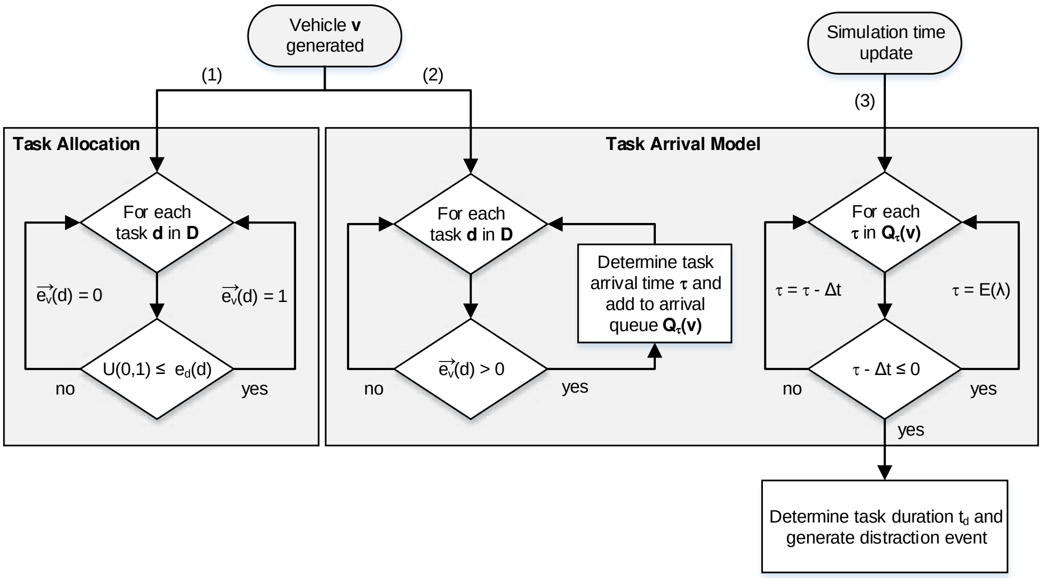


Figure 3.4: Basic flow of operations of the proposed distraction model assuming a numerical update scheme with an update time interval Δt. The numbers in parentheses indicate the sequence of operations.

operations performed by the model for a single vehicle in the simulation. The first step after vehicle generation is the allocation of the vehicle to one or multiple types of distracting tasks, i.e. the creation of the exposure vector $\vec{e}_v$. Based on this allocation, the task arrival model determines the initial (and exponentially distributed) arrival times for all tasks a driver is likely to engage in, and stores them in a task arrival queue $Q_\tau(v)$. Subsequently, these arrival times are decremented by the numerical update time interval Δt in every simulation time step to determine whether or not a distraction event needs to be issued. On each task arrival, a distraction event is generated including both the task's duration and the type of distraction, and sent to the traffic simulation model. Finally, the next arrival time for the respective task is determined, and the vehicle's arrival queue $Q_\tau(v)$ is updated accordingly.

At this point it is worth recalling that the primary purpose of the proposed model is to provide a reasonable approximation of how often drivers engage in secondary tasks, and for how long they engage in them. Thus, it provides only a temporal frame for integrating driver distractions with microscopic traffic simulations. How the engagement in distracting tasks influences the drivers' behavior, or to which extent driving performance deteriorates, however, depends solely on the underlying traffic models.

3.4.6 Model Calibration and Validation

To calibrate and validate our model, we use data that was collected during a comprehensive naturalistic driving study. In their study, Stutts et al. [233] used unobtrusive video camera

Distraction	e_d [%]	n_d	μ_d [s]	σ_d [s]	t_d^{tot}[s]	t_d^{min}[s]	t_d^{max}[s]
Talking on phone	32.9	100	92.65	176.29	9264.8	1.2	1264.2
Dialing phone	35.7	122	12.85	13.41	1567.7	1.0	65.7
Drinking	72.9	1028	5.23	7.4	5378.5	0.3	104.9
Prepare to eat or drink	61.4	1503	15.4	34.7	23146.3	0.1	755.5
Using audio controls	94.3	1539	5.46	8.63	8407.1	0.1	80.3
Using vehicle controls	100.0	2095	4.82	11.53	10104.7	0.1	283.8
Reading or writing	64.3	303	18.43	29.7	5583.9	0.1	282.4
Grooming	57.1	229	11.82	29.77	2706.7	1.0	340.0
Conversing	80.0	1558	74.04	234.5	115349.9	0.1	4827.0
Reaching	100.0	2246	7.58	36.7	17014.6	0.1	1351.0
Other internal distraction	81.4	481	21.55	46.38	10364.9	0.1	496.3
External distraction	90.0	659	26.55	58.87	17497.7	0.4	770.5

Table 3.2: The percentage of drivers engaging in potentially distracting activities e_d, their frequency of occurrence n_d, mean duration μ_d and standard deviation of duration σ_d [232]. The last three columns reflect the total amount of time drivers were preoccupied by a particular activity, and the shortest and longest observed task durations, respectively.

units installed in the vehicles of 70 volunteer drivers to study the drivers' exposure to secondary tasks. These video data were coded based on a detailed taxonomy of driver distractions along with several contextual variables (e.g., traffic level) and measures of driving performance, such as whether the driver's hands were on or off the steering wheel. Each participant was monitored over a period of one week, from which three hours of driving evenly distributed across the total recorded time were coded, resulting altogether in a total of 207.2 hours of data. Based on these data, different types of potentially distracting activities were identified, such as reaching, adjusting vehicle controls, or talking on the mobile phone, and the percentage of drivers engaging in each of the identified activities was determined. Moreover, the duration of these activities (in form of descriptive statistics) as well as their frequency of occurrence were analyzed, providing a comprehensive picture of how drivers are (on average) preoccupied by secondary tasks. Table 3.2 summarizes these findings for those activities drivers were found to engage in most frequently, and all relevant input parameters for our model can be inferred thereof. In fact, we consider a set of twelve different types of distractions D, whose exposure e_d and frequency n_d are set to the values given in Table 3.2. Moreover, the parameters for the theoretical log-normal and gamma distributions to model the duration of any of these tasks are derived from the average duration μ_d and standard deviation of duration σ_d of the empirical distribution using method of moments estimators, as discussed in the previous section.

Validation Results

Based on the calibration procedure discussed before, this section aims for demonstrating the model's ability to accurately reflect how often and for how long drivers on average

Distraction	e_d	n_d	μ_d $[s]$	σ_d $[s]$	t_d^{tot}
Talking on phone	0.59	0.51	0.85	3.45	0.29
Dialing phone	0.26	0.26	0.81	3.68	0.59
Drinking	0.07	0.16	0.65	2.68	0.16
Prepare to eat or drink	0.42	0.39	0.73	2.26	0.19
Using audio controls	0.12	0.05	0.51	1.84	0.09
Using vehicle controls	0	0.09	0.56	1.62	0.16
Reading or writing	0.26	0.02	0.89	3.22	0.21
Grooming	0.16	0.01	1.08	3.43	0.43
Conversing	0.23	0.17	0.71	2.23	0.07
Reaching	0	0.02	0.51	2.11	0.03
Other internal distraction	0.14	0.49	0.79	2.93	0.21
External distraction	0.19	0.21	0.88	2.64	0.15

Table 3.3: Relative errors in percent for different types of distraction and log-normally distributed secondary task durations. Replacing the log-normal distribution with the gamma distribution essentially results in the same descriptive statistics, and thus relative errors in the same order of magnitude.

engage in secondary tasks. For model validation the microscopic simulation framework TraffSim [261], on which Chapter 5 elaborates in more detail, is used, and a similar setup as in the baseline study is considered, comprising a set of 70 drivers and a total driving time of 207.2 hours. Due to it's stochastic nature, the model is run a 1000 times in order to generate statistically reliable results. Thus, all quantities discussed hereinafter correspond to average values. The error measure used to compare the model with the empirical ground truth is the Relative Error (RE) given by

$$RE = \frac{|\hat{x}_i - x_i|}{x_i} \cdot 100\% \tag{3.31}$$

where x_i and $\hat{x}_i$ correspond to the empirical and simulated quantities, respectively. In particular, the RE is determined for the following set of parameters:

- The driver's exposure to that particular type of distraction e_d,
- it's frequency of occurrence n_d,
- it's mean duration μ_d and standard deviation of duration σ_d,
- and the total amount of time drivers engaged with that particular task t_d^{tot}.

An overview of the validation results is given in Table 3.3, which aggregates the RE for all relevant quantities. As can be noticed, the RE remains below one percent for most of the observed quantities. Thus, the model is able to reproduce the descriptive statistics of the empirical data set to a sufficient extent. This holds particularly true for the driver's exposure to secondary tasks, the number of distracting events, and the average and total task duration. The largest deviation from the data was found in terms of standard deviation of task duration. Given that the theoretical distributions used for modeling those durations essentially have the same mean and variance as their empirical counterparts, we argue that that these deviations can solely be attributed to the stochastic nature of the model, and the limited number of realizations of the underlying random variables. For the same reason, it is not surprising that no qualitative differences between log-normally and gamma distributed task durations were found – at least with respect to the first two central distribution moments. However, even though both distributions result in plausible values for the duration of secondary tasks at the first sight, things appear in a different light when also taking into account the smallest and largest observed task durations given in Table 3.2. Although both distributions result in the same descriptive statistics (i.e., mean and variance), the gamma distribution has a stronger bias to smaller values, as can be seen in Figure 3.5. Therefore, the samples drawn from gamma distributed random variables have a lower probability to fall within the reasonable range determined by t_d^{min} and t_d^{max}. While for the log-normal distribution more than 97% of values fall within this range, this is the case for only 68% of all samples drawn from the gamma distribution. In other words, almost one third of gamma distributed task durations are of a length far below t_d^{min}. For the remainder of this thesis, we will thus rely on log-normally distributed random variables to model the duration of distracting tasks.

3.5 Conclusions

This chapter has presented a conceptual framework to incorporate different traits and factors in connection with human driving behavior into car-following models. The framework builds upon the ideas and thoughts postulated in the widely recognized Human Driver Model (HDM), and extends this model with two aspects which have hardly been given any attention in the car-following model literature, namely the temporal variance in the driver's reaction time and the impacts of distracted driving on longitudinal driving behavior. The soundness of our modeling approach is justified based on the everyday and scientific understanding of human driving behavior and recent findings in the field of human factors research. Moreover, we presented a novel approach towards modeling the frequency and duration of distractions in the scope of traffic simulations. The proposed model in a sense provides the temporal frame for the driver's behavioral adaptations while being preoccupied by secondary tasks, and has been verified with the aid of a naturalistic driving study from literature. The models presented in this chapter serve as a basis for evaluating the potential safety and efficiency impacts of automated driving, and will be used to describe the behavior of human-driven vehicles in the scope of the simulations discussed in Chapter 6.

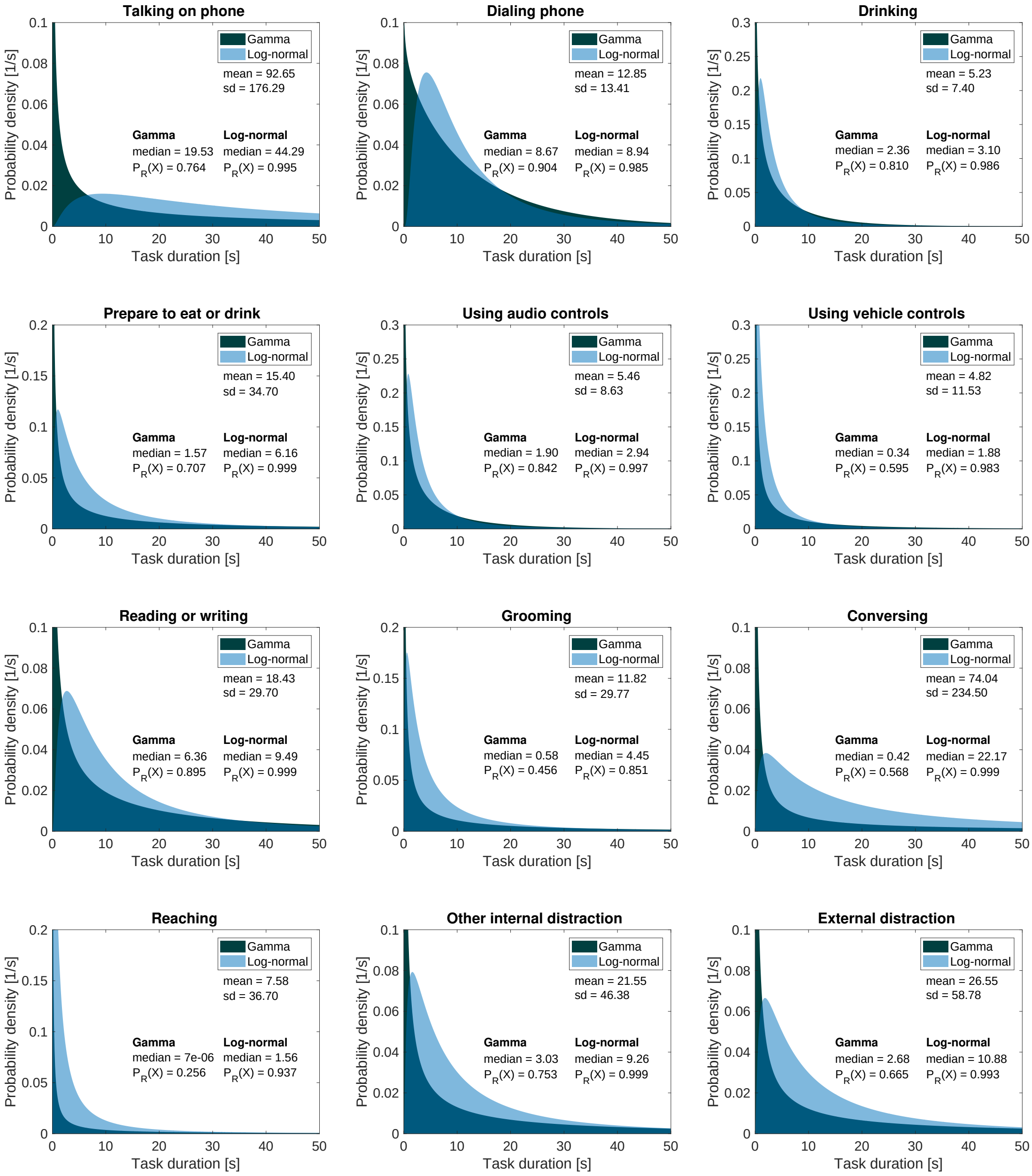


Figure 3.5: Distribution of task duration for the twelve different distracting activities. Each plot is annotated with the mean, the standard deviation and the median of the theoretical distributions, respectively. $P_R(X)$ reflects the probability that samples from the distribution will fall within a reasonable range that is determined by a lower bound t_d^{min} and an upper bound t_d^{max}, i.e. $P_R(X) = P(t_d^{min} < X < t_d^{max})$.

4

Modeling Automated Driving

Parts of this chapter have been published in similar form in:

Ostermayer, G., Lindorfer, M., Mecklenbräuker, C.F. (2019) 'Modeling Human and Automated Driving: Methodological Framework and Simulation-Based Impact Analysis', submitted to the Journal of Intelligent Transportation Systems.

SINCE the deployment of automated vehicle technology will presumably be a long and gradual process [101], considering mixed traffic flows characterized by a varying share of conventional and different levels of automated vehicles is vital when assessing the impact of vehicle automation. To this end, this chapter introduces a modeling framework for mimicking such kind of heterogeneous traffic flows. The proposed framework distinguishes between different degrees of vehicle automation, and integrates various technology-appropriate assumptions related to automated driving with microscopic traffic models. Similar to the models presented in the previous chapter, the framework is formulated in a rather generic way, which makes it applicable a wide range of traffic models. The following sections provide the theoretical foundation and justification for our modeling approach, followed by an in-depth discussion of the models used to mimic different levels of vehicle automation, and the assumptions underlying the proposed framework.

4.1 Introduction

When developing a simulation framework to model automated vehicles or driving assistance systems, it is worthwhile to abide by the internationally recognized taxonomy of vehicle automation as defined by government institutions and the industry [76–78]. The framework developed in the forthcoming sections in particular relates to the definitions of the SAE [77], which distinguishes between six levels of automated driving. For the discussion in this chapter, however, a different categorization scheme is introduced based on how the various levels of vehicle automation are modeled.

No automation. The first level refers to SAE level 0, in which the driver is in full charge of the driving task at all times, and is mentioned here just for the sake of completeness. In the simulations discussed in Chapter 6 the behavior of non-automated vehicles will be modeled using the models presented in the previous chapter.

Partial automation. This level relates to the SAE levels 1 to 4, and thus ranges from driver assistance systems to highly automated vehicles. The common feature of partially automated vehicles as understood in the context of this thesis is that they represent, at least to a certain extent, a combination of human driving behavior and automated driving. More specifically, an automated system might be able to carry out certain aspects of the driving task, or all aspects of the driving tasks within a certain operational domain, such as a specific speed range or traffic situation. On the other hand, this means that the driver has to regain control over the vehicle at some point in time, for example when the system exceeds its boundaries, or in case of an automation failure. A simulation model must take account of such functional limitations, and provide a means to realize transitions from automated to manual driving, and vice versa.

Full automation. The third and last level essentially corresponds to the fully autonomous vehicle, which is capable of handling all driving situations without any human intervention. Contrary to partial automation, the functionality of fully automated vehicles is not restricted to a specific operational domain, i.e. the system is active at all times.

These coarse deliberations form the starting point for the modeling framework which is developed in the forthcoming sections. First, we introduce the ACC model [42], which serves as a baseline model for mimicking the longitudinal dynamics of automated vehicles. Afterwards, we detail how partially and fully automated vehicles are modeled within our framework, followed by a discussion of some technology-related factors that influence the performance of automated driving systems, and how these factors are integrated with the underlying car-following model.

4.2 A Car-Following Model for Automated Driving

Following the discussion in the previous chapter, many of the "traditional" car-following models come into question for modeling the longitudinal dynamics of automated vehicles. This holds particularly true for the IDM, which, though intended to mimic the behavior of human drivers, has frequently been used to model automated driving and even cooperative maneuvering [326–330]. Although this modeling assumption might be profoundly reasonable, not least since a real-world implementation of an ACC system based on the IDM has been presented by Volkswagen [326], the IDM reveals a certain deficiency in situations where the distance to the front vehicle gets considerably smaller than desired, for example as a result of active or passive lane changes [121]. More precisely, the braking strategy of the IDM resolves such situations by exaggerating the braking reaction to regain a desired gap to the preceding vehicle, which in turn results in unnecessarily strong decelerations. While this overreaction might be one possible explanation why smooth lane changes may still result in a traffic breakdown [95], such an over-reactive behavior is certainly not what one would expect from an automated system. In fact, automated vehicles must still react reasonably even if their sensory input, such as distances and relative velocities to preceding vehicles, change discontinuously [121].

4.2.1 Mathematical Description

The ACC model proposed by Kesting et al. [42] addresses this particular issue by introducing a Constant-Acceleration Heuristic (CAH) to determine whether or not the IDM results in plausible braking behavior. Instead of anticipating the worst case at any time, in which the preceding vehicle brakes to a complete standstill, as does the IDM, this heuristic is based on the assumption that the acceleration of the considered vehicle and the vehicle in front will not change significantly within the next few seconds. Under these conditions, the maximum acceleration leading to no collision is given by

$$\dot{v}_{cah} = \begin{cases} \dfrac{v_\alpha^2 \dot{v}_{\alpha-1}}{v_{\alpha-1}^2 - 2 s_\alpha \dot{v}_{\alpha-1}} & \text{if } v_{\alpha-1}\Delta v_\alpha \leq -2 s_\alpha \dot{v}_{\alpha-1} \\ \dot{v}_{\alpha-1} - \dfrac{\Delta v_\alpha^2 \Theta(\Delta v_\alpha)}{2 s_\alpha} & \text{otherwise} \end{cases} \tag{4.1}$$

with

$$\Theta(\Delta v_\alpha) = \begin{cases} 1 & \text{if } \Delta v_\alpha \geq 0 \\ 0 & \text{otherwise.} \end{cases} \quad \text{and } \dot{v}_{\alpha-1} = \min(\dot{v}_{\alpha-1}, a) \tag{4.2}$$

where $v_{\alpha-1}$ and $\dot{v}_{\alpha-1}$ denote the front vehicle's speed and acceleration, respectively, and the condition $\dot{v}_{\alpha-1} = \min(\dot{v}_{\alpha-1}, a)$ is used to avoid artifacts that may be caused by leading vehicles with higher acceleration capabilities [121]. For situations where the IDM leads

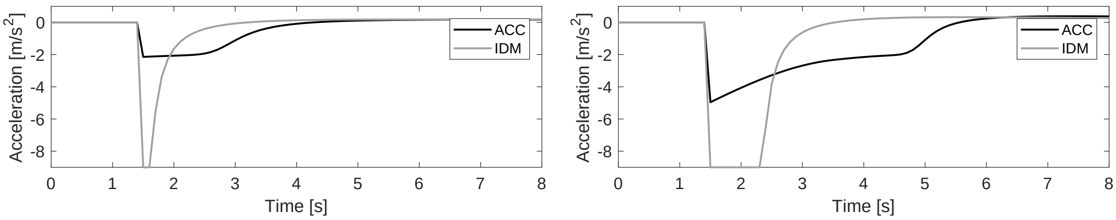


Figure 4.1: Comparison of the braking reaction of the ACC model and the IDM in a cut-in situation where another vehicle merges in front of the considered one (reproduced from [121]). The left situation corresponds to a mildly critical situation where both vehicles drive at the same speed, the right one reflects a critical situation, where the merging vehicle is significantly slower than the considered one. While the IDM applies an emergency brake in both situations, the ACC model only exceeds the comfortable deceleration in the latter case, where an emergency brake is actually mandatory.

to unnecessarily strong braking reactions, e.g. in cut-in situations, the CAH acceleration $\dot{v}_{cah}$ is significantly higher, and thus corresponds to a more relaxed response, as illustrated in Figure 4.1. In order to retain all "desired" properties of the IDM, for example its crash-free dynamics and smooth transitions between acceleration and deceleration regimes [331], the CAH acceleration is however only used as an indicator whether the IDM may result in over-reactive behavior or not [42]. In fact, the acceleration of the ACC model is never lower than that of the IDM, and is even the same if the IDM produces accelerations greater or equal to $\dot{v}_{cah}$. Only in situations where the IDM results in unnecessarily strong decelerations, i.e. $\dot{v_\alpha} < \dot{v}_{cah}$, the ACC acceleration is determined as follows:

$$\dot{v}_{acc} = (1-c)\dot{v}_\alpha + c\left[\dot{v}_{cah} + b\tanh\left(\frac{\dot{v}_\alpha - \dot{v}_{cah}}{b}\right)\right] \tag{4.3}$$

One may notice that the resulting model contains one additional parameter compared to the IDM, which is commonly referred to as "coolness factor" [42]. In the scope of this thesis the coolness factor c will be set to the recommended value 0.99, which was found to give a good compromise between a reckless and an overly timid driving style [121]. Note that the ACC model given by Equations (4.1) to (4.3) is considered as the baseline model for describing the dynamics of any kind of automated driving.

4.2.2 Sensor and Actuator Characteristics

ADAS such as ACC use on-board sensors to acquire information from outside the vehicle and to continuously monitor their ambient environment, including video sensors or ones that are based on cyber-physical sensing technologies such as radar or lidar [127]. These sensors enable the system to "perceive" the world around it by measuring the distance or relative velocity with respect to the preceding vehicle on regular intervals, or by recognizing

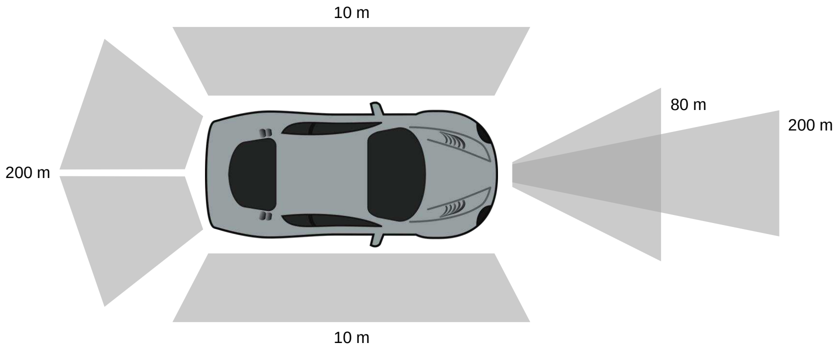


Figure 4.2: Typical sensor arrangement for a conditionally automated vehicle (SAE level 3) [336].

other road users or static obstacles in their environment [332]. Based on this virtual representation of the outside world, ADAS are, compared to human drivers, able to react almost instantaneously to changes in the driving environment. Though the quality of on-board sensors has been improved considerable over the last years, they still exhibit certain limitations with regard to range and accuracy. On the one hand, the sensors' ability to gather information about the vehicle's environment is restricted to a certain coverage area, as illustrated in Figure 4.2. Put differently, these sensors are incapable of recognizing vehicles or other objects that are located beyond their detection range. Moreover, the direct measurements of on-board sensors are usually prone to noise, and therefore appropriate filtering techniques are required to give accurate estimates of the measured quantities [333]. The process of sensing and filtering, in turn, is subject to delay caused by the discrete sampling of the sensors and filtering procedures [334, 335]. This holds also true for the output of the automated driving system, that is, the execution of the desired maneuver (e.g., accelerating, braking). In this regard, the time delay between determining which command to execute and its actual execution is usually due to lags of the powertrain or brake actuators [52]. To account for the mentioned sensor limitations, the following modeling assumptions are made:

- Only vehicles or obstacles within a certain detection range d_s are recognized by the vehicle's sensors. From a modeling perspective, this means that if the distance to the next upstream vehicle is larger than d_s, all relevant input parameters of the underlying car-following model, that are the velocity difference v_α and the net distance s_α with respect to the vehicle in front, are set to zero and a value sufficiently large such that the the interaction term in Equation (3.1) becomes negligible.

- The quantities which are measured by the on-board sensors and forwarded to the automated driving system are subject to delay. Hence, we introduce a sensor delay T_s' which is implemented analogous to the reaction time of human drivers, i.e. by delaying all input parameters of the underlying car-following model.

- Additionally, we consider an actuator delay T_a' representing the time required for the automated system to execute the desired maneuver. This delay is implemented straightforwardly by simply delaying the output of the car-following model, that is, the resulting acceleration. Note that the separation between sensor and actuator delay is motivated by the recent findings in [333], indicating that both types of delay have a different impact on the system state of ACC controllers, and thus different compensation strategies may be applied to mitigate their effects.

4.3 Partial Automation

Partially automated driving as defined in the scope of this thesis refers to a combination of manual and automated driving, i.e. the vehicle might be operated by an automated system under given circumstances, depending on the level of automation or the driver assistance system considered, while the driver has to regain control if the system exceeds its operational limits. The following sections briefly elaborate on such authority transitions, and present three different operational design domains which define the functional limitations of automation. Finally, a simple two-regime model is proposed to differentiate between manual and automated driving, and to model the transitions between both driving modes.

4.3.1 Authority Transitions

Generally defined as "a change from one state or condition to another" [337], transitions in the context of automated driving are most often understood as the activation or deactivation of an automated driving function [338–340]. This transition of control can be initiated either by the driver or by the system, e.g. when its operational limits are exceeded [341, 342], and has a direct influence on the speed and the path of the vehicle, and thus on road safety [337]. It is therefore no surprise that there exists a large body of literature focusing on the implications of such authority transitions on driving behavior and methods to ensure a safe and comfortable take-over process [343]. While transitions from automated to manual driving due to the system's functional limitations can to some extent be expected by the driver as they are part of the intended functionality of automation [344], unexpected transitions initiated by system failures or in safety-critical situations bear the risk that drivers do not always take over when the situation demands [345, 346]. In the scope of this thesis we confine ourselves to the former type of transitions, i.e. those caused by operational constraints of the automated system. More specifically, we distinguish between two types of authority transitions:

- **Driver-initiated transitions.** The driver activates the ADAS and hands over control to the automated system. For driver-initiated transitions of control we assume that the driver turns on the automated driving function as much as possible, that is, as soon as the scenario or the system's operational capabilities permit.

- **System-initiated transitions.** The transition of control is triggered automatically by the system as it leaves its operational design domain, i.e. the scenario or conditions in which it has been defined to operate [347]. As argued above, it is assumed that such system-initiated transitions are expected by the driver, and he or she is therefore able to take over control of the vehicle after a considerable transition time. Transitions from automated to manual driving due to the driver-initiated deactivation of the system are not considered explicitly, since they strongly depend on the driver's subjective perception of whether or not a situation demands for intervention.

4.3.2 Operational Design Domains

As argued in the introductory section, the ability of partially automated vehicles to take over control of the vehicle or to assist the driver is often restricted to a specific operational domain. The SAE [77] defines such an Operational Design Domain (ODD) as the "operating conditions under which a given driving automation system or feature thereof is specifically designed to function, including, but not limited to, environmental, geographical, and time-of-day restrictions, and/or the requisite presence or absence of certain traffic or roadway characteristics". In the scope of this thesis we consider three different ODDs, which will be outlined briefly hereinafter.

- **Speed range.** Contrary to fully automated vehicles, many driver assistance systems enable partially automated driving only within a predefined operating speed range. Traffic jam assistance systems, for example, are capable of taking over longitudinal and lateral vehicle control on highways or in slow-moving traffic and at speeds in the range of 0 to 30 km/h [102], while more advanced systems such as those by Audio [348] or Volkswagen [349] already enable conditionally automated driving at speeds up to 65 km/h. On the other hand, there are also automated driving systems that can operate at the vehicle's full speed range [102], though automation may be restricted to other domains.

- **Driving scenario.** Automation might not only be restricted in terms of a predefined operating speed range, but may also be limited to a particular driving scenario or a specific maneuver. For example, Ebner [350] and Rösener et al. [336] distinguish between more than fifteen different driving scenarios in which assistance may be provided to the driver, including turning, reversing, changing lanes, or free driving. In this thesis we confine ourselves to the two most fundamental scenarios without lateral interactions, that are free driving, i.e. following the lane markings without being influenced by a preceding vehicle, and car-following.

- **Road environment.** Apart from those system inherent limitations, also the road environment may put constraints on the operation of an automated driving system. For example, automation may be limited to a certain type of road (e.g., urban, rural, freeways), specific infrastructure elements such as roundabouts or ramps, traffic volumes, or a predefined geographical area or time-of-day [351].

4.3.3 Modeling Partially Automated Driving

Based on those deliberations, we propose a simple two-regime model to represent the behavior of partially automated vehicles, as shown in Figure 4.3. The model takes into account the vehicle's current operating conditions to determine whether an automated system or the driver is in charge of controlling the vehicle. In other words, whenever a vehicle enters or leaves the ODD specifying the boundaries of the automated driving system, a transition from manual to automated driving is triggered, or vice versa. Naturally, this transition of control will not happen instantaneously. Consequently, whenever such an authority transition is invoked, we consider a transition time reflecting the time required to activate the system or to re-pay attention to the driving task and regain control of the vehicle. Based on our assumption that the driver turns on the automated system as much as possible, it is reasonable to assume a transition time in the order of the driver's reaction time for driver-initiated transitions. For transitions from automated to manual driving, i.e. system-initiated transitions, however, there is ample evidence that the time taken by the driver to take back control of the vehicle is significantly longer. Even though transition times of more than 8s have been reported in the literature for less attentive or distracted drivers [352], recent studies showed that most control transitions lie in the order of 2 and 3.5s [347, 353], or even slightly below [354]. We therefore consider a moderate transition time of 2.5s for all transitions from automated to manual driving. From a modeling perspective, the car-following model of the simulated vehicle is substituted with the IDM including its human factors extensions – in case of a transition from automated to manual driving – or the ACC model after this time has elapsed, respectively.

Determining ODD Boundaries

To determine whether or not a transition from manual to automated driving, or vice versa, needs to be invoked, the ODD of the automated driving system is reevaluated continuously. The ODD may thereby be constrained by (i) an operating speed range, (ii) a particular driving scenario, (iii) the road environment, or combinations thereof. More precisely, for a vehicle to be operated by an automated driving system, all of the following conditions have to be satisfied:

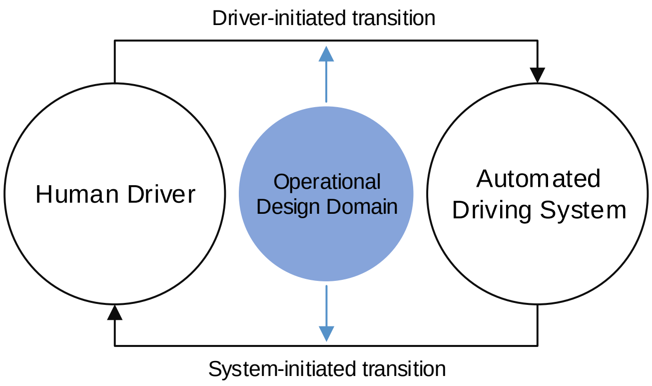


Figure 4.3: Illustration of the two-regime model for modeling partially automated driving. Transitions between both driving modes are triggered as soon as the vehicle enters or leaves its ODD. The car-following dynamics for manual and automated driving are modeled by the IDM and its human factor extensions and the ACC model, respectively.

1. The vehicle's current velocity v_α must fall within a given speed range $[v_{min}, v_{max}]$. Similar to the determination of the driving regime discussed in Section 3.3.1, short-term fluctuations in the vehicle's velocity may, if left unsmoothed, result in alternating and consecutive transitions between manual and automated driving, especially when driving at speeds close to the boundaries of the operating speed range. To avoid such unintentional authority transitions between both driving modes, an EMA filter with relaxation time $\tau = 3s$ is used to reduce the level of speed variation:

$$v_\alpha(t) = \int_0^t v_\alpha(t')e^{-(t-t')/\tau}dt' \tag{4.4}$$

2. The system under consideration supports a certain driving scenario. As mentioned earlier, we consider only two fundamental scenarios without lateral interactions, that are, free driving and car-following. The distinction between both scenarios is made by adopting the same methodology as in the previous chapter, i.e. by comparing the vehicle's time and space headway with the corresponding threshold values.

3. The road environment permits the activation of the automated driving system. In the scope of this thesis we consider the type of road a vehicle is currently driving on as the only environmental constraint for automation, since this kind of information is usually available in most microscopic simulations models.

Finally, if any of the above conditions is not met at any point in time, the system initiates a transition back to manual driving, i.e. the driver has to regain control of the vehicle.

4.4 Full Automation

Unlike partially automated driving, where both the driver and the automated driving system may be in charge of controlling the vehicle at some point in time, fully automated vehicles are capable of handling all traffic situations without any intervention on the part of the driver. In the scope of this thesis we distinguish between two types of full automation depending on whether the system makes use of vehicular communication technologies or not, hereinafter referred to as autonomous and connected vehicles, respectively.

4.4.1 Autonomous Vehicles

Similar to many ADAS such as ACC, autonomous vehicles constantly monitor their environment using a variety of on-board sensors to determine distances or relative velocities to other vehicles, or to detect potentially hazardous traffic situations. Being limited to the information obtained from these sensors, autonomous vehicles are only able to recognize objects within their sensors' detection range, i.e. they are incapable of detecting vehicles or obstacles that are located outside a prescribed range. Unlike human drivers, autonomous vehicles are thus not able to "anticipate" a traffic situation further downstream. Hence, it is reasonable to presume that the velocity of autonomous vehicles should be bounded to values that allow the vehicle to stop safely, even in the worst case, i.e. assuming a standing vehicle right beyond the sensors' reach, or when the preceding vehicle brakes unexpectedly, for example in case of an emergency stop. Based upon the previous works by Reece and Shafer [355] and Talebpour and Mahmassani [48], this safe speed assumption can be expressed as follows:

$$v_{\alpha,max} = \sqrt{2b\,\min(d_s, s_\alpha^{eff})} \tag{4.5}$$

with

$$s_\alpha^{eff} = s_\alpha - s_0 - v_\alpha T_s' + \frac{v_{\alpha-1}^2}{2b} \tag{4.6}$$

where d_s denotes the sensors' detection range. The effective distance s_α^{eff} consists of the actual gap s_α between the subject vehicle and the vehicle in front, the stopping distance s_0, and two terms representing the perception distance of the following vehicle and the braking distance of the leader, respectively. By minimizing over s_α^{eff} and d_s it is ensured that vehicles further downstream affect the subject vehicle only if they are spotted within the sensors' range. For matters of illustration, Figure 4.4 outlines the concept of this safe speed assumption for different deceleration rates b. Finally, it is worth noting that the car-following dynamics of autonomous vehicles are governed entirely by the ACC model, since the system does not require any kind of intervention on the part of the driver.

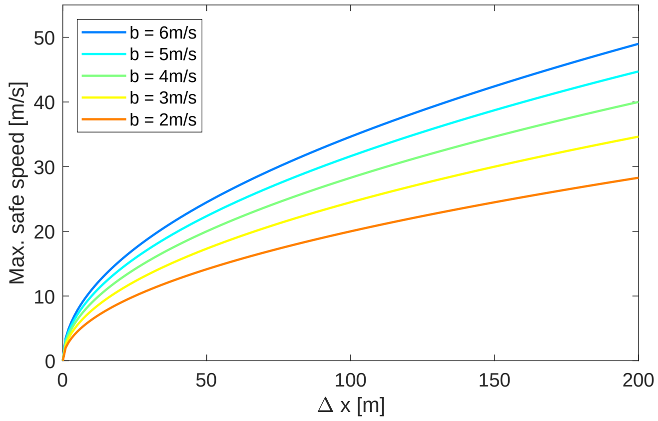


Figure 4.4: Illustration of the safe speed assumption for autonomous vehicles as a function of the relative distance $\Delta x = \min(d_s, s_\alpha^{eff})$. The differently colored lines represent the maximum speed considered to be safe for different deceleration rates b.

4.4.2 Connected Vehicles

Compared to autonomous vehicles, connected vehicles are expected to have the capability to send and receive information to and from other vehicles, or to exchange data with road-side infrastructure using wireless communication links. By utilizing data from other vehicles in their surrounding, connected vehicles are able to obtain more and even better information about their environment, which in turn can be used to optimize vehicle movements, and to enable a safer and smoother control of the vehicle [101]. In this manner, connected vehicles are in a sense able to extend the range of their on-board sensors, and to detect vehicles further downstream even if those are located beyond their sensors' reach.

Abstract Modeling of Vehicular Communication

Wireless communication technologies have received considerable attention within the automotive domain over the last decades, and are expected as one of the main drivers to exploit the full potential of automated vehicles [90, 91]. The range of applications for communication technologies in the context of automated driving is wide, and includes systems to improve the safety and efficiency of traffic operations as well as infotainment and comfort applications [356, 357]. Generally, one can distinguish between two types of communication in a vehicular environment, designated as Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) communication. The former enables vehicles to share information regarding their current state and the drivers' operational decisions, including for example their actual speed, acceleration, or location, with other traffic participants by forming so-called Vehicular Ad-hoc Networks (VANETs) [358], while the latter can be used to gather local or global information about current road or traffic conditions from road-side stations [48]. To facilitate such kind of communications in a highly mobile environment by at the same time meeting the strict requirements with regard to communication reliability, latency, and security [359–361], different communication standards and technologies have been developed or adopted over the years, such as the WLAN-based IEEE 802.11p standard [362], visible light communications [363], or cellular network technologies like Long Term Evolution (LTE) [364, 365]. Compared to the communication in cellular networks, however, wireless communication in a vehicular environment poses a number of unique challenges. This holds particularly true for V2V communication channels, which usually exhibit a rapid temporal variability and non-stationarity due to their unique physical environment, the high mobility of one or both communicating nodes, and the large number of objects that can possibly impair the propagation of radio waves [366, 367]. In the literature, a multiplicity of models has been proposed to simulate vehicular communication channels and their distinctive radio propagation characteristics [368–371]. In the scope of this thesis, however, these characteristics are only considered at a very abstracted level. Rather than making strong assumptions on the underlying communication standard or the properties of the radio propagation channel, we take only the time delay in message transmission due to "non-ideal" communication conditions into consideration. This abstraction harmonizes all properties of the communication channel to a single variable, and thus reduces the number of additional parameters required for simulations to a minimum. Moreover, it is important to note that, in the context of car-following models, the properties of the radio propagation channel are essentially irrelevant, as long as they fulfill the constraints presupposed by those models.

Modeling Connected Driving

As mentioned in the introductory section, connected vehicles are able to send and receive information to and from other vehicles in their vicinity. The European Telecommunications Standards Institute (ETSI) thereby distinguishes between two types of messages being exchanged between road users. Common Awareness Messages (CAM) are generated periodically, usually with a frequency up to 10 Hz, and comprise status information including the vehicle's current position or motion state as well as attribute information such as data about the vehicle's dimensions or type [372]. Contrary, so-called Decentralized Environmental Notification Messages (DENM) are exchanged on demand, and are intended to alert drivers of detected events or hazards on the road, including road-work or signal violation warnings, for example. Hereinafter, only the former type of status messages will be considered. More specifically, connected vehicles repeatedly report their current status to road users in their vicinity, and at the same time receive such kind of information from other vehicles further up- or downstream, provided that those lie within a finite communication range d_c. However, this information might not be available at all times and locations, and may beyond that not be up to date. We therefore consider a transmission delay T_c' for all status messages, which may be used to describe non-ideal communication conditions, as argued before. Consequently, all vehicle-related parameters including position, speed, and acceleration are delayed by T_c' before actually reporting them to neighboring vehicles. To incorporate this information into the underlying car-following model, we use a similar approach as adopted for the spatial anticipation mechanism of human drivers. More precisely, we sum up the respective interaction terms between the subject vehicle and all other connected vehicles further downstream, as outlined by Equations (3.12) to (3.14). Finally, it is worth noting that if no other vehicles with communication capabilities lie within the vehicle's communication range d_c, the car-following dynamics of a connected vehicle essentially correspond to those of an autonomous one.

Delay Compensation

Since the status messages received from other vehicles contain, among others, a time stamp information [372], it is reasonable to assume that connected vehicles are able to compensate for eventual message delays to a certain extent. To be more precise, this time stamp information together with information regarding the (previous) state of other vehicles can be utilized to draw inferences on the current state of neighboring vehicles. Based on the fundamental equations of motion and by assuming a constant acceleration of all vehicles for the duration of the delay, connected vehicles estimate the speeds and positions of other vehicles in their vicinity accordingly:

$$\begin{aligned} v_\beta^{est} &= \left[v_\beta + \dot{v}_\beta T_c'\right]_{t-T_c'} \\ x_\beta^{est} &= \left[x_\beta + \frac{\dot{v}_\beta T_c'^2}{2} + v_\beta T_c'\right]_{t-T_c'} \end{aligned} \tag{4.7}$$

where v_β, x_β and $\dot{v}_\beta$ denote the speed, position and acceleration of a preceding vehicle delayed by T_c', respectively. Finally, the actual parameters considered by the underlying car-following model can be derived straightforwardly taking into account the subject vehicle's current speed and position and the estimated speeds and positions of all other connected vehicles in its vicinity.

4.5 Conclusions

This chapter presented a conceptual framework to model different levels of vehicle automation, ranging from partially automated to fully automated vehicles, i.e. autonomous and connected vehicles. The framework builds upon a widely accepted car-following model for simulating the dynamics of automated vehicles, and incorporates a variety of technology-appropriate assumptions with regard to the vehicles' sensing and communication capabilities into the underlying traffic model. Moreover, we presented an intuitive approach to distinguish between different degrees of automation (or different ADAS) by solely specifying an operational design domains representing the functional limits of automation. In the remainder of this thesis the developed framework will be put to use in order to investigate the potential impacts of automated driving on traffic safety and efficiency by means of microscopic simulations.

5

TraffSim – A Microscopic Traffic Simulator

Parts of this chapter have been published in similar form in:

Lindorfer, M., Backfrieder, C., Mecklenbräuker, C.F., Ostermayer. G. (2017) 'Modeling Isolated Traffic Control Strategies in TraffSim', Proceedings of the 19th International Conference on Computer Modeling and Simulation, Cambridge, United Kingdom, pp. 252-257.

UP to this point, we have proposed a conceptual framework to augment car-following models with a variety of behavioral traits and technology-appropriate assumptions in order to describe the longitudinal dynamics of automated vehicles and the behavior of human drivers. Let us now describe the software that combines all these components into a common simulation model. In this chapter, we present the microscopic traffic simulator TraffSim, a proprietary development within the Research Group Networks and Mobility at the University of Applied Sciences Upper Austria, which was initiated in 2012, and which is still developed further. TraffSim is implemented in the Java programming language, which reveals a number of benefits, including but not limited to platform independence, automated update mechanisms and a commonly known user interface, and provides high modularity achieved by an object-oriented programming paradigm [261]. The framework is the result of several years of teamwork and has been developed in tight collaboration with Christian Backfrieder. In the following, we discuss the requirements and motivation for developing such a framework "from scratch" rather than using existing simulation software, followed by a description of the framework itself and the functionality we consider to be relevant for the present thesis.

5.1 Requirements for a Simulation Framework

In recent years, simulations have frequently been used to study the impacts of ITS or vehicle automation on both traffic safety and efficiency. This holds particularly true for microscopic simulations, where the dynamics and properties of every single vehicle are modeled individually. Over the last decades, numerous simulation tools have been developed and distributed for this purpose, both commercially and as open source. However, rather than using or adopting existing simulation tools, a new simulation framework has been developed at the basis of the research conducted in the scope of this thesis. The reasons therefore are manifold, and are to a large extent motivated by the fact that existing simulation tools cannot always be tailored towards the requirements associated with the scenario or application under investigation, as well as the reduced influence and insights into the underlying simulation environment. Commercial tools such as VISSIM [181] or Paramics [373], for example, only partially allow for the adjustment of driver behavior or vehicle performance, which, however, is often desired. Moreover, when using such tools, one is often confronted with the fact that parts of the simulation framework are undisclosed, i.e. they are a black box to the researcher. Open-source software such as SUMO [374] or the OTS framework [244] overcomes the issue of limited transparency, and is therefore much more suitable for research purposes. However, extending such frameworks is still associated with considerable (development) efforts, as many aspects of the framework might have to be adapted, and integrating new features or models is often not possible in a straightforward manner. Finally, choices in regard of the structure and relations between the individual framework components as well as implementation-specific aspects (e.g., programming language) may hinder the usage of existing simulation tools.

In order to overcome the above mentioned limitations by at the same time having a tool over which one has full control, the simulation framework TraffSim has been developed and extended as part of this thesis. Fundamentally, the development of TraffSim was driven by a number of requirements for which existing simulation tools only partially (or insufficiently) account for:

1. **Modularity.** All functionality within the framework should be separated into independent, interchangeable modules or components which encapsulate different tasks carried out within the simulation environment (e.g., crash detection, vehicle generation). Such a modular design is not only an important prerequisite for requirements 2 and 3, but ultimately results in code which is easier to test and maintain.

2. **Concurrency.** Rather than performing one simulation at a time, it should be possible to run multiple simulations in parallel, with different parameters, or for different scenarios.

3. **Adaptability.** This requirement concerns the ability to change the way objects in the simulation behave, e.g. by exchanging the models governing the longitudinal or lateral dynamics of vehicles, but also more fundamental aspects. For example, it should be possible to change the way lane changes are modeled (e.g., instantaneous or as continuous process), or how vehicles are generated in the simulation.

4. **Extendability.** It should be possible to extend the framework with new features, models, or entities in an easy and comprehensible manner.

5. **Feature richness.** The framework should provide the following functionality:

   (a) Representation of road network (e.g. road segments, lanes, junctions) including facilities for controllers an road-side units (e.g., loop detectors, traffic lights).

   (b) Generation of vehicles.

   (c) Different driver models governing both the longitudinal (i.e., car-following) and lateral (i.e., lane changing) dynamics of vehicles in the simulation.

   (d) Measurement of traffic-related quantities.

In the remainder of this chapter we will elaborate on the simulation framework and how it has been designed to meet the requirements listed above. At this point it is worth noting that TraffSim has not been developed specifically to address the research questions this thesis deals with, but is rather intended to be a general tool for *any* kind of microscopic simulation. However, in the forthcoming sections only those aspects of the framework will be elucidated in greater detail which are of particular importance for the simulations conducted in the scope of the present thesis.

5.2 Overview of the Simulation Framework

This section aims for giving a coarse overview of the developed simulation framework, its core components and the dependencies between them. First, the programming language selected to meet some of the requirements discussed in the previous section is outlined, followed by a brief description of the core simulator components. In the subsequent sections, several important aspects related to the functional requirements of the simulation framework are elaborated, including the road network model, the vehicle generation process, and the measurement of traffic-related quantities.

5.2.1 Programming Language

With the requirements presented in the previous section at hand, one may argue that essentially any programming language which is based on the paradigm of Object Oriented

Programming (OOP) is a reasonable choice for developing a simulation framework. Such OOP languages are based on the concept of objects (e.g., vehicles, traffic lights) which interact with each other through so-called methods or procedures. Each object is thereby a "realization" of a class, which defines the attributes (e.g., vehicle type) and behaviors an object has. In recent years, OOP languages have become increasingly popular as they provide a highly versatile means for the development of large-scale and complex software systems [375], while at the same time offering several benefits such as easy maintenance, modularity, or code re-usability [376]. While there is a significant diversity of such languages, they are by no means similar in terms of complexity and efficiency. Among the most popular and efficient OOP languages are for example C++, C# or Java. For several reasons, Java was selected as the language of choice for the development of the TraffSim framework:

- Long-lasting experience in Java development.
- Computational efficiency and automated memory management.
- Java is a platform-independent language, i.e. programs written in Java can be deployed to a variety of operating systems such as Windows, Linux, or Mac OS X.
- High availability of third-party libraries and easy integration with other development environments (e.g., Matlab).

Rather than being implemented as a plain Java application, the framework is embedded in the Eclipse Rich Client Platform (RCP) environment, which reveals a number of additional benefits:

- Through a plugin-based development paradigm individual software components can easily be added or exchanged as required.
- The application appears in the well-recognized Eclipse user interface, and offers various design concepts such as detachable views, application preferences, or toolbars out-of-the-box.
- Easy deployment and maintenance of software packages through remote update sites.

While the decision to use Java for developing the simulation framework partially comes down to a matter of preferences, the decision for an OOP language does certainly not. In fact, especially in view of the requirements of modularity, adaptability, and extendability, the OOP paradigm with its fundamental concepts such as inheritance, i.e. objects can be based upon other objects and acquire all properties and behaviors of their "parent", and polymorphism, i.e. the provision of a single interface to objects of different types, can be considered particularly suited for building such a framework [375].

5.2.2 TraffSim at a Glance

The conceptual structure of the simulation framework and its higher level components is shown in Figure 5.1. In the following, only the most important parts of the framework are discussed. For further information on technical implementation aspects and a more in-depth coverage of the individual simulator components we refer to [261, 377–379].

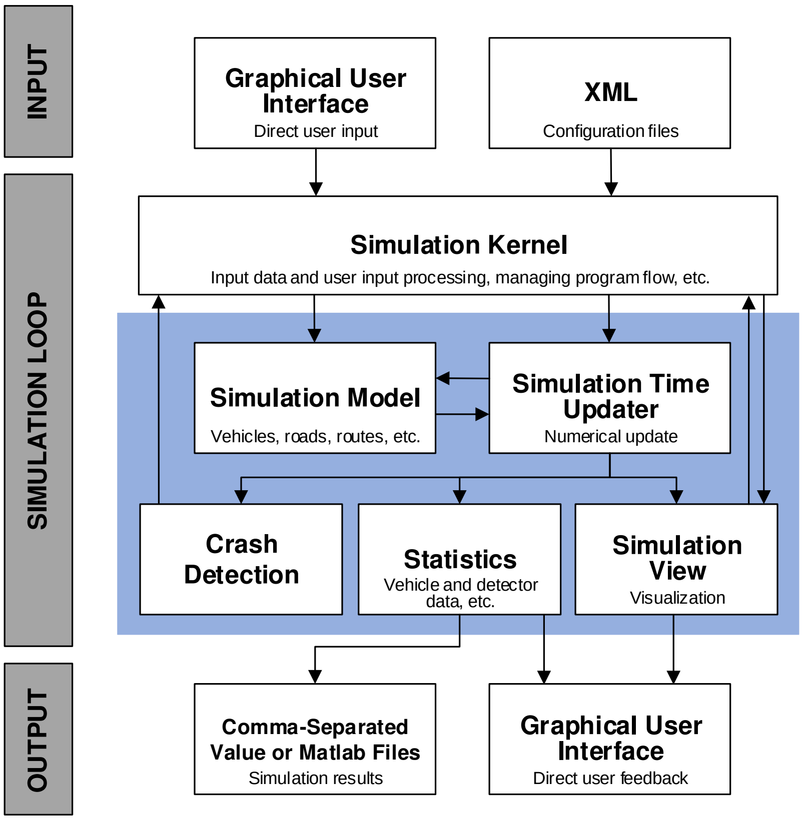


Figure 5.1: General structure of the simulation framework. The blue background highlights those components belonging to a single simulation. Depending on the number of simulations run in parallel, multiple instances of those components may exist within the framework at the same time.

Input Data for a Simulation

In order to set up a simulation project, a number of input data are required which define the basic simulation settings, and which can be provided in form of input files encoded in Extensible Markup Language (XML). At the start of each simulation, a XML parser reads and assembles these files to a virtual simulation model, which contains all data required to run the simulation, such as

- Properties of the considered road network, including the geometry of road segments and meta-data in terms of speed or turn restrictions or the number of lanes.

- Characteristics of all vehicles considered in a simulation run, including vehicle-related properties (e.g. type, length) and routing information. Vehicles can be generated either at predefined points in time or in accordance to a given demand level, as discussed in Section 5.4.

- Parameters for controllers and road-side units (e.g., traffic lights, detectors) such as phase lengths or aggregation intervals.

- Configuration parameters for all models used in the simulation. These models comprise, among others, different car-following models, a lane change model [135], and a physics-based fuel consumption model [380].

Note that the input data provided in these configuration files only specify the initial conditions of a simulation. Additionally, the graphical user interface allows for an interactive control of a simulation, which can be directly influenced at run time by changes in the parameter settings.

The Simulation Loop

The main simulation loop involves all components which are responsible for executing different functionality directly related to the simulation or the overall program flow. The most important components are briefly elaborated below.

- **Simulation Kernel.** The simulation kernel is the core component of the simulation framework, handling all user input provided through the graphical user interface and keeping track of program operations. Moreover, the kernel is responsible for assembling and scheduling new simulations using the provided input data, and for handling the entire simulation life-cycle. In that regard, the simulation kernel is able to manage multiple simulations at the same time, whereby each simulation is run in a separate program thread. This kind of parallelization is particularly useful for batch simulations, e.g. when running the same simulation multiple times, but with different input parameters.

- **Simulation Model.** The simulation model is essentially a data container comprising all information required for a simulation, such as road geometries, vehicle characteristics, driver models, or specifications for controllers and road-side units. The model is constructed once by the simulation kernel prior to the start of the simulation, and maintains all objects during the entire simulation run time.

- **Simulation Time Updater.** Another important component within the simulation framework is the simulation time updater, which is mainly responsible for driving on the simulation progress. As will be shown in the ensuing of this section, the states of all entities (e.g., vehicles, road-side units, etc.) and components involved in the simulation (e.g., crash detection, vehicle generation) are updated at discrete instants in time considering a fixed simulation update interval. For updating the speeds and positions of vehicles, in particular, the framework employs a simple yet effective numerical integration scheme, as discussed in Section 5.2.4.

- **Crash Detection.** This component is responsible for detecting crashes between two or multiple vehicles during a simulation, i.e. to determine whether the trajectories of two or multiple vehicles overlap at a certain point in time. The collision detection mechanism considers both the longitudinal as well as the lateral position of vehicles and is thus able to determine both rear-end collisions as well as crashes resulting from lane changes. Once a collision has been detected, it is up to the simulation kernel to decide how to proceed, e.g. whether involved vehicles should be removed from the simulation, or the simulation should be stopped.

- **Statistics.** During a simulation a wide range of traffic-related quantities can be collected for post-processing purposes and later use. The statistics module is responsible for handling the entire data acquisition process, and does so by making use of so-called statistics collectors, which facilitate different aspects of data acquisition. For example, one collector may record comprehensive trajectory data from all vehicles in the simulation, while a different one gathers cross-sectional data from road-side units. Note that the statistics module is designed in such a way that new collectors can be added straightforwardly on demand to obtain additional quantities from a simulation, if this is required.

- **Simulation View.** The simulation view contains the entire graphical visualization of the simulation, and may be composed of multiple windows representing different aspects of the simulation (e.g., statistics, event log, etc.). Apart from the main view where the road network and all vehicles are visualized, these windows are hidden by default, but can be attached easily at run time through the framework's graphical user interface. Note that the graphical visualization is particularly useful to provide a fast and intuitive understanding of the (complex) dynamics within a simulation, but may also be disabled to improve the computational performance of the framework.

Simulation Output

Data gathered during a simulation can either be displayed in the simulator's graphical user interface to provide direct user feedback at run time, or be written to output files for further post-processing. Further details on data preparation and an overview of the different types of quantities that may be collected during a simulation are given in 5.5.

5.2.3 Simulation Mode

A commonly used classification scheme for traffic simulation models is to divide them according to their level of abstraction, e.g. into microscopic, mesoscopic, or macroscopic models. An alternative approach is a distinction based on how entities within the simulation (e.g., vehicles) change their states (e.g., positions). In our framework, these state changes are modeled in a time-discrete manner, i.e. they occur at explicit instants in time predetermined by the simulation update interval Δt. Put differently, the accelerations, velocities and positions of all vehicles as well as the states of all other entities in the simulation are updated in regular intervals. At the same time, simulations in TraffSim are continuous in space, i.e. all vehicles can be located at any position on the road. This distinguishes our framework from models that are based on cellular automata, which describe traffic systems as a lattice of equally sized cells and vehicles moving from one cell to another [381, 382]. Their discrete nature, however, makes such cellular automata unsuitable for modeling the movement of individual vehicles or for assessing the effectiveness of different driving styles and driver assistance systems, for which continuity in space is an important criterion [121].

5.2.4 Numerical Implementation

As mentioned in the previous section, TraffSim belongs to the class of time-discrete simulation frameworks, i.e. all state changes in the system occur at explicit points in time. The car-following models considered in the scope of this thesis, however, belong to the class of time-continuous models exhibiting the general form

$$\frac{dv_\alpha}{dt} = \dot{v}_\alpha = f(s_\alpha, v_\alpha, \Delta v_\alpha) \tag{5.1}$$

Thus, the acceleration of vehicle α depends on the vehicle's own velocity $v_\alpha(t)$, the net distance $s_\alpha(t)$ and the velocity difference $\Delta v_\alpha(t)$ to the preceding vehicle. From a mathematical perspective, such time-continuous models without an explicit reaction time delay represent a system of coupled Ordinary Differential Equations (ODEs) [383]. In contrast to time-discrete models or cellular automata, these models usually must be solved by means of numerical integration, except for the most trivial cases which are solvable analytically [121]. While in the general literature on numerical mathematics the fourth-order Runge-Kutta (RK4) method is the standard scheme for solving ODEs [384], the use of this method has hardly entrenched in the domain of microscopic traffic simulation (exceptions include [385, 386]). Because of the high complexity and event-oriented nature of traffic simulations, but also for reasons of practicability, many simulation frameworks use a fixed update time step and apply simpler integration schemes such as the Euler method [387], which is used by the open-source simulators SUMO [388] and AIMSUN [163], or the ballistic update mechanism, which assumes a constant acceleration during one time step [121]. The latter approach leads to the following numerical update rules for the velocities and positions of all vehicles during a simulation time step Δt:

$$\begin{aligned} v_\alpha(t+\Delta t) &= v_\alpha(t) + \dot{v}_\alpha(t)\Delta t \\ x_\alpha(t+\Delta t) &= x_\alpha(t) + v_\alpha(t)\Delta t + \frac{1}{2}\dot{v}_\alpha(t)(\Delta t)^2 \end{aligned} \tag{5.2}$$

Remarkably, and although being of the same theoretical consistency order $p = 1$, this scheme was found to be consistently better than Euler's method, requiring up to 70% less computation time for the same accuracy, and even outperforms higher-order integration methods such as RK4 when considering lane change scenarios [383]. For those reasons, the ballistic update mechanism is also implemented in TraffSim, as it is recommended as efficient and robust scheme for integrating time-continuous car-following models.

When an explicit reaction time comes into play, the coupled set of ODEs is translated into a set of DDEs. Hence, the numerical update scheme now depends not only on the update time interval Δt, but also on the reaction time T'. Given that the reaction time is an integer multiple of the simulation update interval, i.e. $T' = n\Delta t$, Equation (5.2) can be generalized straightforwardly by considering the values of all quantities on the right-hand side n time steps in the past[1]. If this is not the case, a linear interpolation is performed, following the suggestions in [127]:

$$x(t - T') = \beta x_{t-n-1} + (1-\beta)x_{t-n} \tag{5.3}$$

where x denotes any quantity on the right-hand side of Equation (5.2), n constitutes the integer part of $T'/\Delta t$, and $\beta = T'/\Delta t - n$ is the weight factor of the linear interpolation. It is worth noting that the length of the simulation update interval also has a significant influence on both car-following and lane change behavior. However, if Δt is sufficiently small, the overall properties of the underlying models are retained. On the other hand, the numerical update scheme given by Equation (5.2) even converges to the exact solution of Equation (5.1) in the limit $\Delta t \to 0$, provided that the applied integration method is consistent [121]. For the simulations conducted in the forthcoming chapter an update interval of 0.1s is considered, which provides a good balance between modeling precision and computational performance.

[1] Note that for the implementation of a reaction time delay some kind of bookkeeping is required, as certain simulation variables might be accessed at a later point in time. To this end, the state of all variables of up to n simulation time steps are maintained in the form of a simple queue, whose size depends on both the actual reaction time and the simulation update interval.

5.3 Road Network

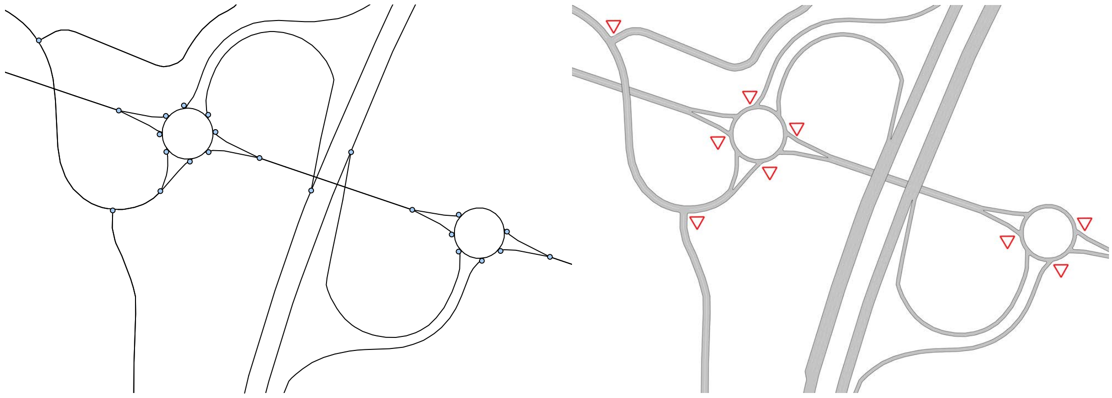
A highly detailed representation of the road network is an important aspect of traffic simulations. The developed simulation framework is capable of providing such a high level of detail by utilizing map data from the OpenStreetMap (OSM) project to generate the road network. These data are not only available for most regions all over the world, but also facilitate the usage of existing editing tools (e.g., JOSM [389]), thus allowing for a fast and efficient pre-processing by at the same time keeping configuration effort minimal. This section elaborates on how these OSM data are used to generate a network representation that is suitable for microscopic simulations, followed by a description of the components which create the network in its entirety.

5.3.1 Network Representation

Generally, a road network in OSM consists of two core elements: nodes representing a single point in space defined by its latitude and longitude, and ways connecting two or multiple nodes to a common path. Nodes can be shared by multiple ways, e.g. in case of an intersection, and essentially define the shape or geometry of a way. Each way, in turn, represents a single road in both driving directions, and may be augmented with additional meta-data such as the number of lanes in each direction, lane restrictions, speed limits, or a road type [390]. The developed framework is capable of extracting these data from the OSM data model, and automatically generates a virtual representation of the road network from it, as illustrated in Figure 5.2. As will be shown in the ensuing, each network consists of a connected grid of lanes along which vehicles can move, and road segments and intersections encapsulating certain higher-level functionality. In principle, such a lane-based approach can be regarded as a trade-off between a continuous and a discrete network representation, where space is usually divided into equally sized cells. While the former generally requires the use of expensive spatial calculations (e.g., road curvature, lateral collisions) and complex models, the drawback of a cellular representation is apparently a loss of precision due to spatial discretization and the simplifications with regard to the vehicles' movements resulting thereof. A lane-based representation, in turn, simplifies the lateral dimension, and thus reduces the required computational effort, while at the same time maintaining a high level of detail in the longitudinal dimension.

Lanes

Lane objects are the basic elements in the road network, and define the possible paths a vehicle can take through the network. Vehicles move along those paths, and are automatically transferred to the downstream or an adjacent lane when reaching the end of the current lane or after performing a lane change, respectively. Put differently, each lane is



a) b)

Figure 5.2: Road network representation in OSM (a) and TraffSim (b).

connected with adjacent lanes both in the longitudinal and in the lateral sense. Apart from the path defining its basic geometry, a lane has various properties such as a length and a width, a speed limit, or potential turn and lane change restrictions, which are inferred from the meta-information provided in the OSM data, and which may influence the road network generation process. Vehicles on a particular lane may request these properties at any point in time, and are offered a number of utility functions such as searching for neighboring vehicles on the own as well as both adjacent lanes, for example. In that manner, both longitudinal and lateral vehicle interactions can be determined efficiently, and provided to the models governing the vehicles' movements, i.e. the car-following and lane change model. For instance, information regarding lane changes that are infrastructure-based (e.g., lane drops or entry lanes) can simply be inferred from the "type" property of a particular lane, indicating whether a lane change is mandatory or not.

Road Segments

Generally, road segments combine one or multiple lanes in both driving directions into logical units – as depicted in Figure 5.3 –, and aim for providing several higher-level functionality for which single lane objects can not sufficiently account for. Most importantly, road segments are used for routing purposes, i.e. to guide vehicles through the network to their desired destination. All vehicles in the simulation follow their very own (but predetermined) route, which is nothing else but a list of road segments in the order they should be passed. Each road segment in turn is capable of providing all the information to the driver models to follow this route. This includes, for example, the number of lane changes required to reach an off-ramp on a highway or to get into the right lane at an intersection under consideration of potential turn restrictions, and the distance within which these have to performed.

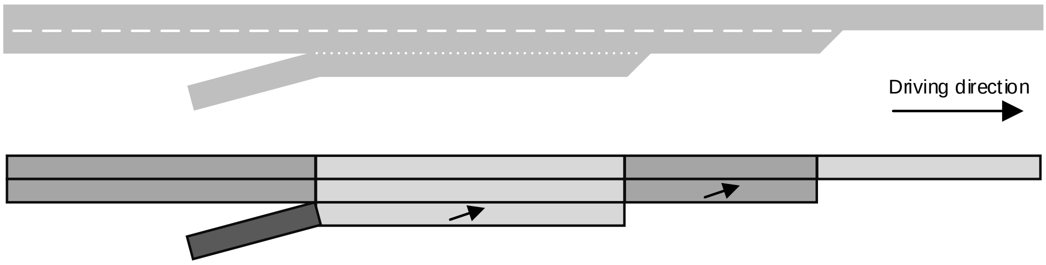


Figure 5.3: Schematic illustration of a lane-based network representation for a simple freeway scenario with an entry lane and a lane drop. Adjacent lanes of the same color belong to the same road segment. Arrows indicate infrastructure-based (mandatory) lane change directions.

Intersections

Apart from lane objects and the higher-level road segments, intersections constitute the third important and probably most complex components in the road network. Basically, an intersection connects at least three adjacent road segments, and consists of several lane-to-lane connections which define all possible paths a vehicle can take through the junction, as illustrated in Figure 5.4. These connections are generated automatically based on the number of adjacent lanes and potential turn restrictions. The framework by default supports different types of intersections, including roundabouts, unregulated intersections, ones regulated with road signs or traffic lights, and combinations thereof. Each intersection is modeled as a separate entity, and is responsible for handling all vehicle approaching and traversing through the intersection, and for determining whether a vehicle is allowed to enter or not. Generally, this decision is based on the evaluation of different priority levels. The highest level of priority is thereby given to traffic lights, which may apply different control logics to provide the right of way for particular approaches to the intersection, followed by road signs (e.g., give way). For unregulated intersections by default a right-before-left-rule as used in most European countries is applied, always giving priority to the vehicle approaching from the right. In situations where multiple vehicles are approaching the intersection from different directions, this may however result in more than one vehicle given equal priority. Under certain circumstances, e.g. when the lane-to-lane connections used by the potentially conflicting vehicles are not overlapping, access may be granted to more than one vehicle at the same time. Otherwise, only the vehicle which is closest to the intersection, i.e. the one with the minimal temporal distance, is granted access.

This priority-based evaluation is performed in every simulation time step, which means that also the priorities assigned to vehicles approaching an intersection might change over time. In fact, there are several situations where an entry grant for a vehicle might be revoked at a later point in time, for example when priorities change due to exit lanes

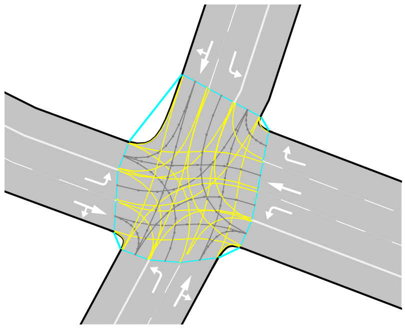


Figure 5.4: A four-way intersection with turn restrictions and all possible lane-to-lane connections.

being blocked, phase changes of traffic lights, or other vehicles arriving earlier at the intersection. For further insights on how such situations are resolved by the framework and other aspects of intersection modeling, the interested reader is referred to [377].

5.3.2 Controllers and Road-Side Units

An important part of a transportation system are components that are able to control and monitor traffic, for example at intersections or at a particular cross-section along the road. Fundamentally, the framework distinguishes between two types of such system components: road-side units and controllers. Similar to other entities in the simulation, these components are updated in regular intervals to execute their desired functionality.

Road-Side Units

In our framework, the term Road-Side Unit (RSU) refers to all infrastructure components located somewhere along the road network, such as loop detectors, road signs, or traffic lights. What all RSUs have in common is that they are stationary in the sense that they are located at a specific location on the road. Moreover, all RSUs in the framework are lane-based, i.e. they are connected to a single lane. Generally, one can distinguish between two types of RSUs depending on how they interact with vehicles in their vicinity. Passive RSUs are able to register vehicles at their location, and are therefore particularly suited for data acquisition at a specific cross-section. Active RSUs, on the other hand, allow for the interaction with bypassing traffic, i.e. they are noticed by vehicles in their vicinity. For example, a vehicle may slow down due to a road sign indicating a lower speed limit, or a red traffic light in front of an intersection. The framework by default supports a number of different RSUs including loop detectors for measuring and aggregating vehicle counts and speeds, road signs (e.g., give way, speed limit, stop), and traffic lights.

Controllers

While several RSUs are able to execute their desired functionality autonomously, others may require a more sophisticated kind of control logic, e.g. to change a traffic light. To this end, the framework makes use of so-called controllers, which may be anything from a simple traffic light controller to a centralized traffic management system. Each controller is connected to one or multiple RSUs (or vehicles), which allows for essentially any form traffic control or optimization. By default, the framework provides a number of different controllers for traffic lights (e.g., fixed-time, self-organizing) as well as a centralized controller allowing for the implementation of a network-wide traffic management system.

5.4 Vehicle Generation

An important aspect of a traffic simulation framework is the process of vehicle generation, which defines the way vehicles enter a road network. In the literature, headway distributions are often used to cope with the stochastic nature of such vehicle arrivals, including the exponential distribution [391,392], the log-normal distribution [393], or more complex ones such as the Erlang, log-logistic, or inverse Weibull distribution [394]. While some of these distributions generate unrealistically small headways, the more complex ones are often parametrized, and therefore require calibration or the introduction of additional parameters [95]. Moreover, none of these distributions considers potential interactions with previously generated vehicles that may influence a vehicle's headway and thus the exact time of arrival. To overcome these limitations, the vehicle generation process in TraffSim is split up into two separate parts, which handle both the arrival of vehicles in the simulation as well as the actual positioning of vehicles on the road network taking into account interactions with preceding vehicles.

5.4.1 Vehicle Arrivals

The first part of the generation process is responsible for describing vehicle arrivals, that is, for determining when new vehicles have to be added to the simulation. In that regard, the framework distinguishes between two types of vehicle arrival, as outlined below.

Predefined Vehicle Arrivals

The first and supposedly most simple type of vehicle generation is that according to a predefined time schedule, where a fixed arrival time is associated with every vehicle in the simulation. Based on this schedule, a decision is made in every simulation time step whether or not a particular vehicle has to be generated. The properties of all vehicles (e.g., type, route, initial speed) as well as their time of arrival are thereby specified prior to the simulation. Although this type of vehicle generation requires considerable configuration effort, it allows for a very precise reconstruction of a particular traffic situation.

Continuous Vehicle Arrivals

When using empirical data (e.g., aggregated detector measurements) to define the traffic demand for a simulation, it is crucial that the traffic entering the network actually matches the observed demand pattern. In other words, this implies that the mean time τ^* between two successive vehicles arriving in the simulation (i.e., the mean gross headway) must be the reciprocal of the current demand $q(t)$, as given by Equation (5.4).

$$\tau^* = \frac{1}{q(t)} \tag{5.4}$$

The current demand may be varied over time by providing different demand levels Q for specific times T. The demand $q(t)$ is then equal to the last value of Q satisfying the condition $T \leq t$. Moreover, the time between any two vehicles arriving in the simulation is equal to τ^*, i.e. vehicles arrive uniformly. In that manner, it is ensured that the number of vehicles generated matches exactly the observed demand. On the other hand, this method may result in a rather flattened demand and thus omit peaks in the demand which may cause a traffic breakdown. Therefore, it is important to note that assuming uniformly distributed vehicle arrivals is only reasonable if the demand levels can be provided in sufficient detail, e.g. in form of detector data aggregated over short periods of time.

Vehicle Type and Parameter Distributions. In contrast to predefined vehicle generators, where the properties of all vehicles have to be specified prior to the simulation, continuous vehicle generators allow to systematically vary these properties for all traffic being generated using random processes. In fact, one is able to provide different probabilities for different vehicle classes (e.g., cars, trucks) to specify for instance the number of trucks as a fraction of the total demand. Whenever a vehicle is being generated, these probabilities are used to determine to which class the new vehicle belongs. Similarly, the entire car-following or lane change logic or the routes vehicles follow during a simulation may be assigned in a random fashion. Moreover, individual vehicle properties (e.g., desired speed or headway) may be drawn from random distributions to incorporate heterogeneity among different drivers.

5.4.2 Vehicle Interactions

One of the main difficulties of vehicle generation is that it has to take into consideration both the demand governing the number of vehicles entering the road network as well as potential interactions between generated vehicles, which are generally subordinate to the models describing the vehicles' movement. Up to this point, we have ignored these interactions. Hence, the arrival time of a vehicle depends solely on the headway prescribed by the current demand $q(t)$. However, there might be situations where this headway is actually too short, for example when the speed of the generated vehicle is considerably higher than that of the previous vehicle, or when the demand is simply too high. In fact, this headway depends to a large extent on the model describing the vehicle's longitudinal movement, i.e. the car-following model. To guarantee that vehicles are generated in consistency with the underlying car-following logic, the generation process is implemented as follows:

- Vehicles are generated at the moment in time determined by the arrival process and at the location of the vehicle generator, which may be at any position of a road segment. The vehicle's initial speed is set either to its desired speed or, if specified, to any other speed value.
- The underlying car-following model is invoked to consider interactions with the previously generated vehicle, i.e. the first downstream vehicle. The vehicle generation is successful if (i) the resulting acceleration is greater or equal to zero, and (ii) there is sufficient space available for the vehicle's desired headway (which is provided by the car-following model) to be generated. If any of these two conditions is not satisfied, the generation process has failed, and the vehicle is scheduled for generation at a later point in time, i.e. in a later time step.

The basic work flow of the vehicle generation algorithm is depicted in Figure 5.5. In every simulation time step all vehicles whose arrival is determined to be in the previous time step (i.e., all vehicles in the arrival queue Q_A) are scheduled for generation, i.e. added to the waiting queue Q_W. Subsequently, for all vehicles in Q_W it is verified whether the vehicle can be generated or not. If the generation of a vehicle is successful, it is placed on the road network and removed from the waiting queue. On the other hand, all vehicles whose generation fails remain in the queue and are generated in a later time step as soon as this is possible. In that manner, headways that are too short for a new vehicle ultimately result in the generation of that vehicle being slightly delayed, by at the same time ensuring that the generation process is consistent with the underlying car-following model.

5.5 Measurement of Traffic-Related Quantities

Measuring and collecting traffic-related quantities is another fundamental aspect of microscopic simulations, and an important prerequisite for the profound assessment of simulation results. Unlike in most real-word scenarios, the velocities and positions of all simulated

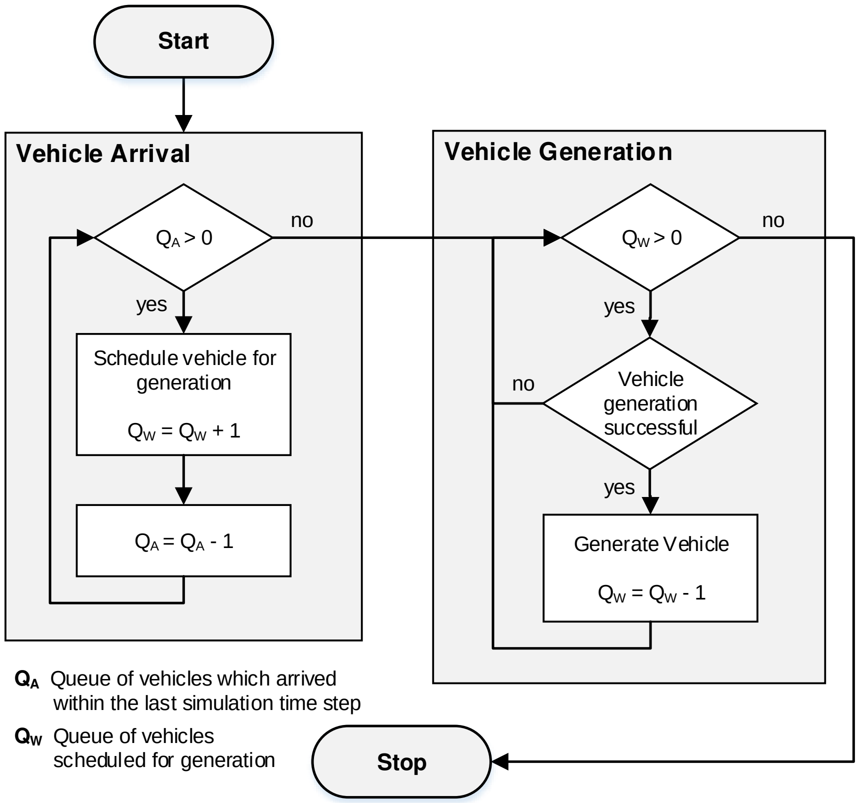


Figure 5.5: Basic flow of operations for the vehicle generation process in a single simulation time step.

vehicles are known at essentially any point in time. It is thus possible to gather a variety of both microscopic and aggregated (macroscopic) quantities during a simulation, and either display them in the simulation user interface for direct user feedback, or write them to output files for later use. In case of the latter, all data gathered throughout the simulation is written to comma-separated value files or to the open MAT-format [395], allowing for a fast and efficient post-processing within the Mathworks Matlab environment [396]. Generally, these data can be classified into three different categories:

- **Vehicle data.** The first category comprises all quantities which can be obtained from a single vehicle's trajectory such as its current position, velocity, or fuel consumption, and, additionally, its ambient environment (e.g., headway, gap to leader, etc.). These quantities can either be recorded in every simulation time step, which apparently results in a large amount of data, depending on the simulation length and the number of vehicles in a simulation, or in an aggregated manner (e.g., total time spent in the simulation, total distance traveled) at the cost of level of detail.

- **Detector data.** In order to measure cross-sectional quantities such as traffic flow or average velocities at a certain position along the road, virtual loop detectors are used serving as the counterpart to real-world sensor systems such as inductive loop or video detection facilities. These detectors register vehicles passing a given cross-section, and are capable of aggregating vehicle counts and speeds over a predetermined period of time.

- **Simulation events.** The third category comprises auxiliary events which occur at explicit time instants and at irregular intervals during a simulation. For example, such events are triggered when a vehicle enters or leaves the simulation, when a collision between two and more vehicles has been detected, or when a lane change is performed.

5.6 Conclusions

Simulations are probably the most widely adopted method to study the impacts of vehicle automation and ITS in general, since empirical investigations and field experiments are most often neither safe nor practical. In this chapter, the microscopic traffic simulator TraffSim, which has substantially been developed further as part of this research, has been presented in minute detail. The simulator combines all the models presented to this point into a single tool, and aims for meeting a number of requirements such as a modular design, support for parallelization, adaptability, and extendability. Since the initial work on TraffSim has started already back in 2012, it has constantly been extended and redeveloped, and has in the meanwhile evolved into a powerful tool whose functionality goes far beyond what is required for the simulations conducted in the scope of this thesis. We have presented the overall structure of the simulation framework and how it is implemented, and detailed some of the fundamental modeling aspects. In the forthcoming chapter the simulator will be put to use in order to investigate the impact of automated driving on the stability of traffic flow, traffic safety, and efficiency using the models presented in the previous chapters.

6 Simulation-Based Impact Analysis

Parts of this chapter have been published in similar form in:

Lindorfer, M., Mecklenbräuker, C.F., Ostermayer. G. (2017) 'Modeling the Imperfect Driver: Incorporating Human Factors in a Microscopic Traffic Model', IEEE Transactions on Intelligent Transportation Systems, vol. 19, no. 9, pp. 2856-2870.

Lindorfer, M., Backfrieder, C., Mecklenbräuker, C.F., Ostermayer. G. (2018) 'Investigating the Large-Scale Effects of Human Driving Behavior on Vehicular Traffic Flow', Proceedings of the International Conference on Applied Human Factors and Ergonomics, Orlando, Florida, USA, 2018, pp. 204-215.

Ostermayer, G., Lindorfer, M., Mecklenbräuker, C.F. (2019) 'Modeling Human and Automated Driving: Methodological Framework and Simulation-Based Impact Analysis', submitted to the Journal of Intelligent Transportation Systems.

THE objective of this chapter is to provide quantitative and qualitative insights on the potential changes automated vehicles could bring to our transportation systems. To this end, it operationalizes the conceptual framework developed in the preceding chapters, and investigates, by means of simulation, the impacts of automated driving on the safety and efficiency of traffic operations, especially under consideration of mixed traffic flows, that is, taking into account different degrees of vehicle automation and several penetration scenarios. First, the string stability of a platoon of vehicles following an exogenous leader is investigated, followed by an evaluation of the potential safety and efficiency effects of vehicle automation using a large-scale road network.

6.1 Stability Analysis

Instabilities in traffic are a prime contributing factor to the emergence of stop-and-go-waves, and are usually caused by drivers failing to adapt their speed to the prevalent traffic conditions, their delayed reaction, or by vehicles changing lanes or braking unexpectedly [121, 397]. Whether such instabilities will ultimately result in a breakdown of traffic flow or not, however, depends on whether these disturbances will grow, or fade away [177]. Studying the stability of traffic flows has first gained attention in the fields of mathematics and theoretical physics in the 1990s [174], and the literature generally distinguishes between two types of stability: local and string stability [213]. The former relates to the dynamics of a single vehicle in response to a fluctuation in the speed of the vehicle in front. More precisely, the vehicle's behavior is said to be locally stable if this disturbance decays with time. If the opposite is the case, i.e. the disturbance increases with time, or at least does not decay, this ultimately results in a collision. It is important to note that local stability is an essential requirement for car-following models, since collisions are usually caused either by mechanical failure or human error rather than being intrinsic in car-following [95]. String stability, on the other hand, is not always observed in empirical data, and refers to the propagation of a disturbance in a platoon of vehicles [48]. More specific, a platoon is called string stable (or asymptotically stable) if the perturbation caused by the first vehicle in the platoon decays as it propagates upstream from one vehicle to the other [398]. String instability, in turn, refers to situations where disturbances, such as errors in spacing or speed, amplify while propagating through the platoon, and eventually results in a breakdown of traffic flow and safety [127]. String stability is generally a more restrictive criterion compared to local stability, since even if all vehicles in a platoon exhibit a locally stable behavior, the entire platoon may still show string instability [333]. In this section, we study the string stability of a platoon as a function of different human factors and under consideration of varying penetration rates of automated vehicles by means of simulations. We start with a description of the simulation setup and the stability conditions considered for our investigations, followed by an in-depth discussion of the simulation results.

6.1.1 Simulation Setup and Initial Disturbance

For our investigations we have simulated a platoon of 100 vehicles following an exogenous leader with a prescribed velocity $v_l = 25m/s$. For the first 500s of simulation time the leading vehicle drives at its initial speed, and all following vehicles are in equilibrium, that is, their velocities and gaps to the vehicle in front are the same, and their accelerations are zero. During the interval $500s \leq t \leq 503s$ a disturbance is introduced into the platoon by the leading vehicle which decelerates with $-2m/s^2$ to $v_l = 19m/s$, which is maintained

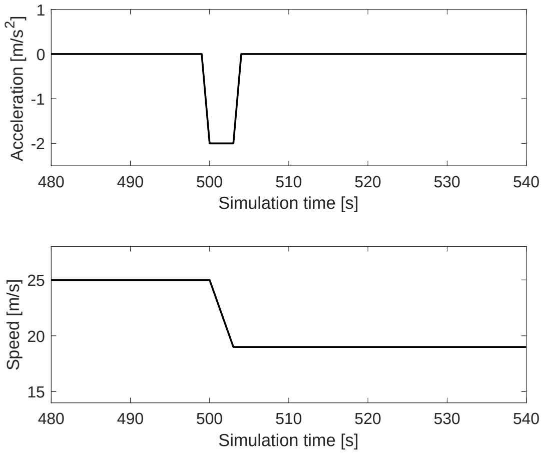


Figure 6.1: Time series of the acceleration and the velocity of the exogenous platoon leader. The braking maneuver at $t = 500$ induces the initial disturbance to the platoon of following vehicles.

until the end of the simulation at $t = 2000s$, as illustrated in Figure 6.1. This braking maneuver serves as a trigger for possible instabilities in the platoon and is considered in all simulations discussed hereinafter. Moreover, for all simulations the basic parameter values given in Table 3.1 are used, which allows for a direct comparison of the simulation results with those from previous studies [127,215]. Additionally, we take into account the physical limits for braking decelerations and consider a maximum deceleration $b_{max} = 9m/s^2$ which corresponds to blocking wheels on dry roads [127], i.e. we restrict the decelerations of all vehicles to values less or equal to b_{max}. Finally, it is important to note that, unless stated otherwise, the platoon is assumed to be a homogenous ensemble of identical driver-vehicle units, which in essence corresponds to identical parameter settings for all vehicles.

6.1.2 Stability Regimes

For the simulation-based stability analysis we adapt a similar methodology as proposed by Treiber et al. [399]. Following this methodology, we distinguish between three different regimes of string stability:

- *Stability regime*: The perturbation introduced into the platoon decays while propagating upstream. In particular, a platoon is considered to be string stable if the condition $|\dot{v}_\alpha(t)| \leq 3m/s^2$ is satisfied for all vehicles at all times and if their accelerations converge to zero at some point after the initial perturbation, i.e. if equilibrium conditions are reached until the end of the simulation.

- *Oscillatory regime*: This regime is characterized by string instability, where perturbations amplify while propagating through the platoon but do not lead to collisions between vehicles. A platoon is said to belong to the oscillatory regime if neither the condition for the stability regime nor the condition for the crash regime is fulfilled.

- *Crash regime*: The crash regime refers to situations where string instability finally results in a collision of two or more vehicles. Essentially, this is the case when the condition $s_\alpha(t) < 0$ is fulfilled for any vehicle in the platoon at some point in time.

6.1.3 Human Factors and their Impact on String Stability

The string stability of the IDM and the HDM under consideration of a finite reaction time, temporal and spatial anticipation have already been studied in numerous researches recently [127, 215, 399]. These studies underpinned the expected detrimental effect of human reaction time on traffic flow stability, and revealed that the anticipative capabilities of human drivers can compensate for these effects to a significant extent. The following investigation thus aims for evaluating the impacts of two aspects which have been disregarded in previous studies, i.e. driver distractions and varying reaction times.

Impact of Driver Distractions

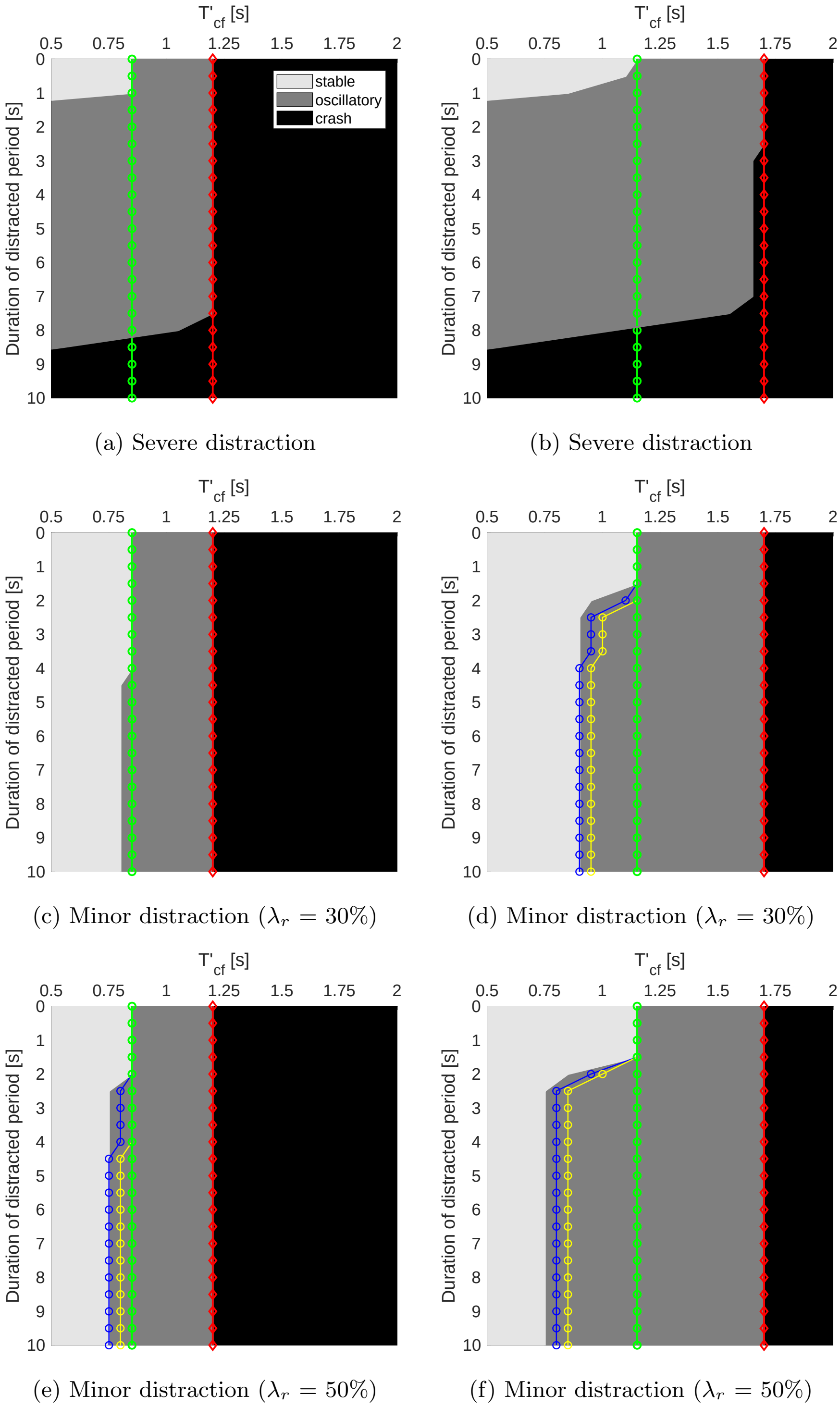
To study the impact of both minor and severe distractions on string stability, let us assume that the driver of second vehicle in the platoon, i.e. the first follower, starts to engage in a secondary task at $t = 500s$, that is, right at the time the platoon leader starts to decelerate. Obviously, this is the most critical in the considered scenario, since the response of the first vehicle to this initial disturbance clearly affects the further propagation of the perturbation through the platoon. Based on those deliberations, we determined the string stability boundaries for the platoon as a function of reaction time T'_{cf} and the duration of the distracted period. Note that for this investigation a constant reaction time is considered, and thus both T'_{fd} and T'_{st} are set equal to T'_{cf}. Figure 6.2 shows the three stability regimes for different simulation setups where the anticipative capabilities of human drivers have been turned on or off, and for both types of distraction, respectively. Moreover, it highlights the respective stability boundaries for the HDM, which results in stable and crash-free dynamics for reaction times of up to 0.85s and 1.2s, respectively. Taking into account the anticipative capabilities of human drivers, both boundaries are shifted to significantly higher values, namely to 1.15s and 1.7s.

Severe distraction. As one might expect, the driver's inability to perceive changes in the driving environment while being severely distracted naturally has the most detrimental impact on both stability boundaries. More precisely, our simulations show that the platoon is only string stable for setups where the distraction lasts no longer than 1.5s. For longer durations of the distracted period, the delayed but significantly harder braking response required on the part of the driver to compensate for the missed stimuli serves as a kind of amplifier for the initial perturbation, and ultimately results in string instability. A similar behavior can be observed for the stability boundary separating the oscillatory and the crash regime, and the explanation therefore is self-evident. In fact, as soon as the duration of the distracted period exceeds a certain duration, the driver of the following vehicle is basically no longer able to react appropriately, or at all, in order to avoid a rear-end collision. In our case this critical threshold lies in the order of 7s, we emphasize however that this threshold has only an illustrative meaning, and obviously depends on a number of different factors, such as the equilibrium speed of the platoon, or the magnitude of the initial perturbation. When taking into account the anticipative capabilities of human drivers, both stability boundaries are shifted to significantly higher reaction times, as outlined in Figure 6.2b. However, and although spatial and temporal anticipation substantially improve string stability in the general case, they do not improve the situation in the two borderline cases, since both are a direct result of the distracted driver's delayed (or missing) response.

Minor distraction. Compared to severe distractions, the impact of minor distractions on string stability was generally found to be less pronounced. As illustrated in Figures 6.2c to 6.2f, the temporary increase in the driver's reaction time affects only the stability limit noticeably, provided that the driver is distracted for a sufficiently long period of time. This is due to the fact that collisions are now not triggered directly by the late or missing reaction of the first follower, but indirectly as a consequence of string instability and the disturbance which propagates upstream through the platoon. Though a general decrease in stability can be observed when prolonging the distracted period, one should note that the platoon remains stable for reaction times in the order of 0.8s even for distractions lasting more than 10s, since drivers in the following vehicles are still able to successfully compensate for the delayed reaction of the distracted driver. Another important observation is that the expected compensatory effect of speed reduction for the duration of the distracted period becomes clearly visible in our simulations. Remarkably, already a slight reduction in the desired speed in the range of 4% to 8% improves the stability boundary markedly, even though this stabilizing effect becomes more pronounced for larger reaction times and higher values of λ_r.

Impact of Varying Reaction Times

The impact of varying reaction times on string stability is analyzed by systematically varying the reaction times T'_{cf}, T'_{fd}, and T'_{st} within reasonable ranges, while all other parameters and the initial conditions discussed in Section 6.1.1 remain as they are. Similar to the previous investigation, we simulated scenarios where the anticipative capabilities of human drivers have been taken into consideration, and ones where not. To put it briefly, our simulations revealed two important findings. First, they indicate that string stability depends primarily on the reaction time T'_{cf}, while varying T'_{fd} and T'_{st} within a reasonable range does not affect both stability boundaries quantitatively. The explanation therefore



(a) Severe distraction

(b) Severe distraction

(c) Minor distraction ($\lambda_r = 30\%$)

(d) Minor distraction ($\lambda_r = 30\%$)

(e) Minor distraction ($\lambda_r = 50\%$)

(f) Minor distraction ($\lambda_r = 50\%$)

Figure 6.2: String stability as a function of reaction time T'_{cf} and duration of the distracted period. The setups in the right column correspond to scenarios where the anticipative capabilities of human drivers have been turned on, i.e. $n_a = 4$. The red lines with diamond markers denote the crash limits for the HDM, the lines with circle markers represent the stability limit for the HDM (green) and the HDM* assuming different speed reduction factors λ_v=4% (blue) and λ_v=8% (yellow), respectively.

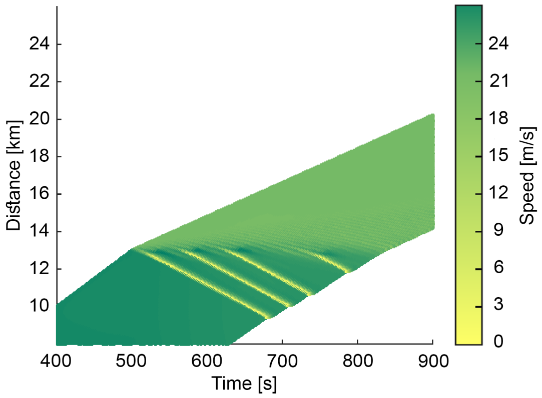
might be as simple as self-evident. On the one hand, all vehicles in the platoon are in the car-following regime most of the time, which explains the insensitivity to T'_{fd}. On the other hand, the impact of T'_{st} becomes noticeable only in standing traffic, that is, presumably after string instability has finally lead to a breakdown of traffic flow.

While no quantitative differences were found with respect to the stability boundaries for a wide range of reaction times, our simulations showed that a variation in T'_{st} noticeably affects the platoon dynamics in the oscillatory regime, and in particular the formation and propagation of stop-and-go resulting from string instability. In fact, we found that T'_{st} has not only a direct impact on the wavelength of the emerging stop-and-go waves, but also on their propagation characteristics. Figure 6.3 exemplifies this relation, and illustrates the spatiotemporal dynamics of the platoon in response to the braking maneuver of its leader for different settings of T'_{st} and a fixed reaction time $T'_{cf} = 1s$. As a general observation, it can be noted that the wavelength of stop-and-go waves basically increases with larger values of T'_{st}. Considering a reaction time of 0.9s, for example, the initial stop-and-go wave is followed by three instabilities of shorter wavelength, while the period of the subsequent stop-and-go waves is significantly higher when increasing the reaction time, as can be seen from Figure 6.3b. For even larger values of T'_{st} (see Figure 6.3c), the emergence of the third and fourth instability are finally mitigated at all, primarily as a result of the slower deformation of the first two stop-and-go waves. Remarkably, a similar stability mechanism has previously been revealed in connection with the car-following model's acceleration parameter [127]. Here, lower acceleration values were found to result in long-wavelength string instability, while higher accelerations lead to short-wavelength traffic breakdowns. The conclusion could be that both mechanisms, though having a very different qualitative meaning, provide a means to describe different patterns of emerging stop-and-go waves, and may thus be particularly useful when calibrating the underlying car-following model to empirical data.

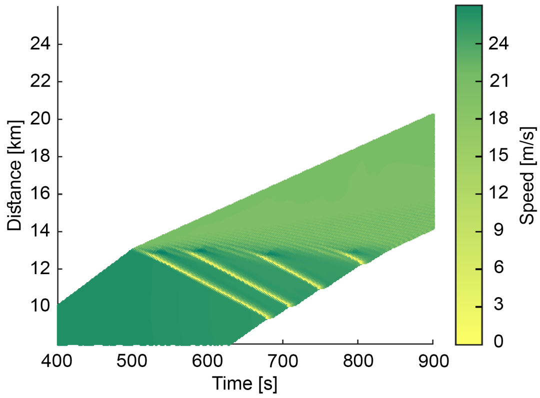
6.1.4 Stability as a Function of Penetration Rate of Automated Vehicles

After providing insights on the impact of distractions and varying reaction times on traffic flow stability and the spatiotemporal dynamics of stop-and-go waves, let us now investigate the string stability of a platoon under consideration of varying penetration rates of automated vehicles. Consequently, and contrary to the previous scenario, the platoon is now not a homogenous ensemble of identical driver-vehicle units, but consists of both conventional and automated vehicles in various proportions[1]. In particular, we determined the stability boundaries for the considered platoon by systematically increasing the share of autonomous and connected vehicles within the vehicle fleet from 0% to 100%. Partially

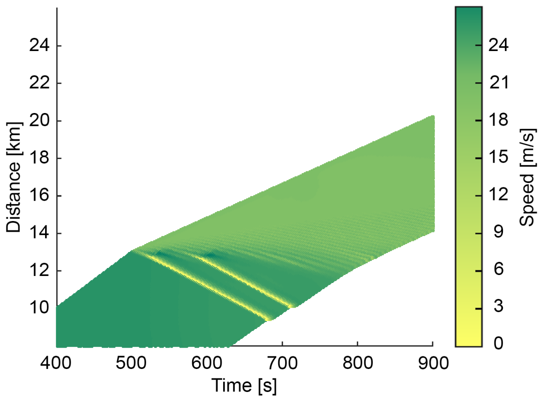
[1]Note that apart from the distinction between conventional and automated vehicles no further inter-driver heterogeneity is considered.



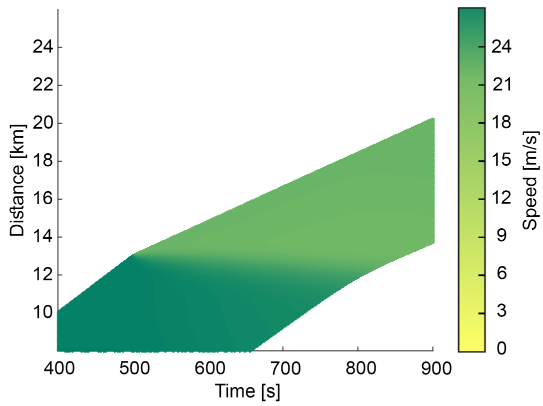
(a) T'_{st}=0.9s



(b) T'_{st}=1.5s



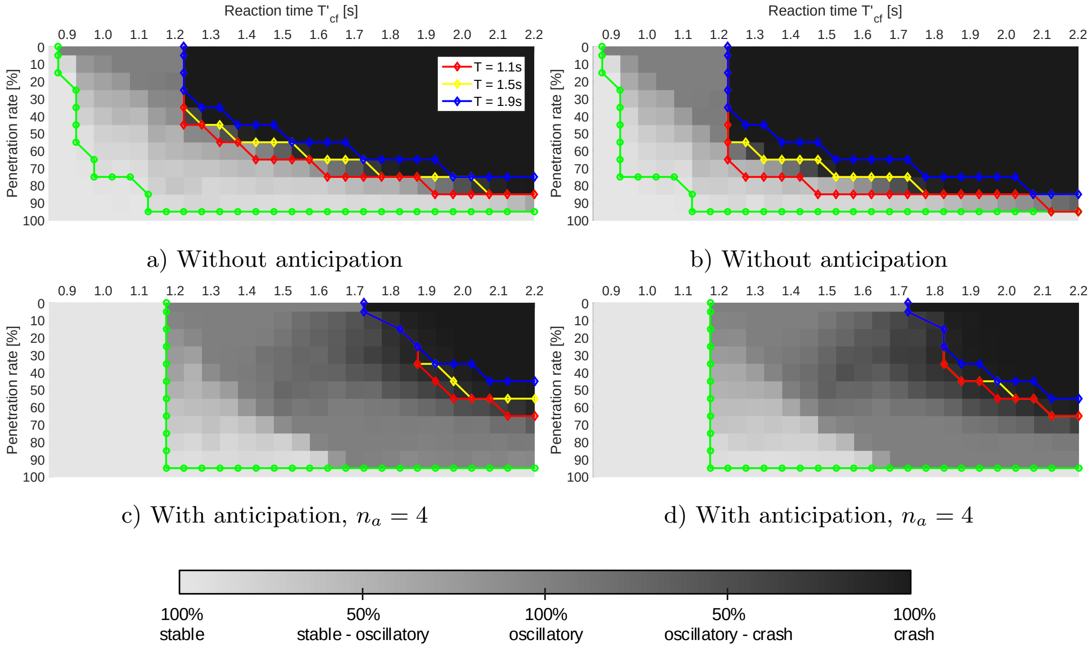
(c) T'_{st}=2.1s



(d) T'_{st}=0.9s, n_a=4

Figure 6.3: Time-space diagram of the platoon in response to the disturbance induced by the exogenous leader. In (a)-(c) the impact of different settings of T'_{st} on the emergence of stop-and-go waves is illustrated assuming a reaction time T'_{cf} of one second and no anticipation. In (d) an identical situation is shown where the anticipation mechanism of human drivers is switched on, i.e. $n_a = 4$.

automated vehicles are explicitly not taken into consideration, since the scenario under investigation essentially comprises only a single driving scenario (car-following), and one may thus assume that, depending on the modeled driving function, automation may either be activated or deactivated at all times, respectively. Since the actual position and order of automated vehicles within the platoon obviously has an effect on the resulting platoon dynamics, as it influences not only whether or not the initial perturbation can be damped right at the onset of braking, but also whether or not connected vehicles may be able to utilize information from vehicles further downstream, the ordering of vehicles is changed in a random fashion prior to every simulation run. The findings presented hereinafter are a result of at least 1000 simulation runs for every distinctive set of parameters.



a) Without anticipation

b) Without anticipation

c) With anticipation, $n_a = 4$

d) With anticipation, $n_a = 4$

Figure 6.4: String stability for different penetration rates of autonomous vehicles as a function of reaction time T'_{cf}. The setups in (a) and (c) assume an idealized and faultless operation of autonomous vehicles, while (b) and (d) represent setups where sensor and actuator delays are switched on.

Impact of Autonomous Vehicles

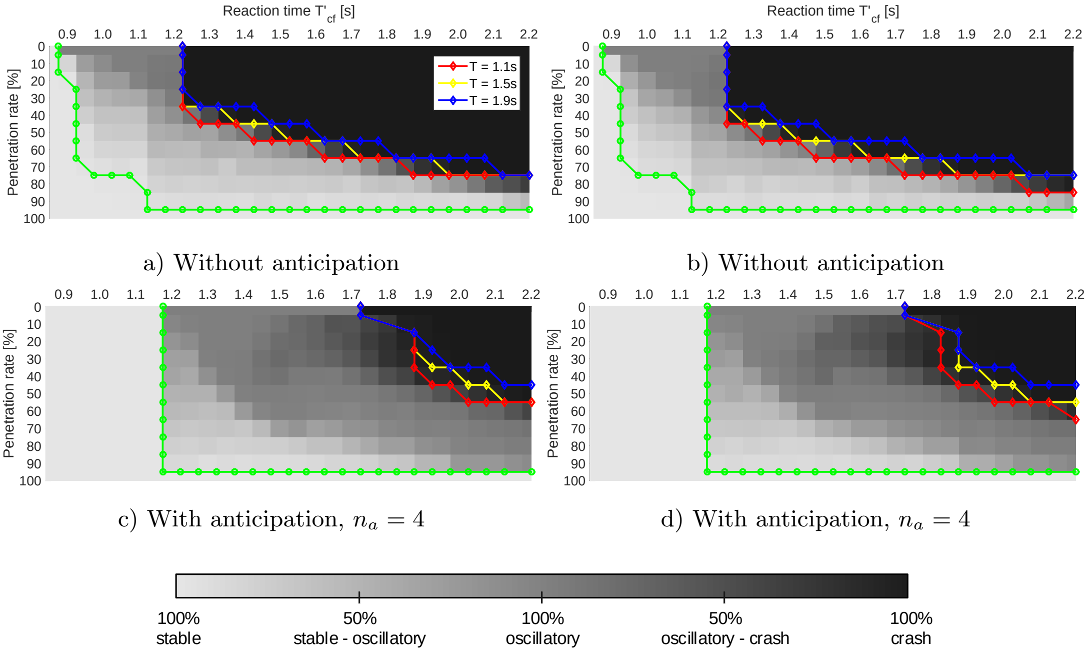
Figure 6.4 shows the stability regimes for the considered platoon for varying penetration rates of autonomous vehicles and as a function of reaction time T'_{cf}. The three stability regimes are thereby represented by different colors, with light gray denoting the stable regime, and dark gray and black representing the oscillatory and the crash regime, respectively. Intermediate color tones indicate that string stability is not only influenced by the corresponding set of parameters, but also depends on the actual ordering of vehicles within the platoon. The color bar is intended as a visual aid to determine the relative share of simulations that ended up in one of the three stability regimes. Finally, the colored lines denote the 95th percentile thresholds for the stability limit (green) and the crash limit assuming different values for the time gap parameter T for autonomous vehicles.

As a first general observation, it can be stated that traffic stability increases significantly with increasing penetration rate of autonomous vehicles. Actually, this is somewhat expected, given that autonomous vehicles are able to react almost instantaneously to the disturbance induced by the platoon leader, and are thus able to more effectively damp the perturbation that propagates upstream. Significant improvements with regard to the crash limit, however, can be observed only at penetration rates in the order of 40% to 50%, even when assuming an idealized and faultless operation of the automated driving system, see Figure 6.4a. Slightly higher penetration rates are required to achieve comparable improvements when considering sensor and actuator delays amounting to 0.3s and 0.2s, respectively, as outlined in Figure 6.4b. What becomes also immediately apparent is that the setting of the time gap parameter T plays also an important role, whereby larger and thus more conservative settings generally result in more stable platoon dynamics. Shorter time gaps in turn necessitate a more “aggressive” control effort on the part of the automated system in terms of larger decelerations, and are thus rather disadvantageous with regards to string stability [400]. However, it is important to note that different headway settings affect only the crash limit noticeable, while the threshold for the oscillatory regime essentially remains unchanged.

Up to this point, the positive impact of autonomous vehicles on string stability is undeniable, however, things are put into a different light when taking into consideration the anticipative abilities of human drivers, as outlined in Figure 6.4c and Figure 6.4d. Not only that the penetration rates required to actually improve traffic stability compared to the baseline scenario are now higher, lying in the order of 60% to 70%, one may also notice that, at low penetration, autonomous vehicles have even a slight negative impact on string stability. This manifests in the darker regions in the oscillatory regime, implying that actually more simulations end up in collisions compared to setups with no automated vehicles. What might seem counter-intuitive at first sight can be explained by the “lack of anticipation” of autonomous vehicles. Contrary to human drivers, which tend to consider more than one leading vehicle whenever this is possible, autonomous vehicles base their decisions solely on information gathered from the vehicle directly in front, ultimately resulting in less stable traffic dynamics. While a platoon of conventional vehicles is crash-free for reaction times up to 1.7s, collisions can already be observed at reaction times in the order of 1.5s for penetration rates of autonomous vehicles below 50%.

Impact of Connected Vehicles

Compared to autonomous vehicles, connected vehicles were found to have a somewhat higher potential with regard to improving string stability, as illustrated in Figure 6.5. For example, the considered platoon is crash-free at a penetration rate of 60% for reaction times up to 1.7s, compared to a penetration rate of 80% of autonomous vehicles that would be required therefor, see Figure 6.5b. Moreover, the platoon is string stable for a considerably larger share of simulations as penetration rate increases, with this effect becoming more pronounced when considering sensor, actuator, and communication delays due to non-ideal communication conditions. Remarkably, we found that even communication delays of up to one second affect the stability boundaries only to a negligible extent, which can be traced back to the simple yet effective delay-compensating strategy adopted by connected vehicles. On the other hand, and similar to autonomous vehicles, the introduction of connected vehicles initially results in a deterioration of string stability when human



a) Without anticipation

b) Without anticipation

c) With anticipation, $n_a = 4$

d) With anticipation, $n_a = 4$

Figure 6.5: String stability for different penetration rates of connected vehicles as a function of reaction time T'_{cf}. The setups in (a) and (c) assume an idealized and faultless operation of connected vehicles, while (b) and (d) represent setups where sensor, actuator, and communication delays are switched on. The communication range d_c of connected vehicles is set to 300m.

anticipation capabilities are taken into account, as shown in Figure 6.5c and Figure 6.5d. The reason therefor is that, especially at low penetration rates, the behavior of connected vehicles essentially corresponds to that of autonomous ones, simply because no other, or too few vehicles with communication capabilities are within the vehicles' communication range. With increasing penetration rate, however, connected vehicles are becoming increasingly able to use information from neighboring vehicles, ultimately resulting in more stable platoon dynamics.

6.2 Large-Scale Impacts of Human and Automated Driving

As mentioned previously, vehicle automation is expected to improve both traffic safety and efficiency considerably, having the potential to solve many problems prevalent on our roads today [34, 401, 402]. While the previous section studied the impacts of automated vehicles on the stability of traffic flow, this section aims for giving quantitative and qualitative estimates of the potential impacts of automated driving on a larger scale, and does so by simulating an urban road network and mixed traffic flows consisting of both conventional and automated vehicles. Hereinafter, we detail the simulation scenario and performance indicators used for our investigation, and review the models used in our

Figure 6.6: Simulated road network representing an extract of the city of Linz in Austria. Blue circles indicate potential bottlenecks in the road network which may cause a significant breakdown of traffic flow given a sufficiently high traffic density. High level roads such as freeways or expressways (speed limit 80-130 km/h) and low-level roads (30-50 km/h) are colored in red and gray, respectively.

simulations. Finally, the impact of the proportion of automated vehicles on traffic safety and efficiency is evaluated under consideration of different degrees of automation and for several penetration scenarios.

6.2.1 Simulated Road Network

The scenario considered for our investigation is depicted in Figure 6.6, and is a simplified representation of the northern part of the city of Linz, Austria. The road network has been generated using publicly available data from OSM, which includes not only the fundamental road geometry, but also additional meta-data such as speed limits, lane restrictions, traffic signs, or road types. As one may notice, the considered scenario consists of different road types, and also includes multi-lane traffic in both driving directions as well as road intersections. Since the underlying OSM data lacks information in sufficient detail with regard to how those intersections are regulated, but admittedly also to mask out the influence of complex intersection logic, we consider only unregulated intersections enforcing a simple priority-to-the-right rule for our investigations.

6.2.2 Preconditions

For all simulations discussed hereinafter, a precondition is that the road network is completely empty before the simulation starts, and the simulation ends once the last vehicle has reached its destination. For our simulations, we consider a set of 4000 vehicles which are distributed uniformly among all dangling road segments in the network, and which enter the simulation one after the other. The start locations, destinations, and routes in between are assigned randomly prior to the simulation for each of those vehicles, and are immutable, i.e. they are fixed for all simulations. Moreover, each vehicle has a predetermined time of arrival, which defines the exact point in time the vehicle enters the simulation, and which is changed from one simulation run to the other in a random fashion in order to wipe out effects that may occur due to the temporal distribution of vehicles during the simulation. The time difference between two vehicles entering the simulation, referred to as Inter-Arrival Interval (IAI), will be varied systematically in our investigations to simulate different levels of traffic intensity, ranging from 500ms, representing rather dense traffic, to 1000ms, which essentially corresponds to almost free-flow conditions for all vehicles.

6.2.3 Performance Indicators

To evaluate the impact of automated vehicles on traffic safety and efficiency, three different performance measures are used. The potential improvements in traffic safety are quantified in terms of an Accident Frequency Rate (AFR) corresponding to the number of collisions observed per 100 driven vehicle kilometers[2]. Whenever a crash happens in the simulation, all vehicles involved are removed from the road network before the simulation is continued. For evaluating the possible impacts of vehicle automation on traffic efficiency, we consider the improvements in the average travel time and fuel consumption among all vehicles. Since the removal of vehicles from the simulation could falsify both measures significantly, a “penalty” is used for all affected vehicles which amounts to the average travel time and fuel consumption among all other vehicles in the simulation. Finally, it is important to note that all quantities discussed in the remainder of this chapter represent average values over at least 100 simulation runs in order to mitigate for stochastic effects caused by the random variation in the vehicles’ arrival time.

6.2.4 Simulation Models

The realistic simulation of human and automated driving, and essentially any nontrivial traffic situation, requires not only models that describe the longitudinal dynamics of vehicles in terms of accelerations and decelerations, but also models capturing the dynamics associated with lane changes. The following subsections review the car-following models and the lane change model considered for our investigation, and discuss additional modeling aspects required for our simulations.

[2]The number of vehicle kilometers driven per simulation is 16769.48 km for the considered scenario.

	Parameter	Value	Literature
IDM/ACC	Desired velocity v_0 [m/s]	30	[127], [121], [152]
	Time gap T [s]	1.5	— " —
	Stopping distance s_0 [m]	2	— " —
	Maximum acceleration a [m/s^2]	1.4	— " —
	Comfortable deceleration b [m/s^2]	2	— " —
HDM/HDM*	Time headway threshold h_t^* [s]	4	[403]
	Space headway threshold h_s^* [m]	80	-
	Reaction time car-following T'_{cf} [s]	0.8	[269], [276]
	Reaction time free driving T'_{fd} [s]	1.2	— " —
	Reaction time standing traffic T'_{st} [s]	1.6	— " —
	Reaction time increase factor λ_r [%]	30	[279]
	Speed reduction factor λ_v [%]	6	[283], [404]
	Number of anticipated vehicles n_a	1 - 4	[215], [127]
Automation	Sensor range d_s [m]	200	[405], [336]
	Sensor delay T'_s [s]	0 - 0.3	[8], [406], [333]
	Actuator delay T'_a [s]	0 - 0.2	— " —
	Communication range d_c [m]	300	[407], [408]
	Communication delay T'_c [s]	0.3	-

Table 6.1: Simulation parameters for human-driven and automated vehicles

Modeling Car-Following Behavior

For modeling the car-following behavior of conventional and automated vehicles we adopt the conceptual framework developed in Chapter 3 and Chapter 4. More precisely, the longitudinal dynamics of human-driven vehicles are modeled using the improved version of the IDM given by Equation (3.5) and under consideration of the human factor extensions[3] presented in Section 3.2 and Section 3.3, while the dynamics of automated vehicles are governed by the ACC model and the assumptions discussed in Chapter 4. Unless stated otherwise, the parameters given in Table 6.1 are applied for both car-following models and their respective extensions. It is important to note that the parameter settings used in our simulations either comply with the recommended parameter ranges of the underlying car-following models, or have been obtained from the literature cited.

Modeling Lane Changes

Lane change models are an important ingredient of microscopic simulations, and determine under which circumstances drivers change lanes, diverge, or merge [409–411]. Unlike car-following models, these models have to consider not only vehicles in front of the subject vehicle but also traffic in adjacent lanes to determine whether or not a lane change is possible. Typically, the lane changing process is considered as a multi-step process. On a

[3]Note that imperfect estimation capabilities, which are modeled using stochastic Wiener processes, are not considered in our investigations.

strategic level, the driver's lane choice is influenced by his or her route in a network, and may additionally be affected by the network infrastructure, e.g. on-ramps, off-ramps, or lane blockages [412]. On the tactical level, the driver prepares and initiates an intended lane change by adjusting the vehicle's speed and relative position with traffic in the adjacent lane, known as synchronization [134, 413, 414]. Synchronization may be performed in both directions, i.e. by the vehicle intending to change lanes as well as by the potential following vehicle on the adjacent lane. The latter case is commonly referred to as gap creation, courtesy yielding, or cooperation [95]. Finally, at the operational stage, the driver's decides whether or not a lane change would be both desired and safe [415].

The lane change model considered in this thesis is designated as Minimizing Overall Braking Induced by Lane Changes (MOBIL) [135], and deals with lane changes at the operational level only. In fact, this is the case for most lane change models in the literature, with only very few exceptions involving also a tactical stage [95]. The reasons for selecting MOBIL as the lane change model of choice are manifold, and will be discussed in more detail hereinafter. We emphasize however that essentially any model could be used for the simulations performed in the scope of this thesis, e.g. the models in [95, 128–137].

The fundamental assumption of MOBIL is that a driver's lane change decision is based on a trade-off between the expected own advantage of a lane change and the potential disadvantage imposed on drivers in the adjacent lanes [135]. More precisely, the decision whether or not a driver should change lanes is governed by both an incentive criterion reflecting the driver's desire to change lanes, i.e. the attractiveness or utility of a lane change, and a safety constraint which takes into account potential effects on neighboring vehicles in the target lane, or the risk associated with the lane change. In fact, the safety criterion guarantees that vehicles in the target lane are not forced to slow down abruptly after the lane change, i.e. it ensures that their decelerations remain below a safe limit. The incentive criterion on the other hand determines if a lane change improves the current situation for the driver in terms of acceleration gain. Unlike other lane change models [121], MOBIL generalizes this incentive criterion to include immediately affected neighboring vehicles as well:

$$\underbrace{\widetilde{\dot{v}_\alpha} - \dot{v}_\alpha}_{\text{driver}} + p \left(\underbrace{\widetilde{\dot{v}_n} - \dot{v}_n}_{\text{new follower}} + \underbrace{\widetilde{\dot{v}_o} - \dot{v}_o}_{\text{old follower}} \right) > \Delta\dot{v}_{th} + \Delta a_{bias} \tag{6.1}$$

where $\dot{v}_x$ and $\widetilde{\dot{v}_x}$ denote the acceleration of vehicle x before and after a prospective lane change, respectively. The first two terms in Equation (6.1) represent the incentive or utility of a lane change for the driver him- or herself, the third term denotes the incentives for the two immediately affected neighboring vehicles, i.e. the old and new follower after the lane change. The parameter p represents the "politeness factor" determining to what extent these incentives are taken into consideration, and ranges from $p = 0$, representing completely egoistic lane-hoppers, to $p = 1$ for selfless drivers, who do not change lanes if there is any disadvantage for one of the following vehicles. Moreover, the model uses a hysteresis threshold $\Delta\dot{v}_{th}$ to suppress lane changes if the overall advantage is only marginal compared to the current situation, and an asymmetry term Δa_{bias} to implement a "keep-right" directive as prescribed in most European countries [135]. Consequently, a lane change is only performed if the driver's own advantage is higher than the weighted sum of disadvantages, i.e. the sum of acceleration losses of both neighboring vehicles, the hysteresis threshold $\Delta\dot{v}_{th}$, and the asymmetry term Δa_{bias}.

As mentioned above, MOBIL describes the utility of a lane change in terms of expected accelerations (or decelerations) of the subject vehicle and the immediately affected neighboring vehicles. Remarkably, this formulation has several advantages compared to gap-based lane change models [127, 135]:

- Any features of the car-following model (e.g., reaction time, anticipation) are automatically transferred to the lane change model.
- Consistency between the car-following and the lane change model is ensured, that is, if the car-following model is collision free, the combination of both models will be collision-free as well.
- Using the car-following model's acceleration function to assess whether or not a lane change is desired and safe allows for a compact mathematical model with just a small number of additional parameters.

For those reasons we decided to select MOBIL as the lane change model of choice for the simulations conducted in the scope of this thesis. We thereby rely on the recommended parameter values proposed in [121, 127], and consider a hysteresis threshold $\Delta\dot{v}_{th} = 0.1\text{m/s}^2$, an asymmetry term $\Delta a_{bias} = 0.3\text{m/s}^2$, and a politeness factor $p = 0.5$ which was found to result in the most realistic lane changing behavior [136].

Modeling Driver Distractions

Even though the car-following model used to describe the behavior of human drivers is capable of modeling the impacts of distractions on driving performance, investigating their large-scale effects demands also for a model defining when drivers are distracted, and how often they are. To this end, we adopt the methodology proposed in Section 3.4, and consider twelve different type of distracting activities drivers are likely to engage in. To calibrate our model, i.e. to specify the frequency of different distractions, the drivers' exposure to those distractions, and their average duration, we consider the parameter values given in Table 3.2. Though these data stem from a rather limited sample of just 70 drivers, they provide a reasonable approximation of how often drivers on average engage in secondary tasks, and for how long. It is important to note that both conventional as well as partially automated vehicles come into question as potential subjects to distraction. In case of the latter, however, driving performance is assumed to deteriorate only in situations where the driver is in charge of control. Though a strict separation between minor and severe distractions is somewhat difficult, since most secondary tasks usually result in a combination of cognitive, manual, and visual distraction, we differentiate between both minor and severe distractions in our simulations. More precisely, among the twelve activities listed Table 3.2, we assume that the tasks "using vehicle controls" and "using audio controls" result in a severe distraction, while all other secondary tasks are considered as minor distractions. Clearly, this is a rather arbitrary assumption, however, we justify our decision with the relatively short average duration of those tasks compared to the remaining activities, which makes it, in our opinion, more likely that the driver actually looks away from the road ahead for the entire duration of the distracted period.

Fuel Consumption Model

Fuel consumption is one of the primary performance indicators used in the forthcoming simulations, and the modeling thereof thus plays an important role. To this end, we adopt a microscopic physics-based model to calculate the fuel consumption of every single vehicle [121]. The model requires speed and acceleration profiles at a high temporal resolution – which are provided by the underlying car-following model – and considers various vehicle- and engine-related parameters to deliver the instantaneous fuel consumption of single vehicles. The following section elaborates on the selected model in more detail, and provides insights on the parameter values used for the simulations discussed hereinafter. For further details on the model, its validation based on driving cycle experiments as well as more general review of fuel consumption and emission models we refer to [121].

Driving resistance. The main factor determining a vehicle's fuel consumption is the driving resistance F, which primarily depends on the vehicle's instantaneous speed and acceleration, and which essentially corresponds to the mechanical force required to maintain those dynamics [121]. Fundamentally, the driving resistance is a superposition of several forces governing the vehicle's dynamics in steady-state conditions (i.e., when driving with constant speed) and dynamic resistances resulting from inertia [416]:

- The solid-state friction (or rolling friction) $F_R = mg\mu$ which is proportional to the friction coefficient μ and the gravitational force determined by the vehicle's mass m times the gravitational acceleration $g = 9.81m/s^2$.
- The uphill (or downhill) slope force $F_S = mg\ \sin(\phi)$ to take into account the gravitational forces at road gradients, where ϕ represents the uphill (or downhill) angle

in radians. In case of the latter, the contribution of F_S is negative, and will be balanced with the other forces.

- The aerodynamic drag $F_A = \frac{1}{2} c_d \rho A v^2$ depending on the density of air ρ, the frontal cross section surface of the vehicle A, its instantaneous speed v, and a drag coefficient c_d indicating how streamlined the vehicle is.
- The initial force $F_I = m\dot{v}$ following Newton's second law "force equals mass times acceleration". In case of a decelerating vehicle this force is negative, and will be balanced with the other forces.

Engine power and consumption rate. Once the driving resistance F is known, the required mechanical power to be raised by the vehicle's engine to overcome this resistance follows directly from the fundamental relation $P_m = Fv$. Moreover, the vehicle requires an additional base power P_0 for the rest of vehicle operations, including lighting, air condition, or to operate actuators and sensors [121]. Taking into account the overrun fuel cut-off of modern vehicles, i.e. no fuel is consumed when the driving force is negative, the overall power P demand can be formulated as follows:

$$P(v, \dot{v}) = \max[P_0 + vF(v, \dot{v}), 0] \tag{6.2}$$

where the maximum condition indicates that no mechanical energy can be recuperated when the driving force is negative. In order to determine the vehicle' fuel consumption rate C, one has to take into consideration not only the overall power demand P, but also the calorimetric energy density of fuel w_{cal} and the efficiency factor γ of the engine [121]. While the former reflects the relation between the amount of chemical energy ΔW_{chem} per volume of fuel ΔC, the efficiency factor is defined as the fraction of mechanical energy ΔW_{mech} that can be converted from a certain amount of chemical energy:

$$w_{cal} = \frac{\Delta W_{chem}}{\Delta C}, \qquad \gamma = \frac{\Delta W_{mech}}{\Delta W_{chem}} \tag{6.3}$$

Finally, the relation between the instantaneous fuel consumption rate C and the overall power demand P can be obtained directly from Equation (6.3), as shown in [121]:

$$C = \frac{P}{\gamma(P, f) w_{cal}} \tag{6.4}$$

where f denotes the engine's speed, and directly depends on the vehicle's speed, the transmission ratio r_t of the selected gear, and the dynamical tire radius R_{dyn} [121].

$$f = \frac{r_t v}{2\pi R_{dyn}} \tag{6.5}$$

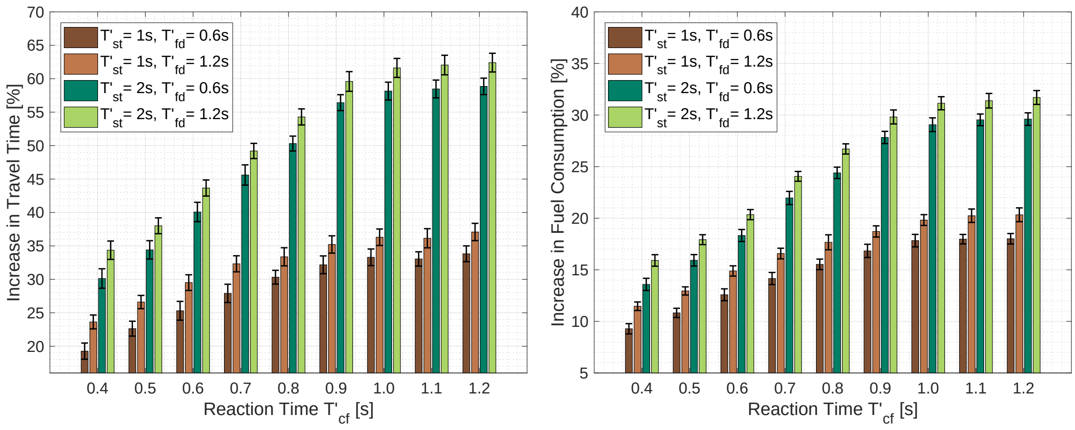
Parameter	**Value**	**Remarks**
Base power P_0 [kW]	3	Typical value for a VW Passat [417]
Vehicle mass m [kg]	1600	Typical value for a VW Passat [417]
Friction coefficient μ	0.02	Rolling resistance of car tires on tar or asphalt [418]
Air density ρ [kg/m^3]	1.3	Corresponding to the air density at ocean level [121]
Cross section surface A [m^2]	2	Typical value for a VW Passat [417]
Aerodynamic drag coefficient c_d	0.3	Most modern cars have a drag coefficient between 0.24 and 0.35 [121]
Dynamic tire radius R_{dyn} [m]	0.286	Taken from [121]
Gear transmission ratios r_t	13.9, 7.8, 5.26, 3.79, 3.09	Taken from [121]
Fuel energy density w_{cal} [kWh/l]	11	Typical value for the energy density of gasoline [121]

Table 6.2: Overview of parameters for the physics-based fuel consumption model [121, 417].

Model calibration. For the sake of simplicity, but also to not unnecessarily increase the already large amount of simulation parameters, we assume a homogenous ensemble of vehicles equipped with diesel combustion engines and with identical physical characteristics. Even though this assumption might be slightly disconnected from reality, we argue that the differentiation between different engine types (e.g., electric powered, hydrogen, hybrid) does not affect the simulation results qualitatively. For a full list of parameters related to the fuel consumption model and their corresponding values considered for the simulations we refer to Table 6.2.

6.2.5 Impact of Reaction Time, Anticipation, and Distractions

Before studying the impacts of automated vehicles, the following sections aim to provide quantitative insights on the influence of human driving behavior on traffic safety and efficiency. Estimating those impacts is of particular importance, since the models presented in Chapter 3 serve as a baseline for the penetration analysis conducted in the forthcoming section, and must therefore provide a reasonable representation of the "status quo". In order to isolate the impact of different model parametrizations, we assume a homogenous ensemble of human-driven vehicles, and systematically vary with those parameters governing the behavior of human drivers, while all other parameters are set to their default values listed in Table 6.1. In particular, we investigate how the drivers' reaction time, their anticipative capabilities, and distracted driving influence travel time, fuel consumption, and accident frequency. Those results are quantified by comparing them with a reference



a) b)

Figure 6.7: Impact of varying reaction times on travel time (a) and fuel consumption (b) compared to the baseline scenario under consideration of an IAI of 600ms, i.e. dense traffic. Error bars indicate the respective standard deviation values.

scenario where all human factor extensions have been switched off, that is, assuming ideally attentive and faultless drivers, which are modeled using the IDM. Note that this reference scenario is entirely collision-free for all of the investigated model configurations and parametrizations.

Varying Reaction Times

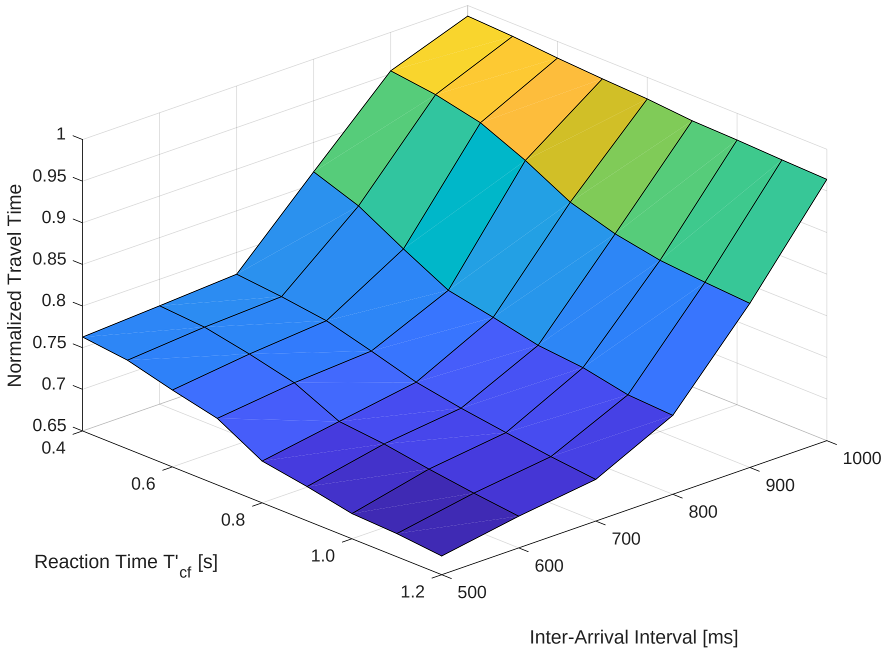
The impact of varying reaction times on travel time and fuel consumption is exemplified in Figure 6.7, which outlines the relative increase in both measures as a function of reaction time for a setup with an IAI of 600ms, that is, dense traffic. What becomes immediately apparent is that the different reaction times have a significant influence on travel time and fuel consumption, and that even for setups with moderate reaction times a substantial increase compared to the baseline scenario can be observed. Fundamentally, this increase can be attributed to the deterioration in traffic stability, which might eventually result in a breakdown of traffic flow and the emergence of stop-and-waves, especially under dense traffic conditions. Unsurprisingly, the reaction times T'_{cf} and T'_{st} turned out to be most influential in our simulations, which is comprehensible given that both have a significant impact on the stability of traffic flow and the deformation of the resulting instabilities, as discussed in Section 6.1.3. Another interesting observation pertains the dependence of the performance measures on the reaction time T'_{cf}. As illustrated in Figure 6.7, both travel time and fuel consumption increase almost linearly for reaction times up to 0.9s. For larger reaction times, however, the relative change in both quantities becomes negligible. The explanation therefor this is that traffic remains largely stable for small reaction times, while the risk of a traffic breakdown as a result of instabilities increases significantly for larger reaction times. Consequently, once such a breakdown has occurred, the increase in travel time and fuel consumption depends primarily on how fast the resulting jam situation dissolves. This, in turn, is to a large extent determined by the reaction time T'_{st}, which becomes relevant only if traffic has come to halt, for example in front of an intersection, or, likewise, in stop-and-go traffic.

Naturally, the magnitude of the impacts on traffic performance depends not only on the actual setting of the individual reaction times, but also on the overall traffic density. Compared to the scenario depicted in Figure 6.7, for example, where an increase in travel time and fuel consumption in the order of 20% to over 60% and 10% to more than 30% can be observed, depending on the parametrization, the deterioration in both quantities ranges only from 0.9% to 2% and from 1.9% to 5% for the same setup and an IAI of 1000ms. Notice that for setups with lower traffic density the relative increase in fuel consumption exceeds that in travel times, which can be ascribed to the considerably larger fluctuations in the vehicles' accelerations due to the drivers' delayed reaction.

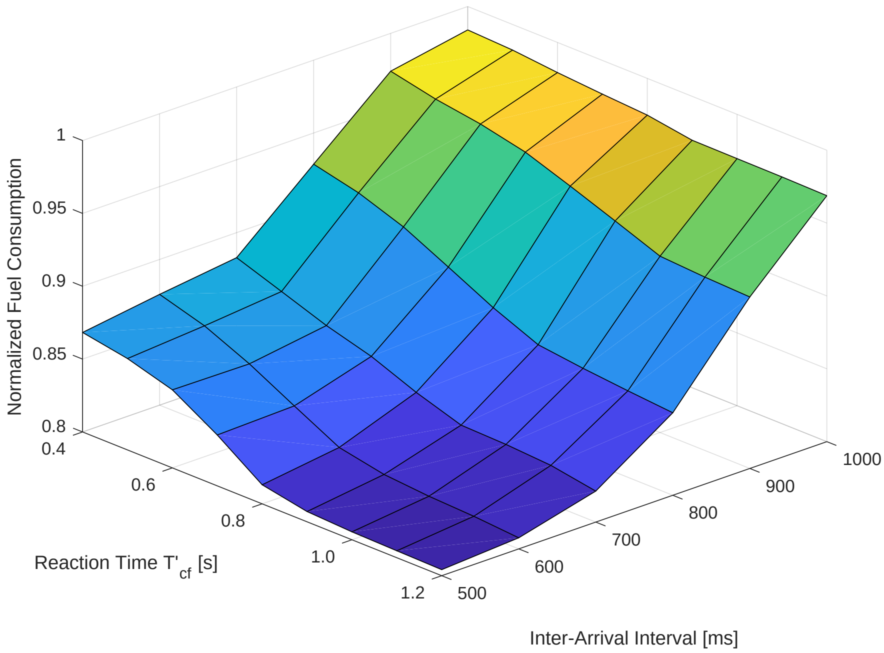
Anticipation

The stability analysis conducted in Section 6.1.3 revealed that the anticipative capabilities of human drivers can compensate, at least to a certain extent, for the detrimental effects of reaction times. Remarkably, this stabilizing effect becomes also evident when considering the impacts of spatial and temporal anticipation on a larger scale, leading to a substantial reduction in both travel time and fuel consumption. For matters of illustration, Figure 6.8 outlines the influence of anticipation on travel time and fuel consumption as a function of reaction time T'_{cf} and IAI compared to setups where spatial and temporal anticipation remain disregarded. Please note that both quantities are normalized with respect to the reference scenario, that is, the scenario without anticipation.

As a first general observation, one may notice that, regardless of the scenario setup, considering the anticipative capabilities of human drivers unexceptionally leads to an overall performance improvement in terms of reduced travel times and fuel consumption, primarily as a result of the associated increase in traffic flow stability and smoother accelerations. This holds particularly true for setups with large reaction times and high traffic densities, i.e. considering short IAIs. On the other hand, there is obviously less potential for improvement when assuming smaller reaction times or lower traffic densities, where traffic can mostly flow freely anyways. Put differently, the influence of both stability mechanisms becomes more pronounced the worse the situation is initially. This explains in part also the shape of both surface plots shown in Figure 6.8. While in case of low traffic densities vehicles are able to travel almost unhindered through the network, a larger number of vehicles inevitably ends up in congestion anyways for setups with high densities, simply because the network is increasingly becoming overcrowded. In either case, there is appar-



a)



b)

Figure 6.8: Impact of anticipatory driving (n_a=4) on normalized travel time (a) and fuel consumption (b) compared to setups where spatial and temporal anticipation have been switched off. In both setups the reaction times T'_{fd} and T'_{st} have been set to 1.2s and 2s, respectively.

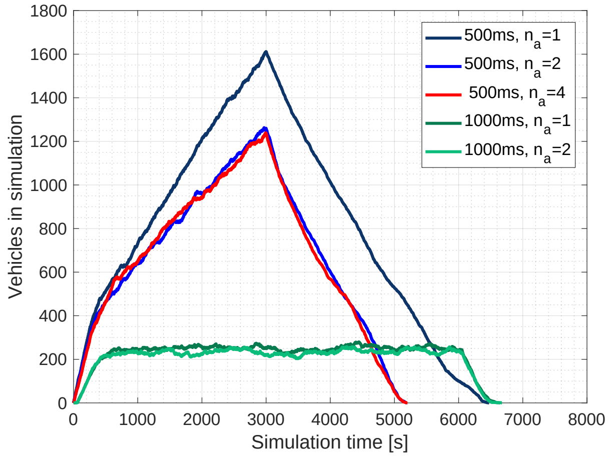
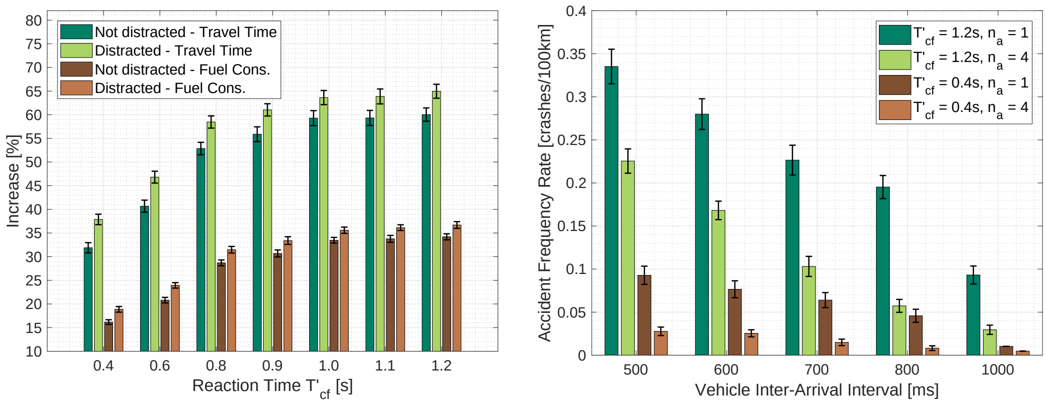


Figure 6.9: Number of vehicles over simulation time for different settings of the spatial anticipation mechanism and distinctive IAIs representing dense traffic and free-flow conditions, respectively.

ently less room for improvement for both anticipation mechanisms, which were found to be most effective when considering intermediate traffic intensities where traffic breakdowns can actually be avoided, e.g. the setups with an IAI of 800ms or 900ms. Nonetheless, with a reduction in travel times and fuel consumption of up to 32% and 20% for scenarios with dense traffic and up to 3.6% and 3.1% under free-flow conditions, it can safely be concluded that both anticipation mechanisms are able to compensate substantially for the negative impacts of reaction times. Another interesting observation is related to the number of vehicles considered by the spatial anticipation mechanism, which has been varied in the range from n_a=1 to n_a=4 in our simulations. While setups with n_a=1 naturally lead to the smallest reduction in travel time and fuel consumption, drastic improvements can be observed when spatial anticipation is increased to n_a=2. On the other hand, no significant changes in both quantities can be observed when further increasing n_a to larger values, indicating that already a consideration of the two next-nearest vehicles ahead might suffice to improve the overall traffic performance considerably. It is worth noting that a similar correlation has been revealed in previous studies in connection with the impact of spatial anticipation on string stability [127]. This effect is also reflected in Figure 6.9, which outlines the number of vehicles on the road over simulation time for different IAIs and a varying number n_a of considered vehicles.

Distracted Driving

So far, we have investigated the impacts of varying reaction times and the drivers' anticipative capabilities on traffic flow efficiency in terms of increased (or reduced) travel times and fuel consumption. The reason why their potential safety effects have remained disregarded up to this point is that the considered scenario is essentially collision-free for



a) b)

Figure 6.10: Impact of distracted driving on travel time and fuel consumption (a) and accident frequency rate (b) compared to the baseline scenario. The reaction time increase and speed reduction factors λ_r and λ_v are set to 30% and 6%, the reaction times T'_{fd} and T'_{st} to 1.2s and 2s, respectively. Figure 6.10a shows the results for a setup with an IAI of 500ms. Error bars indicate the respective standard deviation values.

a large portion of model parametrizations. In fact, collisions can only be observed when increasing the reaction time T'_{cf} to values greater than 1.2s, which seems to be well in line with the findings discussed in Section 6.1.3. However, things appear differently when the detrimental effects of distracted driving are taken into consideration. To this end, the methodology presented in Section 3.4 was used to simulate the drivers' engagement in different types of secondary tasks, and to study their implications on traffic safety and efficiency. As depicted in Figure 6.10a, the temporal increase in the drivers' reaction time as a result of distraction leads to a further deterioration in both travel times and fuel consumption. Under certain circumstances, this increase in reaction time may occasionally even result in (rear-end) collisions between vehicles, if only for setups with a sufficiently high baseline reaction time T'_{cf} in the order of about one second[4]. Compared to those minor distractions, however, severe distractions and the drivers' inability to respond to changes in his or her ambient environment concomitant therewith were found to have a much more serious influence on road safety. This manifests in a marked increase in the AFR compared to setups without distractions, which is illustrated in Figure 6.10b for different reaction time settings and as a function of the vehicles' IAI. As one might expect, most accidents can be observed for setups with a high traffic density, and when assuming moderate to high reaction times on the part of the drivers. Collisions are thereby caused either directly by the distracted vehicle crashing into the vehicle ahead, or are triggered as a result of the disturbance induced by the delayed but stronger braking response. In

[4]Note that in the scope of our investigations no side collisions, i.e. crashes resulting from lane changes, have been observed.

case of the latter, the number of collisions naturally increases with increasing reaction times, as the perturbation may either amplify or attenuate when propagating from one vehicle to the other. What Figure 6.10b also shows is that the risk of collisions can be reduced markedly when taking into account the drivers' anticipative capabilities, and in particular that of indirect collisions resulting from traffic instabilities. On the other hand, the stabilizing effect of both anticipation mechanisms does not pay off in situations where the accident is caused directly by the distracted driver, as discussed in Section 6.1.3.

Synthesis

In this section, we investigated the influence of varying reaction times, anticipatory driving, and distractions on travel times, fuel consumption, and accident frequency using a large-scale urban road network. It is important to note that the findings presented and discussed on the previous pages are primarily intended to provide a better understanding of how the various factors governing the behavior of human drivers influence the considered performance measures, and are thus of a rather illustrative nature. What our simulations clearly show, however, is that the anticipative capabilities of human drivers do not only have a far-reaching effect with regard to string stability, but also significantly affect the collective traffic dynamics on a larger scale. Another key takeaway pertains to the role of distracted driving in the context of road safety. While our simulations produce crash-free dynamics for a wide range of realistic reaction times, this is no longer the case when the driver distractions come into play. Notably, this seems to be well in line with the widely shared notion that distractions, and visual distractions in particular, are a prime contributing factor to a majority of accidents on our roads [206, 241, 242]. Consequently, we argue that the models used in our simulations are capable of providing, at least to a certain degree, a reasonable description of human driving behavior, in particular with regard to the level of road (un)safety resulting thereof, and thus constitute an eligible basis for evaluating the potential safety and efficiency impacts of automated driving.

6.2.6 Safety and Efficiency Effects of Automated Driving

While the previous section provided quantitative and qualitative insights on the impacts of different human factors on travel times, fuel consumption, and accident frequency, the objective of the forthcoming sections is to estimate the potential safety and efficiency effects of automated vehicles. Contrary to the previous investigation, which assumed a homogenous ensemble of identical driver-vehicle units, we now consider mixed traffic flows composed of both human-driven and automated vehicles. The impact of different degrees of vehicle automation is studied by systematically varying the proportion of automated vehicles within the vehicle fleet, and by considering different levels of vehicle automation.

Driving function	SAE level	Speed range	Regime(s)
Jam Assist	2	0 - 30 km/h	car-following
Jam Chauffeur	3	0 - 60 km/h	car-following
Highway Chauffeur*	3/4	0 - 130 km/h	all

*The highway chauffeur is only active on roads of type "freeway"

Table 6.3: Specification of driving functions considered for partially automated driving following the definitions in [102].

Baseline Scenario

To quantify the potential impacts of automated vehicles on traffic safety and efficiency, we consider a baseline scenario without any kind of vehicle automation, that is, all vehicles are operated by human drivers. Thereby, the inherent heterogeneity in human driving style and the drivers' preferences [64, 208] is taken into account by assigning uniformly and independently distributed values to the parameters of the underlying car-following model. Those parameters are varied between 80% and 120% of their average value or within their specified range given in Table 6.1. More precisely, this randomization pertains to the IDM parameters v_0, T, s_0, a, and b, the reaction times T'_{cf}, T'_{fd}, and T'_{st}, and the number of anticipated vehicles n_a. Similar to the spatial distribution of vehicles across the road network, the model parameters for every single vehicle are determined only once prior to the simulation, and remain immutable for all simulation runs. Moreover, it is important to note that this kind of driver heterogeneity is considered only for conventional vehicles, while all automated vehicles are assumed to behave in the same way, implying identical parameter settings for all vehicles.

Automated Driving Functions

Apart from a heterogeneous ensemble of drivers with different preferences and skills, we also take into account different degrees of automation for our investigation, including autonomous and connected vehicles as well as partially automated ones. As far as partial automation is concerned, we distinguish between three ADAS depending on their level of automation and their functional limitations. The different driving functions considered for our investigation as well as their corresponding ODD restrictions are listed in Section 6.2.6. Note that whenever a partially automated vehicle enters or leaves its ODD, a transition from manual to automated driving is triggered during the simulation, and vice versa.

Penetration Scenarios

In order to investigate the impacts of vehicle automation under consideration of mixed traffic flows, i.e. assuming different penetration rates of automated vehicles, we systematically vary the share of automated vehicles in the vehicle fleet. First of all, the penetration

Vehicle type	Baseline	Scenario 2030	Scenario 2050
Conventional	100%	77%	13%
Jam Assist*	0%	3%	12%
Jam Chauffeur*	0%	3%	12%
Highway Chauffeur*	0%	3%	12%
Autonomous	0%	8%	27%
Connected	0%	6%	24%

*Penetration rates of partially automated vehicles are distributed in equal shares among the different driving functions.

Table 6.4: Penetration rates of human-driven and automated vehicles for different simulation scenarios

rate is increased from 0% to 100% for autonomous and connected vehicles as well as for the different types of partially automated vehicles to study their influence individually. Afterwards, we consider two hypothetical market penetration scenarios where the vehicle fleet represents a mixture of human-driven and different types of automated vehicles, as outlined in Table 6.4. Rather than assuming a very high penetration rate of automated vehicles, or even full market penetration, those scenarios take into account the likely deployment path of automated vehicle technology, and are based on a recent estimate on the gradual automation of the vehicle fleet in Germany [105]. Note that, regardless of the penetration scenario, the set of vehicles which is presumed to have automation capabilities is selected randomly prior to each simulation run in order to wipe out possible effects that may occur due to a spatial concentration of vehicles that are equipped with automation technology, and ones that are not.

Travel Time and Fuel Consumption

Let us start with elaborating on the potential impacts of vehicle automation on traffic efficiency in terms of travel times and fuel consumption. To this end, it is referred to Figure 6.11a and Figure 6.11b, which outline the average travel time and fuel consumption per vehicle as a function of penetration rate of automated vehicles, respectively. One thing which immediately stands out is that, regardless of the degree of automation or the driving function considered, both travel time and fuel consumption can be reduced substantially as penetration rate increases. This holds especially true for connected vehicles, which outperform both autonomous as well as partially automated vehicles considerably once a sufficient level of penetration is reached, i.e. given a significant share of vehicles equipped with adequate communication technology. At full penetration, a reduction in the average travel time and fuel consumption in the order of 19% and 10% can be observed for connected vehicles, compared to 14% and 6.6% for autonomous ones. Of particular note is also the almost negligible difference in performance improvements between autonomous vehicles and ones that are equipped with the jam assist or jam chauffeur system, and the

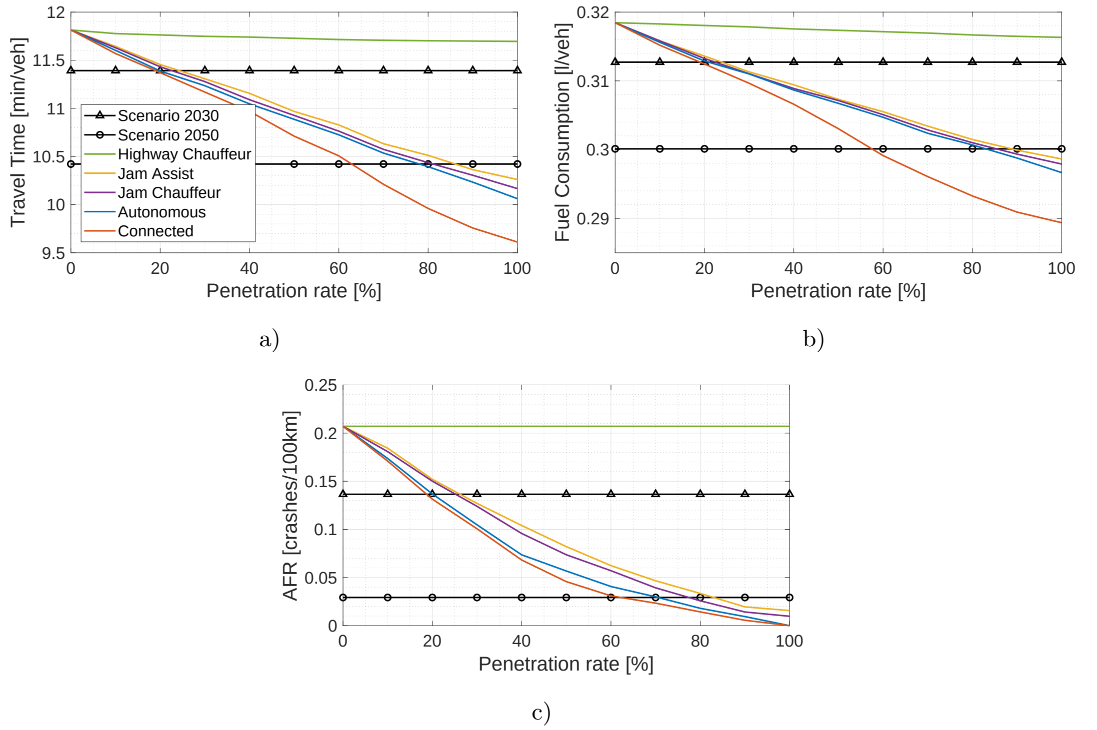


Figure 6.11: Average travel time (a), fuel consumption (b), and accident frequency rate (c) as a function of penetration rate for different levels of automated driving for a vehicle arrival interval of 500ms, i.e. dense traffic conditions. The black lines with markers correspond to the two hypothetical scenarios considering a mixture of conventional and different types of automated vehicles.

insensitivity of both performance measures to increasing penetration rates of the highway chauffeur. This, in turn, can be ascribed solely to the scenario under investigation, and in our opinion underscores the necessity to distinguish between different levels of automation or different driving functions when studying the large-scale effects of vehicle automation. Generally, the observed behavior can be explained as follows. While freeways make up only for a minor part of the considered road network, and thus only a rather small portion of vehicles travels along those roads, almost the entire traffic is handled by lower level roads. Moreover, and in particular for setups with high traffic density, traffic breakdowns start to emerge at the network's bottlenecks (see Figure 6.6), as incoming traffic cannot be dissipated fast enough at the intersections. The resulting traffic jams, in turn, are the prime contributing factor to both travel time and fuel consumption. This also explains the marginal difference between autonomous vehicles and partially automated ones equipped with jam assistance or jam chauffeur systems, as the latter two also allow for a comparably efficient operation in congested and slow moving traffic traffic.

Interestingly, a noticeable reduction in travel time and fuel consumption can also be observed for both hypothetical penetration scenarios, where the vehicle fleet is a mixture of different types of automated vehicles. While for the 2030 scenario the estimated performance improvements lie in the range of 3% to 5%, a reduction in the order 12% in travel time and 6% in fuel consumption can be observed for the 2050 scenario. This is interesting insofar as it provides an indication that not necessarily a high penetration rate of highly automated or even connected vehicles might be required to improve traffic efficiency considerably, but that similar effects might already become visible at earlier deployment stages, characterized by a larger share of vehicles that are only partially automated.

Accident Frequency Rate

A very similar behavior can be observed with regard to the safety impacts of vehicle automation, as illustrated in Figure 6.11c. Generally, the number of collisions (or likewise, the AFR) decreases with an increase in penetration rate of automated vehicles. However, two things are important to note. First, collisions can be observed even at very high penetration rates of automated vehicles. Moreover, accidents can only be avoided completely assuming full penetration, and notably only when considering either autonomous or connected vehicles[5]. The explanation for both phenomena is essentially the same. Even though the number of human-driven vehicles and the total time the driver is in charge of control is reduced significantly with increasing penetration rates and level of automation, there still remains a residual risk that those vehicles which are controlled manually are involved in a collision as a result of distracted driving. Apart from this, it is also noticeable that connected vehicles lead only to a marginal reduction in the AFR compared to autonomous ones. The reason for this is that collisions are primarily caused directly by distracted drivers rather than as a consequence of traffic instabilities. By increasing traffic stability, however, connected vehicles are only able to mitigate collisions in the latter case.

Impact of Traffic Density

Apparently, the potential impacts of automated vehicles on traffic efficiency and safety do not only depend on the overall penetration rate or level of automation, but also vary strongly among different levels of traffic intensity. Figure 6.12 exemplifies this relation by outlining the average travel time per vehicle for different IAIs and assuming a penetration rate of 100% of automated vehicles. As one might expect, the improvements achieved by the deployment of automated vehicles compared to the baseline scenario, i.e. a situation where all vehicles are operated by human drivers, decrease with lower traffic densities. While for scenarios with a moderate to high traffic density such as the setups with an IAI of 500ms or 600ms a reduction in travel time in the order of 14% for autonomous and 19% for connected vehicles can be observed, their impact becomes less pronounced for scenarios

[5]Clearly, this premise presupposes that no accidents happen because of technical or mechanical defects of automated vehicles, or as a result of system failure.

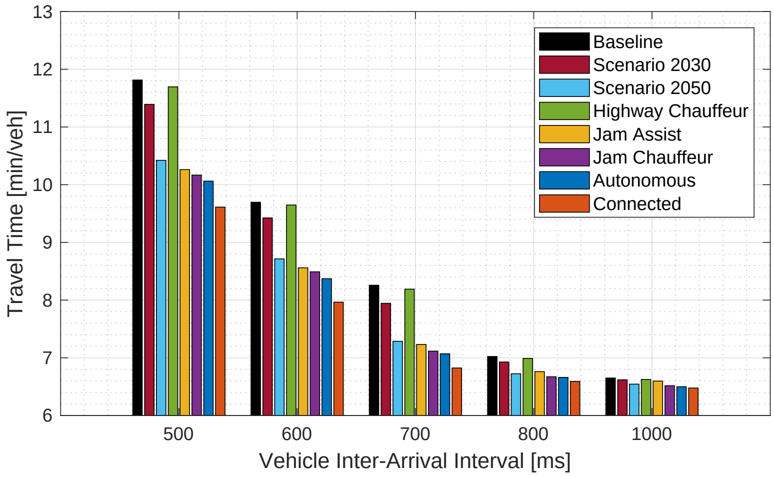


Figure 6.12: Average travel time as a function of IAI for different levels of automated driving and full penetration. The baseline scenario refers to a penetration rate of 0%, i.e. a situation where all vehicles are human-controlled. Note that a higher arrival interval inevitably implies a lower traffic density.

with lower traffic density. Similarly, the achievable improvements of connected vehicles over autonomous ones by making use of V2V communication, which are clearly visible for setups with high traffic density, are almost negligible under free-flow conditions. In fact, in the context of connected vehicles, lower traffic densities have a somewhat similar effect than lower penetration rates, as there is obviously less potential to benefit from the ability to obtain traffic-relevant information from neighboring vehicles.

6.3 Conclusions

The objective of this chapter was to investigate the safety and efficiency impacts of automated vehicles under consideration of mixed traffic flows characterized by a varying share of human-driven and automated vehicles. By means of simulations, we studied the impact of automated driving on the string stability of a platoon in response to a perturbation induced by its leader, and provided quantitative and qualitative insights on the potential large-scale impacts of vehicle automation in terms of reduced travel times, fuel consumption, and accident frequency. Thereby, we considered not only different penetration scenarios by systematically increasing the proportion of automated vehicles in the vehicle fleet, but also different degrees of vehicle automation. All simulations have been carried out using the microscopic traffic simulator TraffSim, which has been presented in minute detail in the previous chapter, and under consideration of the models and assumptions discussed in Chapter 3 and Chapter 4, respectively.

To put if briefly, the main findings of our investigations can be summarized as follows. On the one hand, they provide a strong indication that automated driving might be able to improve the stability of traffic flows substantially, especially when assuming moderate to high penetration rates of automated vehicles and a sufficient level of connectivity. At low penetration rates, however, there is also some evidence that vehicle automation might initially even have a slight negative impact on string stability. On the other hand, our simulations underscored the potential of vehicle automation to improve both traffic safety and efficiency considerable also on a larger scale, whereby the magnitude of those impacts depends not only on the degree of automation and connectivity, but naturally also on the overall traffic density and the scenario under investigation. Moreover, our simulations provide reasonable grounds to believe that a full elimination of human error seems to be a fundamental prerequisite to effectively avoid road accidents, since even at very high penetration rates of automated vehicles and a high degree of automation there still remains a residual risk of crashes caused by distracted or inattentive drivers. A critical and more in-depth discussion of our findings will be provided in the next and final chapter of this thesis, which also gives some recommendations for future research directions.

7

Conclusions and Outlook

THE central research question addressed by this thesis was focused on investigating the potential impacts of automated driving on traffic safety and efficiency, especially under consideration of mixed traffic flows characterized by a varying share of human-driven and automated vehicles. To this end, a microscopic simulation framework has been developed in the scope of this research which aims at describing the longitudinal dynamics of both human-driven and automated vehicles. This framework enables researchers to incorporate a number of factors related to the behavior of human drivers into car-following models, and provides an intuitive mechanism to distinguish between different degrees of vehicle automation. The framework has been implemented in the microscopic traffic simulator TraffSim [261], which has been substantially developed further as part of this research, and which in a sense provided the toolbox required for the investigations conducted in the scope of this thesis. The following chapter summarizes the main findings of these investigations, and gives some recommendations for future research directions.

7.1 Conclusions

With the ultimate goal of providing a better understanding and new insights into the possible impacts of automated vehicles on the safety and efficiency of our transportation systems, but also to facilitate such kind of investigations, this thesis developed a comprehensive modeling framework to describe the behavior of human drivers and the dynamics of automated vehicles microscopically. Our framework integrates a number of behavioral aspects and traits commonly associated with human driving behavior, including reaction times, anticipative capabilities, or distractions, and technology-appropriate assumptions in the context of automated driving, such as sensor and actuator delays, with microscopic traffic models. In this manner, it is able to distinguish not only between manual and automated driving, but also between different degrees of automation. For reasons of tractability and maintainability, the entire framework is formulated in a rather generic way, which makes it applicable to a whole range of traffic models, and thus allows analysts to mix a variety of assumptions and hypotheses with an even wider range of models for driving behavior, without necessitating the development of new models. In the final part of this thesis, the framework has been put to use in order to provide both quantitative and qualitative estimates on the potential safety and efficiency impacts of automated driving using the microscopic traffic simulator TraffSim, which has been developed further as part of this research. In the following, the main findings of these investigations are summarized briefly, followed by a closing discussion in the next section.

Impacts on String Stability

The impact of automated driving on string stability was investigated by studying the response of a platoon of 100 vehicles to a perturbation induced by a braking maneuver of its leader. From our simulations, it is shown that:

- Distractions, and visual distractions in particular, are detrimental for the stability of traffic flows, and result in a strong deterioration of string stability caused by the driver's delayed, and thus stronger, or missing brake response. Moreover, our simulations provide an indication that by reducing their speed while engaging in a distracting task [282–284], drivers are able to compensate for the detrimental effects of distraction to a certain extent, resulting in slightly more stable traffic dynamics.
- The introduction of automated vehicles has the potential to improve string stability substantially, especially when considering higher market penetration rates, whereby connected vehicles were found to have a more stabilizing effect compared to autonomous ones. Our simulations reveal, however, that a moderate penetration rate of about 50% to 60% of automated vehicles is required to achieve significant improvements, which is in line with the existing body of literature [43, 48–51].

- For penetration rates up to 40%, our simulations provide an indication that the introduction of automated vehicles might initially even lead to a deterioration in string stability. Though this might seem counter-intuitive at first sight, the "lack of anticipation" on the part of autonomous vehicles compared to human drivers and the limited possibility to effectively utilize traffic-relevant information from neighboring vehicles in case of low penetration rates are, in our opinion, a plausible explanation for the observed behavior. This finding is interesting insofar as it stands in contradiction to many of the studies reported in the literature, however, it is worth noting that there is actually also some evidence that ADAS such as ACC might only have a limited contribution to string stability at all [52, 53], or might even lead to less stable traffic caused by an aggravation of disturbances [419].

Impacts on Traffic Safety and Efficiency

The potential safety and efficiency impacts of automated vehicles have been evaluated under consideration of a large-scale road network and for several market penetration rates and traffic compositions. The main findings of this penetration analysis are as follows:

- Automated driving has the potential to substantially improve traffic efficiency by reducing both travel times and fuel consumption as penetration rate increases. For our considered urban scenario, these improvements were in the order of 19% (travel time) and 10% (fuel consumption) for connected vehicles, and 14% respectively 6.6% for autonomous vehicles assuming full market penetration and dense traffic conditions. Naturally, the magnitude of these effects becomes less pronounced as penetration rates decreases, and apparently depends on the overall traffic density as well.

- With regard to traffic efficiency, our findings indicate that not necessarily a high penetration rate or degree of automation is required to achieve considerable improvements, but that a significant reduction in travel times and fuel consumption might already come to light at earlier deployment stages, where traffic is characterized by a varying share of human-driven, partially and highly automated vehicles. For our hypothetical 2050 scenario, for example, in which partially automated vehicles make up for more than one third of the vehicle fleet, while autonomous and connected vehicles account for roughly a quarter each, the reduction in travel time and fuel consumption lies in the order of 12% and 6%, respectively.

- Our findings provide a strong underpinning for the widely shared notion that the benefits of automated vehicles for road safety will be substantial, especially in the long term [34, 55, 56, 110]. Notwithstanding any accidents caused by technical or mechanical defects or automation failure, our simulations showed that, at full market penetration, highly automated and connected vehicles are able to prevent all kinds of collisions which involve some element of human error. However, when considering a lower degree of automation and/or incomplete market penetration, road safety cannot be guaranteed with absolute certainty, as a residual risk for accidents caused by distracted or inattentive drivers still remains.

7.2 Discussion

The work presented in the scope of this thesis can be regarded as an attempt towards a more general and overarching framework for modeling the behavior of human drivers and the dynamics of automated vehicles in the scope of microscopic traffic simulations. The strength of the proposed framework clearly lies in the fact that it strictly separates the behavioral assumptions and hypotheses related to manual and automated driving from the underlying traffic models. This separation of concerns also has some favorable practical implications, as it provides the possibility to combine different – perhaps idealized – traffic models with a variety of human factors and technology-appropriate assumptions. At the same time, this rather generic approach allows for the development of simulation models which are modular in their design, easier to maintain, and tractable. Presumably the biggest limitation of our framework at the time of writing is that any aspects which are related to the lateral traffic dynamics, i.e. lane changes, have been left totally unconsidered. This is primarily due to the fact that the lane change behavior of human drivers is still not yet sufficiently understood, and the lack of empirical data that is available in that particular context compared to longitudinal driving behavior [35]. We believe, however, that the generic approach pursued in this thesis could also be eligible to augment existing and idealized lane change models with a number of human factors, though the underlying models and the separation in between might be more complicated and somewhat blurrier compared to models for car-following.

Even though our framework might have a solid empirical foundation based on the pertinent human factors and traffic flow modeling literature, we emphasize that the conclusions drawn from the simulations discussed in this thesis must be viewed in light of the many assumptions made. In fact, we consider our approach as a first step towards a more comprehensive modeling framework, for whose verification indubitably a greater amount of empirical evidence and real-world observations are required – not only with regard to the behavior of human drivers, but also with respect to automated driving. However, by using reasonable assumptions based on the literature and evidence that is currently available, our simulations demonstrated the proposed framework's ability to reproduce feasible and face-valid results with respect to the potential safety and efficiency impacts of automated driving. Though the quantitative significance of our findings might be limited to the very particularities of the investigated scenarios and the models and parameters used in our simulations, they do have a strong qualitative meaning. First, they underscore the pressing need to increase the human factors sophistication in existing traffic models, not only to provide a more plausible description of human driving behavior, but also to achieve a better understanding of the potential impacts of automated driving. What our simulations show is that humans might actually not be too bad at driving after all, which also explains why accidents are, fortunately, still exceptional situations in road traffic, and that certain aspects of human driving behavior, above all the drivers' anticipative capabilities, could also play an important role in the design and development process of automated driving systems. Secondly, our results provide a strong indication that, especially when studying the large-scale impacts of vehicle automation, it is indispensable to not only differentiate between manual and automated driving, but notably also to consider different levels of automation. Both aspects make up a challenge for the transportation research community in the upcoming years, since the models used in our simulations must not only provide a plausible description of human driving behavior or the dynamics of automated vehicles, but also have to be of a manageable complexity in order to allow for large-scale simulations, while at the same time still resulting in reasonable traffic dynamics.

7.3 Future Research Directions

With vehicle automation slowly become a reality, there is now a stronger need than ever to anticipate the potential changes automated driving might bring to our transportation systems. Even though considerable efforts have been put into investigating the impacts of vehicle automation in recent years, many uncertainties still remain – especially regarding the gradual deployment of automated vehicle technology, and how human drivers adapt thereto. In light of these aspects it is not surprising that there is a number of open research questions to be addressed by future researches. In the following, we highlight some directions in which further research is recommended. Though these research prospects are related specifically to the contents of this thesis, they are also relevant for the general transportation research community, and the field of traffic flow modeling in particular.

Lane Change Modeling

The simulation framework developed in the scope of this thesis focuses exclusively on the car-following behavior of human drivers and automated vehicles. The next logical step would therefore be to extend the framework to include also the dynamics associated with lane changes. While several attempts have been made to incorporate more sophisticated human factor mechanisms into car-following models in recent years, this is not necessarily the case for lane change models. In fact, there is still a large discrepancy between what existing lane change models predict and how human drivers really behave [35]. The difficulty in the context of lane change modeling clearly lies in the limited availability of sufficiently detailed empirical data, and the complex decision making process involving operational, tactical, and strategic decisions on the part of the driver. Notwithstanding, there is still some way to go before the lane change behavior of human drivers is fully understood, and considerable efforts will be necessary to implement this behavior and the behavioral adaptations due to vehicle automation in traffic models.

Human Factors Related to Automated Driving

In the field of traffic flow modeling considerable efforts have been put into describing and simulating the behavior of human drivers and the dynamics of automated vehicles over the last years. Though these models incorporate different factors that govern the way human drivers behave, they generally do not account for the drivers' behavioral adaptations that arise from vehicle automation, or the changed role of the driver [420,421]. For example, previous research indicates that automated driving might entail a number of unpleasant side effects such as a degradation of driving skills, reduced vigilance, a loss of situation awareness, mental overload, or fatigue [67–70]. Recently, statistical support for the so-called lumberjack hypothesis has been provided, which states that as the degree of automation increases, those side effects increase as well [422]. Moreover, it is argued that partially automated driving might be particularly hazardous due to the inability of human drivers to remain vigilant for a prolonged period of time [423]. What these studies make clear is that considering the drivers' behavioral adaptations is crucial when investigating the impacts of vehicle automation, and there is thus an increased need for integrating those factors with our traffic models [421].

Integrated Traffic and Distraction Simulation

Integrating human error in traffic simulation models has recently gained increased attention within the scientific community, especially in the field of traffic safety analysis [424]. While traffic models usually describe how these errors translate into a deterioration of driving performance, the model proposed in this thesis allows for the explicit simulation of driver distractions and the integration thereof with microscopic simulation models. Though it was shown that the model is capable of reproducing the average secondary task engagement, i.e. how often and for how long drivers are preoccupied by a potentially distracting activity, to a sufficient extent, it still has its limitations. Those are primarily related to the underlying assumptions that drivers engage in distracting tasks independently from the surrounding traffic conditions, and independently from previous distractions. Both assumptions disregard any contextual and causal dependencies between secondary task engagements, and future work could therefore be devoted to relax those assumptions. This in turn demands for further research on distracted driving in general, since it is still largely unclear how contextual variables influence the drivers' engagement in secondary tasks, and how those tasks are causally related to each other [230].

Vehicular Communication Modeling

It is widely recognized that the deployment of vehicular communication technologies facilitating the exchange of traffic-relevant information either directly between traffic participants or with road-side infrastructure will unlock the true potential of automated driving [90, 91]. This claim is supported by the many studies reported in the literature suggesting that cooperative and connected driving might be able to improve both the safety and efficiency of traffic operations substantially compared to automation on its own. What a majority of these studies implicitly assumes, however, is that communication is functioning flawlessly at all times, without any delays or messages getting lost. The present thesis took account of "non-ideal" communication conditions by means of a transmission delay, recognizing that this is clearly a rather gross simplification. In fact, wireless communication in a vehicular environment poses a number of very unique challenges, not least due to the high mobility of the communicating nodes and the rapid temporal variability and non-stationarity of the radio propagation channel [366, 367]. A quite worthwhile branch of research would obviously be to integrate more complex models for describing the radio propagation characteristics of V2V or V2I communication channels into microscopic traffic simulations in order to bring simulations one step closer to reality.

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List of Acronyms and Abbreviations

ACC Adaptive Cruise Control

ADAS Advanced Driver Assistance System

AFR Accident Frequency Rate

AIMSUN Advanced Interactive Micro-Simulation for Urban and Non-Urban Networks

BASt German Federal Highway Research Institute

CACC Cooperative Adaptive Cruise Control

CAM Cooperative Awareness Message

CAH Constant-Acceleration Heuristic

CC Cruise Control

DDE Delay-Differential Equation

DENM Decentralized Environmental Notification Message

EMA Exponential Moving Average

ETSI European Telecommunications Standards Institute

GHR Gazis-Herman-Rothery Model

HDM Human Driver Model

HDM* Extended Human Driver Model

IDM Intelligent Driver Model

IAI Inter-Arrival Interval

ITS Intelligent Transportation System

LSE Least Squares Estimation

LTE Long Term Evolution

MLE Maximum Likelihood Estimation

MOBIL Minimizing Overall Braking Induced by Lane Changes

NHTSA National Highway Traffic Safety Administration

ODD Operational Design Domain

ODE Ordinary Differential Equation

OOP Object Oriented Programming

OSM OpenStreetMap

OTS Open Traffic Simulation

OVM Optimal Velocity Model

RE Relative Error

RCP Rich Client Platform

RSU Road-Side Unit

SAE Society of Automotive Engineers

SUMO Simulation of Urban Mobility

VANET Vehicular Ad-hoc Network

V2I Vehicle-to-Infrastructure

V2V Vehicle-to-Vehicle

VISSIM Verkehr in Städten – Simulations Modell

XML Extensible Markup Language

List of Symbols

Symbol	Unit	Description
		General
x_α	m	Longitudinal position of vehicle α
l_α	m	Length of vehicle α
s_α	m	Net distance between vehicle α and the vehicle ahead
v_α	m/s	Speed of vehicle α
Δv_α	m/s	Speed difference between vehicle α and the vehicle ahead
h_α	s	Time headway of vehicle α
Δt	s	Numerical simulation update time
		Intelligent Driver Model
v_0	m/s	Desired speed
T	s	Time gap
s_0	m	Stopping distance
a	m/s^2	Desired acceleration
b	m/s^2	Comfortable deceleration
δ	1	Dimensionless acceleration decay parameter
		Human Driver Model
T'	s	Reaction time
n_a	1	Number of spatially anticipated vehicles
V_s	1	Relative distance error
r_c	1/s	Inverse time-to-collision error

		Extended Human Driver Model
T'_{fd}	s	Reaction time in the free driving regime
T'_{cf}	s	Reaction time in the car-following regime
T'_{st}	s	Reaction time in the standing traffic regime
h^*_t	s	Time headway threshold
h^*_s	m	Space headway threshold
λ_r	1	Reaction time increase factor
λ_v	1	Speed reduction factor
		Distraction Model
e_d	1	Driver's exposure to a distracting task
n_d	1	Frequency of occurrence of a distracting task
μ_d	s	Average duration of a distracting task
σ_d	s	Standard deviation of the duration of a task
		Automated Vehicles
d_s	m	Sensor detection range
T'_s	s	Sensor delay
T'_a	s	Actuator delay
d_c	m	V2V communication range
T'_c	s	V2V communication delay
		MOBIL
$\Delta\dot{v}_{th}$	m/s^2	Hysteresis threshold
Δa_{bias}	m/s^2	Asymmetry term for "keep-right" directive
p	1	Politeness factor
		Fuel Consumption Model
P_0	kW	Base engine power
m	kg	Vehicle mass
μ	1	Friction coefficient
ρ	kg/m^3	Air density
A	m^2	Cross section surface
c_d	1	Aerodynamic drag coefficient
R_{dyn}	m	Dynamic tire radius
r_t	1	Gear transmission ratio
w_{cal}	kWh/l	Fuel energy density

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