

Developing Microscopic Traffic Simulation Models for the Transition Towards Automated Driving

Ivan Postigo



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Norrköping 2022



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Abstract

Vehicles with different capabilities for automated driving will gradually be deployed in road transportation systems over the coming decades. Mixed traffic conditions may change the characteristics of the traffic flow dynamics.

Microscopic traffic simulation is used for studying traffic flow dynamics in transportation systems. By simulating the interactions between individual vehicles, effects caused by changes in the road infrastructure, by road closures, or by the number and the types of vehicles can be investigated. Impacts on traffic performance can be analyzed in terms of travel times, travel time delays, queue formations, or vehicle throughput. To evaluate the impact of automated driving on traffic performance using microscopic traffic simulation, existing microscopic driving models need to be further developed to describe automated driving.

The aim of this thesis is to investigate how to further develop microscopic traffic simulation models for automated driving. In this investigation, the aspects to consider in simulation experiments including automated driving are identified. These aspects are the vehicle system, the role of authorities, the role of the users, of the infrastructure, of connectivity features, and of the sensor-based perception of the vehicles. A microscopic traffic simulation experiment showing the possible effects on a motorway in terms of vehicle throughput and travel delays is presented.

A conceptual model that describes how driving automation systems deal with the perception tasks is proposed. Future research directions will focus on implementing this model for perception in traffic simulation platforms and on the modeling of lateral tactical maneuvers.

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Chapter 1

Introduction

The use of motorized vehicles was a defining feature of the 20th century. It shaped societies, brought multiple benefits, and multiple challenges for a sustainable development. While it enabled a more unrestricted mobility of people and goods, it also created environmental issues concerning air pollution, land use, and energy usage. Another defining feature was, and still is, the rapid development of electronics, and of computer and information technologies. Thanks to the development of these technologies, many tasks and processes are now possible to automate. Automation is desired for its potential to improve efficiency, accessibility, and safety, for its potential to reduce operating costs, and to allow people to focus on more productive tasks. The vision of automating processes within the transportation system has existed for decades. It implies reducing the human input to the processes involved both in the management of the system as well as to the tasks involved in the driving activity.

Research on driving automation has been an area of growing interest over the past decade. An early publication (Varaiya, 1993), pointed out the implications of driving automation and the range of driving functions that can be automated by decomposing them into control tasks. The automation of the tasks would be enabled by a combination of different technologies placed both in the vehicle and in the road infrastructure. Over two decades later, uncertainties surrounding the implications of driving automation are still in the process of being answered and require further investigation. Some questions that arise are to what extent the required technologies are ready to enable automated driving, how the deployment of vehicles with these

technologies will take place, whether the infrastructure is ready to safely accommodate these vehicles, how other road users will adapt to these vehicles, and how the transportation system will be altered in terms of traffic efficiency and traffic safety.

The development of simulation tools has allowed to preemptively address many challenges involved in managing and developing transportation systems. Among these tools is traffic simulation. Microscopic traffic simulation is used for transportation planning. It is used to evaluate how changes in the infrastructure or in traffic control strategies would affect the transport system, in terms of traffic jams, queues, travel times, route choices, modal choices, etc. A main benefit of traffic simulation is that it allows to evaluate different possible scenarios in a safe environment and at a low cost. Traffic simulation can be used to evaluate the potential impacts caused by driving automation, and help plan for the deployment of vehicles capable of automated driving.

Among the possible traffic simulation approaches, microscopic traffic simulation provides a suitable platform to evaluate the effects on traffic flow dynamics. Microscopic traffic simulation focuses on the interactions between the different elements involved, i.e., vehicles, other road users, and road infrastructure. It has been used to assess how different driving styles affect road capacity, string stability, and in later years to evaluate the effects of driving support systems on traffic flow dynamics (Treiber and Kesting, 2013). The models used in microscopic traffic simulation to describe these interactions, commonly referred to as microscopic models, include driving submodels such as car-following and lane-changing models which describe human driving and are calibrated against real-world observations. In order to describe automated driving microscopic models have been modified focusing mainly on the car-following behavior and on the expected capabilities of driving automation systems.

The aim of this thesis is to further develop microscopic traffic simulation models to include the different aspects involved in automated driving. Existing microscopic driving models developed for human driving may be suited for automated driving as long as they are able to describe the expected differences between automated and human driving. Driving automation involves different technologies working together and enable new applications like cooperative driving. Many of these technologies are still rather new and have not yet been widely deployed, if at all. This limits the possibility to use observations for

the calibration and the validation of any microscopic model for automated driving.

Realistic near-future scenarios including automated vehicles can be investigated using traffic simulation as long as the tools are made ready. The societal impacts that can be investigated using microscopic traffic simulation are many: effects on traffic safety, environmental effects in terms of fuel efficiency and emissions, and effects in the traffic flow dynamics. These investigations will allow to anticipate and mitigate potential negative effects, and to help catalyze potential benefits of driving automation. The focus of this thesis is on the effects on traffic flow dynamics in motorway road environments during the gradual deployment of automated vehicles. Motorways present less complex environments compared to urban roads, and it might be there where automated driving may first appear. The gradual deployment of automated vehicles involves considering mixed traffic scenarios, which include both automated vehicles and human-driven vehicles at the same time. Automated driving is expected to gradually improve, thus, another consideration is the existence of automated vehicles at different stages of development, which affects the heterogeneity of vehicles present in mixed traffic conditions.

The following chapters provide a more detailed background for the work presented in this thesis, which is structured as follows; chapter 2 presents a description of automated driving, the concepts and terminology, and the expectations on the transportation system as a consequence of driving automation. Chapter 3 presents an overview of microscopic traffic simulation, microscopic models, and the common approaches to model automated driving in traffic simulations. In chapter 4 the objective, method, delimitations, and main contributions of this thesis are presented together with a summary of the included papers and proposed future research directions.

Chapter 2

Automated driving

The development of vehicles fully capable of automated driving, i.e., automated vehicles, is at early stages but is expected to be further developed over the coming years. Modern vehicles are equipped with driver assistance systems that already provide a certain degree of driving automation. This chapter presents concepts and terminology used in the field of driving automation, mostly proposed by the Society of Automotive Engineers (SAE) in its *Taxonomy and Definitions for Terms Related to On-Road Motor Vehicle Automated Driving Systems* (SAE International, 2021). Additionally, the expected impacts of automated driving on the traffic flow dynamics is also presented.

2.1 Concepts and terminology

First and foremost, the term *automated vehicle* refers to a vehicle capable of automated driving. Other terms commonly found in the literature are *autonomous vehicle* or *self-driving vehicle*, other less common terms are *robotic vehicle* or *driverless vehicle*. Terms like *connected automated vehicle* or *highly automated vehicle* can also be found and are used to emphasize specific features of the vehicle. The SAE does not recommend for any of these terms, and instead clarifies that it is the driving activity that is the object of automation and not the vehicle. Thus, the term automated vehicle focuses on its capability for *automated driving*.

The driving activity can be decomposed into different driving tasks and categorized into three levels of skills and control as proposed

by Michon (1985). These are strategic, tactical, and operational levels as seen in Figure 2.1. The term *dynamic driving task (DDT)* is used to refer to the real-time operational and tactical functions required to operate a vehicle. These include mainly the lateral and the longitudinal motion controls, and the object and event detection and response (OEDR).

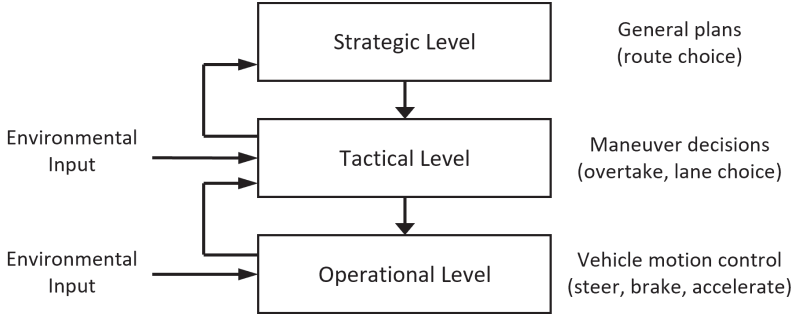


Figure 2.1: Hierarchical structure of the driving tasks (adapted from Michon, 1985)

The term *automated driving system (ADS)* refers to the hardware and software that are collectively capable of handling the entire DDTs. The difference with the more generic term *driving automation system* is on the extent of the tasks being automated. A *driving automation system* automates a specific DDT, examples of these are adaptive cruise control (ACC) or cooperative adaptive cruise control (CACC) systems which automate the longitudinal motion control, or collision avoidance systems which automatically engage the brakes of the vehicle when needed. The ADS centrally controls different driving automation systems which together automate all DDTs.

The *operational design domain (ODD)* is defined by the SAE as the operating conditions under which a given driving automation system or feature thereof is specifically designed to function. These conditions include environmental, geographical, time-of-day, traffic or roadway characteristics, etc. The ODD specification is important. If the conditions are not in place or change along the route, then a transition of control to the driver or a controlled safe stop may be needed. The ODD specification also determines the SAE level of driving automation of a vehicle, these levels are described in the following section.

The concept of *cooperative driving* is an application domain en-

abled by sensors and wireless communications. It involves gathering information and sharing it between vehicles to allow them to interact in a coordinated solution-oriented way. The most prominent goals of cooperative driving are to increase traffic safety and improve traffic flow performance (Herrtwich and Nöcker, 2003). Although not restricted to automated vehicles, the applications of cooperative driving can easily be envisioned without the need of human intervention.

2.2 Levels of driving automation

The SAE defines five levels (1-5) of driving automation for on-road motor vehicles SAE International (2021). The five levels of driving automation differ in the capabilities of the driving automation systems to handle the DDTs and in the roles the driver needs to be responsible for. In addition to the five levels, a level 0 which includes vehicles with driving assistance systems that do not automate any DDT is also included in the SAE categorization. Only vehicles at SAE levels 3-5 are said to be equipped with an ADS. The following are the main characteristics of each SAE level of driving automation.

- **SAE level 0 - No driving automation**

The vehicle may be equipped with driving assistance systems that may provide warnings or momentary emergency intervention. The driver is responsible for all DDTs.

- **SAE level 1 - Driver assistance**

The vehicle is equipped with a driving automation system which can perform part of the DDTs, either the longitudinal or the lateral motion control. The driver performs the remainder of the DDTs, supervises the operation of the driving automation system and determines whether a disengagement is appropriate. The driver is able to disengage the driving automation system immediately.

- **SAE level 2 - Partial driving automation**

The vehicle is equipped with a driving automation system which can perform both the longitudinal and the lateral motion controls part of the DDT. The driver performs the remainder of the DDTs, supervises the operation of the driving automation systems and determines whether a disengagement is appropriate.

The driver is able to disengage any driving automation system immediately.

- **SAE level 3 - Conditional driving automation**

The vehicle is equipped with an ADS capable of performing the entire DDTs within its ODD. The ADS determines whether the ODD limits are about to be exceeded and issues a timely request to the driver to take over control. The driver determines whether to engage the ADS considering the ODD, and is responsible for the drive at all times, even when the ADS is engaged. The driver needs to be receptive to a request to take over control and act in a timely manner. Additionally, they also determine whether the ODD limits are about to be exceeded and whether a disengagement is appropriate. The driver is able to disengage the ADS immediately.

- **SAE level 4 - High driving automation**

The vehicle is equipped with an ADS capable of performing the entire DDTs within its ODD. The ADS will transition to a minimal risk condition when approaching an ODD limit and prompts the driver to be ready to take over control. The driver determines whether to engage the ADS considering the ODD, once the ADS is engaged they are no longer responsible for the drive and become a passenger. The driver may request a disengagement and be given control if appropriate, after the ADS either reaches a minimal risk condition or detects the driver ready to take over, thus, the disengagement may be delayed.

- **SAE level 5 - Full driving automation**

The vehicle is equipped with an ADS with unrestricted ODD which is capable of performing the entire DDTs under all on-road conditions. The driver determines whether to engage the ADS and becomes a passenger. The driver may request a disengagement and be given control if appropriate, after the ADS either reaches a minimal risk condition or detects the driver ready to take over, thus, the disengagement may be delayed.

2.3 Infrastructure support for automated driving

The different elements of the road infrastructure can be categorized into physical and digital infrastructure (Farah et al., 2018). The physical infrastructure, i.e., the road design, can affect sight distances and the possibility to recognize different road elements. Cooperative technologies could help reduce safety risks involved in driving automation and could help improve traffic flow efficiency (Sanchez et al., 2016). The digital infrastructure refers to the elements of the infrastructure that enable wireless communications, sensors to monitor the traffic flow dynamics, high-precision positioning systems, and digital maps. The performance of the ADS can be improved by receiving additional information about the traffic and road conditions. Five levels of infrastructure support for automated driving (ISAD) have been proposed by Carreras et al. (2018). The following are the main characteristics of each ISAD level

- **ISAD level E - Conventional infrastructure**

The infrastructure does not provide any explicit support for automated driving. Automated vehicles need to rely on the on-board sensor system exclusively to recognize the road geometry and road signs.

- **ISAD level D - Static digital information**

Digital map support is available at this level. The map includes detailed road geometry, road signs, and physical reference points. Vehicles need to identify temporary work-zones, recognize state of traffic lights, and interpret information in variable message signs (VMS).

- **ISAD level C - Dynamic digital information**

Information of dynamic road signs, e.g. VMS or variable speed limit (VSL), is provided as support. Warnings, notification of incidents and weather information is available. Vehicles need updates on a regular basis (a few seconds) in order to be able to receive information in time.

- **ISAD level B - Cooperative perception**

The infrastructure is capable of perceiving detailed information about the stream of vehicles and relay this information to the

vehicles. In addition to the stricter connectivity requirements, sensors (e.g., cameras, radars) need to be placed on the road.

- **ISAD level A - Cooperative driving**

The infrastructure is capable of perceiving vehicle trajectories and of guiding vehicles to optimize traffic flow efficiency. Vehicles exchange information with the infrastructure constantly (milliseconds range).

Digital support provided for automated driving	Conventional Infrastructure		Digital Infrastructure		
	ISAD Level E	ISAD Level D	ISAD Level C	ISAD Level B	ISAD Level A
Digital maps with static road information	-	X	X	X	X
Dynamic road information: incidents, weather conditions	-	-	X	X	X
Detailed traffic information: vehicles' speed and positions	-	-	-	X	X
Vehicle trajectories and guidance: speed, gap, lane advice	-	-	-	-	X

Figure 2.2: Levels of infrastructure support for automated driving (ISAD) (adapted from Carreras et al., 2018)

Figure 2.2 summarizes the characteristics of the ISAD levels. The transition towards a prevalent presence of automated vehicles may require to upgrade the road infrastructure. The end goals of cooperative driving to improve traffic safety and traffic flow performance may only be possible with support from the infrastructure.

2.4 Expected impacts of automated driving on traffic flow dynamics

Milakis et al. (2017) presents a summary of the different implications of driving automation. These are divided into three levels. At the

highest level are the societal implications involving effects on air pollution, energy consumption, public health, social equity, and on the economy. The middle level include the infrastructure, land use, and vehicle implications. These involve impacts on road infrastructure, on parking infrastructure, on infrastructure for non-motorized transport, on vehicle ownership, and on vehicle design. At the lowest level are the travel costs, travel choices, and implications in traffic flow dynamics. The effects involved at this level include costs of vehicles and of travel, effects on vehicle and public transport use, and effects on road capacity and congestion.

Motorway capacity is expected to increase based on the assumptions that automated vehicles will show shorter reaction times and keep shorter distance gaps. These assumptions however, may strongly depend on the level of development of the ADS, and on specific connectivity features. The possibility of cooperative driving is expected to increase traffic safety and improve traffic flow performance, by performing well-planned coordinated maneuvers. These applications depend on whether the cooperative technologies that enable them are in place (Sanchez et al., 2016), as well as a traffic management strategy that oversees the transportation system. The potential benefits on traffic flow dynamics may only be observed after a certain market penetration rate of automated vehicles is reached. Lastly, the behavioral adaption of other road users may also play a role which may initially cause other drivers to be more cautious around automated vehicles, causing a decrease in motorway capacity.

Chapter 3

Microscopic traffic simulation

Microscopic traffic simulation is used to investigate the effects on traffic flow dynamics caused by changes in the infrastructure, to plan for road works, increases in vehicle volume levels, or to test traffic control strategies. Results from simulations can be shown in terms of travel times, travel time delays, traffic jam formations, or vehicle throughput. This chapter presents an overview of models for microscopic traffic simulation.

3.1 Microscopic models

Microscopic models describe the motion of each individual vehicle in the traffic stream. In contrast to macroscopic models, microscopic models model the traffic flow through the interactions between the particles that compose it. They can be distinguished between acceleration models (car-following) which deal with longitudinal movements, lane-changing models dealing with lateral movements, and discrete-choice models which deal with specific on-route decisions. (Treiber and Kesting, 2013).

Microscopic models are implemented in traffic simulation platforms. There are many of these platforms available both commercial and open-source. Detailed reviews about these platforms are presented in Barcelo (2010) and in a more recent review by Raju and

Farah (2021). Examples of commercial platforms are PTV Vissim and Aimsun, and of open-source platforms are SUMO and OpenTraffic-Sim. Raju and Farah (2021) show that the most popular microscopic simulation platforms used in recent scientific investigations of automated driving are PTV Vissim and SUMO.

3.1.1 Car-following models

Car-following models were developed to describe a driver's reaction to a preceding vehicle in terms of acceleration and in some cases in terms of speed. These models are considered to be complete if they describe the longitudinal motion of vehicles both under free flow and when approaching other vehicles. Car-following models can be categorized into safe-distance, stimulus-response, and action points models (van Wageningen-Kessels et al., 2015; Olstam and Tapani, 2004; Brackstone and McDonald, 1999).

In safe-distance models vehicles adjust their speed in order to keep a safe distance to the vehicle in front. The car-following model proposed by Pipes (1953) is one such model, it is based on a suggestion found in the California Vehicle Code and later branded as Pipes' rule: 'A good rule for following another vehicle at a safe distance is to allow yourself the length of a car for every ten miles per hour you are traveling'. Another example is the model by Gipps (1981) in which the vehicle is constrained by a desired speed when in free flow conditions, and by a safe speed when following another vehicle. The safe speed constraints vehicles to be able to decelerate to zero speed without colliding with the vehicle in front if it decelerates to standstill. In the Gipps model the speed of vehicle n at time t is calculated as

$$v_n(t + T) = \min \{v_{des}, v_{safe}\},$$

where,

$$v_{des} = v_n(t) + 2.5 \cdot a_n T \left(\frac{1 - v_n(t)}{V_o} \right) \sqrt{\frac{0.025 + v_n(t)}{V_o}},$$

$$v_{safe} = b_n T + \sqrt{b_n^2 T^2 - b_n \left(2s_n(t) - v_n(t)T - \frac{v_{n-1}^2(t)}{\hat{b}_{n-1}} \right)},$$

and,

$$s_n(t) = x_{n-1}(t) - x_n(t) - l_{n-1}$$

where v is the speed, $n - 1$ represents the vehicle in front of vehicle n , a and b are the maximum acceleration and most severe braking a driver wishes to undertake respectively, \hat{b}_{n-1} is the estimated deceleration of the vehicle in front, V_o is the desired speed, T is the driver's reaction time, and $s_n(t)$ is the distance gap between vehicles at time t , calculated by the difference between the position of the vehicles $x_{n-1}(t) - x_n(t)$ minus the length of the vehicle in front, l_{n-1} . An extended version of the model by Gipps was proposed by Krauss (1998). The Krauss car-following model is the default model in the SUMO simulation platform. Another example of a safe-distance model is the car-following model by Newell (2002).

Stimulus-response models propose that a driver's response, or change in acceleration, is due to three possible stimuli, their own speed, the distance to the vehicle in front, or the relative speed. The Gazis-Herman-Rothery (GHR) model (Chandler et al., 1958) is one of the earliest car-following model of this type. The model assumes that the acceleration response at time t , $a_n(t)$, is proportional to the vehicle's own speed v_n , and to the relation between the relative speed and the relative position to the vehicle in front. The formulation for the acceleration is

$$a_n(t) = \alpha \cdot v_n^\beta(t) \cdot \frac{(v_{n-1}(t - T) - v_n(t - T))}{(x_{n-1}(t - T) - x_n(t - T))^\gamma},$$

where α , β and γ are parameters to be determined. Another example for a stimulus-response model is the optimal velocity car-following model (Bando et al., 1995) in which the acceleration response is proportional to the difference between an optimal velocity and the current speed. The optimal velocity is calculated as a function of the distance to the vehicle in front. The intelligent driver model (IDM) (Treiber et al., 2000) is another example of this type of car-following model. The IDM is of particular interest because it has been widely adopted and it includes a variant describing an ACC system which is potentially useful for modeling automated driving. The stimuli considered in the IDM are the vehicle's own speed, the distance to the vehicle in front, and the relative speed. The mathematical representation of the acceleration of the IDM is

$$a_n(t) = a_{max} \left[1 - \left(\frac{v_n(t)}{V_o} \right)^\delta - \left(\frac{s^*(t)}{s_n(t)} \right)^2 \right],$$

where

$$s^*(t) = s_o + \max \left\{ 0, v_n(t) \cdot T_{safe} + \frac{v_n(t) \cdot (v_{n-1}(t) - v_n(t))}{2\sqrt{a_{max}b_{comf}}} \right\}$$

the parameters are a maximum acceleration a_{max} , a comfortable deceleration b_{comf} , a desired speed V_o , a safe time gap T_{safe} , a minimum space gap s_o , and a parameter δ to be determined. $s_n(t)$ is the distance gap to the vehicle in front at time t and $v_n(t)$ is the speed of vehicle n at time t .

Action point or psycho-physical models consider the finite perception threshold of humans. In these models it is assumed that drivers only react to large enough stimuli in contrast to safe-distance and response-stimuli models in which the reactions are continuous no matter how small the changes in stimuli are. The reactions occur only after reaching a threshold, or action point, defined in the relative speed and distance gap domain. An example of this type of car-following model is proposed by Fritzche (1994). In this model five driving regimes are proposed, a *danger* regime in which the distance to the vehicle in front is shorter than a risky distance, a *closing in* regime in which the distance to the vehicle in front is rapidly shortening, a *first following* regime in which the distance to the vehicle is shortening but without need for action, a *second following* regime in which the distance to the vehicle in front is kept by matching its speed, and a *free flow* regime. Another example of this type of car-following models is the one by Wiedemann (1974). An implementation of this car-following model is the default model in the PTV Vissim microscopic traffic simulation platform. Therefore, it is also of interest not only because of the wide use of this platform but also because variants of this model have been developed and are implemented specifically for automated driving (Sukennik, 2018). The model distinguishes between four driving regimes shown in Figure 3.1, a *free flow* or uninfluenced driving regime, a regime when *approaching* slower vehicles, a *following* regime near the steady-state equilibrium, and a *critical situation* where braking is needed to avoid collisions.

3.1.2 Lane-changing models

Lane-changing models describe the processes of changing lanes in multi-lane roads. They include both the decision process and the execution process. Unlike car-following models, there isn't a clear

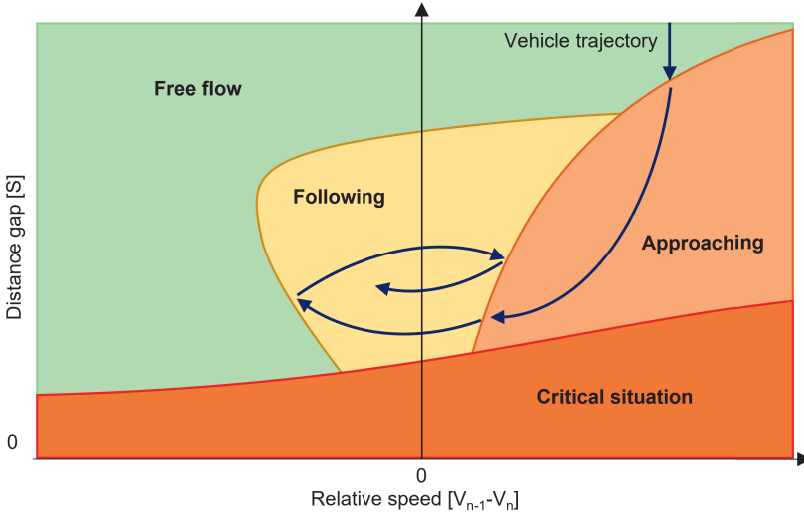


Figure 3.1: Representation of thresholds and regimes of the Wiedemann car-following model. The vehicle trajectory is represented by the arrows. (Adapted from Wiedemann, 1974)

consensus on how to categorize existing lane-changing models. Rahman et al. (2013) classifies them based on the logic used to describe the decision process into rule-based, discrete choice-based, artificial intelligence, and incentive-based models. Zheng (2014) distinguishes lane-changing models based on whether the focus is on either the decision-making process or on the impacts on surrounding traffic caused by the maneuver. Moridpour et al. (2010) presents a classification tree of models into driving assistance and driving decision models, the latter are further classified into operational and tactical models, and even further based on the logic and motivation for the maneuver. Most existing lane-changing models, however, make the distinction between mandatory lane changes and discretionary lane changes (Kessels, 2019).

Gipps (1986) presented a framework for the decision process for lane changes by answering three questions, whether its necessary to change lanes, whether its desirable to change lanes, and whether its possible to change. A main limitation of the process described by Gipps (1986), was that necessary (mandatory) lane changes may not always be possible and therefore not take place. This limitation was later addressed by Hidas (2002) by including a cooperative mechanism

which allowed the execution of mandatory lane changes. Thus, the distinction between mandatory and discretionary lanes changes is also considered by Gipps (1986) by answering the first two questions of his framework. The third question, regarding the feasibility, focuses on the execution of the maneuver. Different lane-changing models have different approaches to give answer to each question. Some models focus on the distance gap in the target lane (distance between new leader and new follower), where the maneuver would take place if the existing gap is large enough. Other models focus on the possible reactions of other vehicles and of the own vehicle that would be caused if the lane-changing maneuver takes place.

3.2 Microscopic traffic simulation of automated driving

Investigating automated driving using microscopic traffic simulations involves not only considering the driving models but also the setup of the experiments. The latter refers to including scenarios considering different market penetration rates of automated vehicles (e.g., Atkins, 2016; Sukennik et al., 2018; Li and Wagner, 2019), and heterogeneity of ADS (e.g., Mintsis, 2019; Olstam et al., 2020). The heterogeneity refers to the expected evolution of ADS over time and also to the possible differences in driving styles between original equipment manufacturers (OEMs). These considerations are important when focusing on the transition towards a prevalent presence of automated vehicles.

The number of scenarios can rapidly increase by just adding a few variables on top of the market penetration rate and the ADS heterogeneity. That, in addition to the required number of replications for each scenario to gather results statistically representative, can lead to very time-consuming experiments. Thus, the scope of each experiment should be well delimited.

One approach to model automated vehicle in traffic simulation models is by using models that describe ACC or CACC systems (e.g., Kesting, 2008; van Arem et al., 2006; Milanés and Shladover, 2014). An open database with data from commercial ACC systems is available and is useful for calibration and validation of microscopic models taking this approach (Makridis et al., 2021).

A different approach is by changing parameters in the car-following models and extending them if necessary. This approach is taken in the

implementation of automated driving logics in the microscopic traffic simulation platform PTV Vissim. The implementation is based on the car-following model by Wiedemann (1974) and assumes a deterministic driving style representing the little to no variations expected in the reactions of ADSs. Details of the implementation of the driving logics for automated driving are given in Sukennik (2018). The four driving logics implemented (i.e. rail-safe, cautious, normal, and all-knowing) represent different stages of development of ADSs.

Chapter 4

The present thesis

This chapter presents the objectives, delimitations and contributions of this work. Summaries of the scientific papers included in the thesis are also presented in this chapter.

4.1 Objectives

The overall aim of this thesis is to further develop microscopic traffic simulation models to include the aspects involved in automated driving. Having microscopic models ready will help traffic planners and transportation authorities anticipate and plan for the deployment of automated vehicles. Additionally, automated driving will enable the possibility for new traffic control strategies and for new applications which can be tested using microscopic traffic simulation.

Developing and implementing simulation models is commonly done by first observing real-world systems and identifying the factors that determine how that system operates. Second by proposing conceptual models that describe the system, third by transforming these conceptual models into simulation models and last by implementing them into simulation platforms. Understanding this process will help further develop microscopic models for automated driving. The following three research questions are formulated to achieve this.

1. **What aspects determine the safe operation of automated driving?**

For the microscopic modeling of automated driving we need to

identify aspects, both internal and external to the vehicles that influence the driving decisions of ADS. Simulation experiments and driving models need to capture the effects of the different aspects in the driving decisions.

2. What are the potential impacts of automated driving on traffic performance on motorways?

Due to the less complex conditions present in motorways compared to other roads (e.g. urban roads), it may be there where automated driving is first introduced. Microscopic models for automated driving have been proposed by adapting models originally developed to reproduce human driving. Mixed traffic conditions may be soon appear on motorways and there is a need to gain knowledge about this possible near-future scenario.

3. What differences between automated and human driving do microscopic models need to capture regarding the perception tasks?

The perception tasks involve the sensing and understanding of the different elements present on the road. Automated vehicles perceive these elements through on-board sensors, connectivity features and object recognition software while human drivers perceive them through their senses and cognitive processes. Microscopic models should capture key differences in perception that influence the decision processes in a way that is consistent, sufficiently generic, accurate, and simple. There is a need to find a modeling approach that captures these differences in a consistent way and at a suitable level of abstraction for microscopic traffic simulation.

Since there is limited possibility to observe automated driving in current transportation systems, the main challenge for proposing simulation models lies in identifying the possible factors involved and how these determine the operation of automated driving. For this reason, when proposing new microscopic models it is important to clearly present and justify the assumptions made.

4.2 Method

To answer the research questions, the work was divided into three sub projects with specific goals. The goal of the first sub-project

is to identify research gaps and state of the practice when studying automated driving using traffic simulations. A literature review was conducted following guidelines for literature reviews for transportation research projects (Avni et al., 2015). In the second sub-project the goal is to understand the potential impacts of automated driving on traffic flow performance on motorways. A simulation experiment was conducted using a commercially available microscopic traffic simulation tool. PTV Vissim was utilized since it includes driving models specifically implemented for automated driving and is a widely utilized tool by traffic engineers and transportation planners. The goal of the third sub-project, based on findings from the first two, is to develop a conceptual microscopic model which describes how an ADS performs the perception tasks. For this, in addition to looking into existing approaches to model human perception (e.g., situational awareness), sensor technologies, vehicular communications and the functional architecture of ADS were studied.

4.3 Delimitation

The focus of this thesis is on microscopic models for automated driving. The focus is on motorway environments since less complex situations and interactions are expected there, it is also where automated vehicles may be first introduced. On motorways, the interactions are expected to be mainly between cars and lorries and not with pedestrians, bicyclists, parked vehicles, public transport stops, or intersections. Additionally, due to its less complex nature, motorways may be the first road environments specified within the ODD of automated vehicles. The type of vehicles focused are light private vehicles, i.e., cars, at SAE levels 3, 4 and 5 of driving automation. Vehicles at this level of driving automation rely on the ADS to handle all DDTs, removing human factors, allowing to focus solely on automated driving. Extending the findings to other road environments and other types of vehicles is left for future research.

The traffic simulation experiment in this thesis focus on the transition period towards a prevalent presence of automated vehicles in the transportation system. For this reason, the experiment focus on mixed traffic conditions by considering varying market penetration rates and heterogeneity of automated vehicles.

The existing uncertainties in several dimensions related to auto-

mated driving, which in addition to the limited possibility to validate microscopic models, could raise questions about the trustworthiness of the forecasts presented.

4.4 Contributions

The objectives presented in section 4.1 were fulfilled with the following contributions:

- Identified the aspects to consider for the development of microscopic models for automated driving.
- Identified the state of the practice to model automated driving in microscopic traffic simulations.
- Quantified current expected potential range of effects on motorways during the transition period involving different styles of automated driving.
- Developed a conceptual microscopic model for the perception tasks for automated driving that is consistent about how the perception performance influences the driving decisions.

4.5 Summary of papers

The three papers included in this thesis are summarized in this section. In paper I, the state of the practice for modeling automated driving in microscopic traffic simulation is presented together with the required aspects that should be considered in microscopic models for automated driving. In paper II results from a microscopic traffic simulation experiment focusing the effects on traffic flow performance caused by heterogeneity of automated vehicles in mixed traffic conditions are presented. Paper III presents a conceptual model for the perception task for automated driving.

Paper I

Modeling Automated Driving in Microscopic Traffic Simulations for Traffic Performance Evaluations: Aspects to Consider and State of the Practice

This paper answers research question 1. The problem found after a literature review was the lack of consistency on the modeling of automated driving. The use of inaccurate terminology and lack of clear descriptions of the assumptions about automated driving made it difficult to interpret results and compare findings between studies. The first goal was to identify what aspects should be considered for the microscopic modeling of automate driving. Six aspects were identified, namely the role of the authorities, the role of the users, the vehicle system itself, the vehicle sensor-based perception, the vehicle connectivity features, and the role of the infrastructure both physical and digital. Figure 4.1 shows how the six aspects and how they define operational and safety constraints that determine whether automated driving is possible given the context. These aspects would also determine how automated driving should take place. The second goal was to review the state of the practice for modeling automated driving with respect to each identified aspect and whether findings from empirical studies were considered. The third goal was to identify the research needs from the empirical side which would provide input for microscopic models. The fourth and last goal was to encourage an inclusion of more detailed description with respect to each aspect in future traffic simulation investigations, to have a more clear frame for the results.

The paper is co-authored by Hannen Farah, Nagarjun Reddy, Yonqi Dong, Narayana Raju, Clas Rydergren, and Johan Olstam. The author of this thesis contributed to the conceptualization and development, and took the leading role writing the paper.

Paper I has been submitted for journal publication.

Contents of Paper I have been presented at:

- Swedish transportation research conference (online), Malmö, Sweden, October 2021.
- 101st Transportation Research Board Annual Meeting, Washington D.C., U.S.A., January 2022.

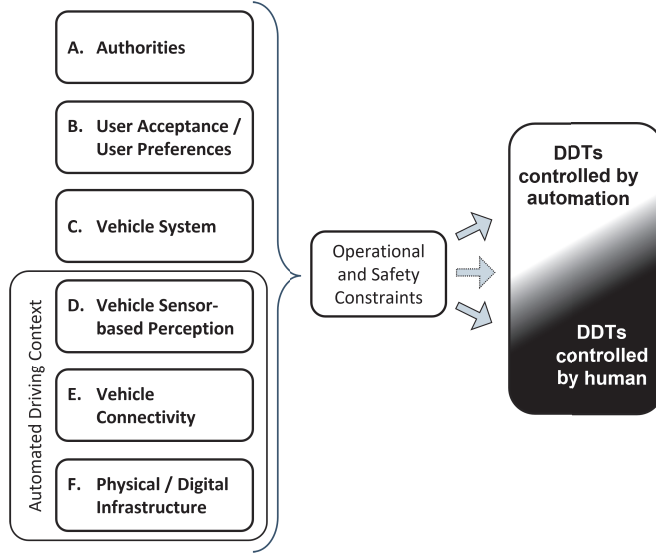


Figure 4.1: Aspects (A-F) to consider for modeling of automated driving in microscopic traffic simulation.

Paper II

Effects on Traffic Performance due to Heterogeneity of Automated Vehicles on Motorways: A Microscopic Simulation Study

Paper II answers research question 2. Previous studies that have used microscopic traffic simulation to investigate automated driving have often quantified the effects on traffic performance by running scenarios with different market penetration rates of automated vehicles. The simulation experiment in Paper II includes scenarios with different market penetration rates of automated vehicles and considered different styles of automated driving coexisting at the same time. Three different driving styles for automated driving were used, they developed within a previous research project and then implemented in PTV Vissim. Effects were measured in terms of vehicle throughput and travel time delays in a motorway network consisting of an off-ramp and an on-ramp. Results showed that the more advanced styles for automated driving would increase the vehicle throughput. The more conservative automated driving style would decrease the vehicle throughput.

The results show no interaction effects between the different driving styles, meaning that vehicle throughput increased as the share of automated vehicles with the more advanced driving style increased.

The paper is co-authored by Clas Rydergren, and Johan Olstam. The author of this thesis contributed to the simulation setup and results analysis, and took the leading role writing the paper.

Paper II has been presented at and published in the proceedings of the *7th International Conference of Vehicle Technology and Intelligent Transport Systems*, pp.142–152, January 2021 Contents of Paper I have been presented at:

- Swedish transportation research conference, Linköping, Sweden, October 2019.

Paper III

Perception Tasks for Automated Driving: A Conceptual Model for Microscopic Traffic Simulation

Paper III answers research question 3. In order to better understand results from experiments similar to the one presented in Paper II, it is necessary to take a closer look at the microscopic models and how the assumptions behind them define these models. Among the differences between the driving logics implemented in PTV Vissim were parameter values that specified the number of vehicles and objects that a vehicle would react to, as well as different values that specified the range of detection. The assumption behind is that automated vehicles will have different means for perception, and that more advanced vehicles would have access to more information through, for example, connectivity features. Paper III looks deeper into this assumption with the goal of proposing a more clear way to describe the perception tasks. A conceptual model that considers the different means of perception of ADSs and also human perception is proposed. By proposing an endogenous model, exclusive and explicit for the perception tasks we aim to capture the essential differences on these tasks between automated and human driving. Additionally, an endogenous model for perception solves the issue of inconsistency between microscopic models (e.g., car-following, lane-changing) that is, one model focuses on vehicles or elements ahead, other model focuses on vehicles on adjacent lanes or behind, leaving no clarity about the whole

context that a vehicle perceives. The model was developed aiming to be generic, accurate, and simple.

The paper is co-authored by Clas Rydergren, and Johan Olstam and is a working paper. The author of this thesis is contributing to the conceptualization, implementation and leading role in writing the paper.

Chapter 5

Concluding remarks and future research

Existing microscopic models for automating driving have focused on the vehicles' capabilities and on describing specific driving automation systems like ACC. However, aspects should not only concern the vehicles but also external factors that will determine how automated driving is handled. In Paper I, six different aspects to consider for the microscopic modeling of automated driving were proposed. The role of the authorities, the role of the users, the vehicle system, the vehicle sensor-based perception, the vehicle connectivity, and the role of the infrastructure. In order to improve the study of the impacts caused by automated driving using traffic simulation, it is necessary to include a clear description on what is considered within the transportation system and how it influences automated vehicles. A challenge is to include these aspects into microscopic simulation platforms, which can be by developing models that directly or indirectly impact driving models or by considering them in the experimental setup of the simulations. Input from empirical studies should be considered to reduce the uncertainties involved.

The simulation experiment presented in Paper II considered three ADSs each showing different driving styles in mixed traffic conditions. Aside from showing a range of effects measured in terms of vehicle throughput and travel delays, the experiment showed some of the shortcomings of the microscopic models for automated driving implemented in PTV Vissim. By looking at the merging maneuvers it

is clear that effort needs to be put in the models for lateral motion control, mandatory lane changes in some cases were just not taking place, which the simulator solved by simply removing the vehicle from the simulation. A large difference in vehicle throughput between the more cautious ADS and the more advance ADSs driving logics was measured. A difference when modeling the different ADSs was in the range of perception and the number of objects perceived. This approach to model the perception by changing parameter values does not capture the difference from how a human driver would perform the perception task and it is clear that there is room for improvement.

A possible approach to model automated driving would be by making parallels to the SAE levels of driving automation. The SAE taxonomy is useful to describe and understand the expected evolution of automated vehicles, and the SAE level of driving automation considered is a common inquiry when studying automated driving using traffic simulation. However, it is important to point out that vehicles at the same SAE level of driving automation may not necessarily have similar driving styles, and that vehicles at different SAE level of driving automation may have similar driving styles. Thus, microscopic models should focus on describing driving styles and not on matching a specific SAE level of driving automation. The expected heterogeneity of ADSs focuses on how different ADSs perform the DDTs differently regardless of the SAE level of driving automation.

Another possible approach to model automated driving is to directly use the software part of ADSs and use the logical processes and algorithms involved in handling the DDTs, instead of developing microscopic models. This approach would eliminate the need for validation as the driving logic is the same as implemented in vehicles. The immediate problem with this approach is that ADSs are currently still under development. The complexity of the algorithms implemented in ADS is such that a powerful on-board computer is an essential component of the ADS in able to compute the processes involved. Microscopic traffic simulation deals not only with one, but with a flow of several vehicles, which means that the computational requirement might make simulation non-viable. Moreover, even with ever-increasing computational power available, the important question is whether such a detailed approach would be practical for the purpose of microscopic traffic simulation. The focus of this thesis is on using microscopic traffic simulation to study the traffic flow dynamics caused by interactions of the vehicles involved, and the hypothesis is

that accurate results can be achieved through an adequate abstraction of both the real-world factors and of the algorithms involved.

Yet another possible approach is by using machine learning algorithms. These algorithms would utilize data in order to learn how to handle the DDTs. It is important to distinguish between the use of such algorithms in the real world and their use in microscopic traffic simulations. In the real world, ADS will make use of these algorithms to detect, classify and recognize objects and events, and possibly for some decision making while driving. These algorithms will be trained using data collected from real observations with the goal of guaranteeing a safe operation, and not necessarily to mimic other drivers. A machine learning algorithm used instead of a microscopic model in a traffic simulation would ultimately mimic the driving behavior of other simulated vehicles, which are based on microscopic models. Machine learning algorithms can be implemented in microscopic traffic simulation for the purpose of testing them, but not suitable for the purpose of studying traffic flow dynamics.

Microscopic models for human driving have been developed based from observations on existing transportation systems. The underlying conceptual models are based on the factors involved when drivers operate vehicles; the desire of drivers to travel at certain speeds, to keep certain distances and accelerations, and on their capabilities to handle the different tasks involved in the driving activity. To further develop microscopic models for automated driving, research can be focused further decomposing the driving activity into individual tasks and identify the possible factors that influence how ADSs and how human drivers would deal with each task differently. However, due to the limited possibility for real-world observations, conceptual models are difficult to validate.

Another approach (presented in Paper I) to enhance the inclusion of automated driving is to have a more explicit structure of the microscopic models within microscopic traffic simulation tools. A proposed approach is to have them organized hierarchically into tactical models, operational models, and models for other aspects to consider.

Future research will focus on simulation experiments using open-source microscopic traffic simulation platforms, which allow to both 'look under the hood' and tweak the microscopic models as desired. These experiments can later be compared to the simulation experiment presented in Paper II both in terms of results and in terms of approaches to model automated driving. Tactical lateral maneuvers

will also be in focus in future research. This topic is an often mentioned research gap, and is a key ingredient for achieving high levels of driving automation (SAE levels 3-5).

Finally, improving or further developing microscopic models makes microscopic traffic simulation an even more powerful and reliable tool for the different stakeholders in the field of transportation. As we move into the future and new technologies are incorporated in transportation systems, new challenges will arise and automated driving is a clear example of this. The ever-changing challenges within the field can be more easily tackled as long as the tools are ready for them.

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Abbreviations

ACC adaptive cruise control

ADS automated driving system

CACC cooperative adaptive cruise control

DDT dynamic driving task

GHR Gazis-Herman-Rothery

IDM intelligent driver model

ISAD infrastructure support for automated driving

OEDR object and event detection and response

ODD operational design domain

OEM original equipment manufacturer

SAE Society of Automotive Engineers

Bibliography

VMS variable message signs

VSL variable speed limit

Papers

The papers associated with this thesis have been removed for copyright reasons. For more details about these see:

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