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Investigation of automated vehicle effects on driver's behavior and traffic performance

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Abstract

Advanced Driver Assistance Systems (ADAS) offer the possibility of helping drivers to fulfill their driving tasks. Automated vehicles are capable of communicating with surrounding vehicles (V2V) and infrastructure (V2I) in order to collect and provide essential information about driving environment.

Studies have proved that automated vehicles have a potential to decrease traffic congestion on road networks by reducing the time headway, enhancing the traffic capacity and improving the safety margins in car following. Furthermore, vehicle movement and driver's behavior of conventional vehicles will be affected by the presence of automated vehicles in traffic networks. Despite different encouraging factors, automated driving raises some concerns such as possible loss of situation awareness, overreliance on automation and degrading driving skills in absence of practice. Moreover, coping with complex scenarios, such as merging at ramps and overtaking, in terms of interaction between automated vehicles and conventional vehicles need more research.

This thesis work aims to investigate the effects of automated vehicles on driver's behavior and traffic performance. A broad literature review in the area of driving simulators and psychological studies was performed to examine the automated vehicle effects on driver's behavior. Findings from the literature survey, which has been served as setup values in the simulation study of the current work, reveal that the conventional vehicles, which are driving close to the platoon of automated vehicles with short time headway, tend to reduce their time headway and spend more time under their critical time headway. Additionally, driving highly automated vehicles is tedious in a long run, reduce situation awareness and can intensify driver drowsiness, exclusively in light traffic. In order to investigate the influences of automated vehicles on traffic performance, a microscopic simulation case study consisting of different penetration rates of automated vehicles (0, 50 and 100 percentages) was conducted in VISSIM software. The scenario network is a three-lane autobahn segment of 2.9 kilometers including an off-ramp, on-ramp and a roundabout with some surrounding urban roads.

Outputs of the microscopic simulation in this study reveal that the positive effects of automated vehicles on roads are especially highlighted when the network is crowded (e.g. peak hours). This can definitely count as a constructive point for the future of road networks with higher demands. In details, average density of autobahn segment remarkably decreased by 8.09% during p.m. peak hours in scenario with automated vehicles. Besides, Smoother traffic flow with less queue in the weaving segment was observed. Result of the scenario with 50% share of automated vehicles moreover shows a feasible interaction between conventional vehicles and automated vehicles. Meaningful outputs of this case study, based on the input data from literature review, demonstrate the capability of VISSIM software to simulate the presence of automated vehicles in great extent, not only as an automated vehicle scenario but also a share of them, in traffic network. The validity of the output values nonetheless needs future research work on urban and rural roads with different traffic conditions.

Acknowledgments

The research behind this master thesis carried out at Ingenieurbüro Schwietering in Aachen-Germany. PTV Group assigned one-year student license of VISSIM 7.00 with the limitation of 10.0 km*10.0 km network size. ASFINAG provided the vehicle input data for the simulation study.

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Erfan Aria

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1 Introduction

Automated vehicles have passed miles of test runs on multiple road types under various traffic conditions. In near feature, a mixed traffic situation is likely to emerge where equipped vehicles with different degree of automation will interact with unequipped vehicle drivers (Gouy, 2013a). Advanced Driver Assistance Systems (ADAS) such as adaptive cruise control, lane keeping assistance or emergency brake assist have already significantly affected the traffic flow. Soon, more assistance systems will be implemented in new vehicles and will affect the traffic performance measures.

In recent decades, growing population has indicated higher transportation demand which caused a bottleneck for traffic networks and further city development (Wei, 2013). Studies have proved that automated driving illustrates the potential to decrease the traffic congestion on road networks by enhancing the traffic capacity, improving the safety margins in car following and reducing time headways (Jamson, 2013).

Despite these encouraging factors, autonomous transportation raises some concerns such as possible loss of situation awareness, overreliance on automation and loss of required driving skills for resuming to manual control. These issues look more critical in case of system failure (Gouy, 2013a). Besides, complex scenarios like merging at ramps, lane closure, overtaking and intersections need more investigation. Bearing in mind that most knowledge related to driving behavior in automated vehicles are based on driving simulator studies, real traffic condition needs to be examined (Amditis, 2015). In addition, effects of the automated vehicles on traffic system must be investigated. Since the number of present automated vehicles in road network can affect the traffic system, different scenarios should be studied to evaluate the consequences of various share of automated vehicles within the network.

While not all investigations can be performed through a field study, microscopic simulation model is a suitable and accessible mean to use. Microscopic traffic simulation software is a simulation tool which measures traffic performance parameters. Traffic simulation models provide the possibility to study the traffic performance of a road network, like density, overall speed, delay etc. and probe the potential congestions within network. In addition, unavailable or partially available technologies, such as car platooning can be examined in a safe simulation environment.

1.1 Aim and Research Questions

The major aims of this thesis work are:

1. To examine the effects of automated vehicles on behavior of conventional vehicle drivers;
2. To investigate the influences of automated vehicles on traffic performance measures;
3. To investigate the possibility to evaluate a typical automated scenario using microscopic traffic simulation models.

The aim will be explored by investigation on the following questions:

- How well can a state-of-the-art microscopic traffic simulation model simulate a share of automated vehicles? Is it possible to adjust a state-of-the-art microscopic traffic simulation model to represent the behavior of automated vehicles by tuning the driving behavior parameters?
- Which measures should be considered to evaluate how well a microscopic simulation software can model the presence of automated vehicles?
- How do automated vehicles affect the traffic performance?
- How comparable are the results with results from previous studies?

1.2 Method Description

A broad literature review in the area of driving simulators and psychological studies followed by clarifying the technical terminologies was done for fulfilling the first aim. Findings from the literature survey served as setup values in the simulation study of the current research work.

In order to achieve the second aim and the subsequent research questions, a specific microscopic traffic model was simulated. In this thesis work, a calibrated traffic network model in VISSIM microscopic simulation software (in German, Verkehr In Städten - SIMulationsmodell) was utilized. A case study consisting of three different scenarios, i.e. one scenario with only conventional vehicles (CV), one with only automated vehicles (AV) and one with 50% conventional and 50% automated vehicles (AV50%), was examined. Different driving behaviors were defined and allocated to conventional vehicles and automated vehicles, i.e. parameters such as gap acceptance, maximum/accepted deceleration, temporary lack of attention, etc. were assigned separately for each type of vehicle. In order to evaluate the traffic performance, numbers of measurement tools such as data collection points and vehicle travel time measurement were applied within the network. Moreover on critical link segments, queue counters were set to evaluate the length and frequency of probable queues. Take into account the thesis hypotheses, detailed analysis of the simulation output answer the research questions from different aspects.

1.3 Outline and Scope of Research

In this thesis work, the effects of automated vehicles on traffic performance measures and driver's behavior are presented. In Chapter 2, ADAS and automation concept in road transport are investigated and benefits and challenges along the road automation are discussed. Besides, technical terminologies in road automation topic, such as ADAS and autonomous transportation system, are clarified. Following, review of former researches from the view of driver's behavior experiencing automated vehicles, driver adaptation and probable behavior changes such as intention of overtaking, visual attention and minimum gap acceptance as well as traffic measure improvement are summarized in Chapter 2. Chapter 3 outlines microscopic traffic simulation with a broad description of applied car following and lane changing model in VISSIM. Last section in this chapter explains the modelling approach of automated vehicles in VISSIM.

The simulation case study, design and description of the scenarios, limitations and finally the simulation results following with discussion and analysis of the simulation output are described in Chapter 4. In this chapter, selected scenarios have been investigated by using a microscopic traffic simulation model to evaluate relevant traffic performance measures. A simulation with conventional vehicles has been performed and compared with two separate scenarios with presence of different percentage of automated vehicles within the network. Chapter 5 presents the conclusion and further research works.

1.4 Hypotheses

1. Due to car platooning and acceptance of shorter gap by automated vehicles, it is hypothesized that the density of the road segments in AV scenario will increase and it will be higher than CV scenario.
2. In AV scenario, smoother traffic flow with less queue in the weaving and off-ramp segment is anticipated.
3. Average travel speed and average travel time are hypothesized to be improved in AV scenario.

1.5 Delimitations and Assumptions

The following delimitations and assumptions have been taken into account:

- All the automated vehicles are assumed to have the same automation level and this level is assumed to be the high automation level.
- The case study only considers three different scenarios of 0%, 50% and 100% share of automated vehicles.
- The output from driving simulator (collected from the literature review) and former research works assumed to be reliable and accurate.
- Driver's lack of attention plays a significant role in road accidents. It is assumed that in CV scenario, 1.0% of drivers have 0.5s temporary lack of attention on driving task in autobahn.
- Three car following behavior parameters in VISSIM, i.e. Look ahead distance, look back distance and number of observed vehicles are served as communication means for automated vehicles with their surroundings. Extensive explanations concerning the mentioned parameters are presented in subsection 3.1.1.
- It is assumed that in AV50% scenario, conventional vehicles will adapt their behavior to the short time headway maintained by automated vehicles, by reducing their own time headway (Gouy, 2013b).

2 From Advanced Driver Assistance Systems to Automated Driving

This chapter narrows down the subject from the idea of automated driving to the benefits and concerns. Different terminologies such as ADAS, Automated driving, Vehicle to vehicle/infrastructure (V2V/V2I) communication and Autonomous Transportation System (ATS) are clarified. Section 2.4 and 2.5 try to answer the first thesis aim in order to examine the effects of automated vehicles on driver's behavior and behavioral adaptation, while the presented content in other sections serves as a buttress in knowledge of road automation and better comprehension of the concept. Finally, the experimental output from former researches in section 2.6 is used as set up values for the microscopic simulation case study.

2.1 State-of-the-art in Automated Transport Systems

Within the last thirty years of study and experiment on vehicle technology, vehicles that are capable of communicating with surrounding vehicles (V2V) and infrastructure (V2I) have been developed. These vehicles can collect useful information about driving environment in order to assist the driver to fulfil the driving tasks and experience a convenient movement (Gouy, 2013a).

In 1939 at the World's fair, General Motors brought up the idea of an automated vehicle for the first time and almost after forty years, Ernst Dickmanns and his team were pioneers for developing the first operating automated car. This work took place at the Bundeswehr University in cooperation with Mercedes-Benz. In 1994, Ernst Dickmanns and his team after around seven years of experiment claimed that their driverless cars were able to drive more than thousand kilometers on the motorway in real traffic condition (Gouy, 2013a). Since that time, the intelligence level of automated vehicles has upgraded from a basic lane centering mode to lane-changing capability and overtaking. Between 2004 and 2007, DARPA Grand Challenge and DARPA Urban Challenge provided a realistic testing environment where the autonomous vehicles from different participants were able to examine the artificial intelligent algorithms, computing technology and technical part like sensor technology for autonomous driving. Autonomous vehicles in these two competitions were dealt with nearly light human driven traffic in a closed test field (Wei, 2013).

At the TechCrunch Disrupt conference in 2010 Google's CEO, Eric Schmidt, mentioned that the future humans should let their cars to be on autopilot. Lately in 2010, Google announced that their autonomously self-driving cars driven around the San Francisco Bay area. Besides, other car manufacturer such as General motors, Volkswagen, BMW, Audi, Volvo and Toyota are also working in this idea, while companies like Intel, Bosch, Tesla and Cisco are developing required hardware and software (TU Automotive, 2015). For example, Intel is developing the artificial intelligent algorithms for critical road situation and moreover to override the driver in case of risky driving (Chiang, 2013). After releasing Google's autonomous driving platform in 2011, Google in 2012 declared that their Lexus and Toyota have driven more than 500,000 km on multiple public roads under various traffic conditions with only a few human interventions

(Wei, 2013, Gouy, 2014). By releasing the video of Google autonomous vehicle by the end of 2013, hopes for having automated and autonomous vehicles in near future has been consolidated (Google, 2014a, 2014b).

Although a lot of efforts have been devoted to elaborate this concept as far as possible, there is still more adjustment needed to present a trustful transportation means. Wei (2013) believed that due to limited capability of autonomous vehicles to perceive and cooperate with driving environment in heavy traffic condition, these vehicles won’t perform as well as human drivers (Wei, 2013). As a supporting statement to that, Jan Becker, director of engineering and automated driving of Bosch, explained that the current sensors are not sufficiently robust to let the driver stay out of the driving loop. Andreas Mai, director of smart connected vehicles at Cisco, added that even Google’s latest autonomous car is only able to drive in pre-mapped area. Nevertheless, it has faced some difficulties while navigating in rainy and snowy weather conditions (TU Automotive, 2015). Due to the obstacles in front of self-driving vehicles, John Capp, GM's director of electrical controls and active safety technology believed that we still have 20 to 30 years to achieve fully autonomous vehicles (USA Today, 2013).

For these reasons we can say that the self-driving or autonomous vehicle would be more of a futurity outcome of next decade.

2.2 ADAS and its Intervening Role

Advanced Driver Assistance Systems (ADAS) are systems that offer the possibility of helping the driver to fulfill the driving task. Moreover, it helps to avoid risky situations, e.g. inappropriately high speed, collision with an object ahead or with a vehicle in the adjacent lane, etc. The success of an ADAS aims to improve traffic safety depends on the functionality of the system and the willingness of people to use them (Haupt, 2014). Improving the level of service (LOS), energy consumption and reduction of CO_2 emissions are the advantages of a successful ADAS.

Table 2-1 outlines a summarized list of the most important ADAS, type and level of their intervention along with a brief description of each system. In order to define the intervention level of different ADAS, Michon (1985) proposed a hierarchical level of the driving task, as he has called them as three levels of skills and control: Lowest level (Operational level), Intermediate level (Tactical level) or Advanced level (Strategic level). On the Operational level, system assists in control-based activities of driving tasks such as steering, braking and speed control. On the tactical level, maneuver control includes compromising with traffic signs, other road users, lane changing, merging and warns driver about threatening collision. At the end, strategic level makes decision concerning driving route and also means of transportation.

Carsten and Nilsson (2001) have distinguished three different types of ADAS intervention. First type offers relevant and irrelevant information to driving tasks such as navigation. This type called ‘Driver information system’. The second category, Driver warning system, alerts driver of threatening hazards like lane departure system. Final type which provides active support with direct intervention to drivers in taking over part of driving tasks, called intervening system.

Lateral assistance prevents drivers from unconscious lane departure and longitudinal assistance precludes from lengthwise collision (Gouy, 2013a).

Table 2-1: List of ADAS including technical supports

Name	Description (Haupt, 2014)	Level of intervention	Type of intervention	Direction of Control
Anti-lock Braking System (ABS)	Reduces the brake pressure in hard braking situation to avoid blockade of the wheels	Operational level	Intervening system	Longitudinal assistance / Lateral assistance
Electronic Stability Control (ESC)	Counteracts the over steer or under steer of the vehicle by the specific breaking of the individual wheels	Operational level	Intervening system	Longitudinal assistance / Lateral assistance
Traction Control System (TCS), also known as Anti-Slip Regulation (ASR)	prevents wheels from spinning in acceleration	Operational level	Intervening system	Longitudinal assistance
Braking Assistance System (BAS)	Provides the necessary pedal pressure in a braking action	Operational level	Intervening system	Longitudinal assistance
Emergency brake assist	Initiates an automatic emergency brake when recognizing critical situations	Operational level	Intervening system	Longitudinal assistance
Adaptive Cruise Control (ACC)	Automatically keeps the distance to the leading vehicle. If no leading vehicle exists, it will keep the driver given speed	Operational level	Intervening system	Longitudinal assistance
Pre-crash warning system	Warns the driver when recognizing critical situations	Tactical level	Driver warning system	Longitudinal assistance
Blind spot monitor	Warns the driver of a threatening collision while lane changing	Tactical level	Driver warning system	Lateral assistance
Lane Keeping assistance (warning/active)	Supports the driver actively in keeping the vehicle in the lane by performing automatic steering corrections	Tactical level	Driver warning system / Intervening system	Lateral assistance
Intelligent Speed Adaptation (ISA) (warning/active)	Supports the driver in keeping the current speed limit by adapting the vehicle's speed automatically to the given speed limits in the driven section	Tactical level	Driver warning system / Intervening system	Longitudinal assistance
Navigation system	Provides route guide information to the driver	Strategic level	Driver information system	-

2.3 Classification of Vehicle Automation Levels

One of the earliest taxonomy of level of automation is the one proposed by Sheridan and Verplank in 1978 in which they have divided automation into ten different levels. Although this is the most cited automation taxonomy (Gouy, 2013a) but from the author of the present thesis perspective, this classification is not optimal and precise enough anymore, since more accurate and specific categorization has been presented by SAE, NHTSA and BASt.

2.3.1 SAE Classification

In January 2014 the Society of Automotive Engineers (SAE) issued the standard J3016 and has categorized automated driving in six main levels (SAE, 2014):

Level 0 - No automation:

This level represents the **Conventional driving** with the complete responsibility of all aspects of dynamic driving by the human driver. In this approach, all the driving tasks have to be handled by the human driver and even in case of any raised warning driver should react to the hazard situation.

Level 1 - Driver assistance:

In this level, the driving mode jointly performs by a **Driver Assistance System (DAS)**, either steering or acceleration/deceleration. For achieving this goal, the DAS uses the information about the driving environment with the expectation that the human driver performs all the remaining aspects of the dynamic driving task. For instance, Electronic Stability Control (ESC) automatically assists the driver with breaking.

Level 2 - Partial automation:

This level of automation, also known as **Advanced Driver Assistance Systems** (**ADAS**), is almost the same as previous level with the following difference that the driving mode executed by one or more DAS of both steering and acceleration/deceleration. Parking with remote control is an example for level 2 application.

Level 3 – Conditional automation:

The driving mode performs by an automated driving system which takes responsibility of all aspects of dynamic driving task. This level of automation, which the appropriate response of the human driver to an intervention request is expected, called **Automated driving**. Some examples of application for this level are as followings (Johansson, 2014):

- Garage parking;
- Parking in multi-level garage;
- Parking in special areas;
- Stop and go.

Level 4 – High automation:

Highly automated driving is more or less the same as level 4 with the main difference that the vehicle can handle all dynamic driving tasks even if a human driver doesn't respond appropriately to an intervention request. One example for high automation level is Safe stop application. Google self-driving car is an example of highly automated driving.

Level 5 – Full automation:

In addition to taking advantage of all the previous levels, full automation can control the vehicle under all types of roadways and various environmental conditions without any need of a human driver. The vehicle fulfills the whole driving tasks relying on the artificial intelligence (AI) software that can analyze and decide in all kind of traffic situation. By describing the characteristics of this level, the reader can conclude that there will be no driver anymore who controls/can control the driving tasks and all people inside the car count as passengers, regardless of their position (Diels, 2014). This final level of automated driving is called **Autonomous driving** which categorized as **Autonomous Transportation System** (**ATS**).

2.3.2 NHTSA Classification

While SAE has defined vehicle automation in six levels, the US Department of Transportation's National Highway Traffic Safety Administration (NHTSA) has another perspective in this regard. NHTSA (2013) has categorized vehicle automation in five levels with different definitions and characteristics:

- Level 0 – No automation
- Level 1 – Function-specific automation
- Level 2 – Combined function automation
- Level 3 – Limited self-driving automation
- Level 4 – Full self-driving automation

The first four levels are somehow comparable to the SAE's taxonomy with some minor differences in the definition, especially in level one. These differences mostly concern the quantity of involved driver assistance systems. But it seems that level four and five of SAE category have been combined and introduced as a unique level of full self-driving automation in NHTSA classification. The definition of level four in NHTSA classification is more close to the last level in SAE classification and it looks that the high automation level was quite ignored. Besides, NHTSA has brought Google car as an example of limited self-driving automation which contradicts to the author's point of view. In fact, level three of automation (conditional automation, comparable to NHTSA level 3) expects the driver to respond appropriately for an intervention request, while the Google car doesn't have control system such as steering wheel to engage the human driver in the driving tasks. Therefore, author believes that Google car can be an example for high automation level (based on SAE classification).

2.3.3 BASt Classification

The German federal highway research institute – BASt (in German: Bundesanstalt für Straßenwesen) has presented an automation classification similar to the SAE. BASt (2013) uses five levels:

- Level 0 – Driver only
- Level 1 – Assisted
- Level 2 – Partially automated
- Level 3 – Highly automated
- Level 4 – Fully automated

Although the above levels are respectively analogous to the five initial levels of SAE, the last two levels of BASt represent other characteristics unlike their titles. To be more clarified, level three and level four of BASt respectively carry the content of conditional and high automation levels of SAE which brings some confusion. In addition, autonomous driving (SAE level 5) has not been taken into account.

Table 2-2: Summery of vehicle automation level. Source: (Smith, 2013)

SAE level	Narrative definition	NHTSA level	BASt level
No Automation	the full-time performance by the human driver of all aspects of the dynamic driving task, even when enhanced by warning or intervention systems	No automation	Driver only
Driver Assistance	the driving mode-specific execution **by a driver assistance system** of **either steering or acceleration/deceleration** using information about the driving environment and with the expectation that the human driver perform all remaining aspects of the dynamic driving task	Function-specific automation	Assisted
Partial Automation	the driving mode-specific execution **by one or more driver assistance systems** of **both steering and acceleration/deceleration** using information about the driving environment and with the expectation that the human driver perform all remaining aspects of the dynamic driving task	Combined function automation	Partially automated
Conditional Automation	the driving mode-specific performance **by an automated driving system** of all aspects of the dynamic driving task **with the expectation that the human driver will respond appropriately to a request to intervene**	Limited self-driving automation	Highly automated
High Automation	the driving mode-specific performance **by an automated driving system** of all aspects of the dynamic driving task, **even if a human driver does not respond appropriately to a request to intervene**	Full self-driving automation	Fully automated
Full Automation	the full-time performance **by an automated driving system** of all aspects of the dynamic driving task **under all roadway and environmental conditions** that can be managed by a human driver		-

2.3.4 Summary of Automation Level Taxonomy

To come in conclusion, Table 2-2 presents the vehicle automation levels according to SAE, NHTSA and BASt. John Absmeier, director of Delphi's Silicon Valley Lab, believes that it’s hard to talk about a technology when everybody has a different idea of what it means (TU Automotive, 2015). Authorities and automakers should come to a unique view of automation and publish a standard which is worldwide applicable. The author imagines that this can accelerate the process of legislation enactment for highly automated and autonomous vehicles, since discussions in this regards still hasn’t come to an agreement.

2.4 Benefits of Automated Driving

According to different studies in the past, Gouy (2013a) collected some valuable statistics and data about the usefulness of ADAS and automated driving. Results of an investigation by Treat et al. (1979) has shown that in 93% of accidents in a 2,258 road accident samples, human error was a contributory factor, while a famous research by Sabey and Taylor (1980) revealed 95% of road accidents are partially and 65% of them wholly due to human errors.

In addition, when the driving task workload exceeds driver’s capability, road accidents occur as a consequence. As an example in a type of error called ‘’looked-but-failed-to-see’’, driver may declare that he didn’t see the object which he collided with, although this object was located in a clearly visible position within his field of view.

To overcome the human errors, benefits of ADAS and automated driving can present a better driving condition in traffic network. Improvement in safety, road network capacity and fuel efficiency are some of their advantages. Previous studies have revealed that the proper choice of various ADAS can improve the overall flow of the traffic network (Kesting, 2008). Furthermore, automated systems bring the possibility to keep tight time headway in road network without affecting traffic safety.

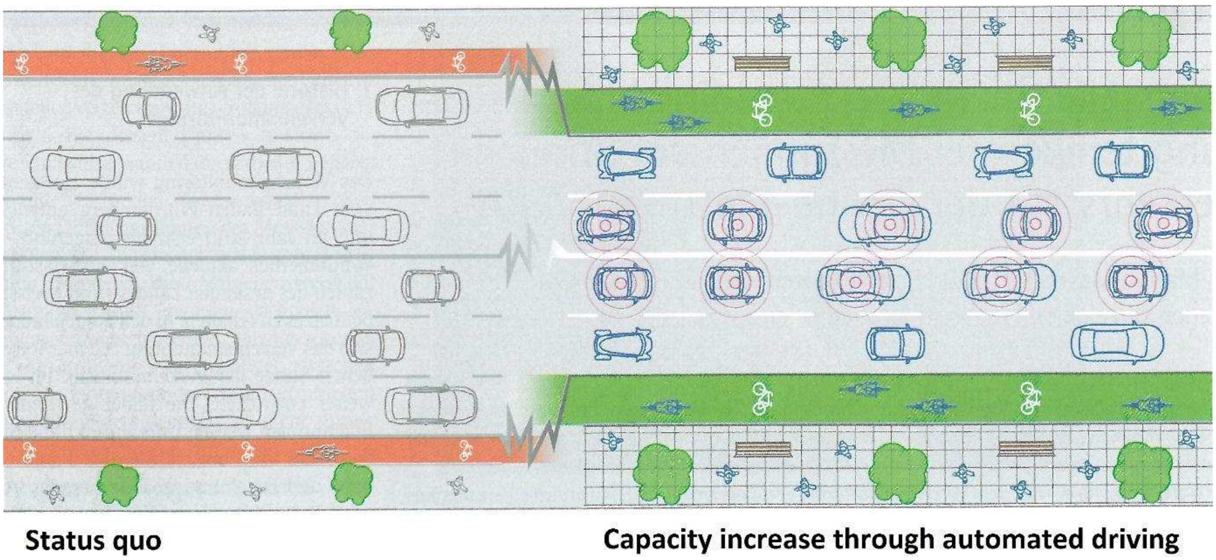

Figure 2-1: Possible potentials by the automated driving. Source: (Rotfuchs, 2015)

A schematic view of the status quo and the future of roadways in presence of automated vehicles is shown in Figure 2-1. As depicted in this figure, by presence of automated vehicles with V2V and V2I communication, Car platooning can be practiced which can practically reduce the gap between vehicles in a platoon. As a result, the capacity of the road network will increase (Ntousakis, 2015). Therefore, the number of lanes can be decreased (which ends up to a denser road) and can be replaced by wider sidewalks and bicycle lanes. In other words, we also encourage passengers to use cleaner transport modes. Thus, saving more space and smoother traffic flow are the effects of automated driving as well. Moreover, it can be assumed that by growth of automated vehicle's presence, the probability of shared use of cars transport mode such as carpooling will be strengthen (Fagnant, 2013). Fagnant and Kockelman (2013) have discussed the annual economic benefits of automated vehicles in the United States. Considering that how much percentage of vehicles in the road network is automated, the amount of benefits is different. In Table 2-3, some of the benefits are mentioned.

Table 2-3: Estimates of annual economic benefits of automated vehicles in U.S. Source: (Fagnant, 2013)

	Percentage of present AV		
Benefit	**10%**	**50%**	**90%**
Lives saved (per a year)	1100	9600	21700
Economic cost savings	\$5.5 B	\$48.8 B	\$109.7 B
Travel time savings (M hours)	756	1680	2772
Fuel savings (M Gallons)	102	224	724
Parking savings	\$3.2	\$15.9	\$28.7
Change in total number of vehicles	-4.7%	-23.7%	-42.6%

By taking a brief view to the figures in this table, we can conclude that the higher the automated vehicles are, the safer roads with less accident we have. This can be indirectly recognized from economic cost savings as well. From traffic performance perspective, having more automated vehicles in road network will result in considerable travel time savings and consequently fuel savings. In addition, higher percentage of automated vehicles can be ended up to lower total number of vehicles on our roads. To interpret this, we can assume vehicles with more passengers (e.g. use carpooling mode) and subsequently more saved parking fees are the outcomes of future automated roads. In other words, automated vehicles can provide the opportunity for having denser vehicle with more passengers rather than more private car.

2.5 Challenges and Concerns

As discussed in previous section, automated driving brings safer transport, higher road capacity, less fuel consumption and smoother traffic flow. In spite of all reassuring technical results, highly automated vehicles raise a range of concerns. Each of them can partially disorganize the driving tasks or potentially endanger the whole movement. Some of the most conceivable automation challenges are listed as below:

Possible Loss of Situation Awareness

Indeed, vehicle automation brings along signs of fatigue. Although in-vehicle tasks potentially distract drivers from their supervisory role, drivers experiencing high level of automation show more tendency to become involved with secondary tasks (Jamson, 2013, Carsten, 2012).

In-vehicle tasks, also known as secondary tasks, are all side activities while driving which may support the driving tasks, whilst the primary task includes all direct driving activities to control the vehicle, e.g. steering, braking and throttling. For instance, activating the windshield wipers, radio tuning, using in-vehicle information systems (IVIS) such as navigation system and using mobile phones are some examples of secondary tasks. It should be considered that in-vehicle tasks can potentially distract the driver form the main driving task and reduce the situation awareness.

Ironically, if the system has low failure rate and high reliability, overreliance on the automation system will reduce the readiness for transition to manual control of the vehicle (Gouy, 2013a, Johansson, 2014). As Merat (2014) has proven, it approximately took drivers around 35-40 seconds to stabilize again their lateral control of the vehicle regardless of fixed or variable transition interval. Even eye fixation and lateral driving precision has shown a 10-15 seconds lag time between automation disengagement and the vehicle control resumption by the driver. Besides, more research on human factor of driver involvement in occasional control of the vehicle is still needed.

Degrading Driving Skills in Absence of Practice

Driving tasks include series of consequent cognitive actions which can be counted as an adventitious skill. In absence of practice, driver will lose these skills to control the vehicle manually (Gouy, 2013a) which could led to wrong decision or longer transition time from automatic to manual.

Poor Monitoring of Driver on the Automated Control System

Apparently, human beings are not well suited for supervising technical systems (Johansson, 2014). Especially when the vehicle drives well enough, driver demonstrate symptoms of tiredness, gets distracted soon with eyes watching off road or amused by infotainment systems (Carsten, 2012, Merat, 2014).

System Failure

All of the above mentioned challenges will be more crucial in case of system failure. All software and hardware are human-made and possible to malfunction or crash. Therefore a new system architecture for highly automated vehicles is needed. Jan Becker, director of engineering and automated driving of Bosch, by stating that the today’s vehicles are fail-safe designed, believes that the future vehicles should be fail-operational produced so that if one of the components fails to operate, the rest of vehicle automatic system afford to continue functioning (TU Automotive, 2015).

Loss of Connection with the Outside World

Automated vehicles and especially autonomous vehicles operate intensely-dependent on the information provided by communication means. And what if the connection is lost?

Information such as positioning for navigation via Global Positioning Systems (GPS) or Assisted GPS (A-GPS), communication to other vehicles (V2V) or infrastructure (V2I) and traffic center are some examples of undeniable need of these vehicles for communication. Supposing that the connection is lost by any chance, future vehicles must be self-sufficient from their surroundings. This is the belief of the Volvo group revealed for "Drive me" project in Gothenburg (VDI, 2015), however Chiang (2013) supposed that advanced techniques such as Global Positioning System (GPS) can make the autonomous vehicles closer to the market. Contradictorily, Delphi's Absmeier believes that even highly accurate GPS is not sufficient to afford all driving challenges (TU Automotive, 2015). To put it in nutshell, vehicles should rely on their own sensors and internal automated systems to function rather than outside requisite. In addition, the performance can be enhanced by incorporating communicated information if they are reliable and stable.

Safety and Security

Nvidia's perspective is to have a centralized super computer to handle all car's numerous sensors which apparently creates a more reliable and efficient system. However, infotainment systems won't merge with other car's functions. Nvidia CEO pointed out that infotainment systems may be under the exposure of hackers which they can access to vehicle control systems remotely. Steffen Linkenbach, director of system and technology for Continental Automotive Systems, believes that the safety features of the car should be independent of the automated driving, so that if any failure happened in automated driving mode, it will not affect the movement task. Especially when the fully autonomous vehicles are presented, the carmaker is responsible to take care of the system safety. On the other hand, indicating SAE ISO26262 Automotive functional safety standard, Jan Becker, director of engineering and automated driving of Bosch, believes that this standard stipulates the sufficient safety requirement for current and future technical system and no special changes needed in the future (TU Automotive, 2015).

In contrast, the author is doubtful about this claim. Are the state-of-the-art automated vehicles safe and robust enough to deal with some critical situations and undefined conditions? For instance (Schoettle, 2015):

- Recognizing unusual traffic participants such as ridden horses or large non-automotive farming vehicles,
- Flooded roadway,
- Downed power line after a hurricane,
- Unexpected explosion and fire on the road,
- Police hand directing or construction crew's directing sign.

Certification and Legislation

In article 8 of Vienna conventional on road traffic, it has been stated that:

> *"Every moving vehicle or combination of vehicles shall have a driver"*

And in article 13:

> *"Every driver of a vehicle shall in all circumstances have his vehicle under control…"*
> (Vienna convention, 1968)

Besides, UN/ECE regulation R79, which is based on Vienna convention, permit the automated steering only at lower speeds (max 10 km/h). Consequently, current legislations are a hurdle for vehicle automation and new amendments are needed.

One of the possibilities of autonomous transportation could be right side overtaking permission. As stated in Chaing et al. (2013), highly automated vehicles will bring the opportunity of both sides overtaking on multi-lane highways (Chiang, 2013). It should be mentioned that this may be a more efficient way of road capacity use, but still concerns about unequipped vehicles interacting with equipped vehicles remain questionable and need further experimental research. The author believes that road administration department and the authorities need to consider this issue on the current driving regulations.

2.6 Driver's Behavior Investigation of Automated Vehicles

The following subsections present the improvement of traffic performance measures and behavioral adaptation of drivers experiencing various traffic conditions and different assistance systems. First of all, the most prominent tool for studying the driver's behavior is described. Platoon behavior of autonomous vehicles and lane changing behavior are considered. Moreover, modeling of driver behavior due to cooperative assistance system is discussed. In addition, behavioral changes of drivers facing highly automated vehicles and driving close to automated vehicles with shorter time headway are briefly discussed.

2.6.1 Driving Simulator

Study on driving behavior and measuring traffic performance parameters can be done via two main methods: Field study or Simulation.

Driving simulators and traffic simulation are two different simulation tools. Driving simulator enables the study on driver's behavior such as gap acceptance, maximum driven speed, intention of overtaking and visual attention, while traffic simulation model facilitates the investigation on traffic networks in order to evaluate traffic performance measures like density, overall speed, delay etc. and probe the potential congestions in network. Each of two simulation approaches can be used for specific purpose and has some advantages and drawbacks. Obviously not all investigations can be performed through the field study, moreover, driving simulator is also a quite expensive method to experiment different parameters of driver's behavior. Therefore, this fact leads the researchers and traffic planners to be meticulous in selection of study tool.

Most investigation of driver's behavior of automated vehicles are conducted by using driving simulators. According to the Weir & Clark report, Gouy (2013a) explained different types of driving simulators. Static or Low-level simulator normally includes a PC with a monitor and simple vehicle control system. Mid-level simulator consists of advanced imaging techniques, a large projection screen, a complete vehicle with all required control systems and probably a simple motion system. Dynamic or High-level simulator typically presents almost 360 degree view together with an extensive moving base. Mentioned types of simulator are illustrated in Figure 2-2 to Figure 2-4.

Gouy (2013a) clarified the preferences of the driving simulator to field studies based on a report by Carsten & Jamson (2011). The advantages of driving simulator can be summarized as:

1. Driving simulator provides investigation of unavailable or partially available technologies on the market and special traffic conditions, such as platooning.
2. Driving simulator presents a safe environment to examine potentially hazardous situations, such as distraction impact of mobile phones or drugs and alcohol usage on driving performance.
3. While many effective factors on driver's behavior cannot be controlled or be tracked in a field study such as traffic density or weather change, driving simulator provides an acceptable controllability of the experimental test. On the other hand, driving simulator has a higher internal validity and lower external validity.
4. Desired performance measures are always accessible in a simulator study (e.g. speed and gap). In contrast, these data are more challenging to obtain from a field study.

Regardless of all described benefits, it's still unclear what the appropriate research tool for any behavioral aspects of the driving task is.

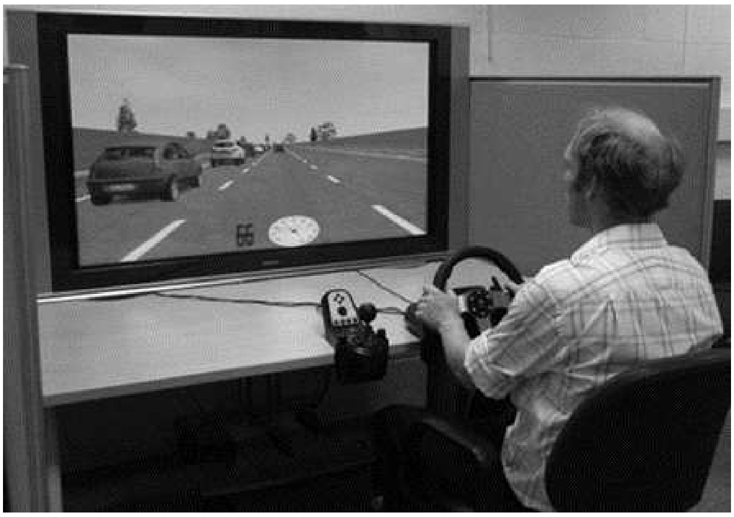

Figure 2-2: Static simulator. Source: (Gouy, 2013b)

Figure 2-3: TRL Mid-level simulator. Source: (Gouy, 2014)

Figure 2-4: VTI Dynamic simulator. Source: http://esv2015.com/technical-demos

2.6.2 Highly Automated Vehicle

Jamson (2013) presented a study conducted at Leeds University, in which 49 drivers (25 male) with the mean age of 36.8 years old and 17.5 years of driving experience took part in a driving simulator experiment. This simulator is a high-level simulator which also records driver eye-tracking and measure driver fatigue. For considering driver behavior, parameters such as lane keeping, speed choice and time-exposed-time-to-collision (TETTC) (in order to assess the longitudinal safety margin) was evaluated. The study was designed in two manual and highly automated level in light (500 Veh/h/lane) and heavy (1500 Veh/h/lane) traffic volume.

The result of this study revealed that drivers using high vehicle automation preferred less lane changing in order to overtake slower moving traffic. In other words, the tendency towards automated-mode disengagement is less, especially in heavy traffic condition although it may increase the journey time. Therefore mean speed was observed to decrease significantly. Safety margins in light traffic condition improved, nonetheless no specific improvement in heavy traffic condition was observed. Evidences show that driving automated vehicle is tedious in a long run, reduce situation awareness and intensify driver drowsiness exclusively when the road is quiet and the traffic is light. The other important factor in automated vehicles is that in-vehicle infotainment systems (such as tuning the radio, playing chosen multimedia stream, route navigation and making phone calls) potentially distract the driver from the supervisory tasks. On the other hand, drivers also incline more to involve in secondary tasks rather than supervisory role. The last two observations bring some sort of concerns in partially or conditionally automated vehicles, while immediate response of the driver for intervention in the vehicle control is vital (Jamson, 2013).

2.6.3 Platoon Behavior of Autonomous Vehicles

In 2013, Chiang and Chan simulated the autonomous vehicles on a Java virtual machine. The focus of the study was on the safety decision of vehicle behavior. Inspiring from the flock movement of animal, they modified the flock algorithm in order to attract vehicles in car following movement. Attraction, repulsion and orientation are the three main rules which especially influence the flock behavior and have been set in order to simulate the steering behaviors in autonomous vehicles. By comparing the performance information of different vehicles, they came up with maximum acceleration (0-100 km/h) and minimum deceleration (80-0 km/h) to 3.19 m/s^2 and -6.97 m/s^2. The mentioned values are used as input for further simulation. Applied algorithm in this work, regardless of the normal maneuver behavior, let the vehicles to overtake the front car from the right side as well as left side.

Following assumptions have been made:

- All vehicles, regardless of the type and size, simulated as autonomous.
- All vehicles completely (360°) detect their surroundings. In other words, every car is totally aware of other vehicles around which approach it.
- 15.85% of the vehicles with the maximum speed of 95 km/h, 68.30% with the highest speed between 95 and 105 km/h and 15.85% above 105 km/h drive in the network. These speed limits have been fed to the simulation program.

Then, they considered six detection areas around the car to define a safety area (bounding box = 4m×3.75m) covering all possible interference of neighboring vehicles. The goal of the system, beside group motion behavior of autonomous cars, is to minimize the waiting time of the vehicle for group movement. Two driving mode has been defined, called ‘push mode’ and ‘non-push mode’ which in push mode, the car behind the group of vehicles pushes itself to join the vehicle group as fast as possible in order to travel together. Considering 3 to 6 vehicles in each group, waiting time in push mode varies from 14s to 33.7s. The waiting time in non-push mode is extremely high and varies from 331.4s to 504.8s. While these results are in a straight three-lane highway, the same scenario with a curved-lane highway was also studied. Although the average gap in both scenarios with the highest density of 60 vehicles is around 16.5 meters, but the shortest distance between two cars in curved-lane scenario is 7.0 meters, while 16.14 meters in straight-lane scenario. Surprisingly, waiting time in non-push mode for a curved-lane highway is less than straight-lane highway, varying from 279.4s to 338.6s. Nevertheless, there is no more concrete information in this report explaining its reason.

All in all, the result showed a steady system with no collision occurred in simulation (recognizable from the shortest distance) and the pushing mode seems more practical and acceptable comparing to non-push mode. The system algorithm can be applied to autonomous vehicle which supports the concept of vehicle to vehicle communication (V2V), but more critical scenarios such as merging ramp should be studied (Chiang, 2013).

2.6.4 Cooperative Assistance Systems in Road Congestion

Laquai et al. (2011) designed an experiment using a low-level driving simulator with 30 drivers (18 male) so that the impact of vehicle to vehicle or infrastructure (V2X) communication on apprising driver about future traffic condition, which forced to be decelerated, be examined. The set up scenario was a non-moving traffic jam on a bad visibility curve within a 1.8 km long three lanes highway with an evenly distributed group of 20 cars. Laquai (2011) believed that 200 meters is the maximum area around the car that can be scanned and covered up by the state-of-the-art radar and ultrasonic sensors.

The output of the driving simulator experiment was depicted into two diagrams showing average speed vs. time and travelled distance vs. time. The findings lead to development of a simplified model of the deceleration phase. This model consists of a section with constant speed trailed by a Gaussian shaped deceleration curve. Later, the scenario was remodeled in the PELOPS (FKA, 2010), sub-microscopic traffic simulation, in order to evaluate the model. For this purpose, the Simulink model was introduced in the processing loop of PELOPS.

As a result, assistance system can raise the safety and reduce the fuel consumption. These are the outcome of early information about upcoming traffic situation. By and large, all drivers managed to decelerate appropriately regardless of their speed. It was found that higher starting speed leads to sharper deceleration and shorter time gap between a warning alert and reaction.

2.6.5 Effects of Short Time Headway on Non-Equipped Vehicle Drivers

Between 2012 - 2014 Gouy et al. (2013b, 2014) conducted series of driving simulator studies using the driving simulator at the Transport Research Laboratory (TRL) in UK. The aim of these studies was to examine the influence of shorter time headway (THW) kept by platoon of automated vehicles on conventional vehicles driving within the network. First study contains three traffic conditions (Gouy, 2013b): Forty-two participants were asked to follow a leading vehicle in a platoon with large THW of 1.0 second, short THW of 0.3 seconds and the last one which the leading vehicle was the only present vehicle. Second study (Gouy, 2014) experimented with thirty participants and the same traffic conditions, but the large THW was 1.4 seconds.

The research instrument in the first study (Gouy, 2013b) was a static simulator and the experimental environment was a 12.5 km route with the free flow speed of 70 miles/h (≈112.65 km/h).

Results of this study revealed that the preferred THW of non-equipped vehicle drivers remains constant, while the adopted THW differentiates significantly according to the applied traffic condition. This headway adaptation has especially observed in the traffic condition with 0.3 seconds THW. It's concluded that presence of equipped vehicles in a platoon with short THW leads drivers of conventional vehicles to drive closer to their preferred limits.

Used driving simulator in the second study (Gouy, 2014) was a mid-level (fixed-based) driving simulator. Driving environment of this study was a three-lane left-hand straight motorway with the UK's speed limit of 112.65 km/h which drivers drove for 16 minutes. The outcome of the second study proved that existence of platoon of vehicles keeping short THW has a notable effect on tactical behavior of non-equipped drivers by mean THW, i.e. participants maintained on average 0.12 seconds smaller THW in platoon condition with THW of 0.3 seconds. Assuming the speed of 93 km/h, this THW difference will lead to a distance of 3.1 meters between vehicles. In addition, it has been observed that numerous participants spent more time under their critical THW threshold of 1.0 second. In other words, drivers tend to reduce their THW while driving close to a platoon of vehicles maintaining shorter THWs.

Nonetheless, none of the aforementioned studies illustrated any carryover effect from confronting short THW to long THW and vice versa.

2.6.6 Lane Changing Behavior

By aggregating what other researches stated, Luo (2014) found that 21% of the highway accidents are associated with lane changes which 10% of them dealing with sideswipe crashes and 11% with angle crashes.

In the last 50 years of microscopic traffic simulation models, there was a slight trend from treating vehicle movements based on fluid dynamic formulas toward individually treating of the vehicles as a particle subject to a group of forces. Although this way of consideration predicts the integrative, long-term parameters, such as average speed in dense traffic, but these models were less successful in modelling the higher cognition level of human driver with strategic consideration. To get a better view of the conscious part of driver's behavior, tactical and strategic behavior are defined.

Tactical behaviors involve actions with temporary benefits. For instance, overtaking, coordinating the speed with the next lane for a safe lane change and quick swerving to escape a hazardous situation are examples of tactical behaviors. Strategic behaviors point to more general decision made by driver to guarantee the whole driving success. Joining folks of vehicle travelling together (platooning), route planning or choosing the appropriate lane in highway are some examples of strategic behavior (Luo, 2014).

Results of the field study conducted by Rosenfeld et al. (2014) showed that the driving type of the drivers has a strong impact on their desired time headway. For instance, when the ACC is disengaged, drivers keep the time headway about 0.8 to 1.2 seconds regardless of their driving type. On the other hand, all driver types chose longer time headway when ACC was engaged. It means that hunters keep a mean time headway of 1.0 second, while gliders peak at about 2.0 seconds corresponding to the maximum gap value. Nonetheless, all driver types were more willing to keep the ACC mode engaged. Supporting this observation, Jamson (2013) concluded that drivers experiencing high vehicle automation, showing less tendency to lane changing (see subsection 2.6.2). Rosenfeld et al. (2014) concluded that driver characterization is necessary in order to adapt automated systems inside the vehicles. This issue is more noticeable to recognize the engagement or disengagement tendency of the ACC by users. Nevertheless, authors have declared that in this study, following items were not available:

- Broad knowledge about traffic patterns;
- Weaving behavior of surrounding drivers;
- Traffic density in right or left lanes of the drivers;

which may clearly impact the driver's decision.

3 Traffic Simulation of Automated Vehicles

Microscopic traffic simulation software is an appropriate tool to study traffic performance of a road network and measure specific performance parameter, such as density, travel time, etc., under different scenarios and traffic conditions. It is also possible to probe the potential congestion within the network. Traffic simulation tools are widely used around the world for transport planning and management. Conducting a simulation study comparing to a field study or simulator study is cheaper and the scenario can be replicated, rerun and modified several times.

Furthermore, not all new ADAS technologies can directly be examined via a field study. Microscopic simulation enables the study on specific ADAS or new driving behavior and evaluate the effect of it on traffic performance. Especially, microscopic simulation software let us define the automated vehicles characteristics and investigate their effects on network traffic performance. An essential component of such tools is a set of mathematical models of driver behavior, like car following and lane changing model but not limited to longitudinal movement models, lateral movement models, and route choice models. The development and calibration of such models rely on an in-depth comprehension of the complexity of driver behavior.

This chapter outlines microscopic traffic simulation with a broad description of applied car following and lane changing model in VISSIM. Section 3.2 explains the modeling approach of automated vehicles in VISSIM.

3.1 Microscopic Traffic Simulation

There are three general categories representing the traffic streams; Macroscopic, mesoscopic and microscopic which represent traffic simulation models according to the level of details from low to high respectively. Microscopic models represent the traffic stream with high level of details (Olstam, 2009), while mesoscopic and macroscopic models exhibit rather packets of vehicles in network or lower details as travel demand between origin and destination.

Microscopic models not only simulate individual vehicles in a network, but also show the interaction with each other and between vehicles and the infrastructures. They provide the opportunity to study and investigate the effects on traffic performance due to changes in the infrastructure (e.g. changed intersection design) or driving behavior (e.g. changes in car following behavior, lane changing, overtaking or behavior due to ADAS) (Olstam, 2009). It's obvious that studying the traffic network let the traffic planners to evaluate the state-of-the-art of the network, investigate the bottlenecks and traffic jams and estimate the traffic performance of the network facing higher demand based on growing population.

Most prominent developed software for microscopic simulation are VISSIM, AIMSUN and Paramics (Olstam, 2009). VISSIM, is one of the well-known microscopic simulation software which is nowadays widely used by traffic engineers and transport planners (PTV, 2015). During the early 1970s, this software was developed at the University of Karlsruhe - Germany. Commercial distribution of VISSIM began however in 1993 by PTV Group (Aghabayk, 2013).

Beside all the benefits such as multimodality, accuracy and ease of use, the high productivity level of VISSIM lets the user to build a model effectively (PTV, 2015).

The traffic flow model in VISSIM, which is based on the continued work of Rainer Wiedemann for car-following process and Wiedemann and Reiter (1992) for lane-changing maneuvers, is a discrete, stochastic, microscopic model with driver-vehicle-units as single objects. The model contains a psycho-physical car following model for longitudinal vehicle movement and a rule-based algorithm for lateral movements which are based on human perceptions and reaction research. Although the calibration parameters are not just limited to the parameters associated with the car following and lane changing model, these parameters cause significant differences in simulation results and directly affect the vehicle interactions (Aghabayk, 2013). Therefore, they should be especially considered. The car following and lane changing models and their associate parameters are explained in the following subsections.

3.1.1 Car Following Model

Two car following models exist in VISSIM: Wiedemann 74 and Wiedemann 99. Both models are based on perception thresholds. A significant difference between them lies in how perception thresholds are implemented (Motamedidehkordi, 2015). The former one is suggested to be applied for urban traffic and merging areas and the latter one is more suitable for interurban (freeway) traffic (PTV, 2014). The concept of Widemann car following model is that the faster moving vehicle driver starts decelerating as soon as he reaches his individual perception threshold to approach a slower vehicle. However, his speed may become smaller than the lead vehicle speed as the results of driver's imperfection in estimating the speed of leading vehicle. This means his speed will fall below that vehicle's speed until he starts to slightly accelerate again after reaching another perception threshold (Aghabayk, 2013, PTV, 2014).

The Wiedemann 74 Car Following Model

Figure 3-1 depicts the car following behavior of a vehicle based on explained logic. Several regimes can be used to describe the follower's behavior. A common setup is to use three regimes: free driving, normal following and emergency deceleration (Olstam, 2009). However, the basic idea of the Wiedemann model is the assumption that a driver is in one of the four driving modes: Free driving, Approaching, following or braking. The first three driving modes are illustrated conceptually in Figure 3-1.

Different parameters in this figure are described as following (Aghabayk, 2013):

- AX: The average desired distance between two cars in a standstill condition.
- BX: The minimum following distance which drivers consider as a safe distance.
- CLDV: The points at short distances where driver perceives that his speed is higher than the speed of leading vehicle.
- OPDV: The points at short distances where driver perceives that he is travelling at a lower speed than his leader.
- SDX: The maximum following distance indicating the upper limit of car following process.
- SDV: the threshold wherein a driver recognizes that he is approaching a slower vehicle.

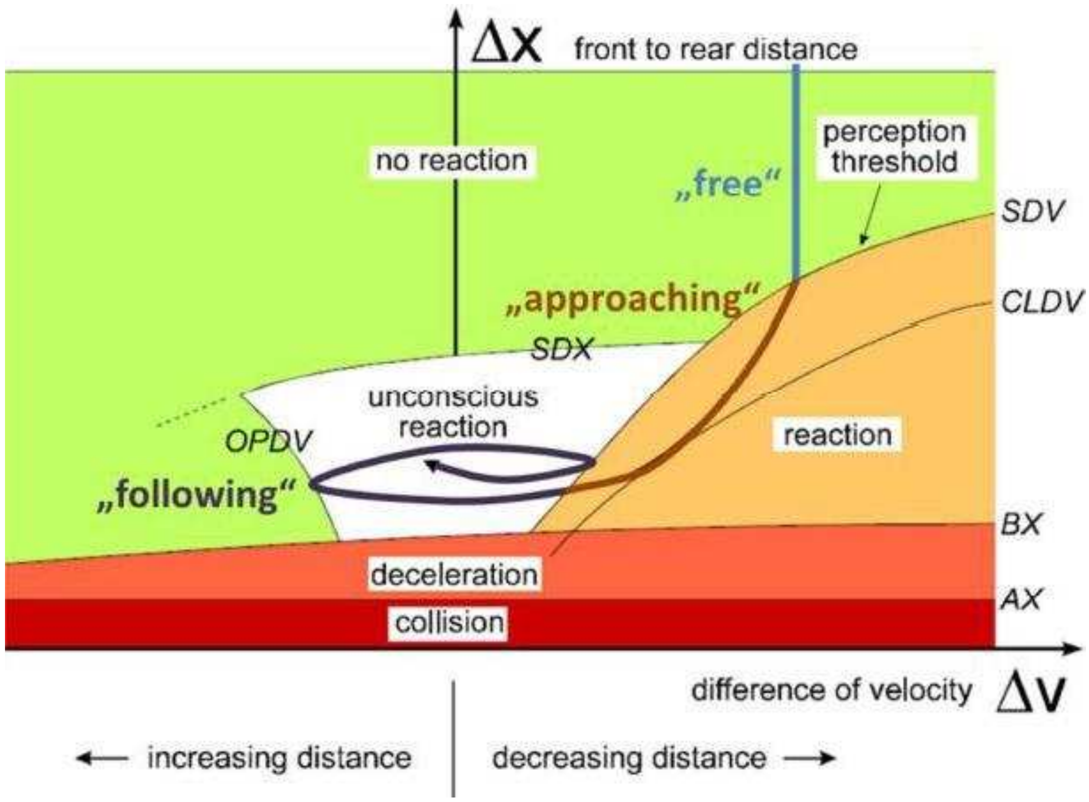

Figure 3-1: Vehicle car following behavior, based on Wiedemann 74. Source: (PTV, 2014, Motamedidehkordi, 2015)

The green area in the Figure 3-1 shows the free driving mode. In this mode, driver tries to keep his desired speed. No influence of preceding vehicles is observable (PTV, 2014). In this condition, the driver can accelerate or keep the same speed and experience relaxation mode. Brown area illustrates the approaching mode. Upon realizing that the vehicle is approaching another vehicle, the driver decelerates to match the leading vehicle's speed as it reaches its desired safety distance while reducing the distance with it. The white colored area in this figure specifies the unconscious reaction of driver or following mode. In this condition, the driver keeps the safety distance more or less constant, but due to imperfect estimation and throttle control the speed difference fluctuates around zero. If the distance difference is less than the minimum following distance (safe distance), the driver undoubtedly decelerates and increases the distance with the leading car, otherwise the collision may occur. The last two conditions have been illustrated by pink and red colored area which shows the breaking mode.

The Wiedemann 99 Car Following Model

As mentioned at the beginning of this subsection, two existed car following model in VISSIM, Wiedemann 74 and Wiedemann 99, are based on perception thresholds with the difference in how perception thresholds are implemented. Some thresholds for the Wiedemann 99 car following model are calculated differently than in the Wiedemann 74 model. Nevertheless, the meaning of each threshold is the same. Figure 3-2 is a snapshot of VISSIM interface showing the parameters associated with Wiedemann99 car following model. The Wiedemann 99 model parameters, which have been adjusted in this thesis work, are defined as below (Aghabayk, 2013, PTV, 2014):

- The ‘Look ahead distance’ parameters determine the minimum and maximum distances and number of observed vehicles in front of a driver within the same link that can be observed in order to react accordingly.
- The ‘Look back distance’ parameters determine the maximum and minimum distances that a driver can see backwards within the same link in order to react to other vehicles behind.
- The ‘Temporary lack of attention’ parameters determine the situation in which vehicles do not react to a preceding vehicle with the specific probability and time duration (except for emergency braking).

The Wiedemann model parameters can be categorized to three part: CC0-CC3 define the thresholds for ΔX, while CC4-CC6 specify the thresholds for ΔV. CC7-CC9 determine the driving activities. The relation between the parameters and thresholds are defined by equations 3-1 to 3-6 (PTV, 2014, Aghabayk, 2013, Motamedidehkordi, 2015).

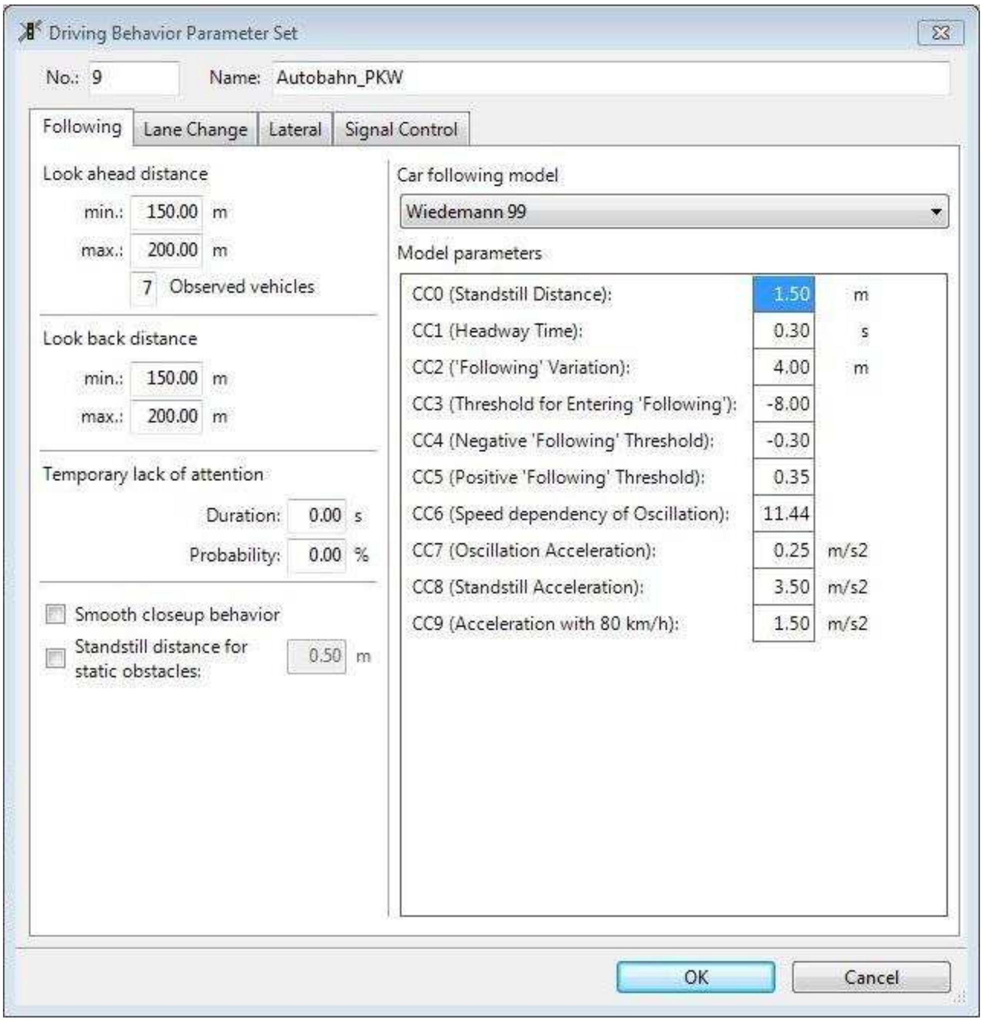

Figure 3-2: Parameter set for car following model Wiedemann 99

CC0: defines the average desired standstill distance (in meters) between two vehicles (rear-bumper to front-bumper). It has no variation.

$$AX = L + CC0 \qquad \textbf{Equation 3-1}$$

where L is the length of the leading vehicle.

CC1: defines the time (in seconds) that the following driver wishes to maintain a certain speed, also known as headway time. The higher this value, the more cautious the driver drives. In case of high volumes this distance becomes the value which has a determining influence on capacity and safety distance (PTV, 2014).

$$BX = AX + CC1 * v \qquad \textbf{Equation 3-2}$$

where v is equal to vehicle speed if it is slower than the leading vehicle; otherwise, it is equal to leading vehicle's speed with some random errors. The error is randomly determined by multiplying the speed difference between the two vehicles by an arbitrary number between 0.5 and -0.5.

CC2: defines a longitudinal oscillation distance difference (in meters) during the 'following condition'. Also, it defines how much more distance, than desired safety distance, the driver allows to keep with the front car before the driver intentionally moves closer to the front car.

$$SDX = BX + CC2 \qquad \textbf{Equation 3-3}$$

CC3: controls the start of the deceleration process, i.e. the triggering of the deceleration process, when the driver recognizes a preceding slower vehicle.

CC4 and **CC5:** define negative and positive thresholds of the speed differences during the following process, closing process and the opening process respectively (Motamedidehkordi, 2015). Low values for CC4 and CC5 results in a more sensitive reaction to the acceleration or deceleration of the preceding vehicle (PTV, 2014). Since the driver's responses are slower in acceleration than in deceleration, the values of CC4 and CC5 are not supposed to be the same, in contrast to VISSIM default values (Motamedidehkordi, 2015).

$$SDV = -\frac{\Delta \mathrm{X} - SDX}{\mathrm{CC3}} - CC4 \qquad \textbf{Equation 3-4}$$

As depicted in Figure 3-1, ΔX is the gap distance between the two successive vehicles, calculated from front-bumper to front-bumper.

CC6: defines the influence of the distance on speed oscillation in the following process. The larger the distance, the more the speed oscillation.

$$CLDV = \frac{CC6}{17000} * (\Delta X - L)^2 - CC4 \qquad \textbf{Equation 3-5}$$

$$OPDV = -\frac{CC6}{17000} * (\Delta X - L)^2 - (\delta * CC5) \qquad \textbf{Equation 3-6}$$

where δ is a dummy variable which is equal to 1 when the subject vehicle speed is greater than CC5 . Otherwise it is equal to 0 (Aghabayk, 2013).

CC7: defines the oscillation of acceleration (in m/s^2) while the vehicle accelerates.

CC8: defines the desired acceleration (in m/s^2) when starting from standstill condition. This parameter is limited by defined maximum acceleration curves.

CC9: defines the desired acceleration (in m/s^2) at the speed of 80 km/h. This parameter is also limited by defined maximum acceleration curves.

3.1.2 Lane Changing Model

In a modeling study conducted by Luo et al. (2014), they headed for formulating the strategic behavior of drivers in multi-lane highways, focusing on the lane change decision. The authors believe that strategic planning is one of the tricky aspects of the driver behavior to model. In 1986, Gipps proposed that lane changing decision is the consequence of determining the following points:

- Necessity of changing lane;
- Possibility of changing lane;
- Desirability of changing lane.

Gipps (1986) continued that the following criteria are the most important factors for the general lane changing model:

1. Physical possibility and safety to change lanes;
2. The location of permanent obstruction, in order to avoid trapping behind;
3. The possibility of gaining speed advantage;
4. The driver's intended turning movement;
5. The presence of heavy vehicles;
6. The presence of so called transit lane for public transport and other high occupancy vehicle use.

According to the driver model presented by Fancher and Bareket (1996), Rosenfeld (2014) clarified the three main driving styles as following:

1. Hunter: This group of drivers normally drive faster than rest of the traffic stream and tend to travel at least 1.6 km/h faster than surrounding vehicles. Hunters, also known as most aggressive drivers, keep the time headway less than 1.2 seconds.

2. Glider: Drivers who do not accept high risks are categorized in this group with longer time headway. This group of drivers usually prefers to drive 1.6 km/h slower than neighboring vehicles and accept time headway higher than 2.2 seconds. Least aggressive driver is another name for this group.

3. Follower: Tending to match the speed with surrounding vehicles, follower's driving style bound between hunters and gliders. Their time headway is approximately near to median headway. That means they have time headway less 2.2 seconds and greater than 1.2 seconds.

Rosenfeld et al. (2014) declared that the Fancher et al. (1996) behavior model is crucial for accurately predicting ACC preferences of drivers, therefore, they described their own ACC's agent model. They focused on the three main key tasks: The appropriate time when agent recommends the user to engage and disengage the ACC and the proper value for ACC to be set to. In order to fulfill this aim, MetaCost algorithm, a general algorithm for making classifiers cost-sensitive by assigning greater weight to minority case in order to increase its recall, has been used. Data for the people's historical driver patterns has been fetched from the Automotive Collision Avoidance System Field Operation (ACAS FOT) study with 96 drivers. In this research, three different data sets were considered:

1. Objective characteristics: dealing with location of vehicle itself, e.g. vehicle speed, gap to leading vehicle, road type, weather condition and road density.

2. Driver characteristics: focusing on driver demographics such as age, gender, education level and income level.

3. Driver's observed behavior: In this study which lasted four weeks, all drivers drove their vehicles without ACC system within first week to acclimate to their vehicles. The result from this week revealed the drivers behavior in terms of Hunter, Glider or Follower.

The authors supposed that adding driver type information is less important since this has been indirectly considered in drivers demographic (Rosenfeld, 2014).

The VISSIM Lane Changing Model

Two general lane changing behavior exist in VISSIM: Slow lane rule and free lane selection. In order to obtain speed advantages or more space, free lane change will be performed. This model considers the situations in which drivers should change their lane in order to reach the next connector of a route, if the desired safety distance in the target lane is satisfied. The driving behavior parameters in VISSIM lane changing model contain the maximum and acceptable deceleration for the lane changing vehicle (own) and the vehicle which will be its follower in the target lane (trailing vehicle) (Aghabayk, 2013). Figure 3-4 depicts the parameters associated with lane changing model in VISSIM. The applicable lane changing parameters are outlined briefly as below (PTV, 2014):

- The ‘Maximum deceleration’ determines the upper bound of deceleration (in m/s^2) for own vehicle and tailing vehicle in a lane change.
- The ‘Accepted deceleration’ shows the lower bound of deceleration (in m/s^2) for own vehicle and trailing vehicle in a lane change.
- The ‘$-1m/s^2$ per distance’ specifies the travelled distance (in meters) (in the deceleration process during lane changing) from the accepted deceleration to the maximum deceleration with the rate of $-1m/s^2$ before the emergency stop.
- The ‘Safety distance reduction factor’ considers a deduction in the safety distances associated with vehicles involved in the lane changing maneuver. Smaller values result in more aggressive lane changing behavior (Aghabayk, 2013).
- The ‘Min. headway (front/rear)’ specifies the minimum gap (in meters) between two vehicles that must be available after a lane change, so that the change can take place (PTV, 2014).
- The ‘Cooperative lane change’ specifies the situation in which the trailing vehicle in the target lane will try to change lanes itself to the next lane in order to make room for the lane changing vehicle. However, the second lane change will occur if it is safe and suitable for the trailing vehicle based on its own route plan (PTV, 2014). Furthermore, a cooperative lane change will be executed if the defined ‘maximum speed difference’ and ‘maximum collision time’ are not exceeded (Aghabayk, 2013). Figure 3-3 depicts an example of cooperative lane changing. During the lane changing of vehicle B, vehicle A behaves in a way as if it would have to change lanes due to a connector at a long distance. Vehicle A accepts its own maximum deceleration and the deceleration of the trailing vehicle C on the new lane, in accordance with the parameters for the necessary lane change (PTV, 2014).

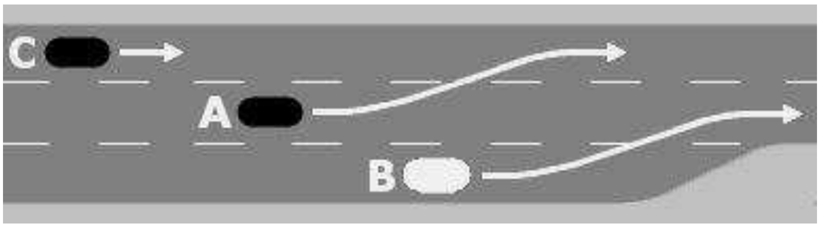

Figure 3-3: Example of cooperative lane changing. Source: (PTV, 2014)

- The ‘Maximum deceleration for cooperative braking’ determines the maximum deceleration (in m/s^2) which the trailing vehicle will accept for cooperation in order to help the lane changing vehicle to execute its maneuver. A higher absolute value will result in more cooperation and thus execute a lane changing (Aghabayk, 2013).
- The ‘Advanced merging’ considers any necessary lane change towards the next connector along the route. This means that more vehicles can change lanes earlier and the probability, which vehicles come to a stop to wait for a gap, will be reduced. This may decrease the waiting time for lane changing and increase the capacity of the road.

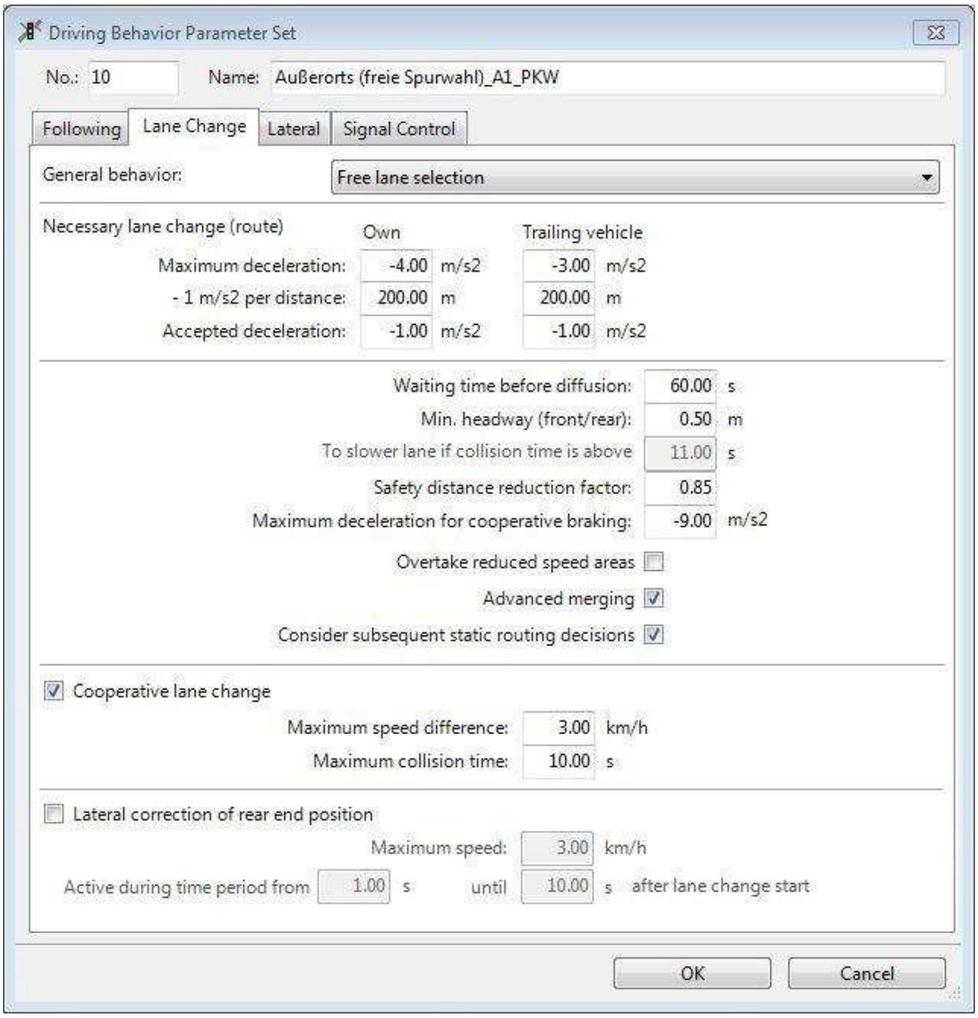

Figure 3-4: Parameter set for lane change model

3.2 Modeling of Automated Vehicles in VISSIM

For fulfilling the first thesis aim, a broad literature review in the area of driving simulators and psychological studies on driver's behavior and vehicle movement was done. Findings from the literature survey served as setup values in simulation study.

'Driving behavior' option in VISSIM gives the user the possibility to adjust the driver model parameters. Car following model Wiedemann 74 and 99 with variety of parameters such as following were set up:

- Look ahead/back distance;
- Number of observed vehicles;
- Temporary lack of attention;
- Standstill distance (CC0);
- Headway time (CC1);
- Following variation (CC2);
- Desired acceleration starting from standstill (CC8);
- Desired acceleration at 80 km/h (CC9).

Concerning lane change behavior, the following parameters were tuned:

- Maximum/accepted deceleration;
- -1 m/s^2 deceleration per distance;
- Safety distance reduction factor;
- Maximum deceleration for cooperative breaking;
- Advanced merging;
- Cooperative lane change.

Lateral movement also provides some adjusting factor like overtaking permission from left and right side which was activated for automated vehicles. By and large, the aforementioned adjustments produce the most realistic result out of this microscopic simulation (see Appendix 1 to Appendix 4).

In order to achieve the subsequent aims and research questions, a calibrated microscopic traffic simulation model in VISSIM was used to calculate relevant traffic performance measures. With respect to the collected data from the literature review, the input data were fed to the scenarios.

In order to develop a methodology and derive the parameter sets for the VISSIM simulation software, Leyn and Vortisch (2014) conducted a research project to ensure the accordance of microscopic traffic simulation and the German highway capacity manual – HBS (in German, Handbuch für die Bemessung von Straßenverkehrsanlagen). Based on this report, further calibration on car following and lane changing behavior values in the current thesis work have been performed. Moreover, desired acceleration and maximum acceleration for passenger cars and desired speed distribution for HGV were calibrated (Leyn, 2014). The applied modifications on driving behavior parameters are shown in Appendix 1 to Appendix 4. As an example, Figure 3-5 depicts the desired speed distribution of 80 km/h adapted for HGV and Figure 3-6 shows the calibrated maximum acceleration curve for passenger cars.

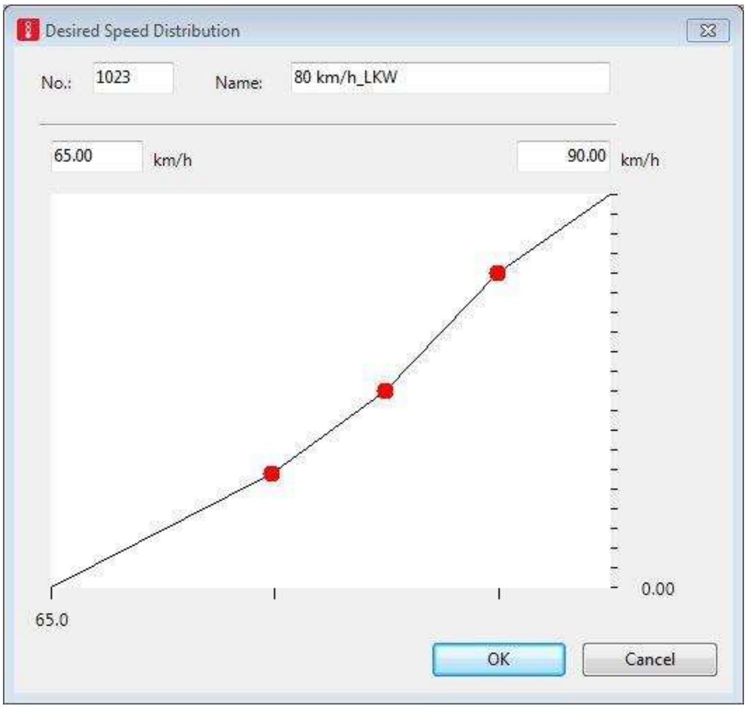

Figure 3-5: Desired speed distribution of 80 km/h for HGV

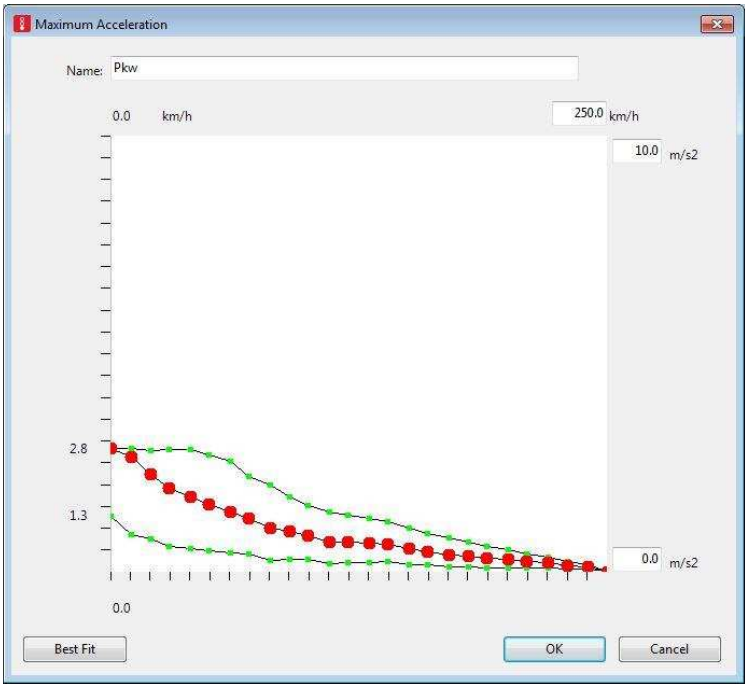

Figure 3-6: Maximum acceleration curve for passenger car

First of all, a basic conventional vehicles (CV) scenario was simulated and preliminary road setup and evaluation tools were located on the network. Table 3-1 outlines the driving behavior parameter sets in CV scenario. Although driver's lack of attention plays a significant role in road accidents (see subsection Possible Loss of Situation Awareness on section 2.5), there is no citable data to prove the duration and probability of temporary lack of attention. However, the author has assumed that 0.5s duration with the probability of 1.0% can indicate the real driving style of drivers in autobahn segment. In order to evaluate the validity of this assumed data and the effect of it on the model, a sensitivity analysis is presented in section 4.4. The majority of highlighted values in Table 3-1 and Table 3-2 specify the modified parameters based on the Leyn (2014) calibration study, such as:

- CC0 – CC9;
- -1 m/s2 deceleration per distance (own);
- Accepted deceleration (own);
- Accepted deceleration (trailing vehicle);
- To slower lane if collision time above;
- Safety distance reduction factor;
- Maximum deceleration for cooperative braking.

The rest of highlighted values, which are explained in upcoming bullet points, are the adjusted parameters by the author. For instance, CC1, minimum look ahead/ back distance, maximum look ahead/ back distance, number of observed vehicles, advanced merging, cooperative lane change, overtaking from both side.

In Table 3-1 and Table 3-2, Off-ramp column represents the weaving segment leading to off-ramp as well as off-ramp segment, while On-ramp column represents the on-ramp segment as well as merging segment to the autobahn.

Table 3-1: Driving behavior parameter in CV scenario

	Link Segment	Autobahn		Off-ramp		On-ramp	
	Vehicle Type	CAR	HGV	CAR	HGV	CAR	HGV
Car Following	Car following model	W 99	W 99	W 99	W 99	W 99	W 99
	Minimum look ahead/ back distance (m)	0,00	0,00	0,00	0,00	0,00	0,00
	Maximum look ahead distance (m)	250,00	250,00	250,00	250,00	250,00	250,00
	Maximum look back distance (m)	150,00	150,00	150,00	150,00	150,00	150,00
	Number of observed vehicles	2	2	2	2	2	2
	Duration of temporary lack of attention (s)	**0,50**	**0,50**	0,00	0,00	0,00	0,00
	Probability of temporary lack of attention (%)	**1,00**	**1,00**	0,00	0,00	0,00	0,00
	CC0 (m)	1,50	1,50	**2,50**	**2,50**	**2,50**	**2,50**
	CC1 (s)	**1,05**	**1,05**	**1,15**	**1,15**	**1,25**	**1,25**
	CC2 (m)	4,00	4,00	**5,00**	**5,00**	4,00	4,00
	CC4	**-0,30**	**-0,30**	-0,35	-0,35	-0,35	-0,35
	CC8 (m/s^2)	3,50	**2,50**	3,50	**2,50**	3,50	**2,50**
	CC9 (m/s^2)	1,50	**1,00**	1,50	**1,00**	1,50	**1,50**
Lane Change	General behavior	Slow lane rule	Slow lane rule	Free lane selection	Slow lane rule	Free lane selection	Slow lane rule
	-1 m/s^2 deceleration per distance (own) (m)	**300,00**	200,00	200,00	200,00	**300,00**	200,00
	Accepted deceleration (own) (m/s^2)	-1,00	-1,00	-1,00	-1,00	**-1,50**	-1,00
	Accepted deceleration (trailing vehicle) (m/s^2)	**-0,75**	-0,50	**-1,00**	**-1,00**	**-1,00**	-0,50
	To slower lane if collision time above (s)	**15,00**	**1,00**	-	**1,00**	-	**1,00**
	Safety distance reduction factor	0,60	0,60	**0,85**	**0,85**	**0,80**	**0,80**
	Maximum deceleration for cooperative braking (m/s^2)	-3,00	-3,00	**-9,00**	**-9,00**	**-6,00**	**-6,00**
	Advanced merging	-	-	-	-	-	-
	Cooperative lane change	-	-	-	-	-	-
	Both side overtaking	-	-	-	-	-	-

After all adjustments on the CV scenario, an automated vehicles (AV) scenario was duplicated from the current CV scenario. For this purpose, the author interpreted the presence of automated vehicles in VISSIM by adjusting the traffic flow parameters and driving behavior of car following and lane changing model. All vehicles in AV scenario similarly were assumed to be highly automated ones. Therefore, no temporary lack of attention in AV scenario has been considered. Table 3-2 summarizes the driving behavior parameter sets in AV scenario. In order to simulate the presence of the automated vehicles, the following values according to the former research works, presented in section 2.6, were entered in VISSIM driving behavior option.

- The maximum coverage area of state-of-the-art sensors in automated vehicles is 200 meters (see subsection 2.6.4 and (Laquai, 2011)). Therefore, Maximum look ahead and look back distance were set to 200 meters. Compared to conventional vehicles setup, this value limits the monitored area to an equal distance of 200 meters in all directions, since the sensors coverage are circular and spherical.

Table 3-2: Driving behavior parameter in AV scenario

	Link Segment	Autobahn		Off-ramp		On-ramp	
	Vehicle Type	CAR	HGV	CAR	HGV	CAR	HGV
Car Following	Car following model	W 99	W 99	W 99	W 99	W 99	W 99
	Minimum look ahead/ back distance (m)	**150,00**	**150,00**	**150,00**	**150,00**	**150,00**	**150,00**
	Maximum look ahead/ back distance (m)	**200,00**	**200,00**	**200,00**	**200,00**	**200,00**	**200,00**
	Number of observed vehicles	**7**	**8**	**6**	**6**	**6**	**7**
	Duration of temporary lack of attention (s)	0,00	0,00	0,00	0,00	0,00	0,00
	Probability of temporary lack of attention (%)	0,00	0,00	0,00	0,00	0,00	0,00
	CC0 (m)	1,50	1,50	**2,50**	**2,50**	**2,50**	**2,50**
	CC1 (s)	**0,30**	**0,30**	**0,30**	**0,30**	**0,30**	**0,30**
	CC2 (m)	4,00	4,00	**5,00**	**5,00**	4,00	4,00
	CC4	**-0,30**	**-0,30**	-0,35	-0,35	-0,35	-0,35
	CC8 (m/s^2)	3,50	**2,50**	3,50	**2,50**	3,50	**2,50**
	CC9 (m/s^2)	1,50	**1,00**	1,50	**1,00**	1,50	**1,50**
Lane Change	General behavior	Slow lane rule	Slow lane rule	Free lane selection	Slow lane rule	Free lane selection	Slow lane rule
	-1 m/s^2 deceleration per distance (own) (m)	**300,00**	200,00	200,00	200,00	**300,00**	200,00
	Accepted deceleration (own) (m/s^2)	-1,00	-1,00	-1,00	-1,00	**-1,50**	-1,00
	Accepted deceleration (trailing vehicle) (m/s^2)	**-0,75**	-0,50	**-1,00**	**-1,00**	**-1,00**	-0,50
	To slower lane if collision time above (s)	**15,00**	**1,00**	-	**1,00**	-	**1,00**
	Safety distance reduction factor	0,60	0,60	**0,85**	**0,85**	**0,80**	**0,80**
	Maximum deceleration for cooperative braking (m/s^2)	-3,00	-3,00	**-9,00**	**-9,00**	**-6,00**	**-6,00**
	Advanced merging	✓	✓	✓	✓	✓	✓
	Cooperative lane change	✓	-	✓	✓	✓	-
	Maximum speed difference (km/h)	**3,00**	-	**3,00**	**3,00**	**3,00**	-
	Maximum collision time (s)	**10,00**	-	**10,00**	**10,00**	**10,00**	-
	Overtaking from both side	✓	✓	✓	✓	✓	✓

- Minimum look ahead and look back distance specify the least possible/visible distance in which a driver can recognize and react accordingly, i.e. this distance can be zero in case that the front or rear vehicle drives as close as possible to this vehicle and block the visibility area of it. Since in highly automated vehicles ADAS will take care of this issue, this parameter will be controlled via vehicle's sensors. Take into account any signal interference and coverage limitation, Minimum look ahead and look back distance were set to 150 meters.

- Number of observed vehicles was separately calculated for each link segment based on the sensor coverage of 200 meters (Laquai, 2011) and the assigned free flow speed. However, this data varies between 6-8 observed vehicles. It is expected that greater number of observed vehicles can represent the communication characteristics of automated vehicles. In other words, each vehicle is aware of more vehicles around and it can react accordingly.

- Automated vehicles bring the possibility to keep tighter time headway in road network without affecting traffic safety (see section 2.4). According to the studies conducted by Gouy (2013b, 2014), Headway time (CC1) was set to 0.3 s. It is expected that vehicles drive closer to the front car and accept a shorter gap. Explicitly, car platooning can be practiced. In addition, denser road segment is anticipated.

- In highly automated vehicles, drivers won't override the setup speed by automated driving mode and the vehicle speed may deviate by ±2 km/h close to the speed limit. Therefore, upper and lower bound of all desired speed distributions were adjusted to ±2 km/h. This adjustment should affect the automated vehicle's speed dispersion.

- Highly automated vehicles communicate with each other and announce their movement decision to the surrounding vehicles. As a result in lane changing situation, the trailing vehicle in the target lane will try to change lanes itself to the next lane in order to make appropriate room for the lane changing vehicle. Thus, 'Cooperative lane change' was activated with maximum speed difference = 3.0 km/h and maximum collision time = 10s (Leyn, 2014). Smoother lane changing with less breaking and full stop is anticipated.

- Due to the fact that highly automated vehicles will be informed about their route decision in advance, they will change lanes earlier towards the next connector along the route. Therefore, 'Advanced merging' was activated. As a result, proper lane changing as timely as possible with less crowded weaving segment is expected. Activation of advanced merging and cooperative lane change should end up to increase the average travel speed, reduce the density in weaving segment and enhance the network performance.

- Overtaking from left and right side were activated (see subsection 2.6.3 and (Chiang, 2013)). This item enables the possibility to overtake from right side, when the conditions for a safe overtaking are fulfilled.

- Vehicle routing decision was set to the early entrance of the vehicles in the network for AV scenario. Bearing in mind that drivers in the CV scenario are informed about their upcoming route decision just 1.0 kilometer earlier than the weaving segment. Sooner awareness of routing decision together with advanced merging let the vehicles start performing their required weaving maneuver earlier toward their final decision.

Finally, a separate scenario was derived from CV and AV scenarios, i.e. 50% of the vehicles have inherited the aforementioned characteristics of automated vehicles and the rest behave as conventional vehicles (AV50%) (see Table 3-1 and Table 3-2). In this scenario, neither conventional vehicles nor automated vehicles have temporary lack of attention. Particularly, the input volume was evenly divided between two existed types of vehicles. However, the interaction between automated vehicles and conventional vehicles is meaningful when conventional vehicles have proper chance to maneuver. In other words, gap acceptance should be in a range that conventional vehicles can handle a lane change in order to overtake or drive toward the off-ramp (see subsection 2.6.5 and (Gouy, 2013b, 2014)). Therefore, time headway for automated vehicles was set to 0.75 seconds (Motamedidehkordi, 2015) and since conventional drivers drive closer to their preferred time headway threshold, the adopted time headway for conventional vehicles was set to 0.9 seconds. It should be mentioned that the conventional vehicle's time headway was picked based on the modification which performed on the CV scenario.

The output from this simulation study is considered to determine the potential positive effects of automated vehicles on network performance measures, such as capacity, density, travel time and average speed. As a future research work, results of this thesis can be further used for implementation in VISSIM to indicate the presence of automated vehicles in traffic network.

4 Simulation Study

4.1 Traffic Network Specification

The modeled traffic network in this thesis work is a segment of the West Autobahn (A1) passing north of Salzburg province in Austria. This section of autobahn is 2,896 meters long with 3 lanes. It should be noted that the weaving area has 4 lanes with the 467 meters length.

The future geometrical design of this area is shown in Figure 4-1. The planned interchange will handle appropriate movement from north and south bound to/from the autobahn via an on-ramp to the east-west direction and an off-ramp from west-east direction.

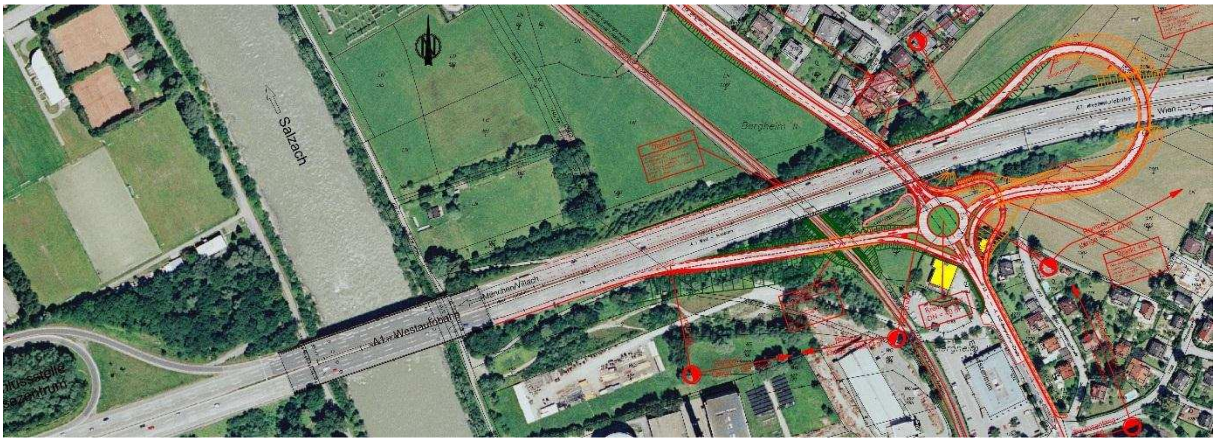

Figure 4-1: Planed status of West Autobahn (A1), Salzburg-Austria. Source: ASFINAG

Austrian autobahn and highway financing stock corporation – ASFINAG (in German, Autobahnen und Schnellstraßen Finanzierungs Aktiengesellschaft) provided the input data for this simulation study. The 15 minutes aggregated and prognosed vehicle inputs are presented in Appendix 5, however the original data kept confidential based on ASFINAG regulations. The employed traffic model was calibrated in terms of desired speed distribution, considering any unrealistic movements of vehicles on the road and finally the result compared with the fundamental diagram on macroscopic level. This traffic model was selected because of following reasons:

- Existence of actual volume data;
- Calibrated model;
- Existence of remarkable road segments such as weaving area, off-ramp, on-ramp, autobahn and urban road all in one model.

The simulation consists of one complete day run with a 15 minutes warm-up time. For the accuracy, the autobahn segment has two separate vehicle inputs with passenger cars and Heavy goods vehicles (HGV). Nevertheless, the supply input for the north and south bound defined as a unique vehicle composition with 98% of passenger cars and 2% of HGV. Free flow speed (FFS) of the road is different based on the segments. First lane of the autobahn and first and second lanes of the weaving segment have FFS_{Car} equal to 85 km/h and FFS_{HGV} = 80 km/h. Second and third lanes of the autobahn as well as third and fourth lanes of the weaving segment have FFS_{Car} = 100 km/h and FFS_{HGV} = 80 km/h. It is obvious that leading segment to the off-ramp or roundabout has smaller FFS between 50-30 km/h for passenger cars and 50-20 km/h for HGV.

In order to have an adequate discharge from off-ramp and prevent vehicles to queue up there, which may lead to generation of a shock-wave at the upstream in autobahn, a traffic signal has been placed on the south-bound around 60 meters before the roundabout to save enough time for the off-ramp to discharge most of the vehicles and don’t let the queue to move backward to the autobahn.

The modeled section of network is shown in Figure 4-2.

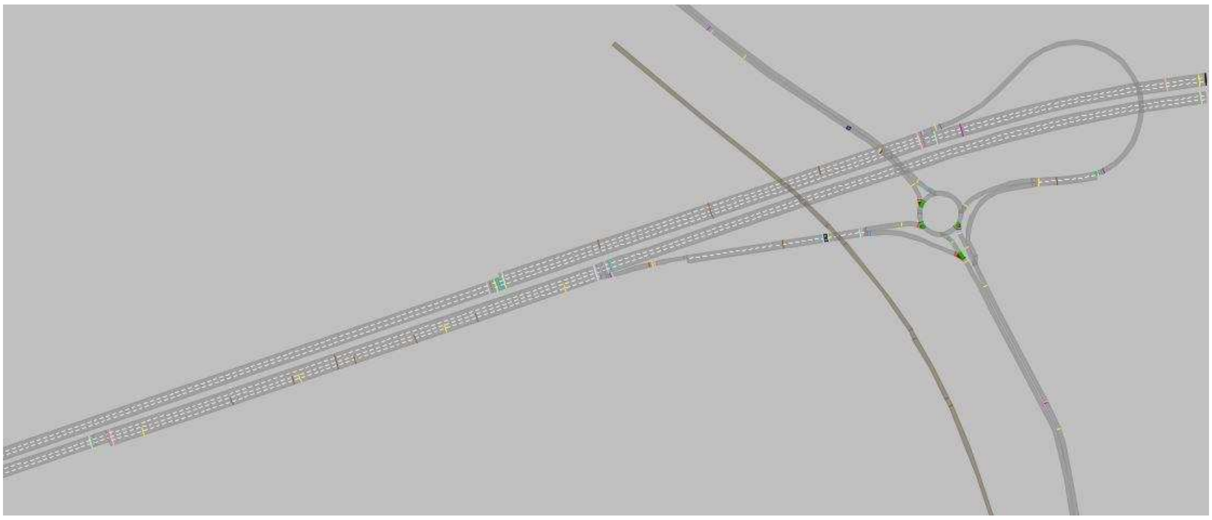

Figure 4-2: Modeled network

4.2 Description of Scenarios

A case study consisting of three scenarios was performed in order to investigate the traffic performance measures in presence of conventional vehicles (CV) and automated vehicles (AV). In addition, interaction between automated vehicles and conventional vehicles seems essential to be studied. Therefore, third scenario is a compilation of two other scenarios in sense of 50% conventional vehicles and 50% automated vehicles (AV50%) inside the network. Each link segment (such as autobahn, weaving area, off-ramp, urban, etc.) was defined independently with specific driving behavior of car following model and lane change behavior for passenger cars and HGV. Detailed information about modeling approach in this study was presented in section 3.2

The focus of this study has been especially drawn to consider the performance measures of east-bound autobahn and the weaving segment leading to the off-ramp which are the critical road segments in the network. Moreover, the lined up queue in off-ramp segment is examined.

4.3 Simulation Results and Discussion

This section outlines the simulation output following with discussion on each result. Density, average travel speed, travel time, queue length and network performance are the measures which are presented. Output data are presented in three different columns: ‘Total’ which represents a 24 hours simulation result, 'A.M.' which represents the results during a.m. peak hours (7:15-8:15) and 'P.M.' which indicates the results during p.m. peak hours (16:15-17:45).

Each scenario was replicated five times and the average results are reported in upcoming subsections. The simulation resolution was set to 15. It should be mentioned that the default value for the simulation resolution is 10, but the PTV (2014) user manual of VISSIM suggests the user to use higher resolution (10 to 20) to have more precise results. However, increasing this parameter will end up to slower simulation speed.

At the end of this section, a sensitivity analysis on the temporary lack of attention is presented and discussed.

4.3.1 Density

The results of the average density measurement are outlined in Table 4-1. The simulation output of CV scenario shows that the daily average density of the autobahn segment is 8.06 veh/km/lane, while this value reduced to 7.90 veh/km/lane in AV scenario. It means that average density of autobahn in AV scenario improved by 2.00% in a long run, while just 1.65% improvement is observed in weaving segment. It should be noted that this slight shift in the daily average density of the weaving segment ends up to a notable change in its LOS from B to A (HCM, 2000).

Specifically during p.m. peak hours with the approximate volume of 1650 veh/h/lane, average density has been shifted from 19.74 veh/km/lane in CV scenario to 18.14 veh/km/lane in AV scenario which shows 8.09% improvement in the road density. Besides, same comparison for the weaving segment shows a 7.85% improvement in this crucial area. In AV50% scenario, average density changed in the same sense. In details, 4.91% improvement in autobahn segment and 4.85% in weaving segment was observed.

As explained above, presence of automated vehicles in road network (either AV, or AV50% scenario) turns out to lighter road segments. In other words, the road capacity increased and the network can handle more vehicles, especially during rush hours. Nevertheless, the hypothesis of a denser road (see section 2.4 and Figure 2-1) remains doubtful. As a matter of fact, density is a function of volume and since the movement demand and number of lanes stayed constant in the AV scenario, therefore this hypothesis can't be examined in this phase of simulation and will be kept questionable as a future work.

Table 4-1: Average density (veh/km/lane) and percentage changes

	East-bound Autobahn			Weaving segment leading Off-ramp		
Scenario	**Total**	**A.M.**	**P.M.**	**Total**	**A.M.**	**P.M.**
CV	8.06	15.41	19.74	6.03	11.26	14.68
AV	7.90	14.80	18.14	5.93	10.92	13.53
AV50%	7.93	15.03	18.77	5.94	11.03	13.97
CV vs. AV (%)	2.00	3.96	8.09	1.65	3.03	7.85
CV vs. AV50% (%)	1.68	2.50	4.91	1.59	2.03	4.85

4.3.2 Speed

Table 4-2 and Table 4-3 outline the average travel speed and standard deviation of speed respectively. The average travel speed of the autobahn segment in p.m. peak hours enhanced from 82.42 km/h in CV scenario to 89.41 km/h in AV scenario and to 86.54 km/h in AV50% scenario which shows 8.48% and 5.00% growth respectively. Mentioned parameter in weaving segment during p.m. peak hours illustrates 7.86% improvement in AV scenario. Results of standard deviation measurement depict a perceptible change in speed dispersion, specifically during a.m. and p.m. peak hours in both road segments.

Standard deviation of speed determines the fact that automated vehicles drive between the predefined ranges of speed which show a less dispersion around mean speed. However, no positive change was observed in a.m. peak hour in AV50% scenario. The larger deviation of speed in AV50% scenario in weaving segment, which caused a -44.44% difference in standard deviation, seems that happened because of a larger queue during a.m. peak hours.

Driving close to the speed limit (with ± 2km/h deviation) and performing the weaving maneuver timely turn out to a remarkable enhancement of average travel speed in presence of automated vehicles. Smoother traffic flow with fewer breaking and less stop-and-go situation let the vehicles accelerate up to the assigned speed limit. This positive effect is significantly highlighted during rush hours.

Table 4-2: Average travel speed (km/h) and percentage changes

	East-bound Autobahn		Weaving segment leading Off-ramp	
Scenario	A.M.	P.M.	A.M.	P.M.
CV	85.41	82.42	86.11	83.21
AV	88.94	89.41	88.82	89.75
AV50%	87.63	86.54	87.85	87.01
CV vs. AV (%)	4.14	8.48	3.15	7.86
CV vs. AV50% (%)	2.60	5.00	2.02	4.57

Table 4-3: Standard deviation of speed and percentage changes

	East-bound Autobahn		Weaving segment leading Off-ramp	
Scenario	A.M.	P.M.	A.M.	P.M.
CV	0.90	2.41	1.09	4.28
AV	0.27	0.50	0.48	0.82
AV50%	0.90	1.39	1.57	2.04
CV vs. AV (%)	69.71	79.29	55.45	80.82
CV vs. AV50% (%)	0.00	42.31	-44.44	52.47

4.3.3 Travel Time

Table 4-4 shows the average travel time in autobahn and weaving segment. Average travel time of the autobahn segment in p.m. peak hour shifted from 53.27 s in CV scenario to 48.47 s and 50.11 s in AV and AV50% scenario respectively. A meaningful change of 7.50% is also perceived in weaving segment between CV and AV scenarios in this time period.

Results of the average travel time look relevant to the output of the average travel speed. Earlier awareness of routing decision leads the vehicles to perform their required weaving maneuver toward their final decision as timely as possible. Moreover, advanced merging and cooperative lane changing let them change to their appropriate lane with less disturbance. Besides, speeding up to the assigned speed limit provides a faster movement within the network. Altogether, driving efficiency enhanced and turned out to a fluent traffic which finally improved the average travel time.

By taking a glance to the linear motion equation, travel time is a function of speed and is directly affected by its alteration. 9.00% in autobahn and 7.50% in weaving segment during the p.m. peak hours are the reduction of the vehicle travel time in AV scenario. In subsection 4.3.5, performance of the whole network is depicted and outlined in terms of total travel time as well as average travel speed and total delay.

Table 4-4: Average travel time (s) and percentage changes

	East-bound Autobahn			Weaving segment leading Off-ramp		
Scenario	**Total**	**A.M.**	**P.M.**	**Total**	**A.M.**	**P.M.**
CV	51.06	51.49	53.27	19.08	19.25	19.96
AV	50.79	48.98	48.47	19.17	18.66	18.47
AV50%	50.27	49.59	50.11	19.00	18.87	19.04
CV vs. AV (%)	0.53	4.87	9.00	-0.50	3.06	7.50
CV vs. AV50% (%)	1.55	3.70	5.93	0.38	1.99	4.60

4.3.4 Queue Measurement

A queue counter in front of the off-ramp and another one in the diverging point of the weaving segment and off-ramp were applied. As it is outlined in Table 4-5, the results of queue measurement in off-ramp show maximum queue length of 155.06 meters long occurred in AV scenario, while the longest queue in weaving segment appeared in AV50% scenario with 125.96 meters long. The maximum queue length occurred in all scenarios is not more than 155 meters, which is still not greater than the off-ramp length with 240 meters long. This shows that the traffic signal, located in the south-bound, is working properly and makes an appropriate pause for the incoming vehicles from off-ramp toward the roundabout.

Table 4-5: Evaluation of queue counter's results

	Maximum Queue Length (m)						Frequency of Queue > 20m					
	Off-ramp			Weaving segment leading Off-ramp			Off-ramp			Weaving segment leading Off-ramp		
Scenario	**Total**	**A.M.**	**P.M.**	**Total**	**A.M.**	**P.M.**	**Total**	**A.M.**	**P.M.**	**Total**	**A.M.**	**P.M.**
CV	78.87	78.87	31.47	120.10	30.31	89.00	7	1	3	30	3	11
AV	155.06	155.06	42.03	46.27	21.51	45.09	17	5	4	14	2	4
AV50%	56.69	40.79	56.69	125.96	32.39	125.96	10	2	5	25	4	8

Second part of the Table 4-5 illustrates the frequency of the queues longer than 20 meters. Shorter queue length with less frequent queues greater than 20 meters in weaving segment in AV scenario shows a successful outcome in this study. On the other hand, the output illustrates worse situation in off-ramp segment in presence of automated vehicles (either AV, or AV50% scenario). Output of this measurement reveals that in off-ramp segment with 2 lanes, queues longer than 20 meters happened 17 times in AV scenario in total, though 10 times in AV50% scenario. It is assumed that higher number of 'Observed vehicles' attribute for automated vehicles, especially in off-ramp with less number of lanes, caused a conservative performance for automated vehicles that produces an unrealistic behavior in this condition. PTV (2014) stated that changing the number of observed vehicles can lead to an unrealistic simulation. Therefore as a future work, it is useful to conduct a sensitivity analysis to verify this issue.

4.3.5 Network Performance Measurement

The network performance results of the whole network are presented in Table 4-6. It should be noted that the result in this table represent, not only the east-bound autobahn and weaving segment, but also all depicted road segment in Figure 4-2. Average travel speed shows 3.7% and 2.28% enhancement in AV and AV50% scenario respectively. Comparison of the daily cumulative delay exhibits a drastic reduction from 2270 hours in CV scenario to 983 hours in AV scenario and 1563 hours in AV50% scenario, which shows 56.69% improvement in AV scenario and 31.16% in AV50% scenario. This indicates a more fluent traffic with less braking and full stop. Direct observation of simulation by author has proved this issue as a fact. Furthermore, keeping a tighter headway by automated vehicles provides the opportunity to practice platooning.

Network cumulative vehicle travel time as well shows slight change in p.m. peak hours. In addition, slight shifts in average travel speed during p.m. peak hours are perceived in both scenarios.

Besides aforementioned reasons, earlier awareness of routing decision for automated vehicles let them perform proper maneuver as timely as possible which reserve the weaving area for emergency lane change or last required maneuver. This ends up to a smoother traffic flow in the whole network and specifically weaving segment.

Table 4-6: Network performance measurement results and percentage changes

	Average Travel Speed (km/h)		Total Delay (h)			Total Travel Time (h)		
Scenario	**A.M.**	**P.M.**	**Total**	**A.M.**	**P.M.**	**Total**	**A.M.**	**P.M.**
CV	81.48	82.08	2270	8896	7905	35947	81542	76314
AV	82.38	85.11	983	5139	2393	36104	80745	73488
AV50%	82.74	83.95	1563	6565	5072	35770	80391	74446
CV vs. AV (%)	1.10	3.70	56.69	42.23	69.73	-0.44	0.98	3.70
CV vs. AV50% (%)	1.54	2.28	31.16	26.21	35.84	0.49	1.41	2.45

4.4 Sensitivity Analysis

As explained in section 3.2, there is a need for a sensitivity analysis to evaluate how much the model is sensitive to the setup value for temporary lack of attention. In order to do that, a duration range between 0 s to 2 s and probability range between 0% to 20% were defined. Separate simulation runs with the minimum and the maximum threshold of these ranges were performed in CV scenario and the output data of density, average travel speed and average travel time of the autobahn segment are shown in Table 4-7.

By taking a glance to the collected data, a trend toward denser link segment following with reduction of average travel speed and increase of average travel time are seen. Direct observation of the simulation revealed that the 2 s lack of attention turns out to shape a queue behind the distracted driver periodically. This of course significantly affects the performance of the road segment. In the scenario of 2 s lack of attention with the probability of 20%, a queue of 45 meters occurred during p.m. peak hour in the middle of autobahn segment.

On the other hand, it should be noted that by increasing the temporary lack of attention values, the model is gradually affected and no abrupt change in the output was observed. However, due to occurrence of the queue behind the distracted vehicle, this value should be used with precise estimation.

Due to lack of time in this thesis work, the temporary lack of attention has only been examined for the sensitivity analysis. Nevertheless, it is useful to perform sensitivity analysis for other parameters such as headway time (CC1), number of observed vehicles and advanced merging.

Table 4-7: Sensitivity analysis on temporary lack of attention and percentage changes

	Density (veh/km/lane)			Average Travel Speed (km/h)		Average Travel Time (s)		
Duration (s) & Probability (%)	**Total**	**A.M.**	**P.M.**	**A.M.**	**P.M.**	**Total**	**A.M.**	**P.M.**
0 s & 0%	8.05	15.25	19.70	85.46	82.44	51.00	51.43	53.25
2 s & 10%	8.19	15.66	20.66	84.15	78.87	51.23	51.74	54.41
2 s & 20%	8.40	15.88	21.70	82.92	73.69	51.45	52.37	55.77
(0 s & 0%) vs. (2 s & 20%) (%)	4.37	4.11	10.13	-2.98	-10.62	0.90	1.83	4.74

4.5 Limitations

In order to simulate the perception of surrounding vehicles and infrastructures (such as traffic lights), driving behavior attribute in VISSIM software let the user to enter three input parameters to simulate the observation behavior of drivers in road network. These parameters are look ahead distance (minimum and maximum), look back distance (minimum and maximum) and number of observed vehicles. The first two parameters define a reaction distance that the current vehicle can see other vehicles in front/behind within the same link. Number of observed vehicles impresses how well vehicles can predict other vehicle's movement within the same link and react accordingly (PTV, 2014). Nonetheless, these parameters cannot appropriately represent the V2V and V2I characteristics of automated vehicles. In fact, radars and ultrasonic sensors work circular and spherical while transmitting movement information and positioning data. The author believes that an add-on seems necessary to be implemented in VISSIM to represent the communication characteristic between vehicles and the driving environment.

In principle, no traffic simulation software simulates vehicle crashes, i.e. the applied simulation algorithm is careless about probable accident or sideswipe crashes. Although model calibration is one of the vital steps of simulation for traffic planners, further direct observation should be drawn during the simulation run. However, it would be of a great help if VISSIM generates an output data about the number of accidents during the simulation run. This can of course help the user to consider it as an adjustment for the later runs. It is nevertheless obvious that estimating occurred accident during the simulation run in a traffic simulation software needs lots of future research.

5 Conclusion

First of all, this thesis work aimed to consider the effects of automated vehicles on driver's behavior. The findings from literature review revealed that conventional vehicles, driving close to the platoon of automated vehicles with short time headway, tend to reduce their time headway and spend more time under their critical time headway of 1.0 second. Additionally, driving highly automated vehicles is tedious in a long run, reduce situation awareness and can intensify driver drowsiness, exclusively in light traffic. Due to the fact of more driver's inclination to involve in secondary tasks, it is worthy to mention that vehicle infotainment systems potentially distract drivers from their supervisory role.

In order to study the influence of automated vehicles on traffic performance measures, the possibility to evaluate a typical automated scenario using microscopic simulation model had to be investigated in advance. VISSIM microscopic simulation lets the user to simulate the presence of automated vehicles within the network by defining their driving behavior. By distribution of the vehicle input between existed vehicle types (conventional and automated vehicles), VISSIM enables the investigation of automated vehicle's effect with different penetration rates (e.g. 0, 50 and 100%). Parameters in VISSIM such as 'Look ahead/ back distance (maximum and minimum)', 'Number of observed vehicles', 'Cooperative lane change', 'Advanced merging' and both side overtaking represent the performance of ADAS in automated vehicles. In addition, accepting shorter time headway and having tighter desired speed distribution close to the speed limit are some examples of possible adjusted measures to show the distinct driving behavior of automated vehicles. Nevertheless, the author believes that other elements must be implemented in VISSIM to represent the communication characteristic of automated vehicles.

By and large, driving behavior of automated vehicles can be implemented as a default setting in VISSIM. It should be noted that more research must be conducted and more accurate input data about the driving characteristics of automated vehicles from car manufacturers should be provided in order to have a correct simulation of automated vehicles.

According to the setup values in this thesis work (see section 3.2), the output of the simulation study showed the positive effect of automated vehicles on traffic performance. In details, average density of autobahn segment in AV scenario remarkably decreased by 8.09% during p.m. peak hours with the approximately volume of 1650 veh/h/lane. Despite the hypothesis 1, that the road density is expected to be higher in AV scenario, no proving result could be concluded in this regard. In fact, density is a function of volume and since the movement demand and number of lanes stayed constant in the AV scenario, therefore this hypothesis cannot be examined in this phase of simulation and will be kept questionable as a future work. On the other hand, results of the queue measurement for the weaving segment showed that the maximum queue length in AV scenario was less than CV scenario and the frequency of happening a queue longer than 20 meters significantly decreased comparing to CV scenario. This result verified hypothesis 2(a) that smoother traffic flow in AV scenario with less queue in the weaving segment was anticipated. Nonetheless, output of queue measurement for the off-ramp segment illustrated worse situation in presence of automated vehicles (either AV, or AV50% scenario), which didn't support hypothesis 2(b). It is assumed that higher number of 'Observed vehicles' attribute for automated vehicles, especially in off-ramp with less number of lanes, caused a conservative performance for automated vehicles that produced an unrealistic behavior in this condition. PTV (2014) stated that changing the number of observed vehicles can lead to an unrealistic simulation. Therefore as a future work, it is useful to conduct a sensitivity analysis to verify this issue.

Average travel speed demonstrated an enhancement in both examined road segments. 8.48% and 7.86% improvement in AV scenario observed in autobahn and weaving segment respectively. In addition, results of the average travel time looked relevant to the output of the average travel speed and showed 9.00% reduction in AV scenario during p.m. peak hours. Earlier awareness of routing decision leads the vehicles to perform their required weaving maneuver toward their final decision as timely as possible. Moreover, advanced merging and cooperative lane changing let them change to their appropriate lane with less disturbance. Besides, speeding up to the assigned speed limit provides a faster movement within the network. Altogether, driving efficiency enhanced and turned out to a fluent traffic. These outcomes verified the hypothesis 3 to illustrate an improvement of average travel time and average travel speed in AV scenario.

Results of the microscopic simulation in this study revealed that the positive effects of automated vehicles on roads are especially highlighted when the network was crowded (e.g. during a.m. or p.m. peak hours). This can definitely count as a constructive point for the future of road networks with higher demands. Result of AV50% scenario moreover showed a feasible interaction between conventional vehicles and automated vehicles. Meaningful outputs of this case study, based on the input data from literature review, demonstrated the capability of VISSIM software to simulate the presence of automated vehicles in great extent, not only AV scenario but also share of automated vehicles, in traffic network. However, driving behavior parameters for other penetration rate of automated vehicles (e.g. 10%-90% or 30%-70%) need more detailed adjustment based on psychological studies. In other words, driving behavior of conventional vehicle drivers must be different while driving in a road with greater percentage of automated vehicles. In fact, when conventional vehicle drivers are aware of higher percentage of automated vehicles in road, it will end up to an overreliance on surrounding vehicles and it can affects their driving attitude, gap acceptance and finally road safety margins.

The validity of the output values nonetheless stays unknown awaiting for more accurate input data about the driving characteristics of automated vehicles and real field studies in future. Besides, more simulation studies on urban and rural roads with different traffic condition must be performed.

5.1 Future Research Work

Several interesting issues as future work were raised in this master thesis. As mentioned in section 2.4, presence of automated vehicles in the network can increase the capacity by keeping tighter headway. However, automated vehicles should keep longer time headway in order to provide proper gap for conventional vehicles to perform desired maneuvers. Therefore, there is still an opportunity to allocate the most left lane especially to automated vehicles. In other words, this so called “Express Lane” will be used by automated vehicles which accept shorter gap. This may be an efficient use of autobahns with higher number of lanes. It is obvious that vehicles in express lane will use other lanes for performing required weaving movements. It should be mentioned that VISSIM state-of-the-art can just allocate the driving behavior to the link segment (and not to specific lane). Thus further implementation to facilitate lane driving behavior need to be considered.

Performance information of automated vehicles such as CO_2 emission and fuel consumption have not been publicized so far, but it is possible to be set up in VISSIM nonetheless. Thus, the economic cost savings, fuel cost saving and emission rate can be calculated as a consequence.

6 Bibliography

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7 Appendix

Appendix 1: VISSIM Calibration for Driving Behavior. Source: (Leyn, 2014)

	Link Segment	Autobahn		Off-ramp		On-ramp	
	Vehicle Type	CAR	HGV	CAR	HGV	CAR	HGV
Car Following	Car following model	W 99	W 99	W 99	W 99	W 99	W 99
	CC0 (m)	1,50	1,50	**2,50**	**2,50**	**2,50**	**2,50**
	CC1 (s)	**1,05**	**1,05**	**1,15**	**1,15**	**1,25**	**1,25**
	CC2 (m)	4,00	4,00	**5,00**	**5,00**	4,00	4,00
	CC4	**-0,30**	**-0,30**	-0,35	-0,35	-0,35	-0,35
	CC8 (m/s^2)	3,50	**2,50**	3,50	**2,50**	3,50	**2,50**
	CC9 (m/s^2)	1,50	**1,00**	1,50	**1,00**	1,50	**1,50**
Lane Change	General behavior	Slow lane rule	Slow lane rule	Free lane selection	Slow lane rule	Free lane selection	Slow lane rule
	-1 m/s^2 deceleration per distance (own) (m)	**300,00**	200,00	200,00	200,00	**300,00**	200,00
	Accepted deceleration (own) (m/s^2)	-1,00	-1,00	-1,00	-1,00	**-1,50**	-1,00
	Accepted deceleration (trailing vehicle) (m/s^2)	**-0,75**	-,50	**-1,00**	**-1,00**	**-1,00**	-,50
	To slower lane if collision time above (s)	**15,00**	**1,00**	-	**1,00**	-	**1,00**
	Safety distance reduction factor	0,60	0,60	**0,85**	**0,85**	**0,80**	**0,80**
	Maximum deceleration for cooperative braking (m/s^2)	-3,00	-3,00	**-9,00**	**-9,00**	**-6,00**	**-6,00**

Appendix 2: Desired Speed Distribution for HGV. Source: (Leyn, 2014)

60 km/h		80 km/h	
Percentage (%)	**Speed (km/h)**	**Percentage (%)**	**Speed (km/h)**
0.00	45.00	0.00	65.00
30.20	54.96	29.50	74.96
50.30	60.04	50.00	80.04
80.20	64.99	79.50	84.99
100.00	70.00	100.00	90.00

Appendix 3: Maximum Acceleration Curve for CAR. Source: (Leyn, 2014)

Speed (km/h)	Acceleration (m/s^2)			Speed (km/h)	Acceleration (m/s^2)			Speed (km/h)	Acceleration (m/s^2)		
	Desired	Lower bound	Upper bound		Desired	Lower bound	Upper bound		Desired	Lower bound	Upper bound
0	2.800	1.260	2.800	90	0.925	0.285	1.725	180	0.364	0.106	0.687
10	2.550	0.843	2.800	100	0.808	0.254	1.500	190	0.305	0.084	0.582
20	2.186	0.700	2.800	110	0.744	0.227	1.389	200	0.256	0.071	0.487
30	1.918	0.602	2.800	120	0.699	0.220	1.299	210	0.207	0.059	0.391
40	1.700	0.527	2.750	130	0.650	0.207	1.204	220	0.158	0.047	0.296
50	1.514	0.467	2.700	140	0.601	0.195	1.108	230	0.108	0.035	0.201
60	1.351	0.417	2.518	150	0.542	0.173	1.003	240	0.069	0.032	0.115
70	1.204	0.375	2.240	160	0.483	0.151	0.898	250	0.000	0.000	0.000
80	1.047	0.315	1.961	170	0.423	0.128	0.792				

Appendix 4: Desired Acceleration Curve for CAR. Source: (Leyn, 2014)

Speed (km/h)	Acceleration (m/s^2)			Speed (km/h)	Acceleration (m/s^2)			Speed (km/h)	Acceleration (m/s^2)		
	Desired	Lower bound	Upper bound		Desired	Lower bound	Upper bound		Desired	Lower bound	Upper bound
0	2.800	1.260	2.800	90	0.925	0.285	1.725	180	0.364	0.106	0.687
10	2.550	0.843	2.800	100	0.808	0.254	1.500	190	0.305	0.084	0.582
20	2.186	0.700	2.800	110	0.744	0.227	1.389	200	0.256	0.071	0.487
30	1.918	0.602	2.800	120	0.699	0.220	1.299	210	0.207	0.059	0.391
40	1.700	0.527	2.750	130	0.650	0.207	1.204	220	0.158	0.047	0.296
50	1.514	0.467	2.700	140	0.601	0.195	1.108	230	0.108	0.035	0.201
60	1.351	0.417	2.518	150	0.542	0.173	1.003	240	0.069	0.032	0.115
70	1.204	0.375	2.240	160	0.483	0.151	0.898	250	0.000	0.000	0.000
80	1.047	0.315	1.961	170	0.423	0.128	0.792				

Appendix 5: Vehicle Input (veh/h)

	Autobahn_East bound		South bound	North bound	Autobahn_West bound	
Time	CAR	HGV			CAR	HGV
15 min	200	30	25	50	150	30
00:00	221	29	25	50	150	29
00:15	221	29	25	50	150	29
00:30	167	29	25	50	96	17
00:45	171	29	25	50	100	12
01:00	142	29	25	50	79	17
01:15	125	42	15	20	92	17
01:30	79	37	15	20	58	17
01:45	96	37	15	20	58	12
02:00	100	37	15	20	67	17
02:15	79	25	10	15	62	29
02:30	129	62	10	15	75	21
02:45	79	50	10	15	79	29
03:00	79	33	10	15	100	33
03:15	92	25	20	20	83	25
03:30	67	62	20	20	75	21
03:45	100	58	20	20	87	21
04:00	104	25	20	20	100	25
04:15	133	71	50	50	87	29
04:30	208	75	50	50	137	50
04:45	208	92	50	50	200	42
05:00	358	100	50	50	237	42
05:15	479	125	150	80	204	33
05:30	654	179	150	80	346	87
05:45	908	158	150	80	504	87
06:00	921	246	150	80	812	96
06:15	1187	200	630	160	996	104
06:30	1812	237	630	160	1350	125
06:45	2583	437	630	160	1691	150

07:00	2699	462	630	160	1975	100
07:15	3374	433	910	270	2333	112
07:30	3549	450	910	270	2379	129
07:45	3591	425	910	270	3066	137
08:00	3224	421	910	240	2949	142
08:15	2745	429	630	220	2637	142
08:30	2679	371	630	220	2379	146
08:45	2566	333	630	220	2000	96
09:00	2579	392	630	220	2066	125
09:15	2266	379	410	230	1650	104
09:30	2216	387	410	230	1645	125
09:45	2249	433	410	230	1683	171
10:00	2212	358	410	230	1296	117
10:15	2124	417	360	290	1050	121
10:30	2395	429	360	290	1383	117
10:45	2674	412	360	290	1333	96
11:00	2458	475	360	290	1262	67
11:15	2445	483	320	310	1212	112
11:30	2345	396	320	310	1171	171
11:45	2629	421	320	310	1254	121
12:00	2633	321	320	310	1083	133
12:15	2529	383	310	400	1216	108
12:30	2695	417	310	400	1100	117
12:45	2562	392	310	400	1212	92
13:00	2595	358	310	400	1141	121
13:15	2783	292	330	410	1162	142
13:30	2824	421	330	410	1237	158
13:45	2833	321	330	410	1383	154
14:00	2612	437	330	410	1308	154
14:15	3099	429	350	380	1254	129
14:30	2958	450	350	380	1246	121
14:45	2970	412	350	380	1275	171
15:00	2716	433	350	380	1250	104
15:15	2899	346	350	440	1333	167
15:30	2816	358	350	440	1312	104
15:45	3378	379	350	440	1283	96
16:00	3732	429	350	440	1254	92
16:15	4566	400	390	570	1321	154
16:30	4116	400	390	570	1370	104
16:45	4128	329	390	570	1416	121
17:00	4378	350	390	570	1720	146
17:15	4803	287	460	580	1512	129
17:30	5157	308	460	580	1787	112
17:45	4345	308	460	580	1620	142

18:00	4020	271	460	580	1316	100
18:15	3616	229	370	460	1279	75
18:30	3416	142	370	460	1162	92
18:45	2849	204	370	460	1154	71
19:00	2366	142	370	460	929	87
19:15	2316	175	260	310	800	58
19:30	1979	162	260	310	879	42
19:45	1879	146	260	310	646	83
20:00	1616	100	260	310	417	54
20:15	1229	129	150	240	462	46
20:30	1154	96	150	240	367	62
20:45	971	92	150	240	329	29
21:00	958	92	150	240	392	42
21:15	958	112	110	250	279	21
21:30	771	154	110	250	300	25
21:45	854	92	110	250	275	25
22:00	608	125	110	250	275	21
22:15	762	96	90	170	267	12
22:30	954	71	90	170	246	8
22:45	946	92	90	170	196	17
23:00	1112	79	90	170	150	8
23:15	521	62	50	90	158	21
23:30	367	92	50	90	129	8
23:45	262	92	50	90	146	42
00:00	217	29	50	90	104	17
15 min	200	30	50	90	100	15

7.1 List of Figures

7.2 List of Tables

7.3 List of Abbreviations

ABS	Anti-lock Braking System
ACAS FOT	Automotive Collision Avoidance System Field Operation
ACC	Adaptive Cruise Control
ADAS	Advanced Driver Assistance Systems
A-GPS	Assisted Global Positioning System
ASFINAG	Autobahnen und Schnellstraßen Finanzierungs Aktiengesellschaft
ASR	Anti-Slip Regulation
AV	Automated Vehicles
BAS	Braking Assistance System
CV	Conventional vehicles
DAS	Driver Assistance System
ESC	Electronic Stability Control
FFS	Free Flow Speed
GPS	Global Positioning System
HBS	Handbuch für die Bemessung von Straßenverkehrsanlagen
HCM	Highway Capacity Manual
HGV	Heavy Goods Vehicles
ISA	Intelligent Speed Adaptation
ITS	Intelligent Transport Systems
IVIS	In-Vehicle Information Systems
LOS	Level of Service
PELOPS	Program for the DEvelopment of LOngitudinal Traffic Processes in **S**ystem Relevant Environment
TCS	Traction Control System
THW	Time Headway
V2I	Vehicle to Infrastructure communication
V2V	Vehicle to Vehicle communication
V2X	Vehicle to X communication
VISSIM	Verkehr In Städten - SIMulationsmodell