Technical University of Munich

Impact of Connected and/or Autonomous Vehicles in Mixed Traffic

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Abstract

The continuous increase of traffic in urban areas is an unavoidable phenomenon which causes congestion, high emissions and frequent traffic accidents. Among different alternatives, connected and/or autonomous vehicles (C/AVs) are considered as a potential solution to these issues. However, a proper investigation of the impacts of C/AVs is required before introducing this technology into transportation systems. Many studies have underlined different aspects of C/AVs, but the impacts varied significantly in each study. The objective of this thesis is to investigate the impact of Connected/Autonomous Vehicles in mixed traffic conditions in urban areas. In order to achieve this objective, a sensitivity analysis was conducted on the driving behaviours of autonomous vehicles (AVs) as well as an impact study of C/AVs in a mixed traffic region for the three most frequently seen driving modules. The study area, Ludwigstraße and Leopoldstraße road axes, is a busy corridor of Munich which has different traffic flow reducing elements: lane merging locations, several mobility hubs and higher traffic flow feeder side streams. For this research, traffic, environmental and safety aspects for every experimental scenario for this area have been studied and possible causes have been illustrated. Analyses took place examining different parameters including traffic (travel time, speed and delay time), environmental (CO_2 and NO_x) and road safety (number of conflicts) variables. The results indicate that the impact of C/AVs is generally positive up to a limit, which is directly connected with the number of interacting vehicles. This study also strengthens previous studies by showing that CAVs are better performers in traffic than AVs. However, both CAVs and AVs have higher traffic performance and fewer road accidents in lower traffic demand cases, although the emission outputs are the same. Moreover, the sensitivity analysis pointed out the role of different driving parameters of C/AVs, among which three parameters were found to be the most influential for AVs: the number of interacting vehicles, look back distance and minimum clearance (front/rear). Overall, this study reveals that the connectivity features of CAVs make them a better alternative than AVs for every possible scenario. However, to gain the greatest benefit, technical and infrastructural development is necessary.

Keywords: Connected and/or autonomous vehicles, traffic performance, emission, safety, sensitivity analysis, driving parameters

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Towards a connected transportation system……

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List of Abbreviations

ACC	Adaptive Cruise Control
AEBS	Automatic Emergency Braking System
AV	Autonomous Vehicle
BASt	Bundesanstalt für Straßenwesen
CACC	Cooperative adaptive cruise control
CAS	Collision Avoidance System
CAV	Connected and Autonomous Vehicle
C/AV	Connected and/or Autonomous Vehicle
C2C	Car to car
C-ITS	Cooperative Intelligent Transport System
COM	Component Object Model
DLC	Discretionary Lane Changes
EA	Evolutionary Algorithms
FDSA	Finite Difference Stochastic Approximation
GA	Genetic Algorithm
GRE	Global Relative Error
GoF	Goodness of Fit
HV	Human driven Vehicle
LIDAR	Light Detection and Ranging ()

MANE	Mean Absolute Normalized Error
MoE	Measure of Effectiveness
ME	Mean Error
MLC	Mandatory Lane Changes
MPE	Mean Percentage Error
MoP	Measure of Performance
NHTSA	The National Highway Traffic Safety Administration
OD	Origin-destination
OQMS	OptQuest/Multistart
PC-SPSA	Principal Components - Simultaneous Perturbation Stochastic Approximation
PE	Percentage error
PET	Post-encroachment time
PSD	Proportion of stopping distance
PSO	Particle Swarm Optimization
RMSE	Root Mean Square Error
RMSN	Normalized Root Mean Square Error
RMSPE	Root Mean Square Percentage Error
SA	Sensitivity Analysis
SAE	The Society of Automotive Engineers
SPSA	Simultaneous Perturbation Stochastic Approximation

SSAM	Surrogate Safety Assessment Model
SUMO	Simulation of Urban Mobility
TTC	Time to collision
V2V	Vehicle to Vehicle
V2I	Vehicle to Infrastructure
W-SPSA	Weighted Simultaneous Perturbation Stochastic Approximation

1 Introduction

In this chapter, the background and motivation behind this study are depicted and the aims of this thesis are presented. It also contains the research questions investigated to fulfill the aim, as well as the scope of work. Finally, the structure of the thesis is demonstrated for ease of understanding.

1.1 Background and motivation

The number of road traffic fatalities continues to rise steadily in the world, although the degree of this trend varies among countries. As per the international road safety report of 2013 from the World Health Organization, 1.24 million people die worldwide from road traffic accidents per year (World Health Organization 2013). Another report published 5 years after, shows this number has increased to 1.35 million worldwide deaths per year or approximately 3,700 deaths per day, which is a matter to be concerned with (World Health Organization 2018). 200 thousand people died in the road accident, alone in USA, in whole 20s that is more than the total number of American soldiers died in the First World War (Norton, P., D. 2008). Germany encountered a 3% increase in the number of road traffic fatalities in 2018 as compared to 2017, amounting to 3,275 deaths in 2018 (International Transport Forum 2019). Most of the accidents originated from one major source: human errors. One study demonstrated the human factors play serious roles in 90-95 percent of total accident incidents, of which about 60 percent is directly originated from human error (Sonja Forward 2008). The human factor is considered as an all-time major aspect for the transportation and mobility industries for improved road safety and lesser crash rates.

In additional to safety aspects, the environmental impacts are severely influenced by transportation activities (European Commission 2011, Tánczos and Török 2008). Such activities affect the environment by adding different pollutants and greenhouse gases in the atmosphere. This state accelerates the negative climate changes. It is one of the severe reasons behind the challenges, currently transportation and mobility industries are facing (Tánczos and Török 2008). European commission indicated the traffic as the only source exists in Europe, where the greenhouse gas emissions are still rising (European Commission 2011).

Despite improved infrastructures, improved vehicle design, and road communications, the road traffic accidents and emissions cannot be successfully minimized. The different form of fuel usage-based taxation plans of the governments are not obtaining the sustainable transportation and mobility goals (Tánczos and Török 2008, Tanczos, K., & Torok, A. 2007). The people and the products must be transported from one place to another place. The demand of transportation cannot be compromised as it is a vital element of development and human existence (Tanczos, K., & Torok, A. 2007). However alternative solutions to mitigate and reduce the negative impacts of the transportation can be taken.

Therefore, in this stage the necessity of vehicle automation became significantly important. Once, the external factors of driving reach the final level of development, the quality enhanced driving environment and efficient transport system rely absolutely on the road users (Bohm and Häger 2015, KPMG 2012). Autonomous automobile technologies are rolling over the industries to get rid of many transportation limitations, among which human error is most serious factor to be overcome (Alonso R. M. et al. 2017, Makridis et al. 2018).

According to Bohm and Häger (2015), vehicles with the self-driving ability, which can be driven without any human interference, are known as autonomous vehicles (AVs). AV technology has progressed swiftly in recent years, which can currently be seen in the different automated features of vehicles in today's commercial market (Morando et al. 2018). The development process of self-driving vehicles has gone through a historical passage.

Although it seems building the autonomous vehicles is an ambition of inceptive stage of automotive development of early part of the 20s of the 20th century (Igliński and Babiak 2017), the root of such technologies is not new. The automotive inventors were planning about AVs soon after the invention of vehicles themselves. In 1925, Houdina Radio Control, a radio instruments supplier founded by Francis P Houdina, took the first attempt to control a vehicle by radio and was able to start the engine, shift the gears and activate the horn successfully (Dormehl and Edelstein 2018, Narayanan et al. 2020). With the untiring advancement of research and maturity of the implementation of computers and wireless communication in the sector of transportation, the development of AVs have made noteworthy accomplishments since then (Liu et al. 2019).

Introduction of AVs in the transportation and mobility, is the revolutionary point in road traffic and the automotive sector where it plays a strong role in solving existing and potential future transportation and environment associated challenges. It is agreed globally that AVs replace the human driving to save the time which transform the everyday driving time to other activities i.e. last moment preparation or attending an online meeting. One can enjoy a movie in the motorway or can take a power nap while traveling. The hassles of safe motor movements (Liu et al. 2018b) and car parking after reaching the destination will be rerouted to autonomous technologies (KPMG 2012). Manufacturers and researchers indicate, on many occasions, that the AVs assure higher safety and user convenience to humans (Bohm and Häger 2015). According to Morando et al. (2018), AVs are predicted to decrease road crashes because most of them are originated from human-errors. Moreover, AVs offer congestion reduction, environment-friendly operations and increment of road capacity (Pierre-Jean Rigole 2014) by platoon building ability, vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communications which enable several additional comfort in the motorway i.e. by reducing vehicle stops at intersections etc (Li et al. 2015). The demand for AVs worldwide is increasing dramatically which indicates the future of the global AVs market. Both existing and new industries are concentrating development and implementation of autonomous vehicles for their coming market demand. Figure 1.1 overviews how existing traditional car manufacturers of developed and developing countries are gradually moving towards AV technologies. Tech-giant countries, like China and South Korea, are accelerating the development of AV by introducing many new AV focused companies.

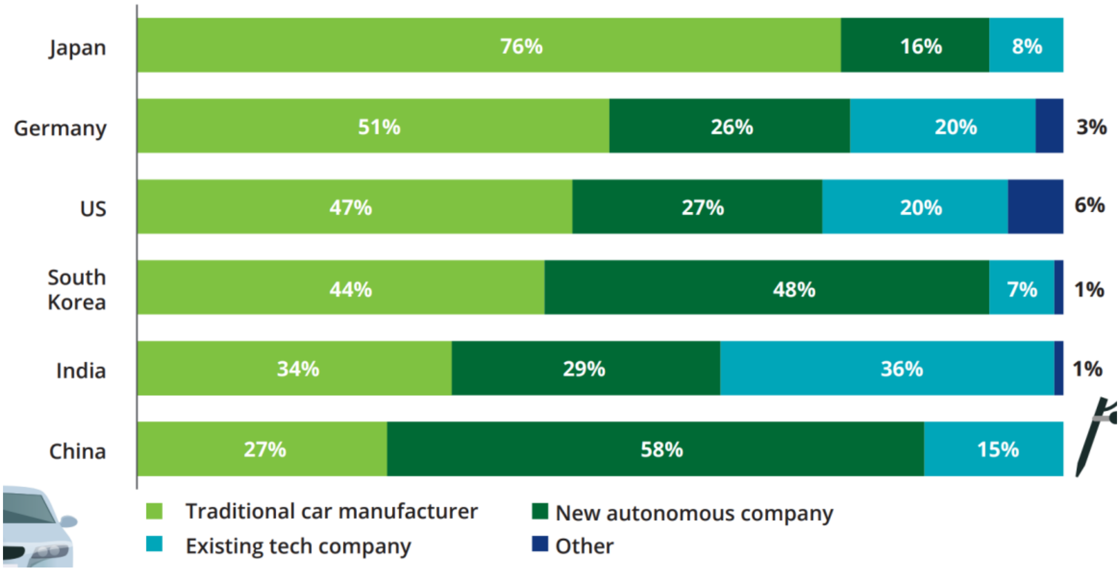


Figure 1.1 Leading countries of the C/AV industry (Deloitte 2016)

The descriptive year basis forecast visualized by Motamedidehkordi et al. (2017) on the expected share of automated vehicles in the German passenger is shown in Figure 1.2 (Motamedidehkordi et al. 2017). This illustration shows a rough idea of the duration of the transition period and the implementation of automated vehicle technologies. The estimation shows that the share of automated vehicles will start to increase considerably from 2020 onwards but may still be lower than 25% of the entire vehicle by 2030 in the German market.

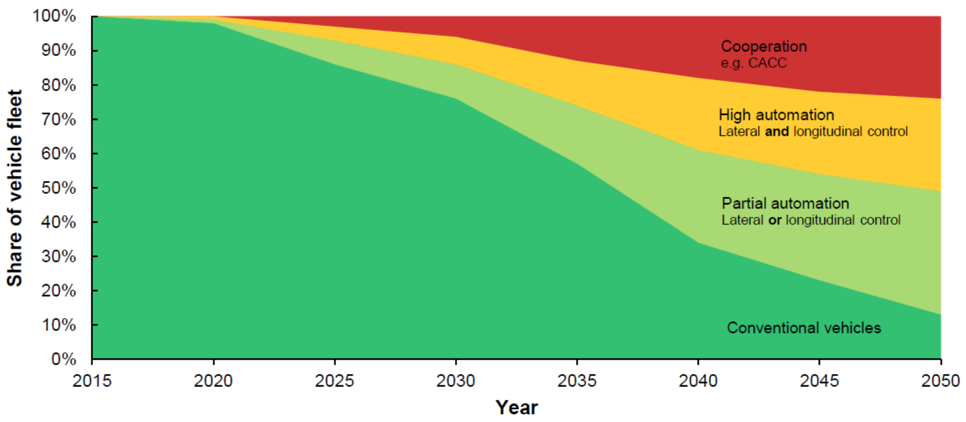


Figure 1.2 Forecast of the share of automated vehicles in Germany (Motamedidehkordi et al. 2017)

The AV with connectivity features are called Connected and Autonomous Vehicle (CAV) which is considered as a key agent of the transportation of future and the Cooperative Intelligent Transport System (C-ITS) (Alonso R. M. et al. 2017). According to Makridis et al. (2018), in upcoming decades, the transport industry will experience an immense change in preparing for Connected and Autonomous Vehicles (CAVs), which will be the reason of the drastic transformation of today's transportation and mobility patterns (Makridis et al. 2018).

The worldwide market of AVs is expected to reach up to 125 million passenger cars with embedded connectivity by 2022 which is a strong indication towards the upcoming connected transportation era (Millman 2018). The automobile industry has taken the cooperative adaptive cruise control (CACC) and the adaptive cruise control (ACC) as very essential technologies which are needed to be implemented in the primary phase of autonomous driving and connected vehicle development. It has direct influences over travel experiences. ACC and CACC logic can be used for successful representation of the behaviour of AVs and CAVs respectively (Makridis et al. 2018). As a result, effective simulator for the transportation impact evaluation of these major changes are important (Makridis et al. 2018, Liu et al. 2018a).

To visualize the impacts of AV and CAV in the current transportation system, before real-world implementation, microscopic traffic simulations can be used with some expert touches. As per Nilsson (1993), simulation is a widely implemented tool for studying the transportation system which investigates several research questions. He added that compared to other methodologies, simulation technique is more efficient and faster approach to obtain traffic data (Nilsson 1993). Past few decades were golden era of the microscopic traffic simulation. Critical states where investigation became expensive, complicated, time-consuming, non-scalable and risky, the microscopic traffic simulation has proven itself unparallelly suitable for insight views (Park and Qi 2005). Worldwide microscopic traffic simulators are being utilized to predict and to depict the characteristics of AVs and CAVs because of ease of use, capability to implement unrealistic models and multiple scenario management. Diversities in automation functions, sensor equipment, and driving logics can create differences in the simulation models. The microscopic traffic modelling techniques depend on the scope of functionalities which the vehicles can offer in today's time or in future (Sukennik 2018). PTV VISSIM is a popular microscopic simulator from PTV group which can be applied as a powerful simulator to deal with different transportation problems (PTV 2011). Currently, thousands of engineers and researchers are using PTV VISSIM to simulate the complex traffic problems worldwide.

In any traffic simulator, the driving behaviour parameters play deciding roles to represent the reality in the simulation models. One great advantage of CAVs among many is that these vehicles travel and exchange information with other entities i.e. vehicles, infrastructure, or traffic systems which makes the reaction time quite shorter comparatively with the human-driven vehicles and the safety headways can be shorter. Short spatial distances between two successive road agents increase the road capacity. Other advantages such as interaction with infrastructures result in early warning of accidents, congestion, or natural calamities, play a vital action in the use of travel time efficiently. These behaviours need to be reflected in the simulation model to perceive what will be the impact in the real world (Makridis et al. 2018).

This thesis is organized to meet and accelerate research goals of a research project of Chair of Transportation Systems Engineering (TSE) of Technical University of Munich (TUM), titled HumAV - Human-like Autonomous Vehicles. This project has a predominated thought that AVs will act with human-driven vehicles as like them which is valid for this thesis as well. As per different driving modules i.e. aggressive, normal, and safe, the driving behaviour parameters need to determine for the connected and/or autonomous vehicles (C/AVs) (Sukennik 2018), representing three different pattern of human driving styles, makes it human-like C/AVs. Vehicles will choose from their allowable range of parameters to follow as per its governing driving modules. These driving modules can be selected directly by the users or by the external communications i.e. Vehicle-to-Vehicle (V2V), Vehicle-to-Infrastructure (V2I), and emergency states. The road and traffic reaction of these modules varies severely. The aggressive driving module can have less safe distance with higher acceleration while a safe driving module is not allowed to reduce the safe distance lower than the allowable limit (Zeidler et al. 2018, Atkins 2016, Sukennik 2018).

The total process for preparing and implementing a model in microscopic simulator consists of several major steps what characterize the model analytically (Wunderlich et al. 2019). The outcomes of microscopic traffic simulator are highly influenced these steps. The number of required simulation runs taken in the process, has significant role in the outcomes of the simulator (Zeidler et al. 2018). Transportation and traffic researchers consider traffic as the stochastic and dynamic event which is created from activities and reaction evolved from the acting active traffic agents while some external factors influencing the system out of the grid. The traffic simulation models must include these governing behaviours because they rely on random variables and samples originated from random distribution to simulate the agent decisions in the model i.e. lateral manoeuvres. According to traffic flow simulation experts, such need of multiple runs to get reliable consequences is a drawback. One needs to make the negotiation between reliable results and computational efforts (Antoniou and Wagner 2014). That's why the least number required of simulation run is a bargaining issue in any microscopic traffic simulation project. Although several approaches and hypothesis are found to obtain the minimum number of the simulation run, a confidential interval based equation is preferred worldwide to identify the least number of runs required for an accepted closeness of simulation results with the real-world data (Antoniou and Wagner 2014, Research, Development and Technology, Turner-Fairbank Highway Research Center 2004).

After deciding the required number of runs, the calibration and validation come to the light. They have essential role in microscopic traffic flow simulation. To obtain greater fidelity and credibility in the microscopic traffic model, the calibration and the validation are performed. Different microscopic parameters i.e. car following, lane merging, and lane changing parameters can be used to perform the calibration and validation (Dadashzadeh et al. 2019b). As per previous studies, in past times, most calibration actions have implemented on the informal practices, and demonstrate a stepwise methodology and instruction for the calibration and validation of microscopic traffic models (Park and Qi 2005). Currently many advanced algorithms are being used to calibrate the models before performing scenario simulations (Yu and Fan 2017b, Vasconcelos et al. 2014, Hussain et al. 2017, Dadashzadeh et al. 2019a, Qurashi et al. 2019b, Qurashi 2018, Dadashzadeh et al. 2019b).

From previous studies, it is anticipated that C/AVs will demonstrate an increment in traffic performance and a lowering of emissions and energy consumption (Makridis et al. 2018, Mattas et al. 2018). Travel time, delay time and speed, what other studies used for such traffic performance exploration (Atkins 2016), can be used to traffic performance investigation for this study as well. Furthermore, the plug-in, EnViVer can be used for calculating the emission to assess the environmental impact for such studies. To perceive the safety implications of C/AVs, VISSIM and Surrogate Safety Assessment Model (SSAM) need to collaborate to find the number of potential conflictions from the simulated data and vehicle trajectories.

The outcomes of this study will demonstrate how human-like C/AVs impact over the traffic, emission and safety aspects in the traffic. Furthermore, it will visualize the interactions of different driving behaviour parameters of AVs in the traffic performances using sensitivity analysis platform.

1.2 Research objective

The first objective of this thesis is to investigate over the impact of human-like C/AVs in the mixed traffic in the urban corridor. To obtain this objective three different driving modules (i.e. aggressive, normal, and safe module) for C/AV will be examined for different HV-AV-CAV ratio for three different traffic flow (i.e. peak hour traffic demand, 20% below peak hour traffic demand and 20% above peak hour traffic demand). The second objective is to examine over the interactions of the driving behaviour parameters of the AVs in the traffic performances.

1.3 Research questions

The following research questions are going to be explored to achieve the objectives of this thesis:

- What will be the impact in the urban network, if HVs are gradually replaced by the C/AVs, in terms of traffic, environment and safety concerns?

- What driving behaviour parameters of AVs play significant roles in the traffic performances?

1.4 Expected contributions

This thesis contributes to the knowledge of methodological and practical level in the following directions:

- It gives a platform to perceive how several driving parameters of HVs can be considered for different driving modules of C/AVs in microscopic traffic flow simulator
- It identifies how human-like AVs impact over the traffic performance, emission and safety
- It proposes the interactions of driving behaviours parameters of AVs in the traffic performance

1.5 Structure

This report contains six main chapters.

- Chapter 1 introduces the background and motivation of the research and study goals. It also indicates give an outline of the expected contributions to the future studies.

- In Chapter 2 is a collective discussion of literature focusing microscopic simulation approaches and different pre-simulation activities such as calibration and validation works. In latter part, it demonstrates C/AV modelling approaches along with different evaluation measures, used by other researchers.

- Chapter 3 illustrates the methods and approaches followed for executing this study.
- Chapter 4 presents the details of the experimental setup developed to meet the study goals.
- Chapter 5 contains the analysis results obtained from the experiments, mentioned in chapter 4. The impact of human-like C/AVs in the mixed traffic and interactions of the driving parameters of AVs are explored to perceive the importance of presence of the automation in the mixed traffic.
- Finally, chapter 6 provides a summary of the report as well as limitations and possible future work of the thesis. Figure 1.3 shows the flowchart of the overview of this thesis.

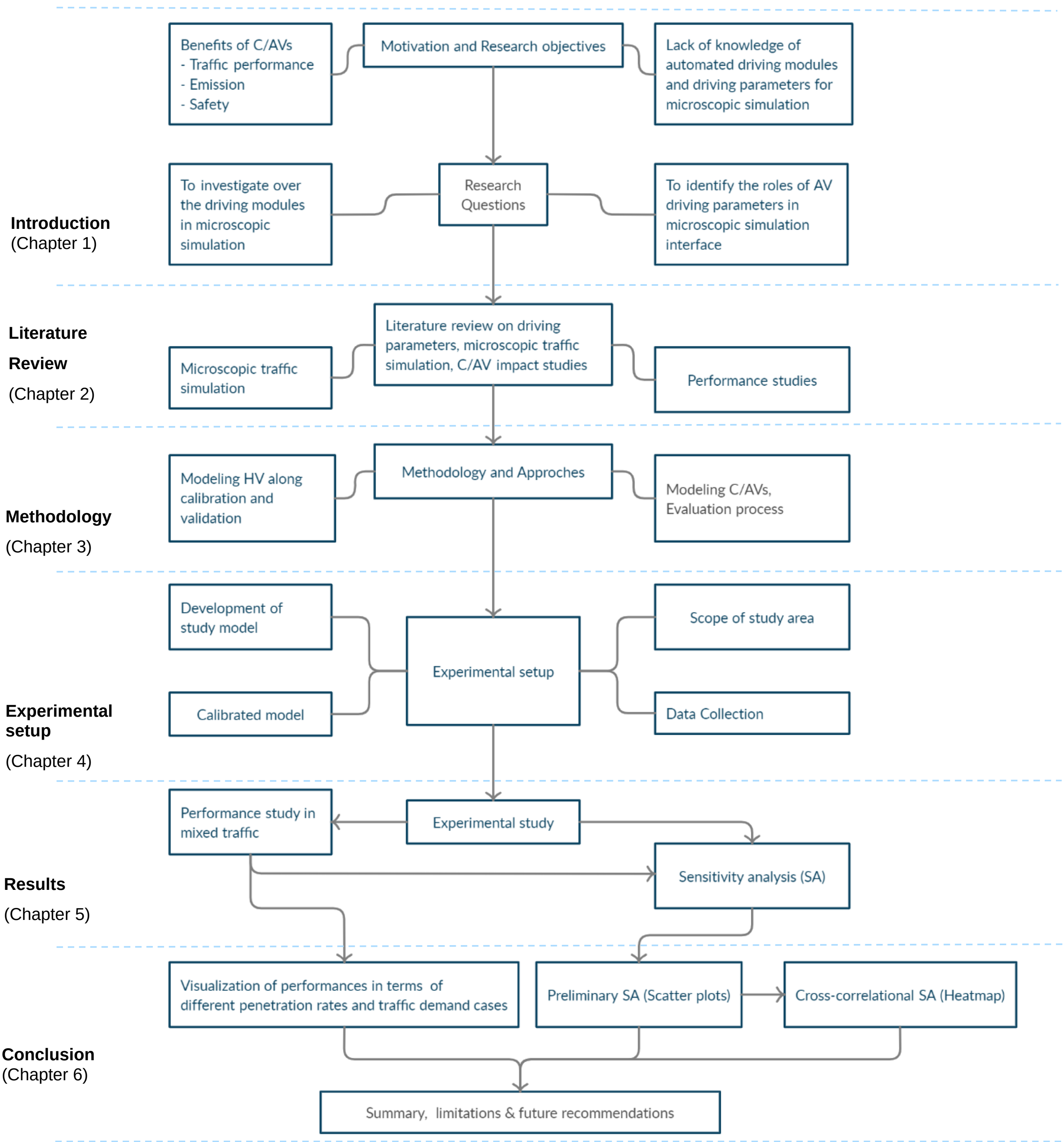


Figure 1.3 Thesis overview

2 Literature review

In this chapter, reviews of previous studies relevant to this thesis are discussed. The entire chapter is divided into three main sections. In the first section, the general procedures and different components of microscopic traffic simulations are evinced that are repeatedly found to help plan the simulation during the literature review. The second section contains a diverse overview of driving behaviour models, followed by an illustration of the different driver behaviour models found in the PTV VISSIM interface. In the last section, a summary of earlier studies on microscopic C/AV simulation and their findings are explored which are developed and tested using different microscopic traffic simulator i.e. SUMO (Simulation of Urban Mobility) developed by the Institute of Transportation Systems at the German Aerospace Center.

2.1 Microscopic traffic simulation

The progression of microscopic traffic simulation techniques of the last few decades is accelerating the computational capacity faster than ever before (Maheshwary et al. 2018). The modern data collection and data management have strong influences over intelligent transportation system (Antoniou et al. 2011a). The researchers of different fields are getting immense opportunity to gain both the micro and macro-level insight of the scientific investigations by the simulation models. Traffic Engineers and researchers all over the world have chosen microscopic flow simulation because, by nature, microscopic simulation is robust and easier to implement. Microscopic Traffic simulation is considered globally a pioneer tool to solve transportation and mobility challenges (Hussain et al. 2017). While the field tests are found to be restrained into the legal and financial matter, microscopic traffic flow simulation is found to be economical and flexible by its methodology which can analyze and evaluate transportation system and most importantly traffic conditions with higher precision under proper jurisdiction (Rakha et al. 1996). The microscopic model collects detailed information on vehicle movements and interactions on a temporal basis which gives a precise representation of transportation interactions in the real world. Proper microscopic simulation demands several parameters to be finalized before performing the concluding run (Federal Highway Administration 2004).

The calibration and validation processes are an indispensable and crucial stage in the microscopic traffic simulation. To control traffic flow characteristics and behaviors, the microscopic flow simulation software comes with many driving behaviour parameters. These parameters are set to the average or a reasonable value (Park and Schneeberger 2003). Number of parameters can be nominated to perform the calibration and validation for a microscopic model. Sometimes these internal parameters cannot be harvested directly from the real world but can be selected using calibration and validation procedures only for creating special components in the simulation environment i.e. vehicle type from future. The process of selection of these inner parameters is drastically shifting from manual methodology to automatic selection processes making the process dynamic (Maheshwary et al. 2018, Prakash et al. 2018, Zhang et al. 2017, Qurashi et al. 2019a, Antoniou et al. 2015b, Hale et al. 2015b, Lu et al. 2015, Antoniou et al. 2011b, Vaze et al. 2009, Balakrishna et al. 2007a).

The traffic simulation models show stochasticity because these models utilize random variables and samples from the random distributions to demonstrate act produced by the simulated items of the microscopic models. One disadvantage of such act is that multiple time simulation run is needed for collecting committed results (Antoniou and Wagner 2014) which makes the investigation of number of required simulation, a principal step in microscopic traffic simulation. The measure of effectiveness (MoE), also known as measure of performance (MoP) and goodness of fit (GoF), are two important topics which are involved to evaluate the calibration and validation quality. Proper scientific understanding and explanations are needed over choosing the MoE and GoF for a microscopic traffic simulation (Antoniou and Punzo 2014).

2.1.1 Number of required simulations run

The traffic flow is a stochastic and dynamic event by nature. It is upshot of activities of the many agents, along with various external occurrences (Antoniou and Wagner 2014). According to Antoniou and Wagner (2014), the microscopic models use the random variables and sample from random distribution. As a result, the models act stochastically what are represented in the simulation. The big con of this event is that several runs of the simulation are required to gain trustworthy outcome. Single run is dangerous and significantly misses other possibilities in the simulation (Antoniou and Wagner 2014). Executing several runs and averaging their outcomes move the result quality towards the expected values of the real distributions. The random number seed is used to select numbers in serial that are imposed to make many decisions in entire model run (Federal Highway Administration 2004, PTV 2011).

It is unpredictable to know the number of runs needed to finalize by any statistical value to satisfy the statistical expectations. A few runs can help to know how many runs might be needed to achieve statistically valid results. One straight plan is that the total number of the run better be increased as the standard deviation of a set of simulation runs is higher, found from initial test. A proper number of recurrences are selected considering the level of significance of the desired results and the permissible percentage error of the estimation (Antoniou and Wagner 2014). Table 2.1 shows different approaches to calculate number of required simulations run.

Sl.	Equation	Previous Studies
1	n = $(\frac{s \cdot t_{\propto/2}}{\mu \times \varepsilon})^2$	(Florida Department of Transportation 2014, Chu et al. 2003, Hollander and Liu 2008)
2	n = $(\frac{s \cdot z}{E})^2$	(Dowling et al. 2004a, Virginia Department of Transportation 2013)
3	n = $(2 \cdot t_{0.025,N-1} \cdot \frac{s}{R})^2$	(Dowling et al. 2002, Dowling et al. 2004b, Oregon Department of Transportation 2011, Washington State Department of Transportation 2014, Transport Roads & Maritime Services 2013, Dowling et al. 2004a)
4	n = $(\frac{s \cdot z}{\mu \cdot \varepsilon})^2$	(Nevada Department of Transportation 2012)

Table 2.1 Model Run Statistical Equations

Where, n = minimum sample size, s = standard deviation of modeled data, ε = acceptable error, E = acceptable error (same units as performance measure used), z = z – statistic from a normal distribution (95% use 1.96), $t_{\propto/2}$ = t – statistic from student's – distribution for 2 – tailed test (n-1 degrees of freedom), μ = mean of performance measure used, R = confidence interval f or true mean (Transport Roads & Maritime Services 2013) considers $\mathrm{R} = {}^1/_2 \text{ precision } (\%) \cdot \mu$

Widely accepted standard equation of number of simulation runs proposed by US department of transportation (Federal Highway Administration 2004):

$$CI_{1-\alpha\%} = 2 * t_{(1-\alpha/2),\, N-1} \frac{S}{\sqrt{N}} \qquad (2.1)$$

Where, $CI_{(1-\alpha)\%}$=(1-α)% confidence interval for the true mean, where alpha equals the probability of the true mean not lying within the confidence interval, $t_{(1\text{-alpha}/2),\, N-1}$= Student's statistic for the probability of a two-sided error summing to alpha with N-1 degrees of freedom, where N equals the number of repetitions and S= Standard deviation of the model results

The simple and straightforward approach of deciding the minimum required number of simulation could be taking 10 simulations run with different random of seed (Federal Highway Administration 2004, Dowling et al. 2002, Oregon Department of Transportation 2011, Virginia Department of Transportation 2013, Florida Department of Transportation 2014, Nevada Department of Transportation 2012). Besides that 5 runs (Truong et al. 2016, MnDOT 2008), 11 runs (Washington State Department of Transportation 2014) and even 20 runs can be also seen (Transport Roads & Maritime Services 2013).

Before determining the required number of simulations, one need to finalize the measure of effectiveness (MoE) for this test. The MoE plays significant role in the determination of required number of simulations. Different agencies have different choice of MoEs. Table 2.2 shows measure of effectiveness used by several agencies to choose number of simulations.

Sl.	Measure of Effectiveness	Agencies
1	Total traffic volume	(Florida Department of Transportation 2014, Washington State Department of Transportation 2014, Nevada Department of Transportation 2012)
2	Total vehicle hours traveled	(Transport Roads & Maritime Services 2013)
3	Speed	(Dowling et al. 2004a, Florida Department of Transportation 2014, Nevada Department of Transportation 2012)
4	Travel times along a corridor	(Florida Department of Transportation 2014, Oregon Department of Transportation 2011, Washington State Department of Transportation 2014)
5	Average vehicle delay	(Oregon Department of Transportation 2011)

Table 2.2 Measure of Effectiveness for determining required number of simulations

Furthermore, some agencies prefer to determine the required number of simulations by two MoE (Nevada Department of Transportation 2012).

2.1.2 Calibration

2.1.2.1 Algorithms

An effective calibration plays a vital role in microscopic traffic simulation for getting useable and trustworthy results from the model. Model preparation can be divided in three stage in model into three steps: 1. Base Model Development 2. Calibration of the Base Model and 3. Model Validation (Hussain et al. 2017). The base model development stage provides the inputs for the calibration stage. It also deals with proper selection of the size of the focus region, preconditions for data collection, and time interval selection. Some circumstances can be precisely avoided during building the base map by selecting the focus areas appropriately such as covering important locations such as intersections, bottlenecks (Hussain et al. 2017).

The researchers of the traffic microscopic simulation field used to rely for a long time on the trial and error based procedures to calibrate the simulation model which used to be a tiresome and time-consuming phase in the traffic flow modelling study (Mehar et al. 2014). This operation consists of using default values for the unique calibration parameters by trial and error to match the real-world data, the measure of effectiveness (MoE) (Park and Schneeberger 2003). Last few years, can be considered as a golden time for calibration as several pioneer studies have been carried out to bring more insightful methodologies to perform the calibration process faster, with higher reliability and efficiency to deal with great numbers of calibration parameters, which have drawn a guideline plan for the modern day's researchers (Park and Schneeberger 2003, Park and Qi 2005, Hourdakis et al., Jobanputra and Vanderschuren 2012). Over the year, Calibration procedures have shifted from single time-consuming manual calibration to efficient automated processes what ultimately make the model more realistic and accurate for the researchers and engineers (Manjunatha et al. 2013, Maheshwary et al. 2018).

The methodology of calibration and validation quite shaped differently now what was unimaginable before (Brackstone et al. 2012). Currently, various optimization methods have been implemented to reduce the difference between the real-world data and simulated outputs (Dadashzadeh et al. 2019b) which include Genetic Algorithm (GA) (Chiappone et al. 2016, Menneni et al. 2008a, Strnad I, Kim et al. Washington, D.C., 2005, Park and Qi 2005, S.M.P. Siddharth and Ramadurai 2013, Manjunatha et al. 2013, Dowling et al. 2004b, Liu Yu et al. 2006 BRT Special Edition), Simultaneous Perturbation Stochastic Approximation *(*SPSA*)* (Spall, J., C. 1998a, 1998b) or Principal Components - Simultaneous Perturbation Stochastic Approximation (PC-SPSA) (Qurashi et al. 2019b) or Weighted Simultaneous Perturbation Stochastic Approximation (W-SPSA) (Hale et al. 2015a, Qurashi et al. 2019b, Qurashi 2018, Antoniou et al. 2015a), Particle Swarm Optimization (PSO) (Boittin et al. 2015), OptQuest/Multistart (OQMS) (Ciuffo et al. 2008), Evolutionary Algorithms (EA) (Menneni et al. 2008b) and mixture of different of optimization techniques (Ma et al. 2007, Yu and Fan 2017a). SPSA was introduced as a random search stochastic approximation algorithm. It is also a gradient-free algorithm which requires a fixed number of objective function evaluations per iteration to approximate the gradient (Spall, J., C. 1998a, 1998b). In contrast to the SPSA, the Finite Difference Stochastic Approximation (FDSA) follows the linear searching method to find the optimum. It needs FDSA less iteration, but more time is required than the SPSA. Therefore, FDSA is not suitable for a bigger network. SPSA on the other hand, works on a random search. It needs less time but more iteration to find the optimum. Now the problem is FDSA's computational effort increases exponentially with increasing problem dimensions and the SPSA will add inaccuracies and converges using a greater number of iterations but will perform better in terms of time and computational effort (Spall, J., C. 1998a, 1998b, Balakrishna et al. 2007b). FDSA provides more accurate gradient approximation than SPSA. SPSA will just add more inaccuracies and will increase the number of iterations. SPSA has some issues with its nature. To deal with the SPSA limitations, two other SPSA provisions have been practiced. PC-SPSA can be used to reduce the network size and complexity. Two major differences of PC-SPSA are: instead of the OD flow vector its PC scores are perturbed and instead of addition and subtraction the gain sequences are multiplied as a percentage change in (Qurashi et al. 2019b, Qurashi 2018). The W-SPSA, on the other hand, deals with the SPSA total network characteristics using weighted factor. When a point of location is important and it does not affect the total network, the interest location should be given more emphasis on the operation. It is found to be best in situations where the correlations body of variables is not homogeneous (Spall, J., C. 1998a, 1998b). This is what W-SPSA deals with. It extends the SPSA with a weight matrix which reflects the temporal and spatial network correlations (Antoniou et al. 2015a).

2.1.2.2 Parameters

Several researchers encountered several different calibration parameters based on different optimization procedures, the number of calibration parameters, the composition of the vehicles, and purposes of the simulation models i.e. alternative measures planning or road safety evaluation. A big number of researches from the past were conducted for human-driven vehicles hence covering all the human behaviours in the street. Therefore, in most of the cases, simulation models were reflecting the selection of similar kinds of parameters for the calibration. Perhaps, some previous studies helped much to gain an insight of Automatic vehicle and Autonomous vehicle in the microscopic simulation (Atkins 2016, Bagloee et al. 2016, Calvert et al. 2017, Trommer et al. 2016, Davidson and Spinoulas 2016, Sukennik 2018). Table 2.3 shows the PTV VISSIM user manual suggests several driving behaviours attributes for different kinds of networks.

Sl.	**COM VISSIM Parameters**	**Parameter Description**	**Range (Dadashzadeh et al. 2019b, PTV 2011)**	**Default (PTV 2011)**
General Parameters				
1	LookBackDistMax	Max. Look back distance [m]	50-200	150
2	LookBackDistMin	Min. Look back distance [m]	0-200	0
3	LookAheadDistMax	Max. ahead back distance [m]	100-300	250
4	LookAheadDistMin	Min. ahead back distance [m]	0-300	250
5	NumInteractVeh	Number of interaction vehicles	0-99	99
6	StandDist	Standstill distance in front of static obstacles [m]	0,00-3,00	0,50
7	FreeDrivTm	Free driving time [s]	N.A	11,0
8	IncrsAccel	Increased Acceleration [m/s2]	1,0-9,99	1,0
9	MinCollTmGain	Minimum collision time gain [s]	N.A	2
10	MinFrontRearClear	Minimum clearance (front/rear) [m]	N.A	0,5
11	SleepDur	Temporary lack of attention - sleep duration	N.A	0,0
Lane-changing model parameters				
12	DecelRedDistOwn	Reduction rate for Leading (own) vehicle [m]	100-200	200,00
13	AccDecelOwn	Accepted deceleration for leading (own) vehicle [m/s^2]	-3 to -0.5	-1,00
14	AccDecelTrail	Accepted deceleration for following (trailing) vehicle [m/s^2]	N.A	-0,50

15	SafDistFactLnChg	Safety distance reduction factor	0,10-0,6	0,60
16	CoopDecel	Max. deceleration for cooperative lane-change/braking [m/s^2]	-6,00 to -3,00	-3,00
17	MaxDecelOwn	Max. deceleration for leading (own) vehicle [m/s^2]	N.A	-4,00
18	MaxDecelTrail	Max. deceleration for following (trailing) vehicle [m/s^2]	N.A	-3,00
19	DecelRedDistTrail	Reduction rate for following (trailing) vehicle [m]	N.A	200,00
20	PlatoonFollowUpGapTm	Platooning - follow-up gap time [s]	N.A	0,60
21	PlatoonMinClear	Platooning - minimum clearance [m]	N.A	2,00
Wiedemann 74 car-following model parameters				
22	W74ax	Average standstill distance	0,50 -2,50	2,000
23	W74bxAdd	Additive Factor for security distance	0,70 -4,70	2,000
24	W74bxMult	Multiplicative factor for security distance	1,00 -8,00	3,000
Wiedemann 99 car-following model parameters				
25	W99CCO	Desired distance between lead and following vehicle [m]	0,60 -3,05	1,50
26	W99CC1DISTR	Headway Time [s] Desired time between lead and following vehicle	0,50 - 1,50	0,90
27	W99CC2	Following variation [m] Additional distance over safety distance that a vehicle requires	1,52 - 6,10	4,00
28	W99CC3	Threshold for entering following state [s] Time is second before a vehicle start to decelerate to reach safety distance (negative)	-15,00 to -4,00	-8,00
29	W99CC4	Negative "following Threshold"[m/s] Specifies variation in speed between lead and following vehicle	-0,61 to -0,03	-0,35
30	W99CC5	Positive "following Threshold"[m/s] Specifies variation in speed between lead and following vehicle	0,03 -0,61	0,35
31	W99CC6	Speed dependency of oscillation [1/ms]	7,00-15,00	11,44
32	W99CC7	Oscillation Acceleration Acceleration during the oscillation process[m/s^2]	0,15-0,46	0,25
33	W99CC8	Standstill Acceleration [m/s^2]	2,50-5,00	3,50
34	W99CC9	Acceleration with 80 Km [m/s^2]	0,50-2,50	1,50
Lateral manuever parameters				
35	LatDirChgMinTm	Lateral direction change - minimum time [s]	N.A	0,0
36	LatDistDrivDef	Lateral minimum distance at 50 km/h (default)	N.A	1,0
37	MinSpeedForLat	Minimum longitudinal speed for lateral movement	N.A	1,0

Table 2.3 Selected driving behaviour parameters with their default values (PTV 2011, Dadashzadeh et al. 2019b)

2.1.3 Validation

Validation validate the model to investigate if it can provide reasonable results for other inputs for the same parameters (Aziz 2018, Park and Won 2003). As per Toledo (2014) the validation is the procedure of inspection, which inspect over the model to study if it can perceive the impact of the changes in the system and its inputs. Although the use of microscopic simulator is getting popularity, still validation does not get much attention in the scientific records (Antoniou et al. 2014). As per Antoniou et al. (2014), user should know simulation models are estimation of actuality that cannot represent the real world precisely. It means perfectly valid model is not a real thing. Such models are created for specific tasks to satisfy specific goals, which are needed to be validated by representative measure of effectiveness (Antoniou et al. 2014).

Two types of approaches are being used for validating the models: visual and statistical (Rao and Owen 2000). Visual representation use graphics to compare the real-world survey data with the generated data. A time-space diagram can be a good example of visual method of validation. Such a heuristic and subjective approach is often inspected by specialist to visually determine if the model is validated or not. In contrary, the statistical validation implements concept of goodness of fit, confidence intervals, and other statistical tests to measure the similitude of the real-world survey data with the generated data (Antoniou et al. 2014).

2.1.4 Selection of Measures of Effectiveness (MoE)

Choosing the appropriate measures of effectiveness (MoE) is a vital step in the calibration and validation process. Measures of effectiveness are the selected parameters for the comparison of simulation results and the field survey data. There are different measures of effectiveness that change with controllable and uncontrollable parameters of the simulation. Travel time, traffic volume, delay time and speed are very common measures of effectiveness for calibration study. Calibration and validation should have different measures of effectiveness for creating a justified and reliable model for future use (Mahmud, S., M., S. et al. 2019, Fransson 2018, Maheshwary et al. 2018, Hussain et al. 2017, Dadashzadeh et al. 2019c, 2019b).

2.1.5 Goodness of fit (GoF)

The goodness of fit (also known as the measure of performance - MoP) of a statistical system specify how well it fits to the observations. The measures of goodness of fit point out the difference between real-world data and the simulation data. Researchers take more than one goodness of fit parameters to describe the performance of the model because of the scope of the GoF (Toledo 2003, Yu and Fan 2017b, Toledo and Koutsopoulos 2004). Some repeatedly used parameters are the root-mean-square error (RMSE), the root-mean-square percent error

(RMSPE), the mean error (ME), and the mean percent error (MPE) (Toledo and Koutsopoulos 2004). Table 2.4 shows that recurred used goodness of fit from previous studies.

Sl.	Name of the parameter	Fitness Function	Previous Studies
1	Normalized Root Mean Square Error (RMSN)	RMSN=$\frac{\sqrt{N.\sum_{n=1}^{N}(Y_n^{obs}-Y_n^{sim})^2}}{\sum_{n=1}^{N}Y_n^{obs}}$,	(Antoniou et al. 2013, Papathanasopoulou and Antoniou 2015)
2	Root Mean Square Percentage Error (RMSPE)	$\text{RMSPE} = \sqrt{\frac{1}{N}\sum_{n=1}^{N}(\frac{Y_n^{sim}-Y_n^{obs}}{Y_n^{obs}})^2}$	(Antoniou et al. 2013, Papathanasopoulou and Antoniou 2015, Toledo 2003)
3	Root Mean Square Error (RMSPE)	Minimize Z (RMSE)=$\sqrt{\frac{1}{N}\sum_{i=1}^{N}(S_{obs1}-S_{sim1})^2}$	(Dadashzadeh et al. 2019c, Toledo 2003, Dadashzadeh et al. 2019b)
4	Mean Absolute Normalized Error (MANE)	Minimize Z (MANE) =$\frac{1}{N}\sum_{i=1}^{N}(\frac{\lvert V_{obs1}-V_{sim1}\rvert}{V_{obs1}}+\frac{\lvert S_{obs1}-S_{sim1}\rvert}{S_{obs1}})$	(Dadashzadeh et al. 2019b, Dadashzadeh et al. 2019d)
5	Mean Error (ME)	ME=$\frac{1}{N}\sum_{n=1}^{N}(Y_n^s-Y_n^o)$	(Toledo 2003)
6	Mean Percentage Error (MPE)	MPE= $\frac{1}{N}\sum_{n=1}^{N}\left[\frac{Y_n^S-Y_n^O}{Y_n^O}\right]$	(Toledo 2003)
7	Theil's	U=$\frac{\sqrt{\frac{1}{N}\sum_{n=1}^{N}(Y_n^{sim}-Y_n^{obs})^2}}{\sqrt{\frac{1}{N}\sum_{n=1}^{N}(Y_n^{sim})^2}+\sqrt{\frac{1}{N}\sum_{n=1}^{N}(Y_n^{obs})^2}}$ U$_M$=$\frac{(\bar{Y}_n^{sim}-\bar{Y}_n^{obs})}{\frac{1}{N}\sum_{n=1}^{N}(\bar{Y}_n^{sim}-\bar{Y}_n^{obs})^2}$ U$_S$ =$\frac{(\boldsymbol{\sigma}^{sim}-\boldsymbol{\sigma}^{obs})^2}{\frac{1}{N}\sum_{n=1}^{N}(\bar{Y}_n^{sim}-\bar{Y}_n^{obs})^2}$ U$_C$=$\frac{2(1-p)\boldsymbol{\sigma}_{sim}\boldsymbol{\sigma}_{obs}}{\frac{1}{N\sum_{n=1}^{N}(\bar{Y}_n^{sim}-\bar{Y}_n^{obs})^2}}$	(Papathanasopoulou and Antoniou 2015, Antoniou et al. 2013, Toledo 2003)
8	Global Relative Error (GRE)	GRE=$\frac{\sum_{i=1}^{n}\lvert Q_{real}-Q_{sim}\rvert}{\sum_{i=1}^{n}Q_{real}}$	(Ma and Abdulhai 2002, Park and Qi 2005)
9	GEH statistics	GEH=$\sum_{t=1}^{T}\sqrt{\sum_{i=1}^{I}(V_i-V_{simulated-i})^2}$	(Paz et al. 2012)
10	Percentage error (PE)	$\delta = \left\lvert\frac{v_A-v_E}{v_E}\right\rvert \cdot 100\%$	(Park and Qi 2005)

Table 2.4 Repeatedly used Goodness of fit in previous studies (Antoniou et al. 2013, Papathanasopoulou and Antoniou 2015, Dadashzadeh et al. 2019c, Toledo 2003, Ma and Abdulhai 2002, Paz et al. 2012, Park and Qi 2005, Dadashzadeh et al. 2019b, Dadashzadeh et al. 2019d)

Toledo and Koutsopoulos (2004) demonstrate that the percent error visualizes directly details of the magnitude of the errors correspond to the average measurement. On the other hand, *RMSE* and *RMSPE* penalize greater errors at a higher rate correspond to the small errors (Toledo and Koutsopoulos 2004). The mean error (ME) and the mean percent error (MPE) statistics show the presence of order under-prediction or over-prediction in the simulated outcomes (Toledo 2003). As per (Toledo 2003), the mean error parameters are handy when imposed separately for single point measurements in the space. Moreover, it gives the perception of the spatial distribution of errors. On the other hand, percent error parameters measure their absolute error counterparts because it comes up with details of the magnitude of the errors relative to the average measurement (Toledo 2003).

Furthermore, the relative error can be seen from Theil's inequality coefficient. U is considered as bounded, $0 \leq U \leq 1$. $U = 0$ is considered a good fit between observed and simulated measurements. On the contrary, for $U = 1$ the fit will be taken as worst. Theil's inequality coefficient is decomposed to three proportions of inequality: the bias (U_M), the variance (U_S), and the covariance (U_C) proportions. These three proportions together become 1 i.e. $U_m + U_s + U_c = 1$. This bias proportion shows systematic error. As per Toledo (2003), these two proportions need to be kept closer to zero. The covariance proportion analyses the remaining error and it should be close to 1 (Toledo and Koutsopoulos 2004, Toledo 2003, Theil 1978).

2.2 Driving behaviour models

Globally, driving behaviour are being studied with many diverse approaches. According to Toledo (2003) driving behaviour models illustrate drivers' decisions concerning vehicle manoeuvres under various traffic conditions. These driving behaviour models inspired by traffic flow models that impact the vehicle movement in the longitudinal direction, and lane merging, and lane changing models, which manipulate the lane selection and gap acceptance behaviour (Toledo 2003). In microscopic traffic simulation, driving behaviour models play a serious role in what can change the outcomes from the simulation severely. Therefore, researchers can perform both conventional and data-driven approaches to improve the competitive quality of insight they get from the simulation. Both approaches have their limitations i.e. conventional approach is mathematical formulas dependent and reflects the traffic flow theories which makes it quite restrictive. In contrast, data-driven approaches are found to be better in terms of flexibility. It facilitates bringing additional information in the model but provides lesser insight into traffic flow theory than conventional models (Papathanasopoulou and Antoniou 2015).

The microscopic traffic simulation model has several sub-models that describe driving behaviour. Sub-models i.e. car-following model, lane-changing models, and lane-merging form the driver behaviour model in the microscopic traffic simulator (Fransson 2018). As per Gao (2008), the outcomes from the traffic simulation model rely significantly on these sub-models. Furthermore, Fransson (2018) indicated that not all driving behaviour carry the same weight i.e. car-following and lane-changing models are two very important sub-models. However, lateral movements are also significant in microscopic traffic flow simulation and typically it is accounted in lane changing models (Fransson 2018).

2.2.1 Conventional driving behaviour models

2.2.1.1 Car following models

Several procedures are available to define the car-following model where the principal goal is to represent how the constrained vehicle responds to changes in relative position and speed of the leading vehicle in an uninterrupted flow (Fransson 2018).

Greenshields model

The fundamental Greenshields model considers a linear relationship between speed and density where the road traffic flow is continuous. The advanced model covers a parabolic relationship between flow and density, additionally between speed and flow (Fransson 2018). Rakha and Crowther (2002) derived from these theories and the set connection between density and space headway as below (Rakha and Crowther 2002, Fransson 2018):

$$h=\frac{(\frac{u_f}{k_j})}{u_f-u} \qquad (2.2)$$

Where h= space headway, u_f= free-flow speed and k_j= jam density

According to the Kehoe (2011), validation for this model can be challenging by field observation as the speed at capacity is equivalent to half the free flow.

Pipes model

Rakha and Crowther (2002) explained regarding Pipes' model, that the follower tries to manage a safe distance from the vehicle in front, a distance that is proportional to the speed. The equation for Pipes'model is shown below (Fransson 2018):

$$d_{min} = [\dot{x}_n(t) - \dot{x}_{n+1}(t)]_{min} = 1.36[\dot{x}_{n+1}(t)] + 20 \qquad (2.3)$$

Where, d_{min} = minimum distance headway, $\dot{x}_n(t)$ = speed value of the leading vehicles and $\dot{x}_{n+1}(t)$ = speed value of following vehicles

(Kehoe 2011) mentioned the Pipes model for ease of validation through field data. This model takes the speed at the capacity to equal the free-flow speed (Kehoe 2011).

Van Aerde model

The Van Aerde model is a non-linear model which is a combination of Greenshields and Pipes models and is being used in INTEGRATION as car-following behaviour. The model formulated as (Fransson 2018):

$$s_n(t) = c_1 + c_3 u_n(t + \Delta t) + \frac{c_2}{u_f - u_n(t+\Delta t)} \tag{2.4}$$

Where, c_1, c_2, c_3= constants, u_n= the speed, u_f= free-flow speed and $s_n(t)$ = front to the front distance between the vehicles in t time.

Fransson (2018) mentioned in his study that Kehoe (2011) think that Van Aerde's model relationship such as speed-flow and the flow-density remain same between the respective curves for the Pipes andthe Greenshields models.

Gipps model

As per Fransson (2018), Gipps model is the basic theory behind the car following model act in the AIMSUN. It surmises that the speed of the following vehicle can be taken as either restricted or unrestricted by the lead vehicle (Fransson 2018). The Gipps car-following model is also known as 'collision avoidance' models. It ensure the safety distance and receives the driving behaviour of the preceding vehicle (Vasconcelos et al. 2014). The idea behind Gipps model is that each vehicle drives as per following vehicle speed this is why the following vehicle can safely be stopped when preceding vehicle brake immediately (Ciuffo et al. 2012). Gipps model formulation is given below (Busch Winter 18 / 19):

$$v(t + T) = min\{v_a, v_b\} \tag{2.5}$$

Where, *va* = maximum attainable velocity and *vb* = maximum possible velocity.

Wiedemann model

VISSIM offers a psycho-physical based model for car-following behavior, which is suggested by Wiedemann in 1974. The Psycho-physical model indicates that the following vehicle reacts arbitrarily to a small change of speed of the leading vehicle. It creates a simulation very close to the real world. Previous studies show that the driver has a progression of points of confinement for the improvements that will prompt a response (MITROI et al. 2016, Toledo 2003, Fransson 2018). The model developed by based on two considerations (MITROI et al. 2016) i.e. the driver of the follower vehicle is not affected by the size of the speed difference for long-distance and a limited speed or distance that points a benchmark and as a result, the driver of the following car will not respond for a short distance. The Wiedemann model presumes four different driving regions: following, free driving, closing in, or braking. These regions are defined by thresholds (or action-points) that explain the stage where driver changes the driving behaviour (Gao 2008, Higgs et al. 2011.). The thresholds of the regions for the Wiedemann 74 model are shown in Figure 2.1. In Table 2.5, the thresholds and regions for the Wiedemann model are detailed explained below by the help of Figure 2.1, the work by Olstam, J. J. and Tapani, A. (2004), and PTV (2011).

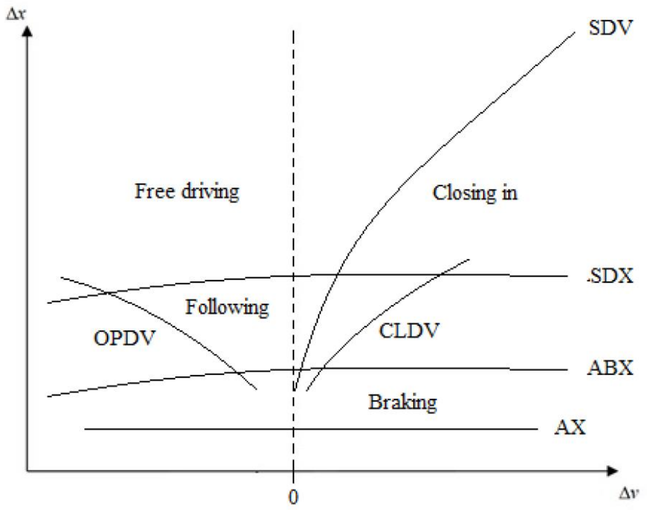


Figure 2.1 Graphical definition of Wiedemann model (Fransson 2018)

Wiedemann Threshold	Description
AX	Represents the desired distance between two standstill vehicles.
ABX	The minimum following distance between two vehicles that travels in approximately equivalent speed.
SDX	Represents the maximum following distance during the same speed conditions as ABX.
SDV	The point at which a driver realizes that he is closing in on the vehicle in front.
CLDV	Defines the point at which a driver becomes aware of minor differences in speed at short, decreasing distances.
OPDV	The point when a driver realizes that he is traveling at a slower speed than the vehicle ahead.

Table 2.5 Threshold definitions for the Wiedemann model (Fransson 2018)

The details of the regions defined by the thresholds in Table 2.5 can be summarized as:

Following

As per Fransson (2018), a driver in this region follows the vehicle ahead and is keeping the safety distance relatively constant. When a vehicle accesses the following location by crossing either the OPDV or SDX threshold, it gets a positive acceleration rate. Furthermore, when SDV or ABX is passed, the driver receive dismissive acceleration rate (Fransson 2018).

Free driving

Usually, the drivers are not confined by any leading vehicles in the free driving areas. As a consequence, the driver choose to travel with maximum acceleration rate to meet its desired speed (Fransson 2018).

Closing in

According to Fransson (2018), the closing in the region take place when the following vehicle choose to decelerate to stay away from a possible confliction with a slower vehicle ahead. It happens when the SDV threshold is passed (Fransson 2018).

Braking

Fransson (2018) mentioned that if the following vehicle is closer to the leading vehicle the driver is in the braking region for desired safety distance control. As the spatial distance between the vehicles is smaller, the driver of the following vehicle decelerates to avoid collision (Fransson 2018). In contrary, the Rakha and Crowther (2002) argue that under steady-state conditions, the car-following model in VISSIM transform to become Pipe's model.

2.2.1.2 Lane changing

As per Fransson (2018), lane changing represents the act of a vehicle moving towards an adjacent traverse lane from its present lane. Some researchers emphasized that lane changing plays an important role in microscopic traffic flow simulation (Mathew 2014, Moridpour et al. 2010). As multiple objectives interfere with each other during performing lane change, this sub-model becomes difficult to model in the simulator. Fransson (2018) has shown that a previous study from Moridpour et al. (2010) holds that lane changing action has a notable impact on the traffic flow properties that might be originated from speed and traffic flow oscillations. They added increasing congestion and capacity drop events are prone to generate from frequent lane changes (Moridpour et al. 2010, Mathew 2014, Fransson 2018). Mathew (2014) and Ramanujam (2007), based on the urge of the lane change, created two groups: Mandatory Lane Changes (MLC) and Discretionary Lane Changes (DLC). These two types are implemented in CORSIM, INTEGRATION, AIMSUN, and VISSIM (Mathew 2014, Ramanujam 2007). According to Mathew (2014), the DLC model has three steps for the stepwise decision-making process. The vehicle continuously needs to explore, if the desired lane change is worthy or not, and finally detect the gap acceptance requirement. Three steps of DLC are demonstrated below:

i. The decision to consider a lane change

Although several factors motivate a road user to perform a lane change, there is always the main thought is to improve the user's driving conditions such as increasing speed (Fransson 2018). Mathew (2014) denotes that motivation of changing lane can be highly motivated by finding out if it is easy for a road user to reach his planned speed within the space gap created between two vehicles (Mathew 2014, Fransson 2018).

ii. Check for the feasibility

Lane change is considered possible if it can be achieved without any collisions between two consecutive vehicles in the traffic. There could be two situations to meet this objective. One could be if the vehicle can reach its expected speed within the time frame and space available without applying the maximum deceleration. Another reason could be if the lag vehicle in the target lane reaches the expected speed and the above deceleration criteria are met (Mathew 2014, Fransson 2018).

iii. Gap acceptance

A gap can be described in time, distance, or speed difference between two platooning vehicles for the lane changing. Many models need two sub-gaps before the total gap i.e. lead gap and lag gap (Mathew 2014). The lead gap is described as the spatial distance between a vehicle and the leader vehicle in the desired lane. On the other hand, the lag gap can be defined as a spatial distance between the vehicle itself and the vehicle behind in the desired lane (Fransson 2018). Figure 2.2 shows the gap definition.

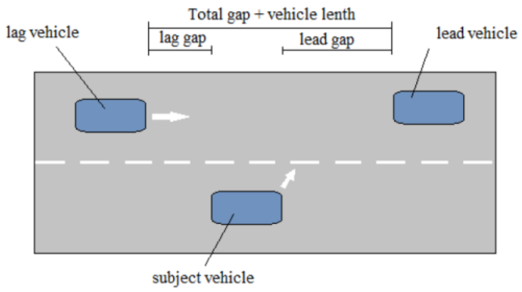


Figure 2.2 Graphical Representation of Gap definitions (Fransson 2018)

Mathew (2014) added two other models that are currently being widely used i.e. Forced merging models and Cooperative models. The Forced merging model represents a scenario where the available gap between the vehicle and the lag vehicle on the desired lane is not big enough to take a lane change but the vehicle chooses to change lane and forces the lag vehicle to decelerate until the gap size is large enough to be accepted. There are two considerations taken for this model (1) driver will keep checking the traffic situation in the target lane before making the last move (2) driver will keep trying to connect with the lag vehicle to verify if his right of way is informed. Once the right of way is accepted, the vehicle will merge with the target lane. If not, the vehicle will repeat (1) and (2) to finalize the right of way (Fransson 2018). Cooperative model does not use the concept of gap acceptance. This model is specifically helpful for the congested traffic state where acceptable gaps cannot exist. The driver in the cooperative system changes the lane by cooperating with other drivers where the lagging vehicle in the target lane reduces the speed to cope up to the lane change of the subject vehicle (Fransson 2018).

2.2.1.3 Merging behaviour models

According to Fransson (2018), merging is a special kind of lane change, which is needed in case numbers of lanes are reduced. Such a situation can be seen in the on-ramp areas. Li and Sun (2012) depict that such forced merge leads to competitive action between the main-line and the on-ramp drivers. This competitive driving behaviour restricts capacity in the merging area. Marczak et al. (2013) explain merging behaviour models use the gap acceptance theory presented. The AIMSUN and the VISSIM practice simple gap acceptance models (Fransson 2018). To assure and manipulate the necessity of changing the lane to the end of the acceleration lane additional parameters are added. VISSIM cannot provide facility for gap acceptance (Farrag, S., G. et al. 2020). In VISSIM interface, such merging behaviours can be represented by adjusting of driver‘s aggressiveness (Marczak et al. 2013, Fransson 2018). Hidas (2005) reported another complex merging model covering forced and cooperative merge properties. It does not offer cooperative merging for the subject vehicle (Hidas 2005). Choudhury, C., F. et al. (2007) tried to manage this problem by including cooperative merging behaviours of both vehicles.

2.2.1.4 Driving behaviour models in VISSIM

This section is an overview of the driving behaviour models found in VISSIM are discussed. In first place, the car following models will be shown, followed by the lane changing options and different parameters for modelling lateral behaviours.

The car-following model in VISSIM

Fransson (2018) described that VISSIM offers two car-following models: Wiedemann 74 and Wiedemann 99. The implemented models on the VISSIM differs from the Wiedemann model presented earlier. One big difference is that the models in VISSIM look for creating more diverse drivers (Fransson 2018). To create a model that makes such heterogeneous behaviour, Higgs et al. (2011.) added that a driver’s perception skill and risk behaviour in VISSIM are modeled by adding random values to each of the thresholds presented in Table 2.4 (Higgs et al. 2011., Fransson 2018). The formulation of the Wiedemann 74 model in VISSIM is shown below (Gao 2008):

$$u_n(t+\Delta t) = \min\left\{\begin{matrix} 3.6 * (\frac{s_{n(t)}-AX}{BX})^2 \\ 3.6 * (\frac{s_{n(t)}-AX}{BX.EX})^2 \end{matrix}, u_f\right\} \tag{2.6}$$

Where BX and EX = Random parameters

The Wiedemann 99 model is a changed setup from the Wiedemann 74 model with the difference that set some other standards to model the network in the simulator (Fransson 2018). (Gao 2008) formulated the Wiedemann 99 model used in VISSIM:

$$u_n(t+\Delta t) = \min\left\{\begin{matrix} u_n(t) + 3.6 * (CC8 + \frac{CC8-CC9}{80} u_n(t))\Delta t \\ 3.6 * \frac{s_n(t)-CC0-L_n-1}{u_n(t)} \end{matrix}, u_f\right\} \tag{2.7}$$

Where, $u_n(t+\Delta t) \cong$ minimum of two speeds. The VISSIM offers several parameters to implement the Wiedemann model to represent the real world in simulation as much as possible. Several parameters are shown in Table 2.6 (Fransson 2018, Toledo 2003, PTV 2011)

Element	**Description**
General Car Following Parameters	
Look ahead distance	Both minimum and maximum distance what a driver can see forward to interact with other vehicles and objects that are in front of or next to it on the same link.
Look back distance	It is equivalent to the Look ahead distance, but represents the spatial distance a driver can see behind his vehicle.
Temporary lack of attention	It is a period during which a driver cannot respond to changes in the preceding vehicles driving behaviour. The duration and the probability define respectively how long and how often the lack of attention occurs.
Smooth closeup behaviours	Decides if a driver may reduce his speed more evenly when approaching a static obstacle.
Standstill distance for static obstacles	Applicable if smooth closeup behaviour is active. Determines at which distance from a static obstacle a driver should stop.
Car following model	It defines what car following model should be implemented.
Number of interaction objects	The total number of preceding vehicles and/or the number of network objects listed below which the vehicle perceives downstream or near to the same link to react to them.
Number of interaction vehicles	The number of preceding vehicles that the vehicle perceives downstream or adjacent to it on the same link to react to them.
Increased Acceleration	It increases the acceleration with which the vehicle follows a preceding vehicle that accelerates. The default value is 100 %
Adjustable parameters for Wiedemann 74	
Average standstill distance	The expected distance between two

	stationary vehicles.
Additive part of the safety distance	Included in the calculation of expected safety distance which is concerned with time requirement adjustments.
Multiplicative part of the safety distance	Included in the calculation of expected safety distance which is concerned with time requirement adjustments.
Adjustable parameters for Wiedemann 99	
CC0 (Standstill distance)	The desired distance between two stationary vehicles. Correspond to AX in Table 1.
CC1 (Headway time)	Indicate the time what driver need to maintain to the preceding vehicle. Higher value yields a more cautious driver.
CC2 ('Following' variation)	Constrain the longitudinal oscillation of a vehicle in relation to the vehicle in front.
CC3 (Threshold for entering 'Following')	Represents the time of the deceleration process what begins in terms of seconds before reaching the safety distance.
CC4 and CC5 ('Following' thresholds)	Control the speed differences during the 'Following' state. Lower values indicate more careful drivers e.g. vehicles will be permitted closer to each other.
CC6 (Speed dependency of oscillation)	Indicates the impact of spatial distance on speed oscillation within the following region.
CC7 (Oscillation acceleration)	Represents the actual acceleration during the oscillation process.
CC8 (Standstill acceleration)	Regulates the desired acceleration when starting from a stationary state.
CC9 (Acceleration at 80 km/h)	Regulates the desired acceleration at a speed of 80 km/h.

Table 2.6 Details of car-following parameters (General and Wiedemann model) (Fransson 2018, PTV 2011, Toledo 2003)

The desired (or expected) distance d is calculated using the following equation (Fransson 2018):

$$d = ax + bx \tag{2.8}$$

Where, bx = $(bx_{add} + bx_{mult} * z)*\sqrt{v}, v$ = vehicle speed [m/s] and z = value of range [0,1] which is normal distributed around 0.5 with a standard deviation of 0.15.

Regarding Wiedemann 99, Fransson (2018) stated that CC0, CC1, and CC8 are the greatest influences over the merging behaviour during the calibration stage. This assumption is made based on the definitions presented in Table 2.5, from which it can be assumed that the spatial distance between vehicles and their aggressiveness can be manipulated.

Lane changing Model in VISSIM

There are two types of lane change models in the VISSIM, named as necessary lane change and free lane change. Both are dependent in the spatial distance between the emergency stop areas in the road track. The controllable parameters are connected to the desired safety distance of the trailing vehicle for the Free lane change case. PTV (2011) mentioned that the first step when a vehicle is ready to shift from the lane in VISSIM interface is to look for an appropriate time gap (headway) in the destination flow (Fransson 2018, PTV 2011). The entire set of parameters available for lane change model in the VISSIM interface is shown in Table 2.7 (PTV 2011, Fransson 2018)

Element	Description
General behaviour	Depicts the type of overtaking that will be allowed. The available options are either Free lane selection, where overtaking is allowed in any lane, or Right-Side Rule respectively Left Side Rule.
Necessary lane change (route)	Introduces deceleration thresholds for the own vehicle and the trailing vehicle the aggressiveness of the necessary lane change can be set.
Waiting time before diffusion	Defines maximum time a vehicle will stay at the emergency stop position waiting to perform a necessary lane change. If the waiting time crosses the specified value the vehicle will be taken out.
Min. Headway (front/rear)	The minimum remaining spatial distance needed between two vehicles after a lane change.
To slower lane if collision time	The minimum time headway that needs to be found in the slower lane in order to make a faster vehicle traverse to it.
Safety distance reduction factor	Defines the amount of safety distance between vehicles that need to be reduced during the lane change phase. The value 0.6 indicates that the safety distance is reduced by 40% compare to the standard value.
Maximum deceleration for cooperative braking	Defines how the trailing vehicle will manage cooperative braking.
Overtake reduced speed areas	Defines if lane-dependent speed restrictions will be considered or not. If this parameter is not included, vehicles will not run lane change upstream in a reduced speed region. Thus, any reduced speed restrictions in the target lane will be ignored.
Advanced merging	This option permits more vehicles to transfer lane at an earlier point, and by decreasing the risk of vehicles stopping to wait for a merging option which can be done by taking the speed of the nearby vehicles into account in addition to the immediate emergency stop distance. If inactive, a vehicle may not break/cooperate with another vehicle.
Consider subsequent static routing decisions	Defines whether a vehicle leaving a static route will be considered for other routing decisions ahead when choosing lane or not.
Cooperative lane change	Represents the possibility of a vehicle to observe if a vehicle is found in a nearby lane. It intends to change to its own lane and hence will try to change lane itself to allow the lane change.
Lateral correction of the rear end position	Defines the lateral position of a vehicle in the line with the middle of the lane after a lane shift.

Table 2.7 Definition of lane changing parameters in VISSIM (Fransson 2018, PTV 2011, Toledo 2003)

Whaley (2016) has indicated some lane-changing parameters with the greatest impact on the traffic merging behaviour which includes cooperative lane changing, reduction factor for safety, advanced merging, and low headway distance.

Lateral behaviour Model in VISSIM

VISSIM interface can manage both the lateral orientation in the current lane and the overtaking lane. According to Fransson (2018), all vehicles are planned to take the entire lane width in the VISSIM. Moreover, it is also possible to put a vehicle to the location itself in the middle, on the right side, and on the left of the lane. The set of parameters concerned with the lateral driving behaviour in VISSIM are listed in Table 2.8

Element	**Description**
Desired position at free flow	Describes the vehicle's lateral position within its lane during free flow.
Keep the lateral distance to vehicles on next lane(s)	Represents vehicles‘ adaptation of their lateral positions to the vehicles in the nearby lane by keeping the minimum spatial distance.
Diamond shape queue	Agents are represented as rhombuses instead of rectangles, yielding a more realistic shape of a built-up queue.
Minimum longitudinal speed	Represents the minimum longitudinal speed required for a vehicle to move laterally.
The time between direction changes	Depicts minimum simulation time between two lateral movements in opposite directions.
Collision time gain	Defines minimum time gain to be met between a vehicle and an obstacle ahead in order to relate a change in lateral movement.
The default behaviour when overtaking vehicles on the same lane or adjacent lanes	Describes permission or prevention of vehicles in the non-lane bound traffic to overtake on the same lane, either to the left, right, or both.
Minimum lateral distance	The available distance between vehicles while overtaking in the same lane.
Consider the next turning direction	A vehicle will not pass a vehicle on the same lane if there is a risk for the crash at the subsequent turning connector.
Exceptions for overtaking vehicles of the following vehicles classes	Represents vehicle classes with a driver behaviour that varies from the default one can be defined.

Table 2.8 Definition of lateral behaviour parameters in VISSIM (Fransson 2018, PTV 2011, Toledo 2003)

2.2.2 Data-driven behaviour models

Connected autonomous vehicles (CAV) and autonomous vehicles (AV) can be considered as an improved road safety measure because the human error, which is the most alarming source of accidents, can be avoided through the implementation of CAV and AV i.e. driving mistakes (Virdi et al. 2019, Campbell et al. 2010). The safety of the passengers can be assured if autonomous vehicles sense its surrounding environment precisely and take safe maneuvers according to the sensors received data (Katrakazas et al. 2019). The decision-making capacity for vehicle maneuvers and risk assessment of the surrounding environment is part of planning modules of autonomous vehicles (Katrakazas et al. 2015, Lefèvre et al. 2014). The need for such sensitive planning modules is extensively required particularly for dense traffic conditions and regions with inconsistent traffic flow dynamics where collisions are most prone to happen (Mahajan et al. 2020). It is experienced from previous studies that researchers go with different data-driven approaches. Nevertheless, the standard methodology seems to less prone to change severely.

In these cases, data-driven approaches are found to be quite useful for microscopic traffic simulation for autonomous vehicles (Mahajan et al. 2020). The data-driven car following behaviour models are flexible which allows the corporation of other additional information to the model. Unlike traditional models, the data-driven models do not provide much detailed concept of the traffic flow theory (Papathanasopoulou and Antoniou 2015, Mahajan et al. 2020) but they provide provision to model more complicated situations. They deal with complicated situation such as weak lane discipline situations, and incorporate additional variables, such as weather, fleet composition, flow levels, and road characteristics. However, using data driven approaches, predicting vehicle trajectories in the vicinity of AVs are computationally difficult to be prepared and, therefore, not appropriate for the online implementation (Lefèvre et al. 2013, Gindele et al. 2010). A great number of data is needed to be learn to predict the vehicle manoeuvres and travel plan of the special vehicles in the real-world (Ziegler et al. 2014b, Gindele et al. 2015). These data can be obtained from the simulation or real-world demonstration (Ziegler et al. 2014a).

2.3 Microscopic simulation of C/AVs

The Society of Automotive Engineers (SAE International 2018) has categorized self-driving cars based on the features and automation level, which propose six different levels. Level 0 indicates no automatic control and level 5 indicates no human intervention (SAE International 2018). Table 2.9 demonstrates different levels of automation as per SAE International (2018), Gasser and Westhoff (2012) and National Highway Traffic Safety Administration (2013)

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

Table 2.9 Levels of driving automation as defined by the SAE (SAE International 2018), the German Federal Highway Research Institute (BASt) (Gasser and Westhoff 2012), and the National Highway Traffic Safety Administration (NHTSA) (National Highway Traffic Safety Administration 2013)

The following section depicts each level and holds an increasing amount of automation (Alawadhi et al. 2020):

- Level 0: Vehicles of this level are totally managed by human-driver and no automation.
- Level 1: Vehicles of this level come with atleast one aspect of automation.
- Level 2: In this level, vehicles are capable to manipulate the steering and the speed. Self-parking can be possible with some assitance from human-driver.
- Level 3: Vehicle of this level has ability to take total control of different decisions: overtaking.
- Level 4: Vehicle of this level are almost self-driven but not for all state. Human-drivers are still wait for the charge.
- Level 5: This is the current highest level of automation, currently assumed. No driver is required in this level for any circumstances. At this point the vehicle is known as AV what becomes CAV, when connectivity features such as V2V and V2I are offered by the vehicle.

Several researchers concentrated on several aspects of C/AVs. Table 2.10 demonstrates previous microscopic traffic simulation studies targeting C/AVs.

Previous Studies	Traffic Simulator	Car following model	Focus vehicles	Study area	Investigation parameters
(Fernandes and Nunes 2010)	SUMO	Extended Gipps-model	Automated Vehicle	Freeway	Performance
(Lee and Park 2012)	VISSIM	VISSIM Default	Connected Vehicle	Arterial	Performance
(Li et al. 2013)	VISSIM	VISSIM Default	Automated Vehicle	Arterial	Safety and Performance
(Jin et al. 2013)	SUMO	SUMO Default	Connected Vehicle	Arterial	Safety and Performance

(Qian et al. 2014)	SUMO	SUMO Default	Connected and Automated Vehicle	Arterial	Performance
(Guler et al. 2014)	MATLAB	NA	Connected Vehicle	Arterial	Performance
(Bohm and Häger 2015)	VISSIM	VISSIM Default	Automated Vehicle	Arterial	Performance, Safety and Emission
(Wu et al. 2015)	VISSIM	VISSIM Default	Connected Vehicle	Arterial	Performance
(Genders and Razavi 2015)	PARAMICS	Modified Behavior	Connected Vehicle	Arterial	Safety
(Atkins 2016)	VISSIM	VISSIM Default	Connected and Automated Vehicle	Arterial and Freeway	Performance
(Talebpour and Mahmassani 2016)	Own Simulator	IDM	Connected and Automated Vehicle	Freeway	Performance
(Wan et al. 2016)	PARAMICS	PARAMICS Default	Connected Vehicle	Arterial	Performance and Consumption
(Guériau et al. 2016)	MovSim	IDM	Connected Vehicle	Freeway	Safety and Performance
(Letter and Elefteriadou 2017)	CORSIM	CORSIM Default	Automated Vehicle	Freeway	Performance
(Rahman et al. 2018)	VISSIM	IDM	Connected Vehicle	Freeway	Safety and Performance
(Mirheli et al. 2018)	VISSIM	VISSIM Default	Connected Vehicle	Arterial	Safety and Performance
(Tajalli and Hajbabaie 2018)	VISSIM	VISSIM Default	Connected Vehicle	Arterial	Safety
(Rahman and Abdel-Aty 2018)	VISSIM	IDM	Connected Vehicle	Freeway	Safety
(Zeidler et al. 2018)	VISSIM	VISSIM Default	Connected and Automated Vehicle	Freeway	Performance

Table 2.10 Chronicle order of previous simulation-based studies for connected and automated vehicles

Versatile researches have highlighted several aspects of microscopic simulation and its impacts on AVs and CAVs. While some researchers have chosen to work on engineering aspects i.e. how should we choose driving parameters for the autonomous vehicles in the simulator for different scenarios (Zeidler et al. 2018, Sukennik 2018, Toledo 2003), some researchers investigated over the impact on the economy, city, environment and traffic safety (Atkins 2016, Calvert et al. 2017, Fransson 2018, Pierre-Jean Rigole 2014, Bohm and Häger 2015). To investigate different user cases (driving maneuvers) of C/AVs, researchers experimented over arterial and freeway which highlights several manoeuvres (longitudinal, lateral and merging) and interactions (V2V, V2I, Signal) (Atkins 2016, Sukennik 2018, Toledo 2003).

2.3.1 Features of CAVs

The gradual progress of connectivity features in the vehicles is influenced by traffic of the present world and it will take immense shape in the coming future. Automation features such as connectivity to other vehicles and infrastructure, building the vehicle platoons, and automatic driving modules play a strong role both in the urban motorway and freeway (Calvert et al. 2017). Furthermore, study indicated that in first implementation stage C/AVs should be self-driven and self-sufficient as infrastructure development will take certain time to give full functionality freedom from the connectivity feature (Parmar 2018). Table 2.11 presents several vehicle connectivity features that are currently available for use and under investigation for future C/AVs.

Feature Category	Sub-Category	Functions
Vehicle to Vehicle connectivity (V2V)	Lane Control	It enables the ability to maintain the lane safety
	Adaptive Cruise Control (ACC)	It keeps a safe distance from the vehicle ahead.
	Vehicle-to-Vehicle (V2V) Communication	The heart of a connected vehicle technology to enable vehicles interaction together to manage the safety aspects.
	Platoon formation	Forming the platoon is an advancement of V2V system. Vehicles of same direction make formation towards same direction with same speed and distance.
Vehicle to Infrastructure Connectivity (V2I)	Automatic Emergency Braking System (AEBS)	This feature is responsible for an automatic break of the vehicle to stay away from a possible collision.
	Light Detection and Ranging (LIDAR)	Technology to determine the distance and to identify the objects.
	Street Sign/ Signal Recognition	A software interface to process the sensor data which identify road signs and react to the signal.
	Object or Collision Avoidance System (CAS)	This feature is responsible for multiple functions to avoid the collision to the objects which integrates detection or identification system.

Table 2.11 Currently available vehicle connectivity features (Tempo Automation 2019, Haas and Friedrich 2017)

To implement these features of the C/AVs in the microscopic simulation, currently different functions (event script files) are attached in the simulator. VISSIM 11 or later version has extensive functionalities to model C/AVs (Sukennik 2018). VISSIM 2020 comes with inclusively (using Graphical User Interface- GUI) and exclusively (using Component Object Model- COM) implementation of platoon building, signal influence, V2V and V2I connectivity (PTV 2011, Sukennik 2018, Atkins 2016).

2.3.2 Driving parameters of C/AVs in VISSIM

The standard approach to model C/AVs can be building modified version of the Wiedermann 99 as Wiedermann 74 does not offer lots of options for customized modelling (Sukennik 2018). In other words, the human alike C/AVs are subset of conventional driving behaviours and can be obtained with proper jurisdiction to match different autonomous driving modules. Some extensively created simulator-integral and user-defined parameters are totally dedicate to match the characteristics of AV and CAV to enhance its automation features in VISSIM interface (Atkins 2016, Sukennik 2018, Zeidler et al. 2018, Toledo 2003, Bohm and Häger 2015).

Furthermore, external script files are used to model extensive features of C/AVs. Table 2.12 depicts special parameters required to model C/AVs in the VISSIM interface which distinguish it from conventional vehicles.

Sl.	COM VISSIM Parameters	COM VISSIM Interface	Autonomous Parameter Description	Range	Default
1	EnforcAbsBrakDist		Enforce absolute braking distance	True/ False	False
2	UseImplicStoch		Use implicit stochastics	True/ False	True
3	NumInteractObj	IDrivingBehavior	Number of interaction objects and vehicles	0- 10	2
4	NumInteractVeh			0 - 99	99
5	W99cc0		Headway based on leader vehicle class	0,60 -3,05	1,50
6	W99cc1Distr			0,50 - 1,50	0,90
6	IncrsAccel		Increased acceleration	1,00 - 9,99	1,00
7	Platooning		Platooning	2 - 9999	7
8	AddOccupancyDistribution	IOccupancyDistribution	Occupancy distribution (with/out zero passengers)	1,00 – 4,00	1,00
9	ConsVehInDynPot	ILink	Consider vehicles in dynamic potential	True/ False	False

Table 2.12 Special parameters required to model Connected and Automated Vehicles in the VISSIM (Sukennik 2018, Atkins 2016, Zeidler et al. 2018)

These parameters manipulate the features of autonomous vehicles in the VISSIM interface inclusively and exclusively. VISSIM interface provides scope to the users to change from the graphical interface in addition to the available COM interface for exclusive changes.

Enforce absolute braking distance

This attribute assures collision-free brake, even when the leading vehicle takes a surprise stop. Enforce absolute braking distance also works for vehicle's lane changes to avoid confliction on the major locations of the network (Sukennik 2018).

Use implicit stochastics

This attribute assures that the vehicle uses any internally set stochastic variation. Using the implicit stochastics significantly shows affects in the safety distance, the desired acceleration-deceleration and the approximate uncertainty for braking decisions. Deactivating the use of implicit stochastics is justified for all AVs, which avoids modelling the human-driver's flaws in the simulation environment. (Sukennik 2018).

Number of interaction objects and vehicles

VISSIM 10 has divided this attribute into two sub-categories. The number of interaction objects refers to interaction among the vehicles and infrastructures/ road objects: reduced speed areas, stop signs, priority rules and red signal head. In contrary, the number of interacting vehicles indicate connection among the real vehicles (Sukennik 2018).

Headway based on leader vehicle class

The headway indicates the a safety distance between two vehicles, which is selected as per the driving modules. (Sukennik 2018).

Increased acceleration

The AVs, especially if they are using car to car (C2C) communication which makes it CAVs, can use a shorter headway. The vehicles can have higher than 100% of incresed acceleration but it should respect the limit of maximum acceleration (Sukennik 2018).

Platooning

Through this attribute the vehicles can close the gap to a preceding vehicle to become a trailing vehicle of a platoon.

Occupancy distribution with zero passengers

This attribute defines an experimental occupancy distribution for the empty autonomous vehicles (without passengers)

Consider vehicles in dynamic potential

According to Sukennik (2018), The action between vehicles and pedestrians is mainly modelled as conflict areas, which blocks a certain region if a vehicle or pedestrian is within the region or approached it. In such case, other agents are not allowed to use this region. Vehicles holding a conflict region can be taken in the dynamic potential for conflicting pedestrians. In example for a pedestrian link if this function is activated, pedestrians will not stop at a blocked conflict region, but will try to move around it through the gaps between queued vehicles. That's why the lanes of a pedestrian link must be appropriately narrow.

Connectivity features i.e. V2V and V2I are implemented with additional scripts written by users as per their requirements. Interaction to the traffic signal or reacting with ahead vehicle can be operated spontaneously using scripts in the COM or even in the VISSIM GUI itself (Sukennik 2018, PTV 2011).

2.3.3 Impact of C/AVs

Studies show that C/AVs will grab high attention over current travel modes at some point in the coming years which will have a strong influence over the transport, society, economy, mobility, and environment (Maunsell et al. 2014, Hörl et al. 2016, Bohm and Häger 2015, Pierre-Jean Rigole 2014, Fransson 2018, Lang et al. 2018). For a long time, researchers are using different experiment setups to seek the impacts of automation in transportation system. Gora et al. (2020) stated that there is no universal standard for microscopic modelling of the C/AVs in today's date so different researchers' approach, with different methodology and algorithms, to the implementation phase. Same study added that as there is no unique mathematical model for building such experimental models, these models can be generated from conventional vehicle models based on strong assumption concentrating microscopic or macroscopic level of details. Furthermore, they pointed an important assumption of the C/AV modelling. That is C/AVs will act more predictably than the human-driven vehicles (Gora et al. 2020). Such versatile approaches among researchers, consequence a variation among outcomes from different studies. These outcomes can be used to understand the cause and effect relationships of the inputs (assumption) and outputs (performance). Such system visualizes the impacts what probably will take place by these C/AVs.

Different factors play role in C/AVs to create such variations in the outcomes than the conventional vehicles (Sukennik 2018). The basic expectations from the C/AVs are reduction of travel time, delay time, emission and possible confliction with higher speed. All together these factors affect the road capacity. According to Litman (2018), different factors need to work together positively behind an increment of traffic capacity in the network.

In general C/AVs are supposed to maintain proper safe distance and follow road codes appropriately. As these vehicles establish communication, it decreases the required safe distance for driving which influence the road capacity (Shi and Prevedouros 2016, Hörl et al. 2016). The platoon formation ability of CAVs significantly increase the network efficiency and improve the traffic performances (Haas and Friedrich 2017). Moreover, information about other vehicles i.e. travel plans can be a good reason to avoid traffic jams and it will provide better traffic flow. A good example can be action of the intelligent vehicle in the intersections (Yang et al. 2016). Bertoncello and Wee (2015) indicated a reduction of traffic crashes by 90% possible by C/AVs. Furthermore, redeveloped infrastructure i.e. traffic system and parking system focusing connected automatic vehicles will have the capacity to gain more benefits than simply maintaining the traffic which is slowing down the approaching vehicles near the intersection, directing to free parking or transmit driver the information for optimal dispatch according to the current demand (Hörl et al. 2016). These organizational and planning diversities of C/AVs make them behave and interact differently than the HVs.

Impact over Traffic performance

The general idea of introducing the C/AVs in the network is that they may have proportional positive influence in the traffic performance. Li and Wagner (2019) performed an experiment for different penetration rate of AVs for different traffic flow cases of motorway in the SUMO interface, shown in Figure 2.3. Their study used travel time as traffic performance indicator. The study has shown that the travel time reduces significantly for higher AV penetration for both highly and lightly congested traffic. The high reduction of the travel time take place in the presence of the 10-30% of AV penetration. That is an improvement of 10-12% of travel time from the base travel time. However, this reduction process of the travel time become stagnant when AV reaches 90% penetration (Li and Wagner 2019).

Furthermore, Morando et al. (2018) stated for an increasing penetration rate of AVs, delay reductions will take place for the signalised intersection scenarios which eventually lead to efficient transportation system.

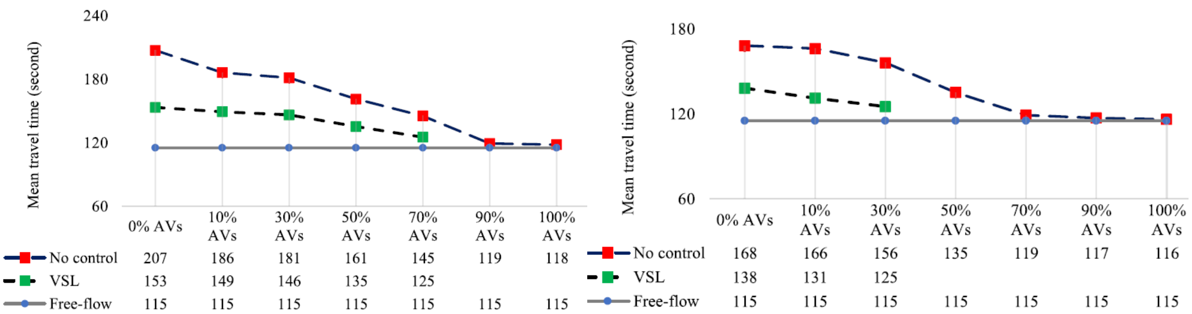


Figure 2.3 Mean travel time over the networks for different traffic conditions: heavily congested traffic and lightly congested traffic (Li and Wagner 2019)

Makridis et al. (2018) argued Shladover, S., E. et al. (2012) that there will be negative impacts in the network from the low rate of the C/AV penetration. Both Makridis et al. (2018) and Mattas et al. (2018) pointed on such behaviours and they linked this pattern with the increase headways used by the AVs. Makridis et al. (2018) used harmonic average speed to evaluate the network's performance, by comparing the two harmonic speeds, average network speed and average desired speed, with each other. It indicates the magnitude of the congestion (Makridis et al. 2018). The harmonic average speed of the vehicles (km/h), presented in the network, is computed using the following equation:

$$HS_{sys} = \frac{N_{sys}}{\sum_{i=1}^{N_{sys}} HS_i} \tag{2.9}$$

Makridis et al. (2018) depicted three possible demands (estimated, increased, and decreased demand) in the study. This former study counted second-peak-hour demand and demonstrated the scenarios in the ternary plots. Each side indicates a state of 100% presence of a particular vehicle in the study area, which the corner is marked with. The region inside the triangle represents the different participation ratios of AVs, CAVs, and HVs, in the combination of vehicles. A specific point in the inner region of this ternary plots, represents a specific combination of formerly mentioned three vehicle types. In Figure 2.4, these three ternary plots depict visualization for the three different traffic demands, where the colour level indicates the harmonic average speeds over the network (Makridis et al. 2018, Mattas et al. 2018). This study demonstrated that introducing autonomous vehicles over the city network has a negative impact, at a lower ratio. These negative impacts originated from increasing headways, in contrast to the human-driven vehicles, which are implemented for safety related issues. In other words, the autonomous vehicles are not planned to take the risk which results in conservative headway thresholds on the road. Meanwhile, HVs are prone to taking risks while driving and they try to interact, depending on the manoeuvres of neighboring vehicles. The negative influences of the presence of an autonomous vehicle are significant in bottlenecks, where the merging or lane changing takes place, because the gap taken by AVs is larger, and maximum deceleration is lower than in the HVs. Additionally, the maximum acceleration of the AV, currently seen in the ACC system, is significantly lower than in the HVs. This feature, perform a significant role in the reduction to the traffic flow in the downstream of the bottleneck, which ultimately deteriorates the condition in the upstream of a bottleneck (Makridis et al. 2018, Mattas et al. 2018). On the contrary, the network has shown a good response in the presence of the CAVs, and it improves for higher participation of CAVs in every individual unique scenario. When more CAVs are added to the network, the influence of the CAVs becomes more progressive. CAVs that follow AVs or HVs, behave as simple AVs as the connectivity and cooperation property will be missing. It is perceivable that, for lower CAV penetrations, the possibility of connected travel will be low as well. The possibility of CAVs connectivity increases when there are more CAVs available in the network. Previous studies indicated that with higher penetration of CAVs a few positive changes will take place in the network: spatial gaps can be shorter, easy lane change manoeuvres, stable and steady traffic streams. As there is no or less traffic breakdown, the traffic flow will move without any viscosity effect in the network. In consequence, the harmonic average network speed stays higher in every traffic scenarios (Makridis et al. 2018, Mattas et al. 2018).

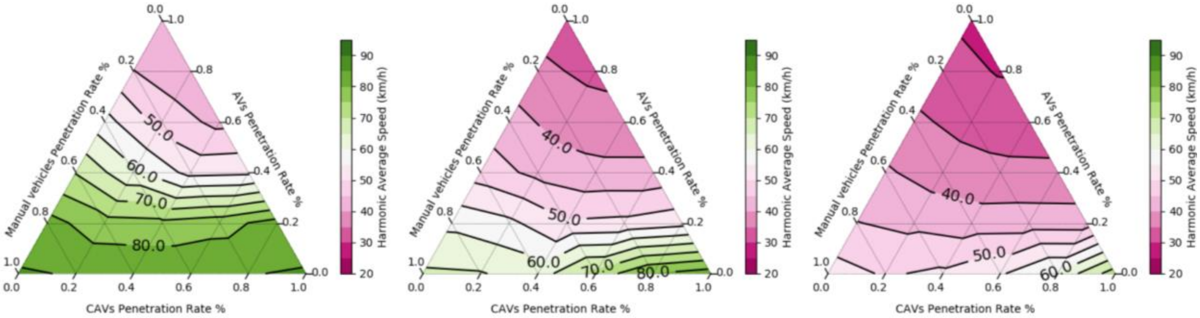


Figure 2.4 Harmonic speed over the networks for different traffic conditions: 80% of peak demand, 100% of peak demand and 120% of peak demand respectively (Makridis et al. 2018)

The investigation over the CAVs performed by the Ekram and Rahman (2018) depicted that increasing CAV penetration found to be good in the traffic in terms of average speed and travel time, for higher CAV penetration. Figure 2.5 shows that over time different increasing CAV penetration ratio improved the traffic performance.

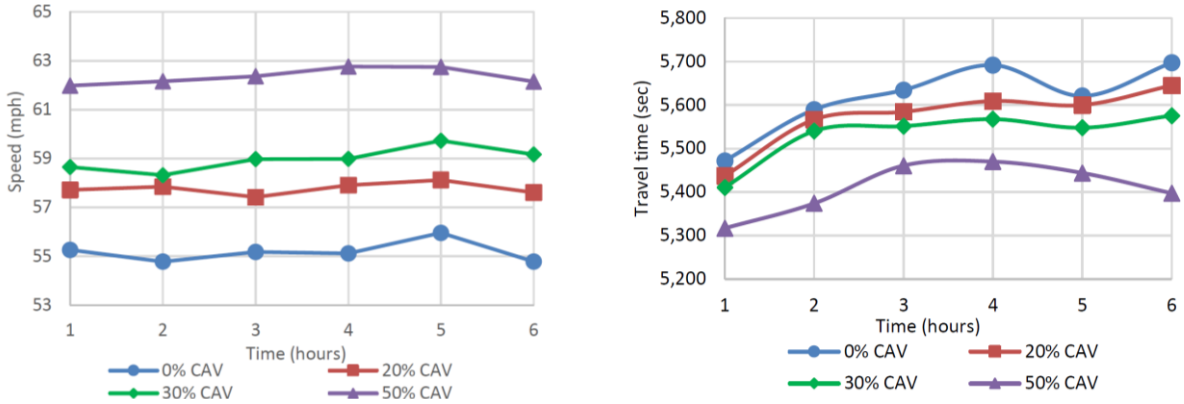


Figure 2.5 Comparison among different CAV penetration: Speed and travel time (Ekram and Rahman 2018)

Impact over Emission

According to Igliński and Babiak (2017), accurate exploration of the impact of AVs in the reduction of greenhouse gases is not an easy task because many variables play role in the transportation system. There will be more variables, which might not be present today, in future mobility system. They indicated that there will be a reduction of 40-60% of the emission than today's state, pointing the fact of changing mobility model and behavioural changes among the road users for their daily travel plan.

In the other side, Bohm and Häger (2015) used EnViVer which computes the emission and determines emission of carbon dioxide, nitrogen oxide and particle pollution that is explained in later sub-section (2.4 Evaluation Measures). Bohm and Häger (2015) shows that the impacts of AVs in the network are positive. Figure 2.6 denotes that the change of CO_2, NO_x and PM_{10} emissions for the human driven vehicles and autonomous vehicles have been changed for high traffic flow. These emissions have been decreased when autonomous features have been introduced in the traffic. The corresponding percentage changes were 20% for CO_2, 25% for NO_x and 9 % for PM_{10} where all HVs are replaced by AVs.

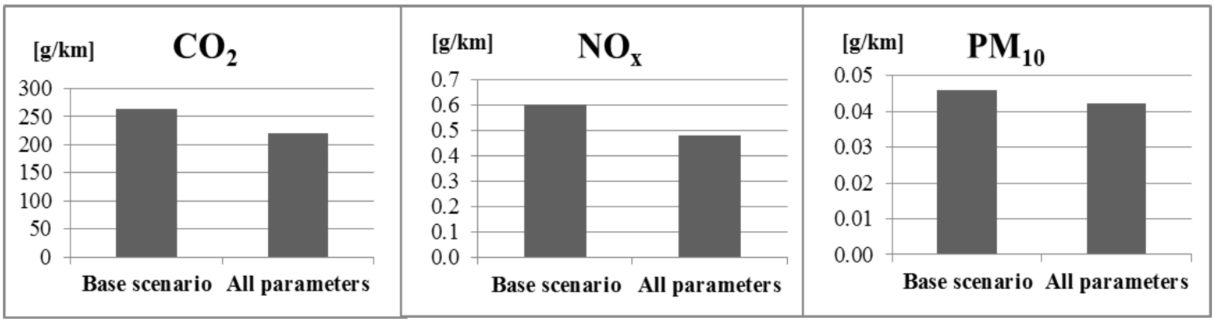


Figure 2.6 Comparison of HVs and AVs emission scenarios: CO_2, NO_x and PM_{10} (Bohm and Häger 2015)

In contrary, a SUMO based study of Papantoniou et al. (2020) indicated that if the energy systems of AVs are similar to the HVs, AVs will exhibit higher emission (CO and NO_x) for their higher participation rate in the road traffic. The summary of their study has been shown in the Table 2.13 and Figure 2.7. Such higher emission is generated from the behavioural changes of the autonomous vehicles of the network.

AV penetration	CO (mg/s)	NO_x (mg/s)
0	0.22	55
25	0.22	56.2
50	0.23	58
75	0.23	60.8
100	0.22	65

Table 2.13 Average emission of different scenarios: CO and NO_x (Papantoniou et al. 2020)

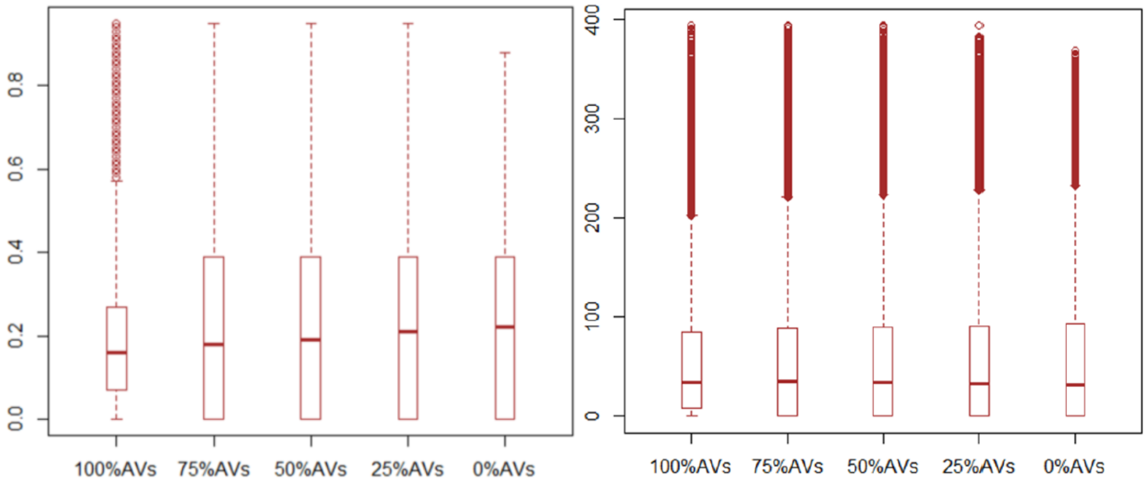
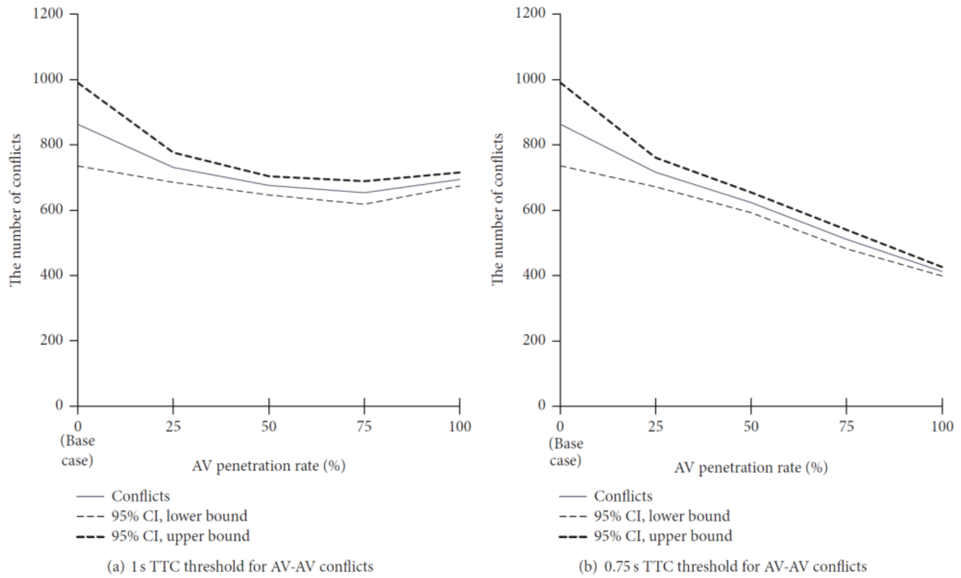


Figure 2.7 Box plots of different AV scenarios: CO emission and NO_x emission (Papantoniou et al. 2020)

Impact over Safety

Morando et al. (2018) performed a simulation-based surrogate safety measure approach to evaluate the impacts of AVs in the signalized network in terms of conflicts. The details of simulation-based surrogate safety measures are described in 2.4 Evaluation Measures. Two different times to collision (TTC) threshold for AVs are taken for their study. Like previously noted studies, the number of conflicts between AVs overall is decreased but for higher TTC value the conflictions increase after 75% AVs participation. Morando et al. (2018) denotes this phenomenon as after reaching 75% AV penetration rate, due to shorter headways, AVs are prone to have conflicts with each other. Figures 2.8(a) and 2.8(b) shows the total number of conflicts and relevant 95% confidence intervals for different AV participation ratios for both the 0.75-second and 1-second TTC thresholds,



(a) (b)

Figure 2.8 Total number of conflicts by AV penetration rate for the signalized intersection (Morando et al. 2018)

Li and Wagner (2019) have also investigated over the safety aspect of the AV. They used TTC (Time to collision) as performance indicator. Their study exhibit reduction of TTC with increasing AV penetrations but there is a negative impact in the initial stage, 10-30% AV penetration. After 30% of AV penetration, there are improvements for both traffic cases (Li and Wagner 2019).

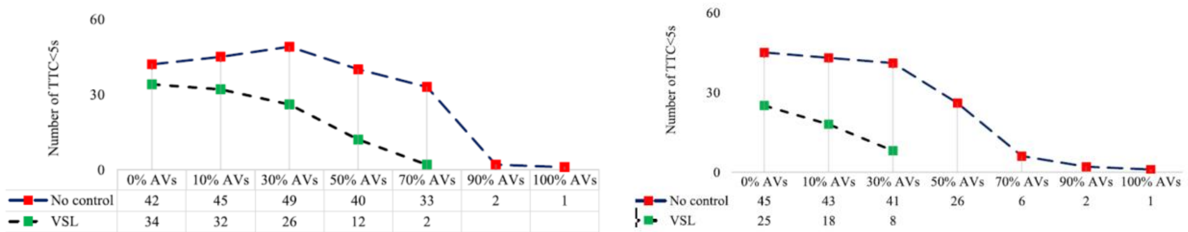


Figure 2.9 The number of TTC<5 sec over the networks for different traffic conditions: heavily congested traffic and lightly congested traffic (Li and Wagner 2019)

Virdi et al. (2019) experimented the safety aspect of the CAV. For the lower penetration ratio, according to them, CAV get more human-driven vehicles around who tend to drive in the network irregularly and less cautiously. It results in more potential conflicts in the lower participation ratios. Figure 2.10 depicts how potential conflicts tend to decrease over increasing CAV participation in the signalized intersection because of the proper connectivity among the vehicles and infrastructures. These conflicts are categorized by the type of vehicles that participated in the simulation. The “M-M” explains a human-driven vehicle following and interacting with another human-driven vehicle, “A-M” represents a human-driven vehicle following a connected and autonomous vehicles, and finally, the “M-A” represents a connected and autonomous vehicles following a human-driven vehicle. Interactions between two connected and autonomous vehicles are excluded by the authors, as the connected and autonomous vehicle is considered as safe for their interactions with each other (Virdi et al. 2019). Similar results in term of reduction of accidents have been found by Xu et al. (2019) that has shown that crashes from CAVs are mainly originated from the weak interactivity between CAV and HV. Using statistical analysis, their study has demonstrated that attention need be conserved for negative impacts of the mixed traffic flow of HV and CAV during the transitional period when the CAVs cannot utilize their 100% efficency (Xu et al. 2019).

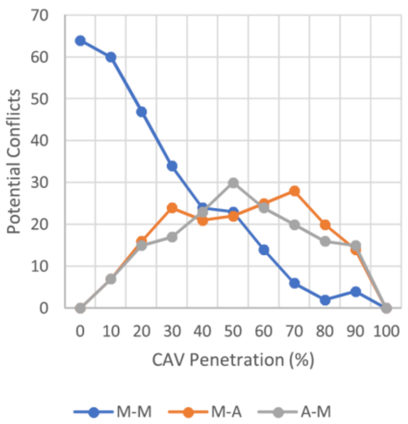


Figure 2.10 Number of potential accidents for signalized intersection in the microsimulation environment (Virdi et al. 2019)

Appendix A denoted other studies, which are used to perceive the impacts of C/AVs, initially listed by Narayanan et al. (2020).

2.4 Evaluation Measures

2.4.1 EnViVer

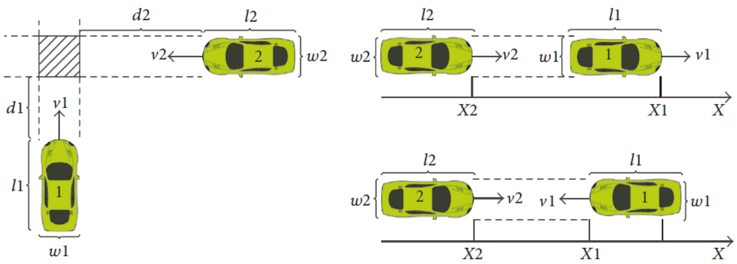
The EnViVer visualizes the emissions from a simulation model. It is built based on VERSIT+ exhaust emissions model from TNO. The VERSIT+ emissions model can build emission models for CO_2, NO_x, and particle matter (PM_{10}) for any type of vehicle. The pollutant emissions are obtained from vehicle trajectories and some combination of other information what can be generated in PTV Vissim as the output on special request. The EnViVer is supplied and distributed by the Vialis and the PTV. The stockholders and decision-makers of the projects can take their critical decision based on the impact scenarios from the EnViVer (www.tno.nl. 2020).

2.4.2 Surrogate Safety Measures

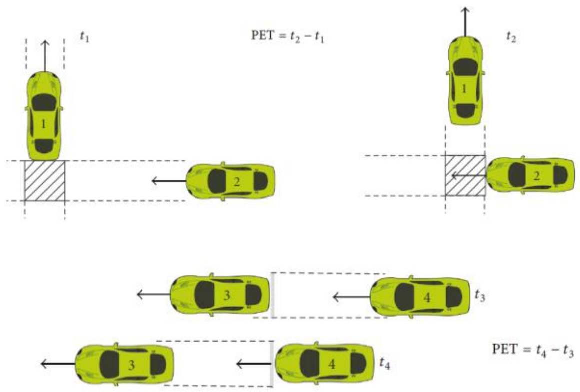
The microscopic traffic simulation programs i.e. PTV VISSIM, are often implemented with automated conflict analysis programs, SSAM (Surrogate Safety Assessment Model). SSAM is a simulation-based analyst for surrogate safety measures (U.S. Department of Transportation 2008) which uses the trajectory files (*.trj) collected from the microscopic traffic simulator. The main reason to use surrogate safety measures is to look into the potential confliction in the network. The SSAM uses some useful measures to define the conflictions of the networks, such as time to collision (TTC), post-encroachment time (PET), deceleration rate (DR), gap time(GT), and proportion of stopping distance (PSD) (Morando et al. 2018, U.S. Department of Transportation 2003, Young et al. 2014, Essa and Sayed 2016, Goh et al. 2014). The TTC can be explained as the desired temporal duration of two vehicles to conflict each other, if both of them remains on the same lane with same former speed. TTC is a widely accepted surrogate safety measure because of its major role in the confliction (Saunier 2010, Morando et al. 2018). The following equation can be used to calculate TTC (Saunier 2010):

$$\text{TTC} = \begin{cases} \frac{d_2}{v_2} & if\ \frac{d_1}{v_1} < \frac{d_2}{v_2} < \frac{d_1+l_1+w_2}{v_1} \\ \frac{d_1}{v_1} & if\ \frac{d_2}{v_2} < \frac{d_1}{v_1} < \frac{d_2+l_2+w_1}{v_2}\,\text{(side)} \\ \frac{X_1-X_2-l1}{v_2-v_1} & if\ v_2 > v_1 \text{(rear end)} \\ \frac{X_1-X_2}{v_1+v_2} & \text{(head on)}, \end{cases} \tag{2.10}$$

where V1 and V2 are speeds, $l1$ and $l2$ are lengths, $w1$ and $w2$ are widths, $X1$ and $X2$ are positions of the vehicles. $d1$ and $d2$ are spatial distances to conflict areas. Furthermore, the PET is the time difference between those vehicles who are about to conflict in common place, if one of them does not move on or get slower. PET, defined as the time difference between when the leading vehicle occupies a location and when the trailing vehicle arrives at this location, is usually used to identify conflicts in combination with TTC (Chen et al. 2017a). Figure 2.11 illustrates situations for TTC and PET calculations (Saunier 2010).



(a) Time to collision (TTC)



(b) Post-encroachment time (PET)

Figure 2.11 Results acceptance criteria based on statistical confidence limits (Saunier 2010, Morando et al. 2018)

Studies have shown that TTC equals to or less than 1.5 seconds make insecure circumstance in the road network (Morando et al. 2018, Dijkstra et al. 2010, Gettman et al. 2008, Truong et al. 2015). TTC = 1.5 second can be granted for all HV possible collisions i.e. HV-HV or HV-AV or HV-CAV. Conflicts among autonomous tech-vehicles may allow lower TTC as their reaction time is faster than human reaction time (Morando et al. 2018).

2.4.3 Evaluation criteria

According to Hellinga (1998), choosing the threshold for adequacy of specific model results is an important task. The selection of the right measure of effectiveness along with planning for an acceptable range of values for that measure sometimes become complex but very important as they play severe role in the ultimate decision making process (Hellinga 1998). After obtaining the appropriate field data, it might be conceivable to evaluate the mean and variance based of the measure of effectiveness. Afterward, statistical confidence limit can be imposed originated from mean and variance that can be used as evaluation criteria (Hellinga 1998, Aziz 2018). Figure 2.12 depicts calibration acceptance criteria as per the statistical level of significance.

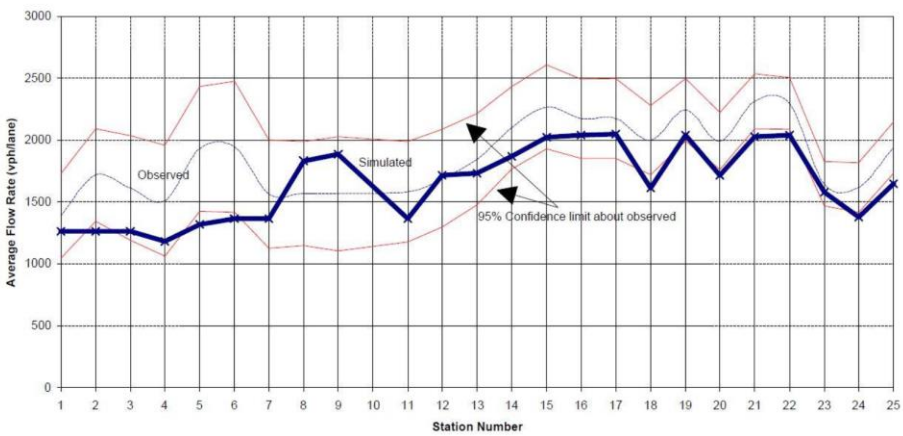


Figure 2.12 Results acceptance criteria based on statistical confidence limits (Van and Rakha 1996)

2.4.4 Sensitivity Analysis of Impact

The sensitivity analysis (SA) can be a strong expression to demonstrate the influences of different input parameters of microscopic traffic model in the performance outcomes (Lownes and Machemehl 2006). A principle role of the SA is to rank the input parameters based on the output uncertainty, which helps to reduce the computational cost and to create good results (Punzo et al. 2014). In easy words, SA investigates the simulation scenarios to identify which input parameters are paramount in influencing the simulation outputs (Sfeir et al. 2018). Although, most of the time SA is being used to reduce the number of input parameters for the calibration, it proves to be a fine tool to visualize the interaction of the input parameters in the system. Other features of SA are detecting technical errors, escalating the simplification, adjusting the model to manage the system uncertainty (Punzo et al. 2014).

The correlation of these parameters can be shown using multiple graphical representations i.e. scatter plot, heatmap (Chung et al. 2005). Researchers perform the sensitivity analysis with different methodology to fulfil their target outcomes of the simulations. Implementation of optimization algorithms is very common in the typical SA. Researchers collaborate data-mining techniques i.e. the Bayesian Networks, optimization algorithms, general variance based (García-Herrero et al. 2020), variance-based method based on Sobol sequences (Sfeir et al. 2018), and perform various search method i.e. grid search in the platform of the SA (Liu et al. 2014). Punzo et al. (2014) listed several approaches, which develop sensitivity of a simulated model: (1) input and output scatter plots, (2) one-at-time (OAT) sensitivity analysis, (3) the elementary effect test, (4) the sigma-normalized derivatives, (5) the partial correlation coefficient analysis, (6) the standardized regression coefficient analysis, (7) Monte Carlo filtering, (8) metamodelling, (9) factorial analysis of variance (ANOVA), (10) the Fourier amplitude sensitivity test, and (11) the variance-based method based on the Sobol decomposition of variance. Choosing appropriate driving parameters for sensitivity analysis depends on the nominated performance indicator: traffic, safety or emission measures (Habtemichael and Santos 2012). A recommended SA approach could be a two steps experimental setup. Starting with the first stage of SA, by plotting the correlational scatter plots for all the parameters combinedly and demonstrate them for individual parameters. By identifying the most significant parameters from several, this reduces the computational time in total (Sfeir et al. 2018, Prionisti and Antoniou 2012, Liu et al. 2014).

Figure 2.13 shows the results of the first stage of SA taken by Sfeir et al. (2018) in the scatter plot formation. Using the scatter plot, the trend of 4 different input parameters (i.e. maximum speed, normal deceleration, maximum acceleration and reaction time) were studied to find the influential parameters.

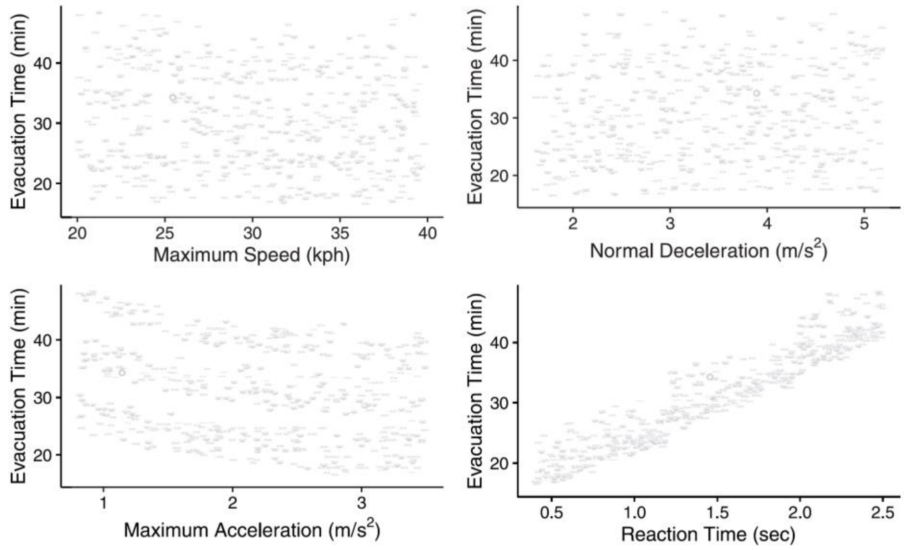
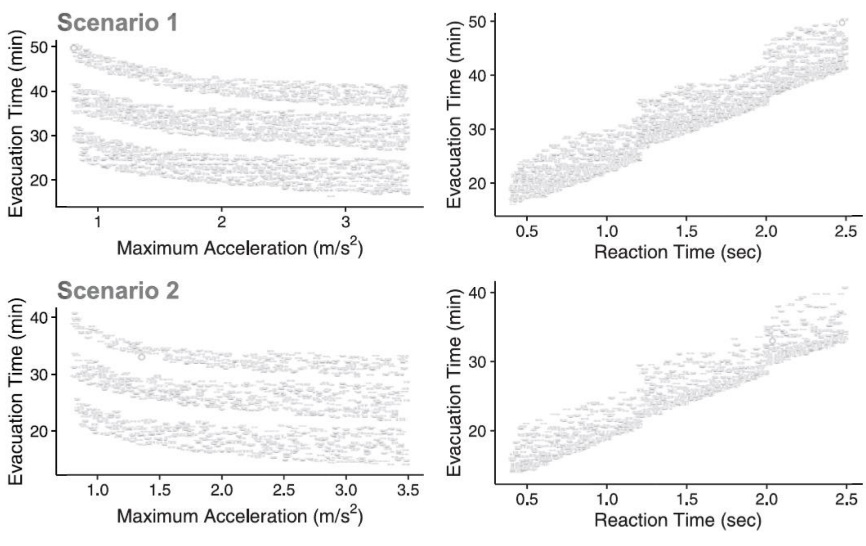


Figure 2.13 First stage of SA, Scatter plot (Sfeir et al. 2018)

In the second stage, more detailed and advanced analysis can be performed for few parameters for the insight perception. Sfeir et al. (2018) performed a variance-based method based on Sobol's decomposition of variance which can calculate and measure the sensitivity for the finally chosen model input parameters (Sobol 1998, Sfeir et al. 2018). A search operation of pseudo-random and quasi-random numbers can be generated for getting faster convergence and smoother graphical representation of the results (Sfeir et al. 2018). Figure 2.14 shows the results of second stage of SA for different scenarios performed by (Sfeir et al. 2018). In the second stage, different scenarios are studied for only two lastly selected input parameters i.e. maximum acceleration and reaction time.



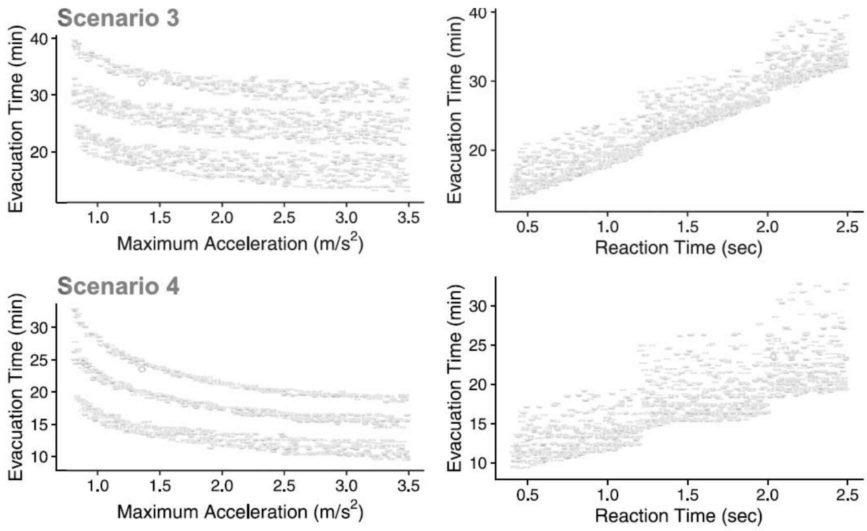


Figure 2.14 Scatter plot from quasi-random numbers for selected input parameters (i.e. Maximum acceleration, reaction time) for 4 scenarios (Sfeir et al. 2018)

3 Methodology

In this chapter, different methods and approaches are demonstrated which are used to perform essential tasks of this study. Calibrating and validating are very crucial part of the microscopic traffic simulation. These steps play vital role in developing the base model, which are detailed in this chapter. In second place, development of the human-like C/AV models in the VISSIM are presented. Moreover, description of the processes and assumptions for HV and C/AV are elaborated for proper perception. Lastly, the approaches to evaluate this study are presented to obtain base understanding of performances evaluation process before reaching the impact study and sensitivity analysis.

3.1 Modelling Human-driven Vehicles

The HVs of this study are developed from the VISSIM default passenger car. HVs come with only one driving module, normal module. HVs are expected to take more risks and break speed limits sometimes. The expected interactions and reactions from HVs are stochastic and heuristic by nature. The HVs model of this study are planned in way to represent reality in simulation environment as much as possible.

3.1.1 Model Calibration and Validation

Calibration and validation process of the microscopic traffic simulation is considered crucial because it make the model realistic and appropriate for all inputs. Figure 3.1 shows the sequence of calibration and validation what this study has followed which is highly inspired by Hellinga (1998). The study goals determine what data to be obtained from the real world. On the other hand, Study goals influences the collection of data which includes what to collect and how to collect. Study goals and field data together to determine appropriate measure of effectiveness (MoE) for the calibration and validation process. Moreover, study goals and field data also decide what criteria to be calibrated which is 37 parameters in total for this study. The results are compared with MoE if it matches or not. Result matching leads to decision of final simulation model and accepted criteria parameters for future use. Validation phase evaluates the criteria parameters responses with the MoE where the model scalability in any scenarios is ensured. As currently advanced level C/AVs are absent, the calibration and the validation are performed only for the human-driven vehicles for this study.

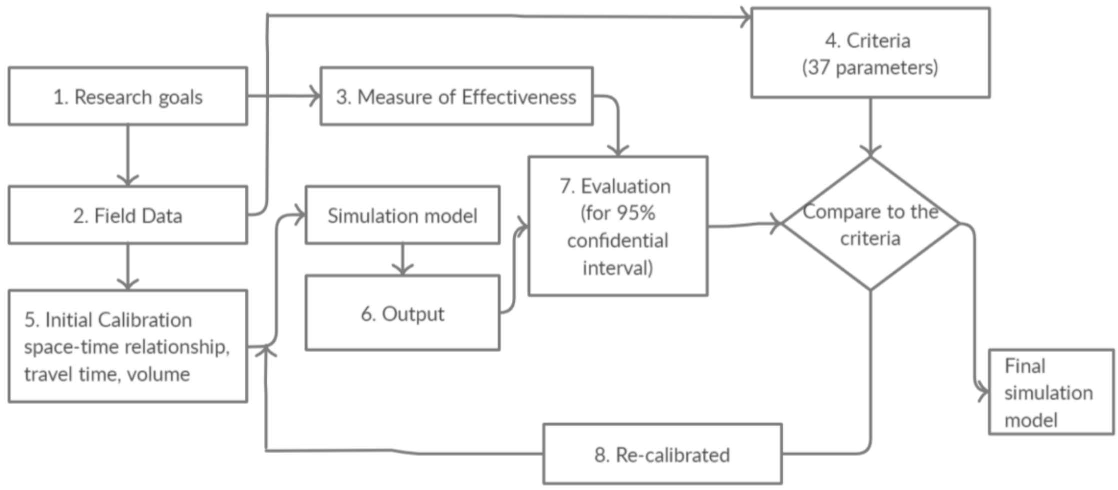


Figure 3.1 Process of calibration (Hellinga 1998)

3.1.1.1 Model Calibration

Simultaneous Perturbation Stochastic Approximation

Simultaneous Perturbation Stochastic Approximation (SPSA) is presented by (Spall, J., C. 1998a) which is an iterative optimization algorithms (Spall, J., C. 1998a, Qurashi 2018). As per Qurashi (2018), SPSA needs two evaluations for the given objective function to calculate its gradient for the minimization. The SPSA's performance is determined by fundamental parameters which are manually been checked as per (Spall, J., C. 1998b).

Sl.	Parameters	Significance
1	θ	The decision variable
2	c, γ	To specify c_k(where k is the iteration number)
3	a, A, α	To specify a_k
4	c_k, a_k	Gain sequence
5	Δ	Random vector based on Bernoulli distribution

Table 3.1 SPSA Parameters (Qurashi 2018)

In one side, the c_k defines the magnitude of perturbation in the decision variable θ. On the other side, the a_k defines the magnitude of minimization for θ in each iteration. c_k and a_k are being specified as:

$$c_k = \frac{c}{(k)^\gamma} \tag{3.1}$$

$$a_k = \frac{a}{(k+A)^\alpha} \tag{3.2}$$

So that: $a_k > 0, c_k > 0, a_k \to 0, c_k \to 0, \sum_{k=0}^{\infty} a_k = \infty,\ \sum_{k=0}^{\infty} \frac{{a_k}^2}{{c_k}^2} < \infty$

Where parameters c and a are defining the magnitude of gain sequence c_k and a_k and γ, α and A define the pattern of reduction in c_k and a_k with the increase in number of iterations (Qurashi 2018).

Major steps with SPSA

According to Qurashi (2018), the SPSA is an iterative process which contains four major steps within an iteration. Table 3.2 shows the 4 major steps of SPSA.

Sl.	SPSA Step	Description
1	Perturbation	Perturbation of the decision variable by summing and deducting the gain sequence for ck times a random vector resulting in two variables θ^{+} and θ^{-}. From the equation, it is seen that the random vector Δ increases half of the vector variables by ck and reduces the remaining half to make the θ^{+}. On the other hand, for θ^{-}, sign changes for the ck, so the vector variables that were increased before are reduced while increasing the other half. $$\theta^{\pm} = \theta \pm c_k \triangle$$
2	Objective function evaluation	The objective function evaluation consists of two times evaluation as per θ^{+} and θ^{-} from perturbation step. The objective function f() specify the difference between the observed and the simulated traffic data based on the goodness of fit. $$y^{\pm} = f(\theta^{\pm})$$
3	Gradient Approximation	Third step means to approximate the gradient by taking the difference between the outputs from the objective function y_{+} and y_{-} dividing it by the perturbation magnitude $c_k \times \Delta$ $$g' = \frac{y^{+} - y^{-}}{2c_k}\begin{bmatrix}\Delta_1\\ \Delta_2\\ \vdots\\ \Delta_h\end{bmatrix}$$
4	Minimization	The gradient is approximated in this step. Here the gain sequence a_k is used to minimize the decision variable. θ_k is the minimized decision variable estimated at iteration k. $$\theta_{k+1} = \theta_k - a_k {g'}_k(\theta_k)$$

Table 3.2 Four steps of Simultaneous Perturbation Stochastic Approximation (Qurashi 2018)

Algorithm

The imposition of SPSA on a calibration problem where car following parameter needed to be set for desired level of matching needs some modifications from the basic SPSA algorithm. Figure 3.2 shows the flow chart of SPSA which is followed for this study that is inspired from Qurashi (2018).

1. It start with calculating the gain sequence parameters

2. In second step, the plus perturbation is made where a function is used to assign new perturb parameters.

3. In third step, the minus perturbation is made where another function is used to assign new perturb parameters.

4. Then the gradient is evaluated.

5. Finally, the minimization take place and it assign new perturb parameters.

6. The best result is stored.

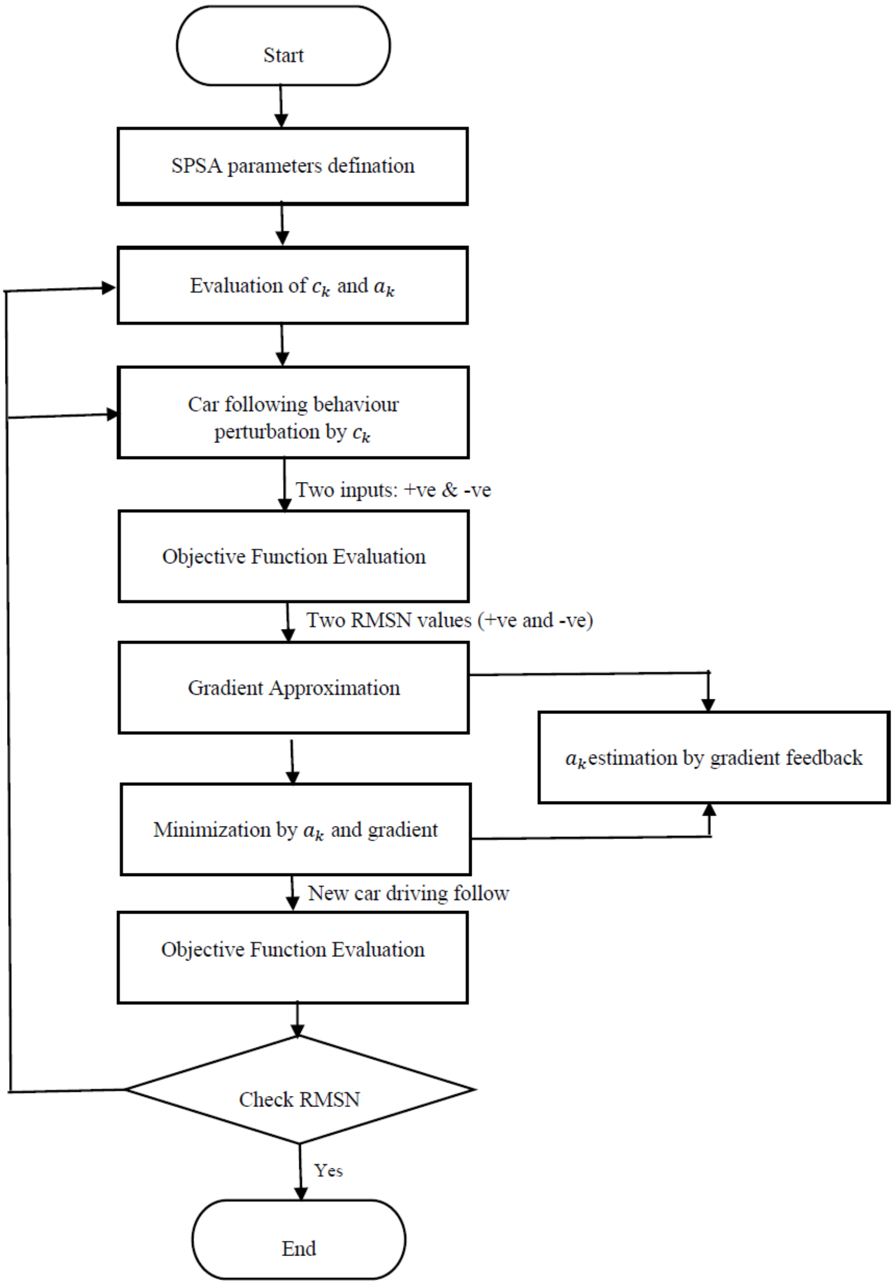


Figure 3.2 SPSA Flow chart (Qurashi 2018)

Constraint Parameters

The SPSA algorithm took, total 37 driving parameters from microscopic simulation environment which are focused for the calibration of this study. Table 3.3 listed all the driving behaviour parameters which are used as constraint for the SPSA with their minimum and maximum value. Their range between the minimum and maximum values can be taken as constraints for the SPSA calibration. These constraints have both positive and negative ranges where the parameter values kept changing gradually.

Sl.	IDriveringBehavior	Parameter Description	Minimum Value (Dadashzadeh et al. 2019b, PTV 2011)	Maximum Value
General Parameters				
1	LookBackDistMax	Max. Look back distance [m]	50	200
2	LookBackDistMin	Min. Look back distance [m]	0	200
3	LookAheadDistMax	Max. ahead back distance [m]	100	300
4	LookAheadDistMin	Min. ahead back distance [m]	0	300
5	NumInteractVeh	Number of interaction vehicles	0	99
6	StandDist	Standstill distance in front of static obstacles [m]	0,00	3,00
7	FreeDrivTm	Free driving time [s]	N.A	
8	IncrsAccel	Increased Acceleration [m/s2]	1,0	9,99
9	MinCollTmGain	Minimum collision time gain [s]	N.A	
10	MinFrontRearClear	Minimum clearance (front/rear) [m]	N.A	
11	SleepDur	Temporary lack of attention - sleep duration	N.A	
Lane-changing model parameters				
12	DecelRedDistOwn	Reduction rate for Leading (own) vehicle [m]	100	200,00
13	AccDecelOwn	Accepted decelaration for leading (own) vehicle [m/s^2]	-3	-0.5
14	AccDecelTrail	Accepted decelaration for following (trailing) vehicle [m/s^2]	N.A	
15	SafDistFactLnChg	Safety distance reduction factor	0,10	0,60
16	CoopDecel	Max. decelaration for cooperative lane-change/braking [m/s^2]	-6,00	-3,00
17	MaxDecelOwn	Max. decelaration for leading (own) vehicle [m/s^2]	N.A	
18	MaxDecelTrail	Max. decelaration for following (trailing) vehicle [m/s^2]	N.A	
19	DecelRedDistTrail	Reduction rate for following (trailing) vehicle [m]	N.A	
20	PlatoonFollowUpGapTm	Platooning - follow-up gap time [s]	N.A	
21	PlatoonMinClear	Platooning - minimum clearance [m]	N.A	
Wiedemann 74 car-following model parameters				
22	W74ax	Average standstill distance	0,50	2,50
23	W74bxAdd	Additive Factor for security distance	0,70	4,70
24	W74bxMult	Multiplicative factor for security distance	1,00	8,00
Wiedemann 99 car-following model parameters				
25	W99CCO	Desired distance between lead and following vehicle [m]	0,60	3,05
26	W99CC1DISTR	Headway Time [s] Desired time between lead and following vehicle	0,50	1,50
27	W99CC2	Following variation [m] Additional distance over safety distance that a vehicle requires	1,52	6,10

28	W99CC3	Threshold for entering following state [s] Time is second before a vehicle start to decelerate to reach safety distance (negative)	-15,00	-4,00
29	W99CC4	Negative "following Threhold"[m/s] Specifies variation in speed between lead and following vehicle	-0,61	-0,03
30	W99CC5	Positive "following Threhold"[m/s] Specifies variation in speed between lead and following vehicle	0,03	0,61
31	W99CC6	Speed dependency of oscillation [1/ms]	7,00-	15,00
32	W99CC7	Oscillation Accelaration Acceleration during the oscillation process[m/s^2]	0,15	0,46
33	W99CC8	Standstill Acceleration [m/s^2]	2,50	5,00
34	W99CC9	Acceleration with 80 Km [m/s^2]	0,50	2,50
Lateral manuever parameters				
35	LatDirChgMinTm	Lateral direction change - minimum time [s]	N.A	
36	LatDistDrivDef	Lateral minimum distance at 50 km/h (default)	N.A	
37	MinSpeedForLat	Minimum longitudinal speed for lateral movement	N.A	

Table 3.3 Driving behaviour parameters used as constraints for SPSA

Normalization

The c_k and a_k coefficients responsible for the change in perturbation and minimization are applied by normalizing them by an average value. Normalization approaches are taken from a previous study done by Qurashi et al. (2019a), which has two perturbations and one minimization steps in the process as well.

Perturbation: $z^{\pm} = z_k \pm z_k \times c_{k\Delta}$ (3.3)

Minimization: $z_{k+1} = z_k - z_k \times a_k g'$ (3.4)

3.1.1.2 Model Validation

As mentioned in the literature section, there are different approaches to validate the model and all of them lead to same objective that is reusability of the model for other inputs. A visual validation such as time space-diagram for validating the mixed traffic condition demonstrates uniqueness in the traffic (Raju et al. 2018). Unlike the homogenous traffic, the lateral behaviour becomes significant for mixed traffic cases highlight the cause-effect relationship transparent.

3.2 Modelling C/AVs

The C/AV provides a possibility to improve the travel and impact experiences in the transportation industry. To simulate such technologies in the microscopic traffic simulation, one need to keep eyes on several vehicle behaviours: acceleration-deceleration behaviours, longitudinal behaviours, lateral behaviours and gap acceptance behaviours for the lanes. The CAVs can travel closer together which means it creates greater capacity by allowing higher density in the traffic flow. The Special driving behaviours, CAV connectivity and improved infrastructures can significantly influence the current traffic flow (Atkins 2016). The connected and/or autonomous vehicles use their own driving module in the microscopic traffic simulator. This study considers three major driving modules of autonomous vehicles, currently available in the industries. The driving module are titled as aggressive, safe and cautious. These can be initiated from Wiedemann 99 car-following model inclusively and exclusively. The driving modules taken for this study are inspired from European Union’s Horizon 2020 funded project “CoExist” (Sukennik 2018).

Aggressive

This driving module of the C/AVs is considered to have cognizance, predictive and safety maintenance features which lead to smaller gaps for all kinds of manoeuvres in the network. This driving module increases the road capacity (Sukennik 2018).

Safe

On the other hand, the safe driving module of the C/AVs reacts like a human-driver with some more abilities and features. Features such as capability to measure the spatial distances and speeds of other vehicles up to a certain range (Sukennik 2018).

Cautious

Finally, cautious driving module is considered to be perfect road code follower which always maintain a safe behaviour towards all vehicles. According to Sukennik (2018), the cautious driving module always assures active brick wall stop distance.

In microscopic traffic flow simulation, these C/AV features are imposed by an additional function. VISSIM interface implements this feature by enforce absolute braking distance. This module also come with capability to act in the unsignalized intersections and to take the lane change manoeuvres. The vehicles will be tended to maintain large gaps in the road (Sukennik

2018). Table 3.4 shows additional setting for the C/AVs. See section 2.3.2 Driving parameters of C/AVs in VISSIM for more information.

Driving logic	Enforce absolute breaking distance	Use implicit stochastics	Number of interaction vehicles	Increased desired acceleration
Aggressive	OFF	OFF	1	110%
Safe	OFF	OFF	1	100-110%
Cautious	ON	OFF	>1	100%
HVs	OFF	OFF	1	100%

Table 3.4 Setting for AV features (Sukennik 2018)

3.2.1 Functions

The autonomous vehicles are considered to interact deterministically instead of stochastically like the human-driven vehicles which has significant role in the acceleration and deceleration behaviors. The simulator can control the extension of desired acceleration, desired deceleration, maximum acceleration and maximum deceleration of individual vehicles in the network, if it is a requirement for the modelling (Sukennik 2018).

3.2.2 Distributions

Desired speed

The desired speed shows an influential presence in the obtainable travel times and link capacity. The real speed is a product of the interactions of the vehicle with other road agents and infrastructures in the simulator. However, vehicle comes with its own desired speed which is determined by a distribution. HVs take larger spread of desired speeds what have been observed. Moreover, the autonomous vehicles can travel with a much lower spread because AVs are prone to maintain the speed limits. That lead difference of desired speed distribution between HVs and AVs (Sukennik 2018).

Time

The time is one of the essential distributions, especially for the Wiedemann 99. It influences the capacity. CC1 which is one of the Wiedermann 99's parameters, is the time distribution of the speed-dependent part of desired safety distance. As per Sukennik (2018), the distribution will be empirical or normal for each time distribution, showing randomness and uniqueness. Such randomness feature can be closed by deselecting use implicit stochastic (Sukennik 2018).

3.2.3 Spatial extent

Study area in the simulation environment can be spatially segmented where different autonomous driving logics are needed to be implemented. Sukennik (2018) explained that there could be an autonomous vehicle priotorized region in the urban location, where the vehicles could be in aggressive driving logic. However, in the same time in another part of the urban area, the cautious driving logic may be highly recommended because of insufficient AV friendliness. To achieve this, the link behaviour needed to be set. The network needs to cover all the possible behaviours of the AVs and the setting up the link behaviour type to the links. It will lead to the same vehicle to different driving modules in designate locations of the network (Sukennik 2018).

3.2.4 Model parameters

Different microscopic traffic simulator offers different features to model a new vehicle model in the simulator. The Wiedermann 99 of VISSIM offers several features and methodology to create the C/AVs in the interface. Table 3.5 and Table 3.6 respectively present the parameters what are modified to match the driving modules of C/AVs and several designated parameters for the C/AVs what are chosen for this study.

Sl.	IDriveringBehavior	Parameter Description	Aggressive	Normal	Cautious
General Parameters					
1	LookBackDistMax	Max. Look back distance [m]	150,00	150,00	150,00
2	LookBackDistMin	Min. Look back distance [m]	0,00	0,00	0,00
3	LookAheadDistMax	Max. ahead back distance [m]	250,00	250,00	250,00
4	LookAheadDistMin	Min. ahead back distance [m]	0,00	0,00	0,00
5	StandDist	Standstill distance in front of static obstacles [m]	0,50	0,50	0,50
Wiedemann 99 car-following model parameters					
6	W99CCO	Desired distance between lead and following vehicle [m]	1,00	1,50	1,50
7	W99CC1DISTR	Headway Time [s] Desired time between lead and following vehicle	0,6	0,9	1,50
8	W99CC2	Following variation [m] Additional distance over safety distance that a vehicle requires	0,00	0,00	0,00
9	W99CC3	Threshold for entering following state [s] Time is second before a vehicle start to decelerate to reach safety distance (negative)	-6,00	-8,00	-10,00
10	W99CC4	Negative "following Threhold"[m/s] Specifies variation in speed between lead and following vehicle	-0,10	-0,10	-0,10
11	W99CC5	Positive "following Threhold"[m/s] Specifies variation in speed between lead and following vehicle	0,10	0,10	0,10
12	W99CC6	Speed dependency of oscillation [1/ms]	0,00	0,00	0,00

13	W99CC7	Oscillation Accelaration Acceleration during the oscillation process[m/s^2]	0,10	0,10	0,10
14	W99CC8	Standstill Acceleration [m/s^2]	4,00	3,50	3,00
15	W99CC9	Acceleration with 80 Km [m/s^2]	2,00	1,50	1,20
Lane-changing model parameters					
16	MaxDecelOwn	Max. decelaration for leading (own) vehicle [m/s^2]	-4,00	-4,00	-3,50
17	MaxDecelTrail	Max. decelaration for following (trailing) vehicle [m/s^2]	-4,00	-3,00	-2,50
18	AccDecelOwn	Accepted decelaration for leading (own) vehicle [m/s^2]	-1,00	-1,00	-1,00
19	AccDecelTrail	Accepted decelaration for following (trailing) vehicle [m/s^2]	-1,50	-1,00	-1,00
20	CoopDecel	Max. decelaration for cooperative lane-change/braking [m/s^2]	-6,00	-3,00	-2,50
21	SafDistFactLnChg	Safety distance reduction factor	0,75	0,60	1,00
Lateral manuever parameters					
22	MinSpeedForLat	Minimum longitudinal speed for lateral movement [km/h]	3,60	3,60	3,60

Table 3.5 Modification of driving behaviours to match the C/AV driving modules (Sukennik 2018, PTV 2019, Atkins 2016)

Sl.	COM VISSIM Parameters	Autonomous Parameter Description	Aggressive (Modified)	Normal (Modified)	Cautious (Modified)
1	EnforcAbsBrakDist	Enforce absolute braking distance	False	False	True
2	UseImplicStoch	Use implicit stochastics	False	False	False
3	NumInteractObj	Number of interaction objects and vehicles	10	2	2
4	NumInteractVeh		5	3	2
5	W99cc0	Headway based on leader vehicle class	Listed in the Table 4.14		
6	W99cc1Distr				
7	IncrsAccel	Increased acceleration	110%	105%	100%
8	Platooning	Platooning	3 (Arbitrarily selected for the study corridor)		
9	AddOccupancyDistribution	Occupancy distribution (with/out zero passengers)	relevant to public transport		
10	ConsVehInDynPot	Consider vehicles in dynamic potential	True	True	True

Table 3.6 Dedicated parameters required to model C/AV in the VISSIM (Sukennik 2018, Atkins 2016, Zeidler et al. 2018, PTV 2019, 2011)

Furthermore, the V2V and V2I features of connected and autonomous vehicles are imposed by both COM interface and additional scripts. Table 3.7 shows the implementation techniques of connected features for this study.

Feature Category	Sub-Category	Implementation method
Vehicle to Vehicle connectivity (V2V)	Lane Control Adaptive Cruise Control (ACC) Vehicle-to-Vehicle (V2V) Communication	VISSIM/ COM interface
	Platoon formation	VISSIM interface
Vehicle to Infrastructure Connectivity (V2I)	Automatic Emergency Braking System (AEBS) Object or Collision Avoidance System (CAS) Slowing down to intersections	Event script file

Table 3.7 Implemented automation features

3.2.5 Assumptions

This study considers that the C/AVs will not work from central processing system which means each agent will be individual and will react as per the state of the network. The vehicles will get feed from the observation and nearby vehicles' reactions. There will be no influence from entire city network state. Furthermore, the central traffic control system is omitted in this study so that it can match the human driven vehicles and separate agent-based reactions. Sub-urban and freeway may not be suitable for the zonal traffic control system because of lack of infrastructures (i.e. detectors, processor and transmitter) what are essential to accelerate the control as a zonal pattern.

3.3 Evaluation process

3.3.1 Traffic performance indicators

This study used average travel time, average delay time and average speed as traffic performance indicators. The average travel time is one of the most basic measure in transportation system. It represents the average time required to travel from one point to another over a specified route by all vehicles under on-site traffic conditions. On the other hand, the average delay time indicates the average time of all vehicles lost by traffic friction items and traffic control devices adding extra periods in the travel time. Both of them give an impression of the traffic conditions and indicates level of service of the road (Macababbad, R., J., R., M. and Regidor, J., R., F. 2011, Salter, R., J. 1989). Speed as a performance indicator is a strong expression towards the capacity and the queue condition (Sharma, H., K. et al. 2012, Akçelik

2003). If the road is congested and reached the capacity, it will demonstrate lower speed (Sharma, H., K. et al. 2012, Salter, R., J. 1989).

3.3.2 Emission evaluation process

The EnViVer used the vehicle trajectories and additional information to compute the emission of the focus study area of this thesis. Additional details required for this study are (Eijk et al. 2014):

- **VehNr**: Number of Vehicle
- **Type**: Number of Vehicle Type
- **VehTypeName**: Name of the Vehicle Type
- **ToD**: Simulation Time as Time of Day [hh:mm:ss:ms] (preferred) or
  t: Simulation Time [s]
- **vMS**: Speed [m/s] at the end of the simulation step

The vehicle trajectories and other information are obtained as output from the VISSIM after running the microscopic simulation.

3.2.3 Safety evaluation process

This study used the trajectory files in Surrogate Safety Assessment Model (SSAM) to investigate on number of potential conflicts. These vehicle trajectories are generated from the VISSIM. SSAM has no built-in function to determine possible collisions by the vehicle type but it is capable to provide the vehicle IDs which are responsible for the conflicts. Later, related vehicle types can be identified from the VISSIM interface seperately. Lastly, it can estimate possible confliction by vehicle types: HV-HV,HV-AV, and AV-AV (Morando et al. 2018). This study has been carried out for two sets of TTC i.e. 0.75 and 1.5 sec for constant value of PET (1.5 sec).

3.2.4 Sensitivity Analysis

The two steps sensitivity analysis (SA) has been implemented to obtain the perception of the influential parameters. The experiment is planned on the AV models for 8 input parameters which are closely related to microscopic simulation of AVs. These parameters have been selected from as per viewpoints from the Co-Exist project (Sukennik 2018). Table 3.8 show the microscopic traffic input parameters chosen for preliminary SA.

Sl.	Parameters	COM VISSIM Parameters	Range	Description
1	Accepted deceleration (own)	AccDecelOwn	-3 to -0.5 m2/s	This parameter demonstrates the lower bound of the deceleration for the own vehicle for lane change
2	Look ahead distance (maximum)	LookAheadDistMax	0 – 300 meter	Maximum spatial distance a driver can see in front and side to interact for other road users.
3	Look back distance (maximum)	LookBackDistMax	0 – 300 meter	Maximum spatial distance a driver can see in backside to interact for other road users.
4	Minimum collision time gain	MinCollTmGain	0.5 – 5 sec	This parameter represents the minimum value for collision time gain for the next vehicle or infrastructure.
5	Minimum longitudinal speed for lateral movement	MinFrontRearClear	0 – 2.5 meter	Minimum longitudinal speed allows for lateral movements which assures vehicles' lateral maneuver they come near to the stop.
6	Number of interacting vehicles	NumInteractVeh	0 – 99	Number of vehicles affects a particular vehicle in the lane
7	Standstill distance	W99cc0	0.6 – 3.05 meter	The desired spatial standstill distance between two vehicles.
8	Headway time	W99cc1Distr	0.5 – 1.5 sec	The time that a driver wants to keep constant with other vehicles.

Table 3.8 Microscopic input parameters for creating preliminary SA for AVs (Sukennik 2018, PTV 2011, 2019, Essa and Sayed 2016)

To save the computational effort, the second step SA comes with lesser number of input parameters for studying the insight of the AV models. Two parameters such as number of interacting vehicles and minimum longitudinal speed for lateral movement have shown significant influences in the first stage of the SA which leads to the extension of SA with these parameters. The average travel time has been used as performance indicator for both steps of the sensitivity analysis as it reflects how the total network efficiency is affected from the continuous changes.

4 Experimental setup

In this chapter, details of the experimental setups for this study has been discussed. At first, a demonstration of choice of study area and data collection process have been described as this experimental set has been built up on them considering them as the base. Secondly, the development of study model and additional components are illustrated which are essentially followed and taken for this study. Figure 4.1 shows the process of the experiment setup inspired and evolved from the studies done by other researchers, to meet the goals of this study.

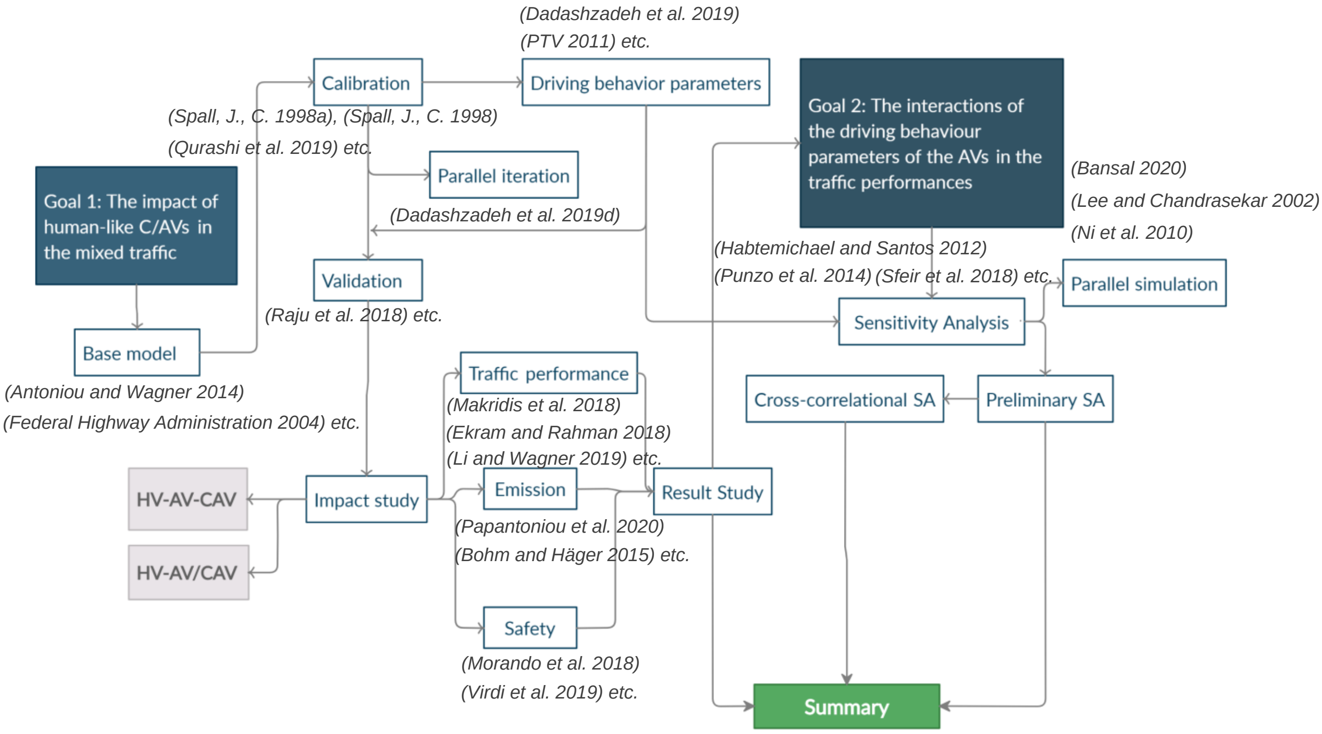


Figure 4.1 Process of the experimental setup

Although the initial plan was to implement parallel programming techniques in the different calibration algorithms: SPSA, FDSA and in the execution of the sensitivity analysis, it was not implemented. Hence, it provides a research provision for extension of this study. Furthermore, Figure 4.2 shows the organigram of the microscopic traffic simulation for this study that is inspired from a former study (Virdi et al. 2019). The base demand was obtained and processed from real traffic and the network was modelled to precise enough to detail the existing infrastructure. The overall approach taken in this study is to proxy the impacts of CAVs in an existing traffic condition. The VISSIM, a microscopic traffic simulation software from PTV, has been used to perform the simulation. Moreover, EnViVer and SSAM have been used for additional inquires such as impact over emission and accident. The car following models which are supplied in the VISSIM have been used to represent the human-driven vehicles for lane behaviours. To represent the C/AVs in the VISSIM interface, along with available car following behaviours, additionally the behaviours of ACC, and CACC technologies are implemented.

The vehicle to vehicle (V2V) and vehicle to infrastructure (V2I) connectivity assure the reflection of real world into the model which are stored as the external control algorithm. The surrogate safety assessment module assures proper visualization of probable accidents while the EnViVer check the emission of the study area.

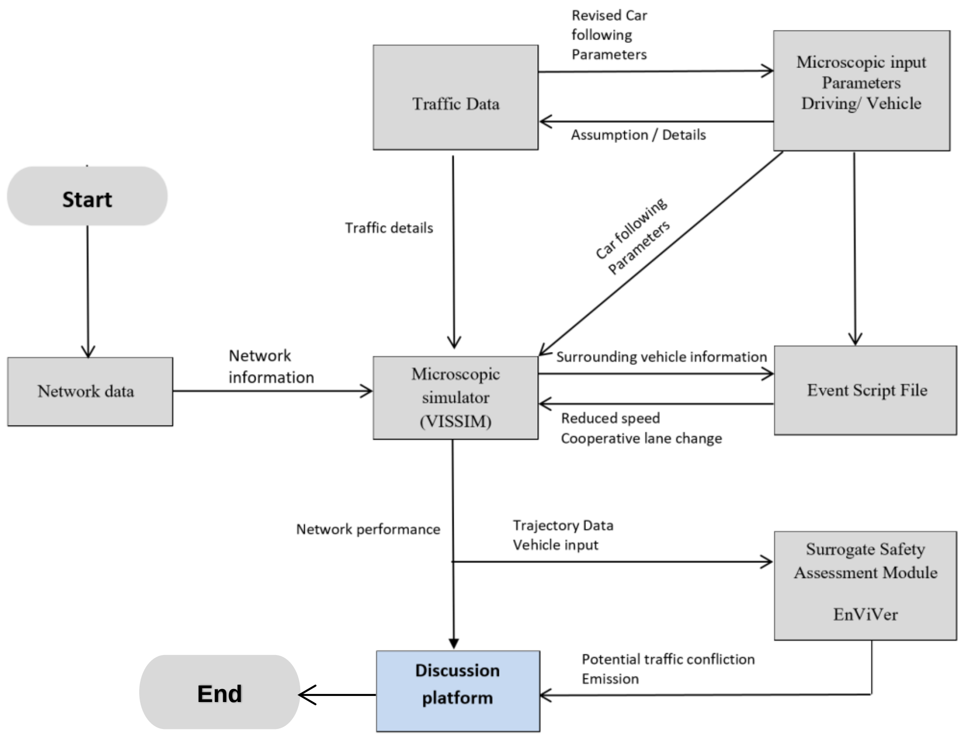


Figure 4.2 Organigram of the microscopic traffic simulation

4.1 Study Area

The area for this study was selected based on the presence of different driving manoeuvres i.e. lateral manoeuvres, for the human-driven vehicles (HVs) and, connected and/or autonomous vehicles (C/AVs). Two major urban built-up streets in Munich, Germany: Ludwigstraße and Leopoldstraße which is also the continuation of Ludwigstraße, are modelled for the experiment. The combined length of these two nominated streets from north direction to south direction is 2.5 km approximately (Aziz 2018). Ludwigstraße and Leopoldstraße carry-out several mobility hubs and commercial areas, which make it one of the busy corridors of the Munich. Moreover, this corridor is part of the bicycle focused other transportation and mobility projects of the Munich: RASCH and RadOnTime (Bogenberger 2020), as this corridor takes higher number of bicycle riders. Due to presence of several mobility hubs, intersections, merging points and public transportation stops, the road performances tend to drop in the peak hours. This study recognizes 10 signalized intersection of the mainstream where 6 major intersections are taken for this research, served to collect the data and to measure the impacts. The major and minor streams from the study area are listed in Table 4.1

Sl.	Major street (South-North Direction)	Minor street (East-West Direction)
1		Von-der-tannstrasse
2	Ludwigstrasse	Theresienstrasse
3		Schelingstrasse
4		Fransz-josephstrasse
5	Leopoldstrasse	Herzogstrasse
6		Ungerestrasse

Table 4.1 Details of the study area

Figure 4.3 describes the major intersections and streams of the Ludwigstraße and Leopoldstraße which are chosen for this study.

Figure 4.3 Geographical location of the study area: Ludwigstraße and Leopoldstraße

4.2 Data Collection

Both primary and secondary data were used to prepare the simulation model to reflect the real world in simulation appropriately. Due to time constraint, traffic data were obtained in the form of video clips from a former master thesis conducted by Hossein (2018) in the chair of traffic engineering and control, Technical University of Munich. However, traffic control details, road control measures, and geometry of the network were supplied by Aziz (2018) and Hossein (2018) from their master theses. Furthermore, several field trips are performed, and quality of the data is preserved by recounting of vehicles from the video clips.

4.2.1 Traffic Demand Data

The traffic demand data were gathered from the real-world by setting a camera in each major intersection of Ludwigstraße and Leopoldstraße. As the proper location for data collection camera was missing so only six major intersections were chosen for performing the microscopic simulation. These clips were manually counted again to match the customized time interval of this thesis. In total, four types of vehicles taken into the account for generating current state in the VISSIM which are HV, truck, normal bike and cargo bike. The Pedestrian and public transport like buses and tram are not included in the assessment for this study. AVs and CAVs are included additionally to develop the model for assessment. Each AV and CAV models come with three different driving modules which are planned based on literatures and assumptions to match their inner objectives (PTV 2011, Evanson 2017, Toledo and Koutsopoulos 2004, Toledo 2003). Figure 4.4 shows the vehicle inputs in the study area from different locations.

The microscopic simulation model in the VISSIM interface for this study was limited to peak hour intervals (17:00-18:00) to match previously accumulated field data (Hossein 2018). The field data of traffic volumes and the vehicle turning ratio were manually acquired from the video clips which were recorded by a previous master student as part of his master thesis activities (Hossein 2018).

1	2	3	4	5	6	7	8	9	10	11
Brienner Straße	Oskar-von-Miller-Ring	Von-der-Tann-Straße	Theresienst-raße	Schelling-straße	Franz-Joseph-Straße	Martiusstraße	Herzogstraße	Feilitzsch-straße	Rheinstraße	Fuchsstraße
(Car +HGV, Bike): (410, 214)	(223, 85)	(566, 110)	(75, 68)	(156, 134)	(320, 149)	(69, 173)	(260, 12)	(102, 32)	(964, 232)	(548. 116)

Figure 4.4 Vehicle input in the study area

4.2.2 Traffic Signal Data

The traffic signal control data of intersections of the study area is supplied by the chair of traffic engineering and control, Technical University of Munich. Furthermore, the traffic control data also made by Landhauptstadt München and contain present signal groups of the intersections, the inter green matrix, and the different signal programs with different cycle time (the 70s, 90s, 120s). These data were used by the former two master thesis (Aziz 2018, Hossein 2018).

4.2.3 Traffic Infrastructure

The network geometry data and road control measures, to prepare the microscopic simulation model, were supplied by two former master students Hossein (2018) and Aziz (2018) who conducted their master theses in the chair of traffic engineering and control, Technical University of Munich. These road geometry data include layout plan of every intersection, detailed information of each link, lane width, stop line, pavement marking as well as signal head location. All these network geometry data were generated by Landhauptstadt München. Later on, several field investigations were made to match the road improvements. The speed reducer and priority regions are implemented to avoid congestion and possible collision in the traffic. Table 4.2 shows the reduced speed distribution and deceleration rate for different vehicles.

Sl.	Vehicle Class	Desired speed distribution (km/h)	Deceleration
1	HV	15-25	2
2	Truck	12-20	1.5

Table 4.2 Reduced speed area (Aziz 2018)

4.2.4 Measure of Effectiveness

This thesis focused on a particular time interval of peak hour (17:00-18:00) for the microscopic traffic simulation. Vehicles volume and real-world vehicle trajectories (GPS position) were accumulated from a previous master thesis (Hossein 2018). Figure 4.9 demonstrates the space-time relationship of a vehicle. Vehicles volumes were not able to represent the effect of driving behaviours in the microscopic simulation model as time intervals were quite coarse to detect the impact after taking the average of each output. At this point in the study, vehicle trajectories became quite useful. The travel time data were used to calibrate the model for driving behaviour parameters. Finally, space-time was used to demonstrate the validation phase.

4.2.5 Vehicle Data

The vehicle data specifically vehicle type available in the traffic, composition to be implemented in the model, are manually obtained from the video clips which are mentioned in previous subsection (4.2.1 Traffic Demand Data). Table 4.3 shows the types of vehicle what are implemented in the simulation model.

Sl.	Vehicle Type	Sub-Type (VISSIM interface)	Desired Speed (km/h)
1	HV	HV	40
2	Truck	Truck	30
3	Bike	Normal Bike + Cargo Bike	N. Bike: 15, C. Bike: 12

Table 4.3 Type and desired speed of vehicles

4.3 Development of study model

Development of simulation model in the microscopic traffic model environment is done in several stages. The development process starts with the implementation of road geometry and then implementation of road control. After finding and customizing appropriate car following behaviours, the link behaviours are taken care of which are precise method to represent different concerns of the reality. In second phase, the traffic demand is issued for chosen time horizon. After this stage, number of simulation and calibrated model is finalized. Finally, once the base model undergo through the validation phase and simulation can be charged for required outputs, development of base scenario is completed. Figure 4.5 visualizes the base model prepared in the VISSIM interface for this study.

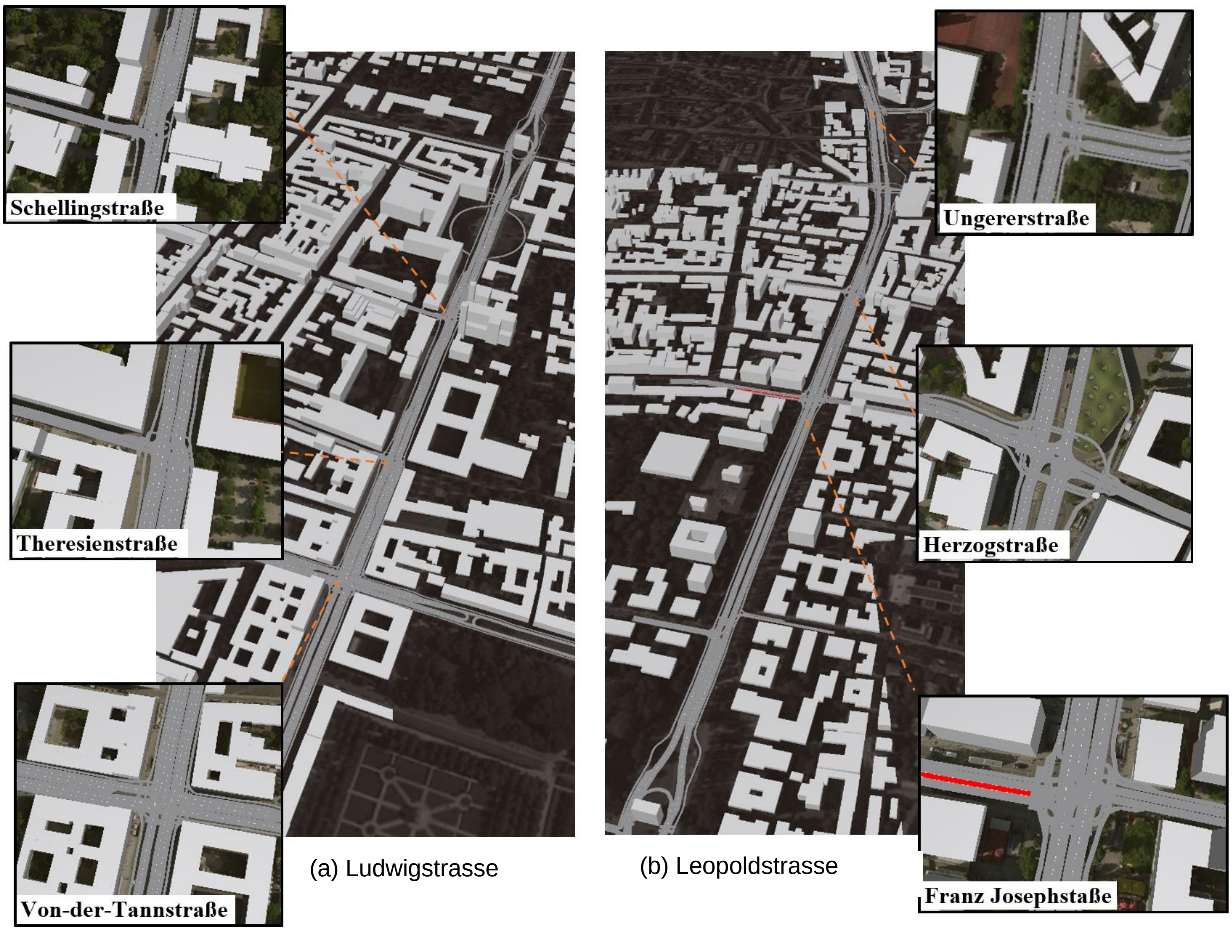


Figure 4.5 Base model in the VISSIM interface

4.3.1 Components of model

Several scenarios have been tested to perceive the impact of various mixtures of HVs, AVs and CAVs. Table 4.4 shows scenarios for the traffic impact study of different penetration percentage of C/AVs for three traffic demand cases: 20% below peak hour, peak hour, 20% above peak hour, and only one driving module, normal. Table 4.5 deepen the insight investigation of the safety and emission along with the traffic performance. Another 11 scenarios have been taken for three traffic demand cases and three different driving modules: aggressive, normal, cautious.

Sl.	HVs %	AVs %	CAVs %
1	100	0	0
2	0	100	0
3	0	0	100
4	75	13	12
5	13	75	12
6	13	12	75
7	50	25	25
8	25	50	25
9	25	25	50
10	25	37	38
11	37	25	38
12	37	38	25
13	0	50	50
14	50	0	50
15	50	50	0

Table 4.4 Combination of 3 vehicle combinations

		Penetration rate of C/AVs (%)										
		0	10	20	30	40	50	60	70	80	90	100
Penetration rate of HVs (%)	0											X
	10										X	
	20									X		
	30								X			
	40							X				
	50						X					
	60					X						
	70				X							
	80			X								
	90		X									
	100	X										

Table 4.5 Combination of 2 vehicle combinations

4.3.2 Car following behaviours

Generally, the microscopic traffic simulation software come with its own car following techniques besides customizable behaviours. VISSIM has its predefined car following behaviours which can represent most possible scenarios of real world. As this study covers three different driving modules which are different by behaviours from each other's, and need AV and CAV for assessment, several self-prepared behaviours are generated which can match the AV and CAV functionalities. Table 4.6 shows the car following models and link behaviours to their corresponding vehicle types, assigned for this study.

Sl.	Name	Vehicle Classes	Driving Behaviors
1	Urban (motorized)		Wiedemann 74
2	Right-side rule (motorized)	HV, Truck	Wiedemann 99
3	Freeway (free lane selection)		Wiedemann 99
4	Cycle-Track (free overtaking)	Normal Bike, Cargo Bike	Wiedemann 74
5	Urban motorized- Selected lanes	HV, Truck	Wiedemann 74
6	Urban (biker)	Normal Bike, Cargo Bike	Wiedemann 74
7,8,9	AV/CAV aggressive/ safe/ cautious	AV/ CAV	Modified Wiedemann 99

Table 4.6 Generated car following models

4.3.3 Conflict areas

Conflict areas are indicated in the VISSIM interface for safety reasons at intersections where two or more links/ connectors cross each other. Figure 4.6 depicts the conflict areas of

Münchner freiheit intersection. Right of way is implemented in two phases. First, bicycle has right of way priority over the motorized vehicles and secondly major traffic stream flows i.e. N-S and S-N, enjoy right of way over minor traffic stream flows i.e. E-W and W-E.

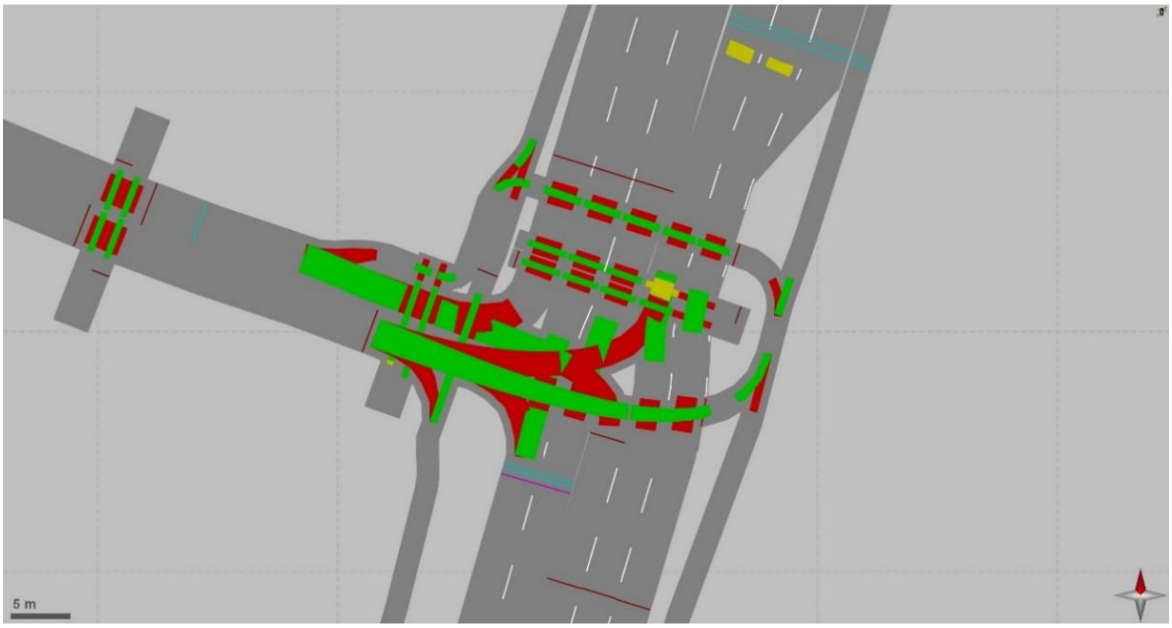


Figure 4.6 Conflict area management in VISSIM (i.e. Ludwigstraße-Schellingstraße)

4.3.4 Signal controllers

There are ten signalized intersections located in the study area that indicates to ten fixed time signal controllers are installed in this study area. All intersections are cycle time of 90 seconds (Hossein 2018).

4.3.5 Data collection points

To obtain the data from the network and to get an impression of the performance of the traffic, several data collection points were introduced in each lane for 6 nominated intersections in their both directions i.e. N-S and S-N which are 12 in total for the HV lanes (Motorway). Motorway and bicycle lanes have separated data collection points installed in their own lanes which mean bicycle lanes have equal number of data collection points. They are responsible to measure the traffic volume, delay and travel time in their designated lanes.

4.3.6 Error check

Error checking is considered as crucial phase in the microscopic traffic simulation. The VISSIM has its own interface where the base model undergo through test process after the coding with default parameter sets or setting the model in the GUI directly. This verification phase involves rechecking of all input data i.e. review of network connectivity, link parameter, vehicle input data and static routing decision, link and driving behaviour types.

Moreover, the 3D animation undergo through this process to review the network so that notable errors can be found (Hossein 2018, Aziz 2018).

4.3.7 Number of simulations run

As mentioned earlier (2.1.1 Number of required simulations run) the minimum required number as per confidence interval can be estimated by equation below.

$$CI_{1-\alpha\%} = 2 * t_{(1-\alpha/2),\, N-1} \frac{S}{\sqrt{N}} \tag{4.1}$$

Where, $CI_{(1-\alpha)\%}$=(1-α)% confidence interval for the true mean, where alpha equals the probability of the true mean not lying within the confidence interval, $t_{(1\text{-alpha}/2),\, N-1}$= Student's statistic for the probability of a two-sided error summing to alpha with N-1 degrees of freedom, where N equals the number of repetitions and S= Standard deviation of the model results.

However, for confidence interval 95% and traffic volume as measure of effectiveness for determining the minimum number of required simulations, the requirement become quite high which makes computational effort quite high and time consuming. The required number of simulations found from bicycle analysis is greater than the result found from HV analysis. Both are time consuming for microscopic simulation, especially when volume is taken as a measure of effectiveness and calibration iterations are not determined. However, it is important to assure the 95% confidence interval. As, this study is investigating over HVs, AVs and CAVs, only HVs had been approached for deciding over number of required simulations. Table 4.7 and 4.8 show the number of required of simulation for HVs and Bicycle, respectively.

Sl.	Location	Standard Deviation	Mean	Confidence Error (5%)	t value	N
1	Vondertann(N)	46	858	42,9	2,306	24,4557
2	Theresienstrasse(N)	47	838	41,9	2,306	26,7637
3	Schellingstrasse(N)	48	835	41,75	2,306	28,1156
4	Franz Josephstasse(N)	43	1004	50,2	2,306	15,6066
5	Herzogstrasse(N)	35	1169	58,45	2,306	7,6269
6	Ungererstrasse(N)	25	749	37,45	2,306	9,4788
7	Vondertann(S)	23	591	29,55	2,306	12,8860
8	Theresienstrasse(S)	28	1234	61,7	2,306	4,3805
9	Schellingstrasse(S)	27	1275	63,75	2,306	3,8154
10	Franz Josephstasse(S)	28	1256	62,8	2,306	4,2284
11	Herzogstrasse(S)	34	1214	60,7	2,306	6,6736
12	Ungererstrasse(S)	30	1281	64,05	2,306	4,6664

Table 4.7 Calculated number of simulations required for 95% confidential interval of HVs

Sl.	Location	Standard Deviation	Mean	Confidence Error (5%)	t value	N
1	Vondertann(N)	18	361	18,05	2,306	21,1529
2	Theresienstrasse(N)	12	316	15,8	2,306	12,2695
3	Schellingstrasse(N)	19	337	16,85	2,306	27,0449
4	Franz-Jo-sephstasse(N)	16	343	17,15	2,306	18,5136
5	Herzogstrasse(N)	17	290	14,5	2,306	29,2375
6	Ungererstrasse(N)	18	288	14,4	2,306	33,2352
7	Vondertann(S)	15	279	13,95	2,306	24,5931
8	Theresienstrasse(S)	13	281	14,05	2,306	18,2101
9	Schellingstrasse(S)	17	265	13,25	2,306	35,0142
10	Franz Jo-sephstasse(S)	14	270	13,5	2,306	22,8753
11	Herzogstrasse(S)	16	283	14,15	2,306	27,1960
12	Ungererstrasse(S)	16	304	15,2	2,306	23,5685

Table 4.8 Calculated number of simulations required for 95% confidential interval of Bicycles

Table 4.9 demonstrates the microscopic simulation setting in the VISSIM interface taken for this study.

Sl.	Parameter	COM VISSIM Parameters	Default Value (PTV 2011)	Value	Description (PTV 2011)
1	Period	SimPeriod	3600 sec	4200 sec	Simulation time in simulation seconds
2	Random Seed	RandSeed	42	40	This can lead to different results from simulation. A comparison of these simulation results allows you to compare the effect of stochastic variations.
3	Number of Runs	NumRuns	5 – 20, dynamic assignment needs more	10	Number of simulations runs performed in a row
4	Random Seed Increment	RandSeedIncr	1	3	Indicates the difference between seeds for multiple simulation runs

Table 4.9 Simulation setting in VISSIM

4.3.8 Data Collection Interval

Data collection parameters are used to manipulate the output to match the real-world data collection interval. As real-world traffic volume was collected in 15 min interval, the data collection interval in the VISSIM interface should be 15 min interval as well. The VISSIM Data collection system also define the warm-up time of the model. Usually warm-up time is a warm-up period of 15 to 30 minutes is enough. As the total network distance is 2.5 km and the desired speed for HV is taken as 25 km/hr, 10 min warm-up time will assure a total shifting of a vehicle from southmost intersection to the northmost intersection and vice versa. Table 4.10 shows the data collection interval for this study.

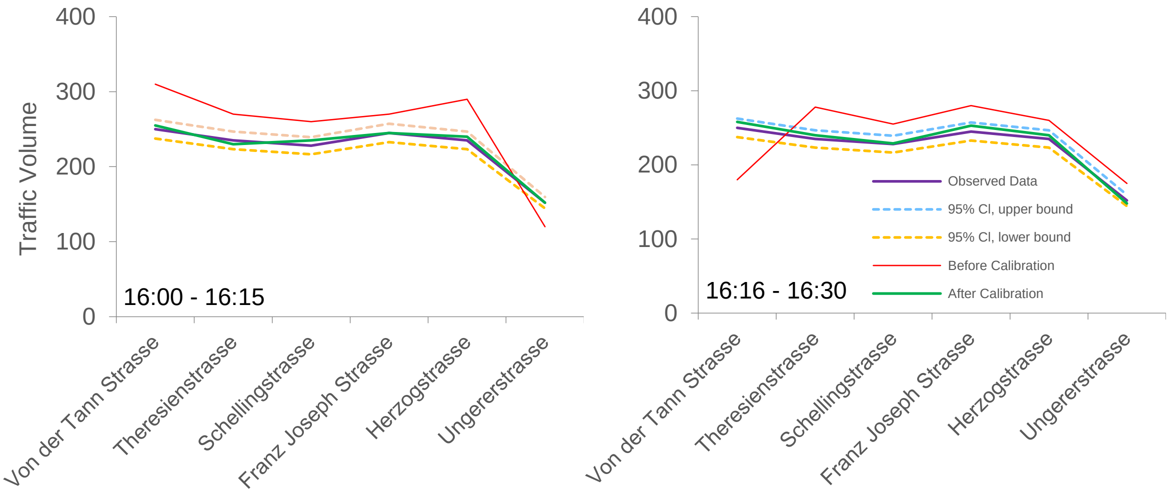
Sl.	Interval	Time Range (second)
1	Warm-up (10 min)	0 – 600
2	1st interval	601- 1500
3	2nd interval	1501-2400
4	3rd interval	2401-3300
5	4th interval	3301-4200

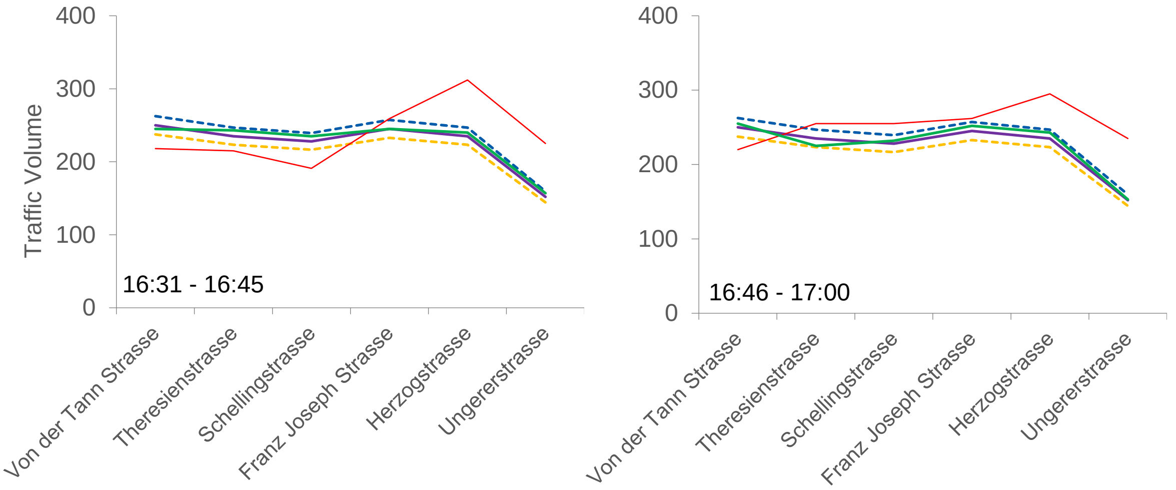
Table 4.10 Data collection interval plan

4.3.9 Model Calibration

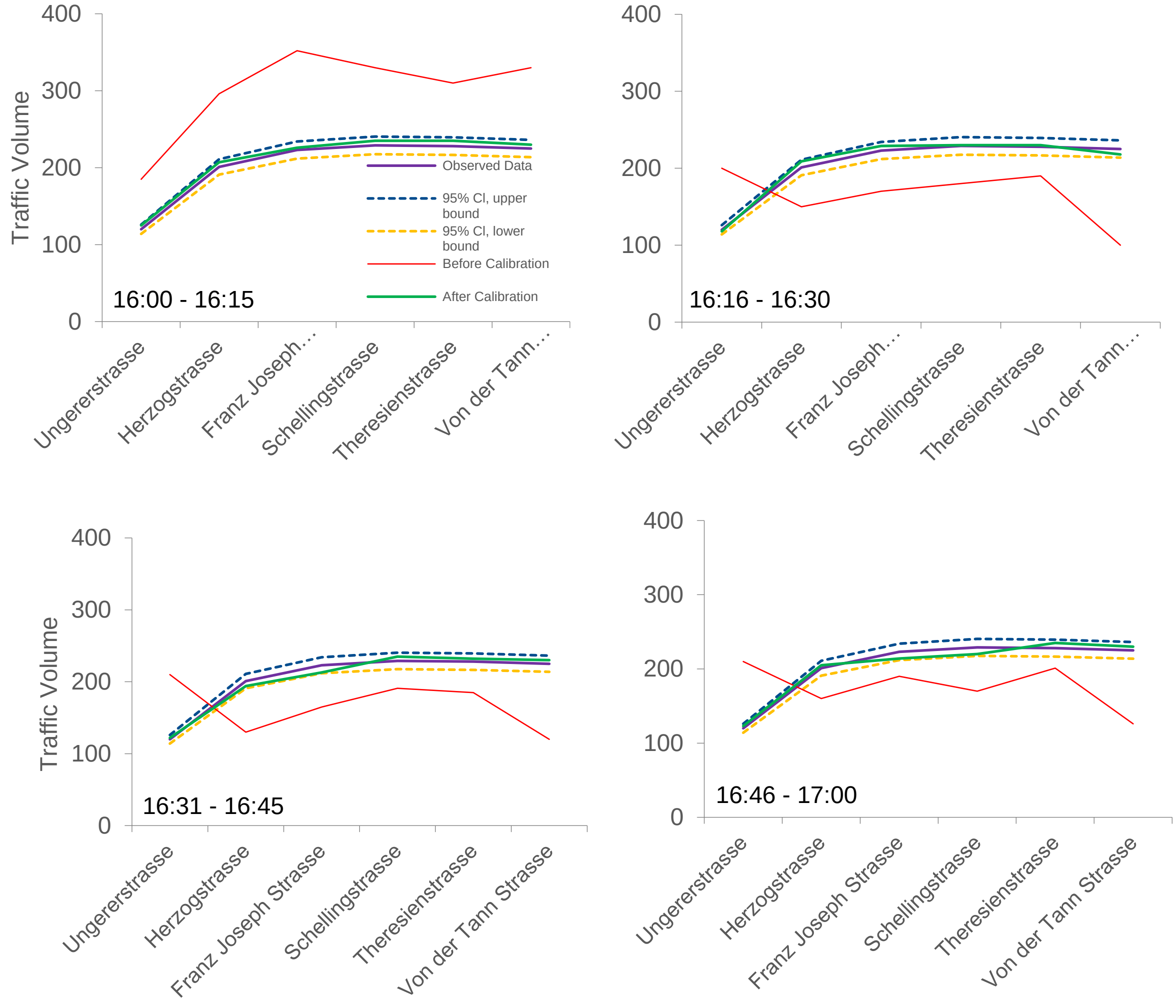
After performing successful the model becomes calibrated model. In this study, calibration has been performed for the traffic volume for every 15 min time interval. Figure 4.7 shows calibration performance in the traffic volume diagram which has four-time segments, dividing a peak hour into four quarters, matching real-world data collection procedure. Calibration has done for both direction both south to north and north to south direction. For both directions, after calibration simulation results matched real-world observed data in its +/- 95% confidential interval perimeter, shown in the figure below.

Moreover, to strengthen the outcome of the volume calibration, speed profile has been checked for the study model. Speed profile has been shown in the Figure 4.8. Compared visualization of two speed profiles, observed and after calibration, shows that a stable realistic speed profile is generated after performing the calibration for this study for every time segment and for both directions. The entire calibration study has been developed for the HVs because currently only HV traffic is available for the experiments.



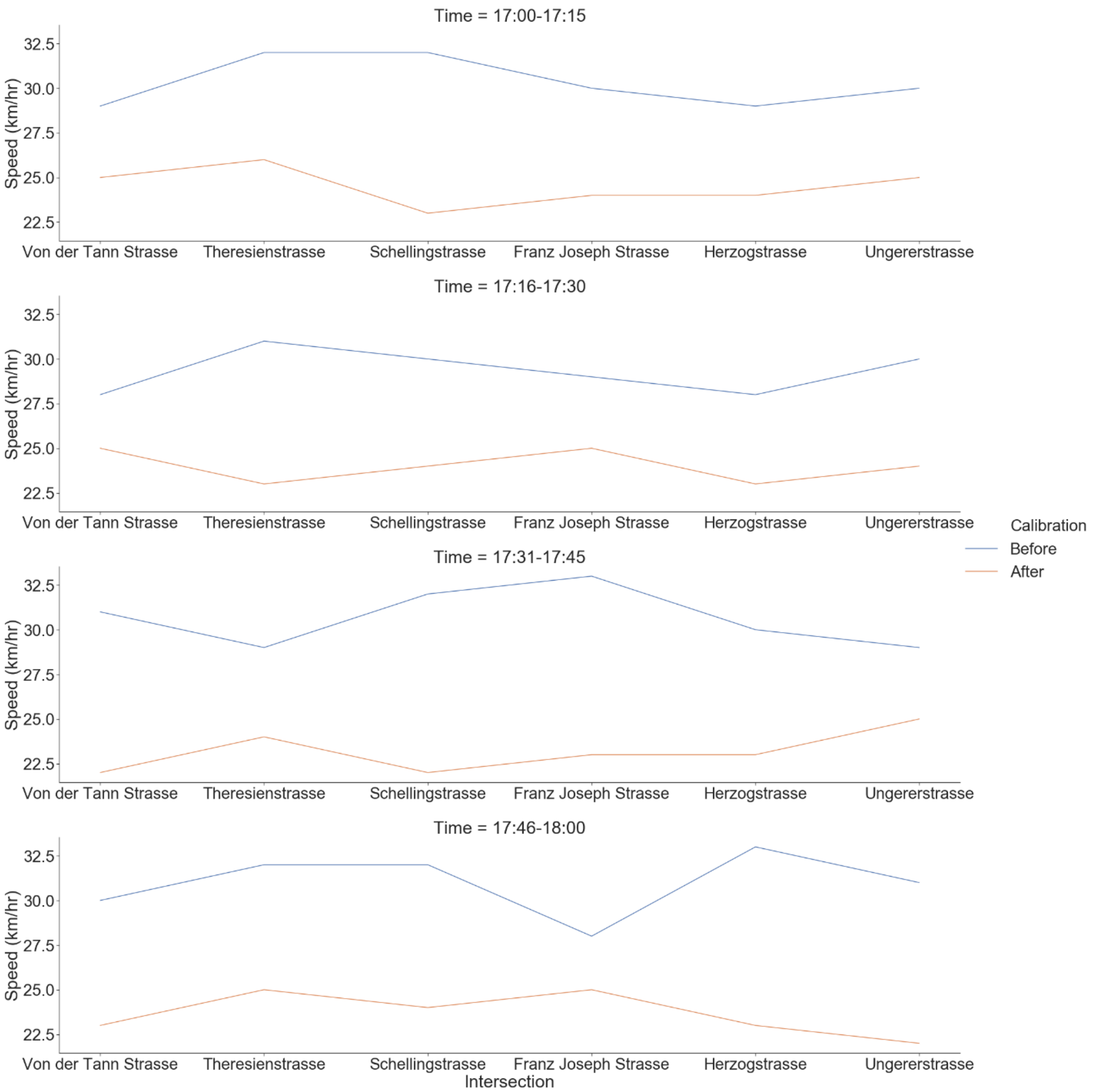


(a) Direction: South to North

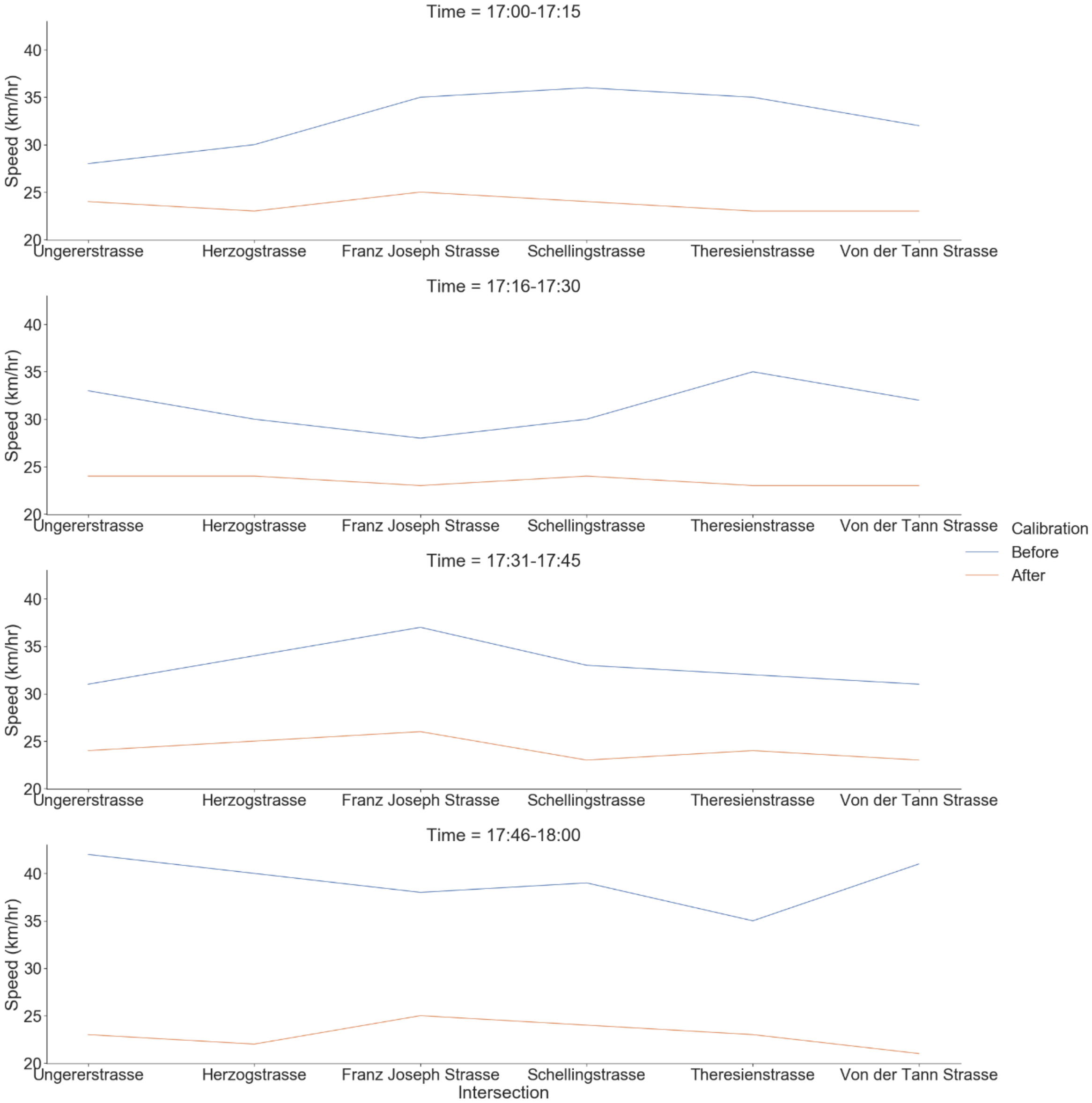


(b) Direction: North to South

Figure 4.7 Both direction traffic volumes for all six intersections (HVs)



(a) Direction: South to North



(b) Direction: North to South

Figure 4.8 Both direction speed for all six intersections

As volume and speed profiles are stable for the model, currently updated parameters can be used for validating the model. Table 4.11 listed the final values of the 37 criteria parameters from the calibration phase of this study, which are being used for further processes.

Sl.	IDriveringBehavior	Parameter Description	Ranges (Dadashzadeh et al. 2019b, PTV 2011)	Calibrated Values
General Parameters				
1	LookBackDistMax	Max. Look back distance [m]	50-200	150
2	LookBackDistMin	Min. Look back distance [m]	0-200	100
3	LookAheadDistMax	Max. ahead back distance [m]	100-300	300
4	LookAheadDistMin	Min. ahead back distance [m]	0-300	5
5	NumInteractVeh	Number of interaction vehicles	0-99	99
6	StandDist	Standstill distance in front of static obstacles [m]	0,00-3,00	0,50
7	FreeDrivTm	Free driving time [s]	N.A	11,0
8	IncrsAccel	Increased Acceleration [m/s2]	1,0-9,99	3,00
9	MinCollTmGain	Minimum collision time gain [s]	N.A	2,00
10	MinFrontRearClear	Minimum clearance (front/rear) [m]	N.A	0,5
11	SleepDur	Temporary lack of attention - sleep duration	N.A	0,0
Lane-changing model parameters				
12	DecelRedDistOwn	Reduction rate for Leading (own) vehicle [m]	100-200	200,00
13	AccDecelOwn	Accepted decelaration for leading (own) vehicle [m/s^2]	-3 to -0.5	-1,00
14	AccDecelTrail	Accepted decelaration for following (trailing) vehicle [m/s^2]	N.A	-0,50
15	SafDistFactLnChg	Safety distance reduction factor	0,10-0,6	0,60
16	CoopDecel	Max. decelaration for cooperative lane-change/braking [m/s^2]	-6,00 to -3,00	-3,00
17	MaxDecelOwn	Max. decelaration for leading (own) vehicle [m/s^2]	N.A	-4,00
18	MaxDecelTrail	Max. decelaration for following (trailing) vehicle [m/s^2]	N.A	-3,00
19	DecelRedDistTrail	Reduction rate for following (trailing) vehicle [m]	N.A	200,00
20	PlatoonFollowUpGapTm	Platooning - follow-up gap time [s]	N.A	0,60
21	PlatoonMinClear	Platooning - minimum clearance [m]	N.A	2,00
Wiedemann 74 car-following model parameters				
22	W74ax	Average standstill distance	0,50 -2,50	1,50
23	W74bxAdd	Additive Factor for security distance	0,70 -4,70	1,00
24	W74bxMult	Multiplicative factor for security distance	1,00 -8,00	2,00
Wiedemann 99 car-following model parameters				
25	W99CCO	Desired distance between lead and following vehicle [m]	0,60 -3,05	1,50
26	W99CC1DISTR	Headway Time [s] Desired time between lead and following vehicle	0,50 - 1,50	1,50
27	W99CC2	Following variation [m] Additional distance over safety distance that a vehicle requires	1,52 - 6,10	4,00
28	W99CC3	Threshold for entering following state [s] Time is second before a vehicle start to decelerate to reach safety distance (negative)	-15,00 to -4,00	-8,00

29	W99CC4	Negative "following Threhold"[m/s] Specifies variation in speed between lead and following vehicle	-0,61 to -0,03	-0,40
30	W99CC5	Positive "following Threhold"[m/s] Specifies variation in speed between lead and following vehicle	0,03 -0,61	0,35
31	W99CC6	Speed dependency of oscillation [1/ms]	7,00-15,00	11,44
32	W99CC7	Oscillation Accelaration Acceleration during the oscillation process[m/s^2]	0,15-0,46	0,25
33	W99CC8	Standstill Acceleration [m/s^2]	2,50-5,00	4,00
34	W99CC9	Acceleration with 80 Km [m/s^2]	0,50-2,50	1,50
Lateral manuever parameters				
35	LatDirChgMinTm	Lateral direction change - minimum time [s]	N.A	0,0
36	LatDistDrivDef	Lateral minimum distance at 50 km/h (default)	N.A	1,0
37	MinSpeedForLat	Minimum longitudinal speed for lateral movement	N.A	1,0

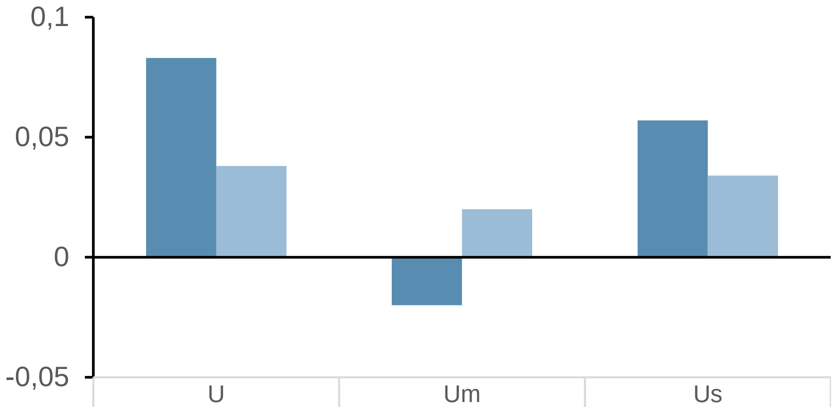
Table 4.11 Calibrated values of selected driving behaviour parameters

4.3.10 Post-Calibration Parameters

As calibration process move further, the GoF, RMSN, RMSE, RMSPE and MPE, reduces, which indicate the simulated data is getting closer to the observed data. Table 4.12 shows GoFs used for this study. An expectable value of goodness-of-fit (GoF) determines final step of calibration. Figure 4.9 shows the Theil's coefficient before and after the calibration, which are changed after calibration indicating success of the calibration. After sixty-five iteration, final desired value of GoF have been obtained for this study. Figure 4.10 shows the calibration results for RMSN for both directional traffic volumes. There were sudden drops in the RMSN plot up to 37 number of iteration but after that progress became slower. Once the plot faced the convergence, it indicated enough of iteration is done for this study.

GoF	Before Calibration	After Calibration
RMSN	0,116	0,055
RMSE	30,085	13,4
RMSPE	0,137	0,063
MPE	-0,0011	0,0006

Table 4.12 Goodness of fit measures



	U	Um	Us
Before Calibration	0,083	-0,02	0,057
After Calibration	0,038	0,02	0,034

Figure 4.9 Theil’s coefficient

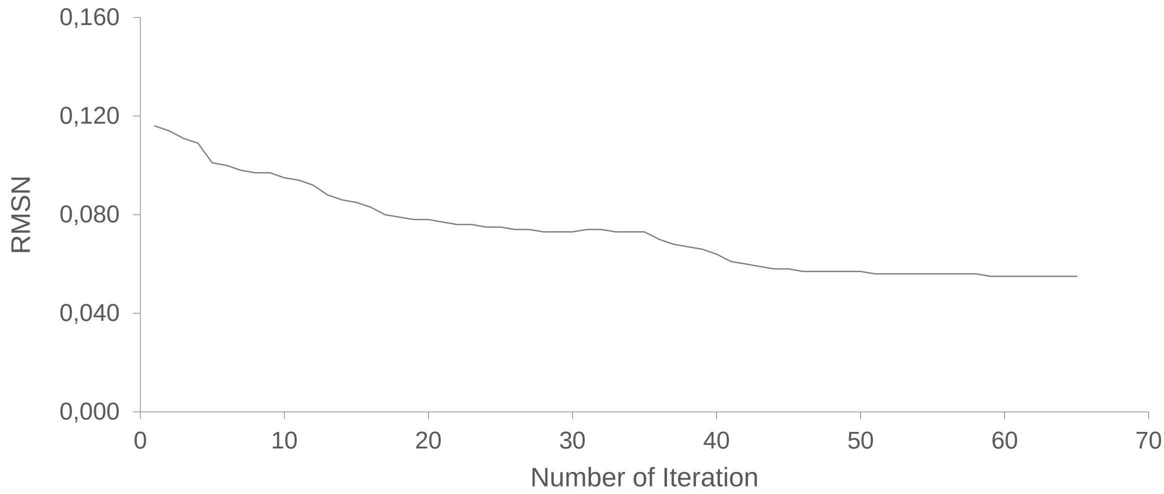


Figure 4.10 RMSN vs No of Iteration

4.3.11 Model Validation

The validation process assures that the simulation model will show similar responses for any data for the calibrated parameters. As visual approach of validation has been used in this study by plotting a time-space diagram. It indicates vehicles displaced in the corridor over the time in reality and in the simulation. Figure 4.11 visualizes the time-space diagram for simulated model and real-world collected data. Time-space diagram has been prepared for both direction: South-North and North-South direction. The results of the time-space diagram have been interpreted for 95% confidential interval., indicating accuracy of the acceptance.

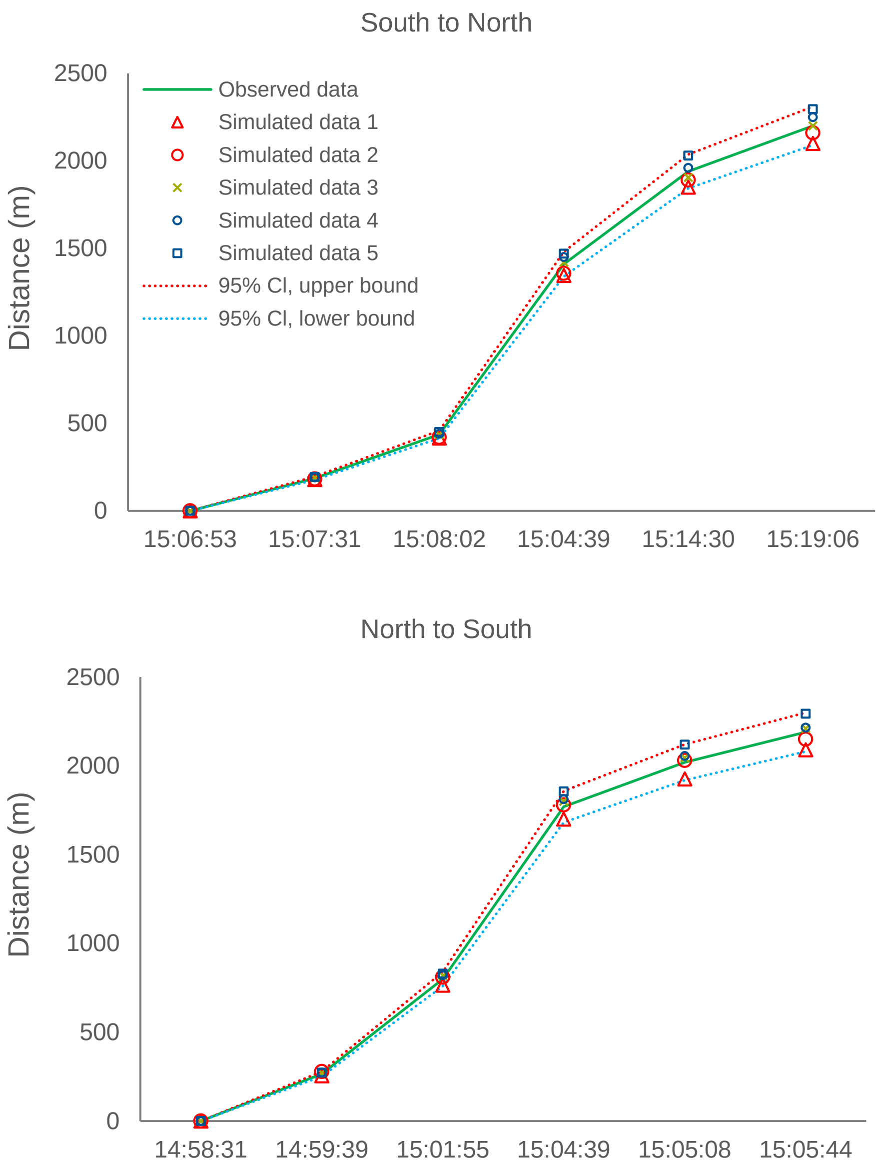


Figure 4.11 Space-time diagrams for both direction

5 Results

This chapter presents the results from experimental scenarios demonstrating aspects of the presence of C/AVs in mixed traffic for the future transportation system. Several parameters of autonomous vehicles played significant roles in the microscopic traffic simulation that represented such vehicles in the real world. The sensitivity analysis over those parameters showed how the traffic performances change in the realistic defined ranges. The scenarios originated from different traffic demand cases (i.e. the peak hour, 20% below the peak hour and 20% above the peak hour) for different vehicle types (i.e. HVs, AVs and CAVs) and their driving modules (i.e. Aggressive, Normal and Cautious). In brief, this chapter draws lines over following occurrences:

- Impact study of C/AVs in the mixed traffic, for same driving modules and fixed parameters of HV-AV-CAV
- Sensitivity analysis of driving parameters of AV in the mixed traffic, for same driving module and fixed amount of AV penetration

As stated above, all the investigation scenarios for the impact study have unchanged recommended values of driving parameters to make the comparison unambiguous. The details of recommended values used for the HVs-AVs-CAVs are given below:

- Table 2.3 – Recommended values of selected driving behaviour parameters for HVs
- Table 3.5 – Recommended values of selected driving behaviour parameters for C/AVs' three driving modules of C/AVs
- Table 3.6 – Recommended values of dedicated parameters of C/AVs

Only the normal driving module of C/AVs underwent the process to match significantly the HVs' standard driving behaviours. The other two driving modules, cautious and aggressive, were programmed to demonstrate higher differences in performance compared to the HVs. To make an optimistic future scenario, the sensitivity analysis considered 60% of the AV share in the study area in order to obtain maximum stable responses of the traffic performance from the AVs' counterpart.

To explore the presence of C/AVs in mixed traffic and to perceive the influences of the AV parameters, a total of four hundred ninety-six scenarios have been tested in this study, excluding the sixty-six scenarios for calibration and validation. The performance data was collected from the simulation in every fifteen min to match the observed real-world data. Data collection was withheld for the first ten min, as this period is considered as a warmup time. The basic experimental scenario consisted of peak hour traffic (16:00-17:00), with the presence of HV-AV-CAVs exchanging harmoniously for the normal driving module. Moreover, three traffic demand cases represented three possible conditions of the study area. Traffic demand 20% below the peak hour represented the low level of traffic, peak hour represented the currently allowable amount of traffic and 20% above the peak hour represented the maximum capacity of vehicles in the study area. Each scenario has been executed for 10 simulation runs in provision for normalizing the outcomes and to avoid the randomness of a solo simulation as discussed in previous section (4.1.7 Number of simulations run). The results show variations in the responses of different scenarios, which are induced from various internal and external factors i.e. connectivity features and edging with the capacity.

5.1 Evaluation of Mixed Traffic

The network performances which are influenced by the penetration of AVs and CAVs in the network, are derived for different traffic flows. This combinational impact of HV-AV-CAV have been studied for the mixed traffic in terms of travel time, speed, delay time. In addition to that a subset of these experiment cases, was studied to get deeper impression over the emission and safety aspect in the network. At the end, sensitivity analysis for the AV parameters are evaluated in terms of travel time and speed. Table 5.1 shows the significance of the performance indicators taken for this study:

Sl.	**Parameter**	**Unit**	**Significance (PTV 2011)**
Traffic Performance Indicators			
1	Travel Time	Second	Average travel time of the vehicles between two sections
2	Speed	km/hr	Average speed at the end of the time step
3	Delay Time	Second	Average difference between optimal (ideal, theoretical) driving time
Emission Performance Indicators			
1	CO_2	gm/km	Average CO_2 emission per gm per km of the study area
2	NO_x	gm/km	Average NO_x emission per gm per km of the study area
3	Total number of stops	-	Average number of stops (cumulative)
Safety Indicator			
1	Number of conflicts	-	Possible conflicts for given Time to collision (TTC) and post-encroachment time (PET)

Table 5.1 Description of the performance indicators

The average travel time of the network is an important performance indicator for this study. Reduction of travel time is a positive indicator for the network. The average speed relates to travel time. When the spatial distance of two locations is constant, higher speed can reduce the travel time. The delay time, on the other hand, acts as quality control for the travel time. Vehicle delay time is subtraction of the theoretical travel time from the actual travel time in the VISSIM interface. If a vehicle travels without any intrusion in the road by other vehicles or traffic signals, that travel time is called theoretical travel time. Lower travel time and lower delay time indicate higher speed in the road. All of these passively represent the road capacity. As per Friedrich (2016), a significant increment can be seen in the network capacity, if AVs run in the network which assures efficient use of the road infrastructures. Furthermore, the emissions and safety aspect relate to the traffic performance indicators. A capacity reached road demonstrates higher emission and higher possibility of unsafety. Through this process of congestion increment the number of stops increases as well.

5.1.1 HV-AV-CAV in Mixed Traffic

The proportions of HVs, AVs, and CAVs play major roles in mixed traffic, which can be seen in traffic performances i.e. travel time, speed and delay time. A total of forty-five scenarios have been investigated for this section. Results are depicted below using ternary plots, which are useful for showing the impacts of three variables from the simulation model. Figure 5.1 shows the travel time corresponding to the demand at 20% below the peak hour, at the peak hour, and at 20% above the peak hour. Each axis presents the proportion of penetration of a certain vehicle type, ranging from 0 to 1. The inner area of the ternary plot provides different possible HV-AV-CAV combinations. The plots indicate travel time changes for three traffic demand cases. The colours inside the plots depict the status of different traffic performances based on different combinations of HVs, AVs, and CAVs. The first impression from the ternary plots for the travel time is that CAVs demonstrate better performances than AVs and HVs for different demand cases. Increasing the proportion of CAVs by a certain amount reduces travel time more quickly than when increasing the proportion of AVs by the same amount. With higher AV-CAV penetrations, network encounter lesser travel time than any of other combinations with higher penetrations of HVs. As AVs and CAVs come with diverse types of features, such as connectivity, early speed reduction and, management of distance, the traffic performance increases for higher C/AV penetrations. These additional strategies offered by C/AVs work better for peak hour demand and 20% below the peak hour than 20% above the peak hour demand case for the same study corridor. The number of interacting vehicles plays role in this phenomenon. With increasing traffic in the road, the interaction of the vehicles intensifies as the communication continuity remain stable in the network.

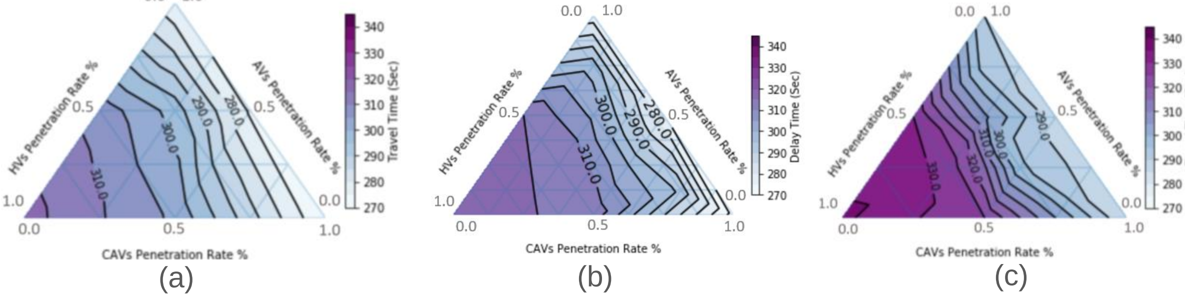


Figure 5.1 Average travel time of the network: (a) 20% below peak hour traffic flow, (b) Peak hour traffic flow and (c) 20% above peak hour traffic flow

A controlled corridor with the same volume of traffic needs a higher speed to reduce the travel time, which was expressed in Figure 5.1 as well. For the case of speed, a similar pattern can be seen for all three demands: peak hour, 20% below the peak hour and 20% above the peak hour . A higher AV-CAV penetration outperforms a higher HV-AV penetration in every possible similar combination, which can be seen in the ternary plots of Figure 5.2. The cause behind improved speeds remains the same.

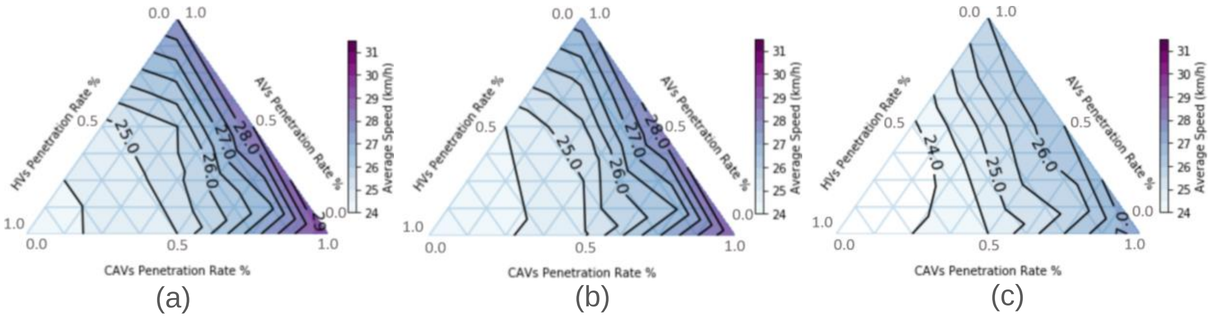


Figure 5.2 Average speed of the network: (a) 20% below peak hour traffic flow, (b) Peak hour traffic flow and (c) 20% above peak hour traffic flow

Figure 5.3 shows the delay time for the same scenarios mentioned above. Delay times strengthen the statements of the other performance indicators, travel time and speed. Scenarios with a lower travel time and a higher speed tend to have a lower delay time and a lower number of stops (Aziz 2018, Hossein 2018). The delay time reduces more quickly for a higher AV-CAV penetration, as expected. The reasons of such anticipated improvements reinforce the previous two performance indicators.

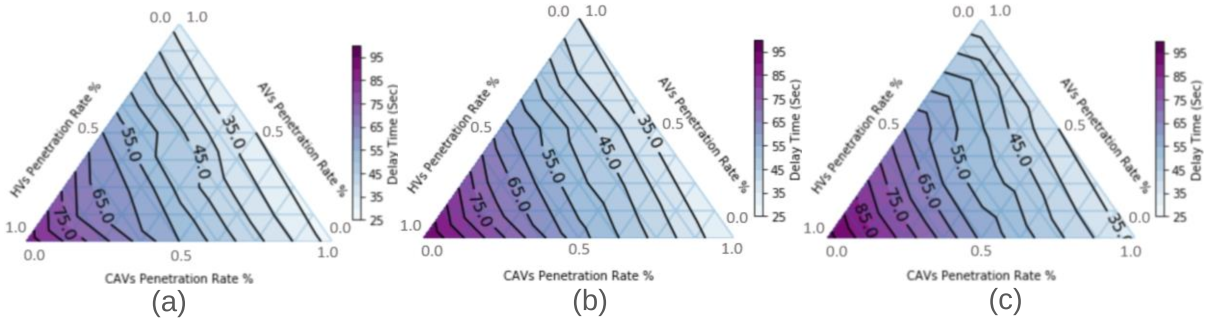


Figure 5.3 Average delay time of the network: (a) 20% below peak hour traffic flow, (b) Peak hour traffic flow and (c) 20% above peak hour traffic flow

Based on the results of above, it can be said that introduction of automation in the network overall performs better than HVs. There are not that much of the changes for the lower amount of penetration of automation in the transportation system. Significant changes can be seen in the models, once automation participation ratio reaches certain level. The normal driving module for this thesis interact optimistically positive for the travel time, speed and delay time. CAVs show better performance because additional properties CAVs conserve higher competency in the network. The ability to make platoon, slowing down to the signal and interacting with other vehicles make the CAV a strong actor in the traffic.

More automation in the network, assure higher efficiency of the automation itself because vehicles can communicate to each other and react with other intelligently. For higher number of vehicles in the network, number of interacting vehicles need to be higher but to study the variability, it was kept constant to 3. This result lowering of traffic performances again in the network for high traffic demand after reaching the yield point.

5.1.2 HV vs. AV/CAV in Mixed Traffic

This subsection deepens the insight of the 5.1.1 for two extreme scenarios. What if HVs are gradually replaced either by (i) AVs or by (ii) CAVs? What will be the impacts of different driving modules of C/AVs in the traffic, emission and safety? To commence this investigation, 88 scenarios have been analysed, by varying the driving modules and traffic demands of models of 5.1.1.

5.1.2.1 Traffic Performance

Figure 5.4, the travel time scatter plots of AV and CAV reinforce the conceptual gains of the section 5.1.1 in addition some additional information about driving modules. As CAVs have additional features than HVs and AVs, here too, the CAVs use lesser travel time in contrast to the other vehicle types. A gradual shifting of the travel time can be seen for different traffic demand cases. The lowest travel time is achieved faster for the higher demand. Availability of required number of vehicles in the network causes earlier yielding of the travel time. The travel time yields into lowest value in the range of penetration between 50- 70% C/AV penetration. This phenomenon can be connected to the fact that number of interacting vehicles play major role in the performance as it is discussed in the previous section (5.1.1 HV-AV-CAV in Mixed Traffic). If there are lots of vehicles in a segment of the network than allowable interacting vehicles, the performance ought to drop as most of them are not interacting after yielding point. In summary, with significant higher quantity of traffics, the interacting vehicles range passes the number of vehicles in the street.

Likewise, different traffic demand cases demonstrate difference in the performances, the driving modules show differences in the traffic performances as well. The cautious and aggressive driving mode illustrate higher and lower travel time respectively, than the normal driving mode. Cautious driving modes conserve the safe measures in high level which elongate the travel time than normal state. In contrary, the aggressive maintain closer gaps with surroundings and react aggressively in the intersection so travel time reduces and capacity of the segment increases for same amount of traffic demand.

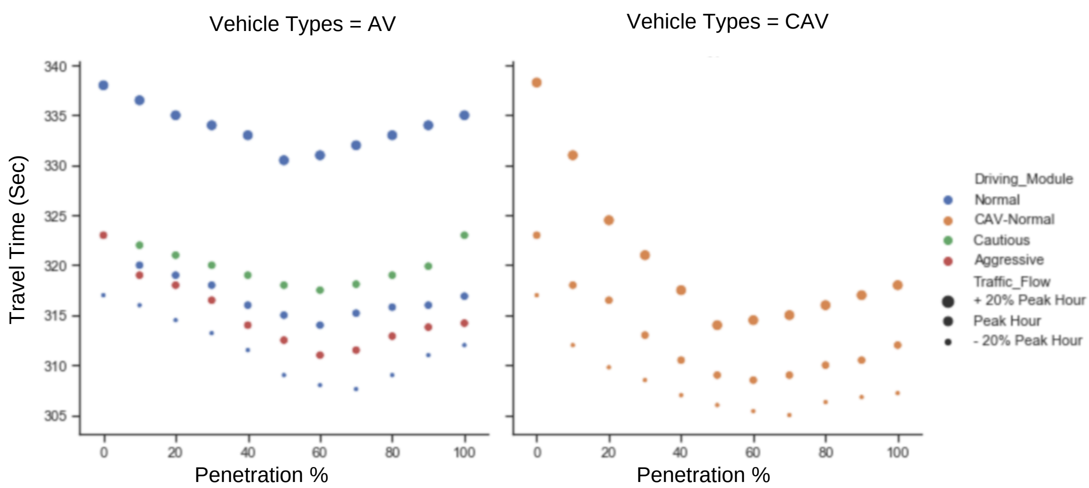


Figure 5.4 Impact of automation in average travel time

A similar trend can be experienced from the Figure 5.5 for the speed as speed and travel time act together, experienced in previous section (5.1.1 HV-AV-CAV in Mixed Traffic). Here too, the traffic demand cases and driving modules depict similar trend but inversely. To exhibit a concave shaped travel time plot, the speed plot needs to be a convex shaped.

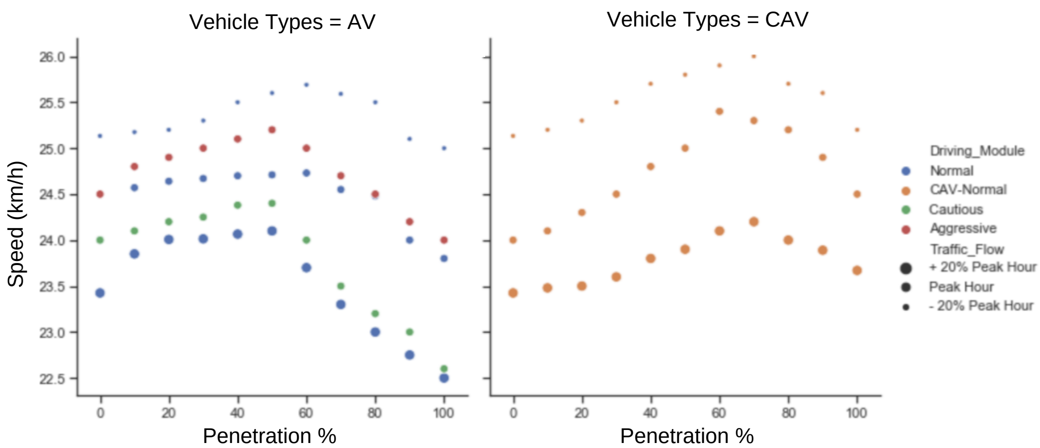


Figure 5.5 Impact of automation in average speed

The delay time is also affected similarly like previous two traffic performance indicators what can be seen in the Figure 5.6. Delay time maintain similar concave shape like travel time. Automation features such as early slowing down in the intersection, collision prevention measures and connectivity of the C/AVs deduce the delay time in general and hold similar trend like its ancestors.

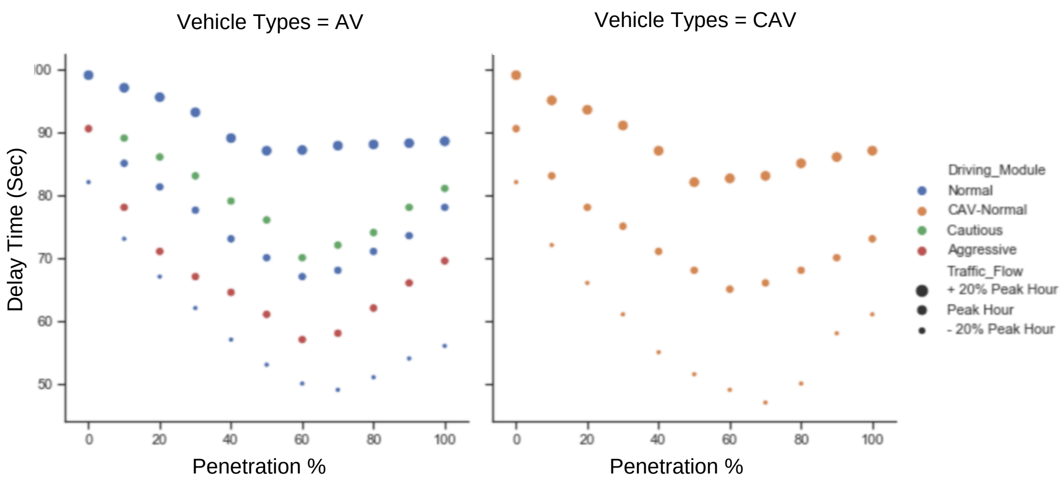


Figure 5.6 Impact of automation in average delay time

5.1.2.2 Emission

C/AVs can come with different energy system: fossil fuel, hybrid energy (U.S. Energy Information Administration 2018). The C/AVs can provide different emission than HVs, even though they might hold similar energy source like HVs because of its driving behaviours in the network. As stated in previous sections (5.1.1 HV-AV-CAV in Mixed Traffic and 5.1.2.1 Traffic Performance), there are remarkable changes observed in the traffic performances after adding automation in the network. Besides the energy source, emission also relays on traffic performances i.e. delay time and number of stops (Pandian et al. 2009, Kellner 2016). In consequence, the C/AVs express differences in the emission.

This difference of emission can be perceived from the bar charts in Figure 5.7. They demonstrate the environmental impacts of C/AVs in terms of CO_2 and NO_x from different penetration rates and different traffic demand cases. The emission outcomes are presented by average value for individual scenarios. As the network has proven itself efficient for a range of 50-60% penetration and afterward the status deteriorates, similar patterns can be seen again for the emission. After reaching this range, due to limitation of interaction between vehicles, emission gradually increases as vehicles start losing the interactions among them. In one side, vehicles lack of connections after certain penetration level but on the other side, the C/AV safety concerned action assure relatively slower increment of the emission. The CAV shows promising responses towards the emission.

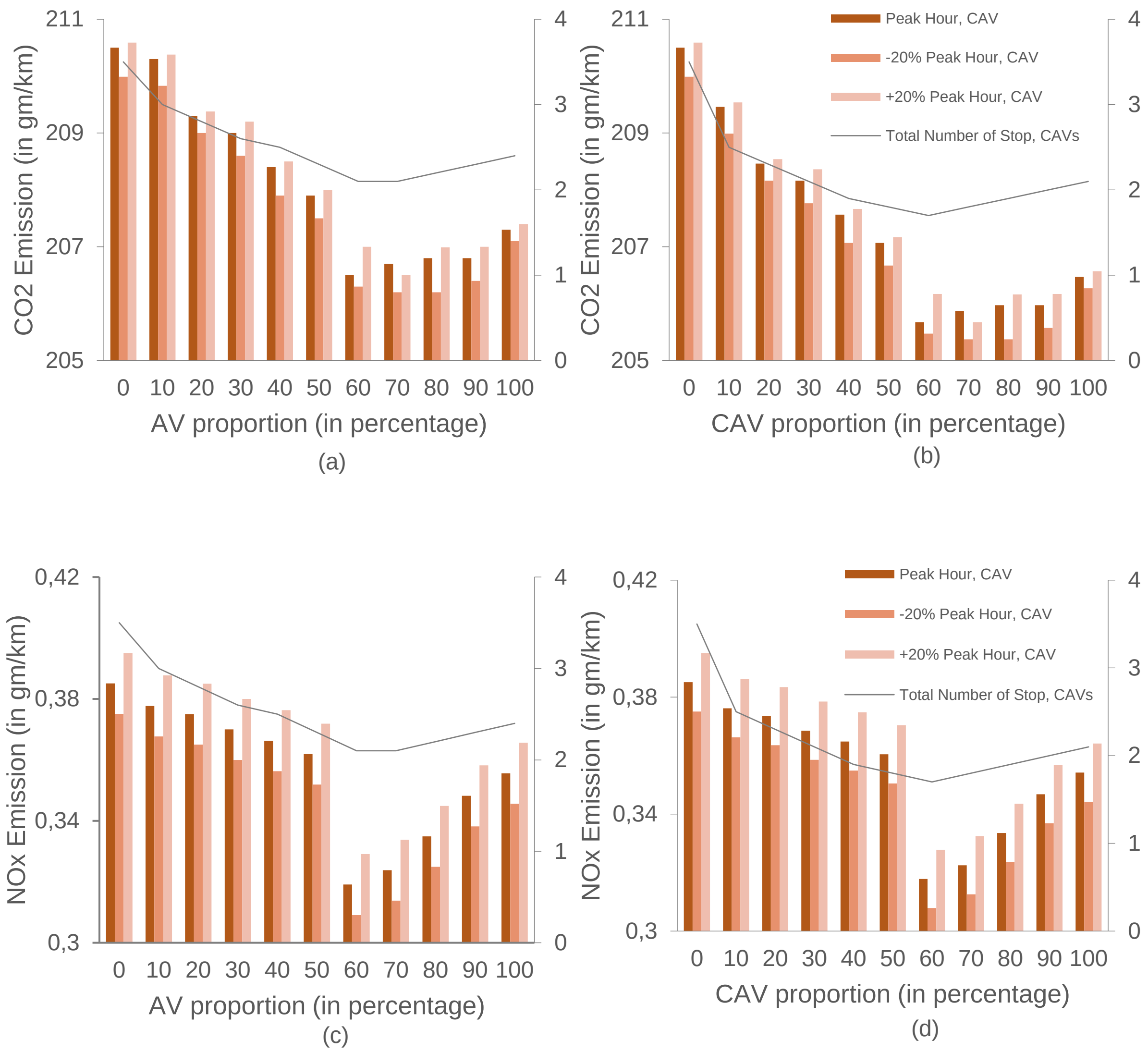


Figure 5.7 Impact of automation in emission (a) CO_2 emission for AVs, (b) CO_2 emission for CAVs, (c) NO_x emission for AVs and, (d) NO_x emission for CAVs

5.1.2.3 Safety

The safety aspect of introduction of C/AVs in the network has positive responses. Figure 5.8 depicts the safety aspects in terms of total number of conflictions for different traffic demand of C/AVs. The safety can be set on for two different value of TTC, TTC = 0.75 sec and 1.5 sec as per the discussion in previous section (4.5.3 Safety evaluation process). Some observations have been repeated as like previous performance studies, traffic performance and emission. In first place, smaller the TTC, higher will be the number of potential conflicts in the network. For smaller TTC, the system defines more conflictions in the traffic manoeuvres. Secondly, higher the traffic demand, higher will be the total number of conflicts because vehicles confrontation each other's in higher frequency which lead to higher possible conflictions. Thirdly, the turning point of the performances are still in the range of 50-60% and the reason of such recurrence of the trends is same as previous subsections (5.1.2.1 Traffic Performance and 5.1.2.2 Emission). Lastly, the CAVs encounter relatively lesser numbers of conflicts in the network as they come with additional connectivity features.

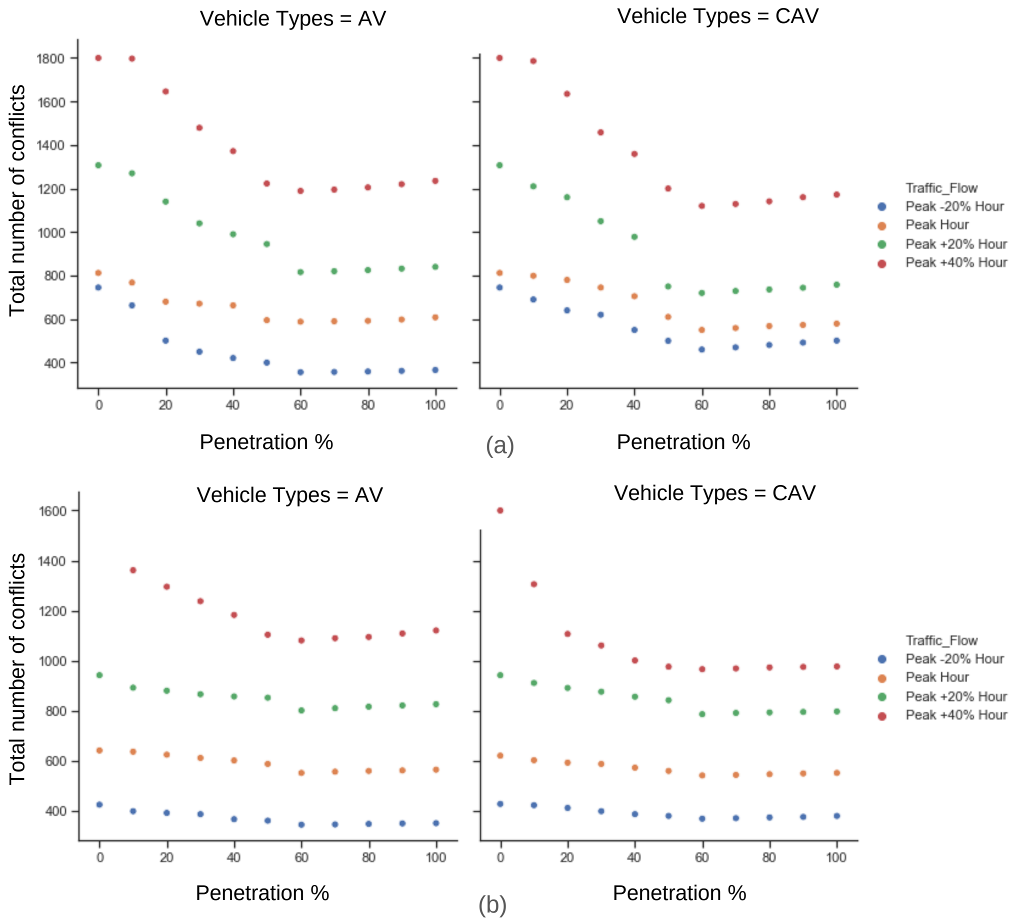


Figure 5.8 Impact of automation in safety (a) TTC = 0.75 sec, PET = 1.5 sec and (b) TTC = 1.5 sec, PET = 1.5 sec

5.2 Sensitivity Analysis of AV parameters

Three hundred thirty scenarios of different combinations of AVs have been investigated for eight driving parameters of autonomous vehicles which significantly impact the performance in the road traffic. The sensitivity analysis (SA) is performed in two steps, preliminary sensitivity analysis and cross-correlational sensitivity analysis. In the preliminary stage, eighty-eight scenarios are scrutinized to find the presiding driving parameters from eight driving behaviour parameters. In the cross-correlational sensitivity analysis, two hundred forty two scenarios are investigated to create the SA for the dominating parameters found from the preliminary stage. An AV penetration value of 60% is considered to be on the conservatively stable side of the simulation. A lesser number of AVs will demonstrate a lesser impact in the scenarios originated from the presence of AVs. In opposition, a higher number of AVs might bring severe changes in the real world's driving behaviours, which can be seen in the previous sections (5.1.1 HV-AV-CAV in Mixed Traffic and 5.1.2 HV vs. AV/CAV in Mixed Traffic). For higher penetration, the scenarios of mixed traffic move towards fully automation scenarios, which can be studied better with different consideration (Chen et al. 2017b). The entire SA is experimented for the peak hour demand to eliminate the effect of under or over presence of the vehicles in this controlled study corridor.

5.2.1 Preliminary Sensitivity Analysis

Preliminary SA has been performed for total eight driving parameters: look ahead distance, look back distance, number of interacting vehicles, minimum collision time gain, minimum clearance (front/rear), accepted deceleration, standstill distance and gap time distribution. The results of preliminary sensitivity analysis plotted in Figure 5.9.

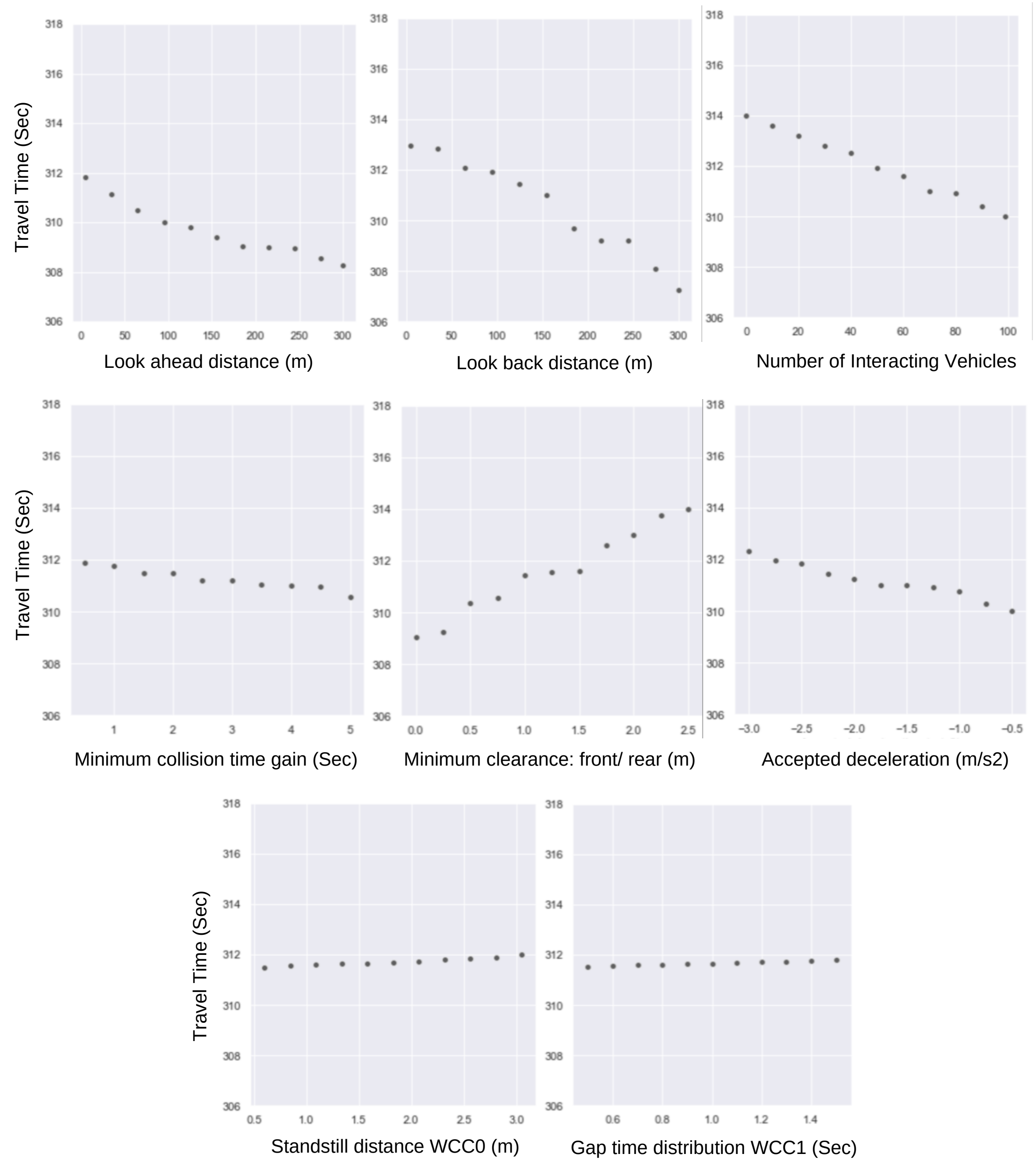


Figure 5.9 Preliminary sensitivity analysis for eight driving parameters

The travel time is used as performance indicator as it has shown quite distinguishable responses for this study corridor in previous sections (5.1.1 HV-AV-CAV in Mixed Traffic and 5.1.2 HV vs. AV/CAV in Mixed Traffic). Two patterns of responses can be seen from the scatter plots above: proportional and inversely proportional behaviour towards the performance indicator. Travel time increases proportionally in a given range with each increment of minimum clearance: front/ rear or standstill distance or gap time distribution. On the other side, look ahead distance, look back distance, number of interacting vehicles, minimum collision time gain, and accepted deceleration show inversely proportional responses towards the performance indicator in a given range.

Although all of the driving parameters show impacts in the form of differences in travel time, three of them show significant changes. Figure 5.10 shows the percentage of variations between the initial and final value of individual driving parameters.

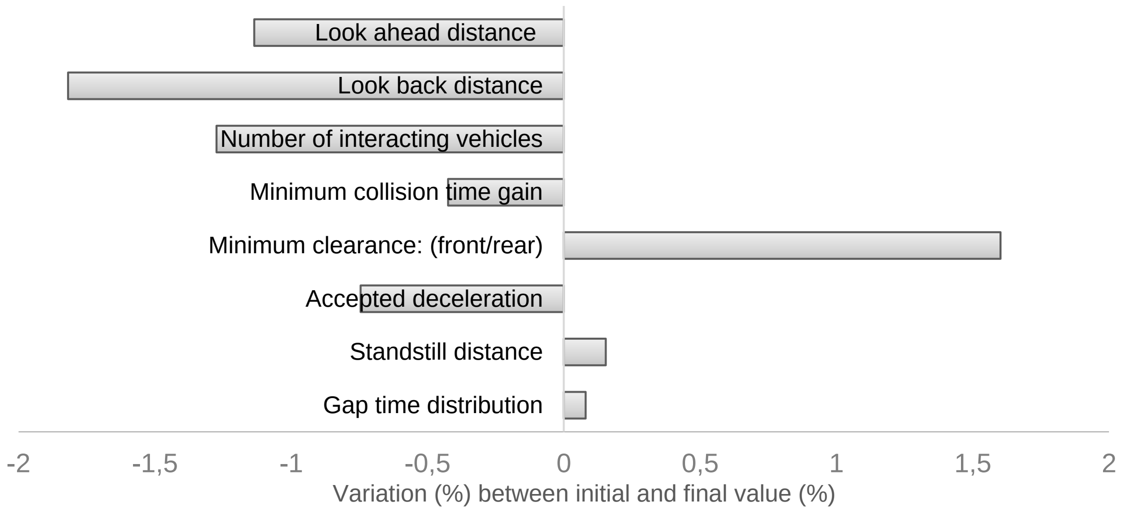


Figure 5.10 Percentage of variation

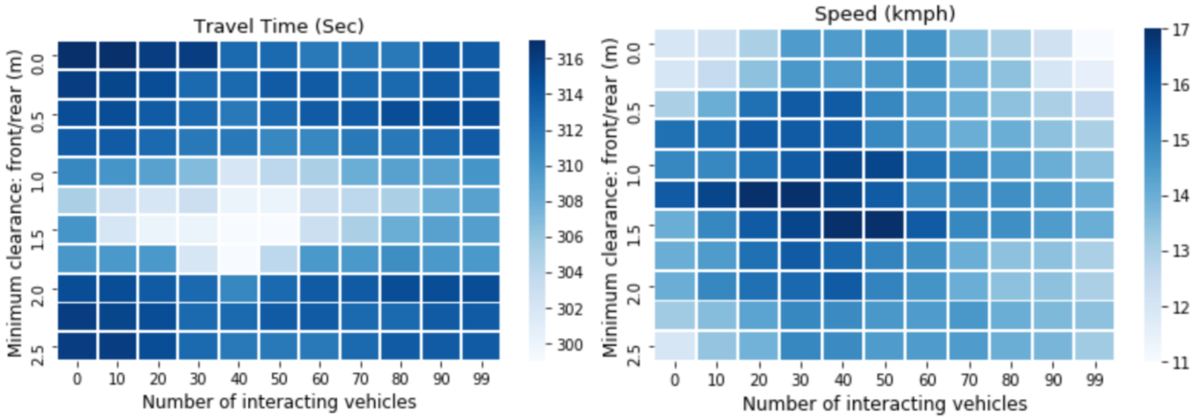
The look back distance, number of interacting vehicles and minimum clearance (front/rear) show domination than any other parameters, in the travel time. At this point, further sensitivity analysis can be carried out for three most influential driving parameters: number of interacting vehicles, minimum clearance (front/rear) and look back distance.

5.2.2 Cross-correlational Sensitivity Analysis

The final stage of the sensitivity analysis has been planned for two sets of driving parameters: 1. Minimum clearance (front/ rear) and number of interacting vehicles and 2. Look back distance and number of interacting vehicles. These two sets will create an experimental arrangement of two cross-correlational sensitivity analyses, where the number of interacting vehicles is presented in both setups. Two traffic performance indicators, travel time and speed, have been used to strengthen the outcomes of the SA. The results of the final SA are presented in

Figures 5.11 and 5.12 using a heatmap. The heatmap is a good demonstration for the impact study that was generated from the combination of the driving parameters. The heatmap in Figure 5.11 depicts how two driving parameters, one with proportional and another with inverse proportional behaviour, respond jointly in the scenarios. The lowest region of travel time, the optimum, is found in the range between 1.0 – 1.75m of minimum clearance: front/ rear and 30 – 50 of number of interacting vehicles.

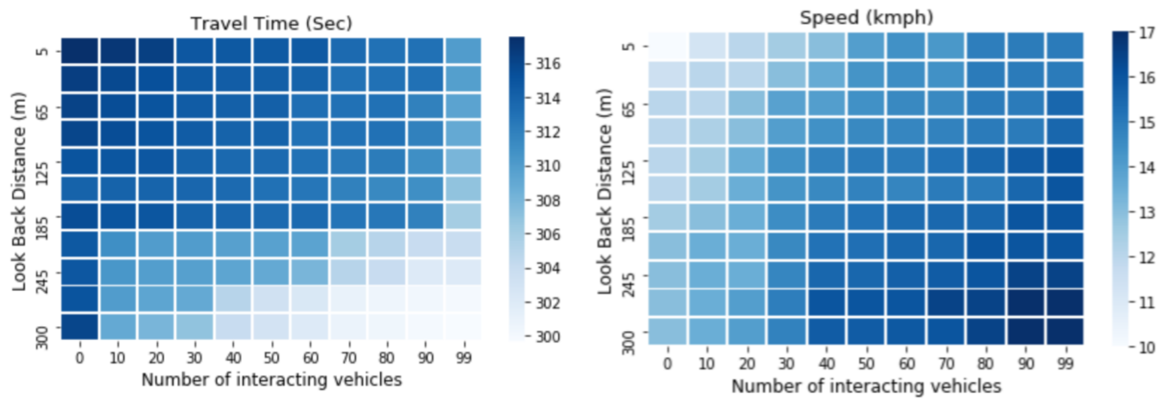
Similarly, the performance indicator speed becomes distinguishably high in the same range of driving parameters. This strengthens the impression of the travel time heatmap.



(a) (b)

Figure 5.11 Cross-correlational sensitivity analysis for minimum clearance – number of interacting vehicles (a) Average travel time and (b) Average speed

On the contrary, the heatmap in Figure 5.12 depicts how two inversely proportional driving parameters correspond to one another in the scenarios. In this category of cross-correlational SA, travel time significantly decreases and speed increases for a higher number of interacting vehicles and greater look back distance.



(a) (b)

Figure 5.12 Cross-correlational sensitivity analysis for look back distance – number of interacting vehicles (a) Average travel time and (b) Average speed

6 Conclusion

This chapter summarises this entire research work and demonstrate the limitations of this study along with the future recommended works.

6.1 Summary and research findings

The first goal of this research was to investigate in the impact of human-like C/AVs in the mixed traffic in the urban corridor for different driving modes and three possible traffic demand cases. The second goal was to examine in the interactions of the driving behaviour parameters of the AVs in the traffic performances. The experiment has been planned to meet the goals of this study in an efficient way. The summary of this study is depicted in the Figure 6.1.

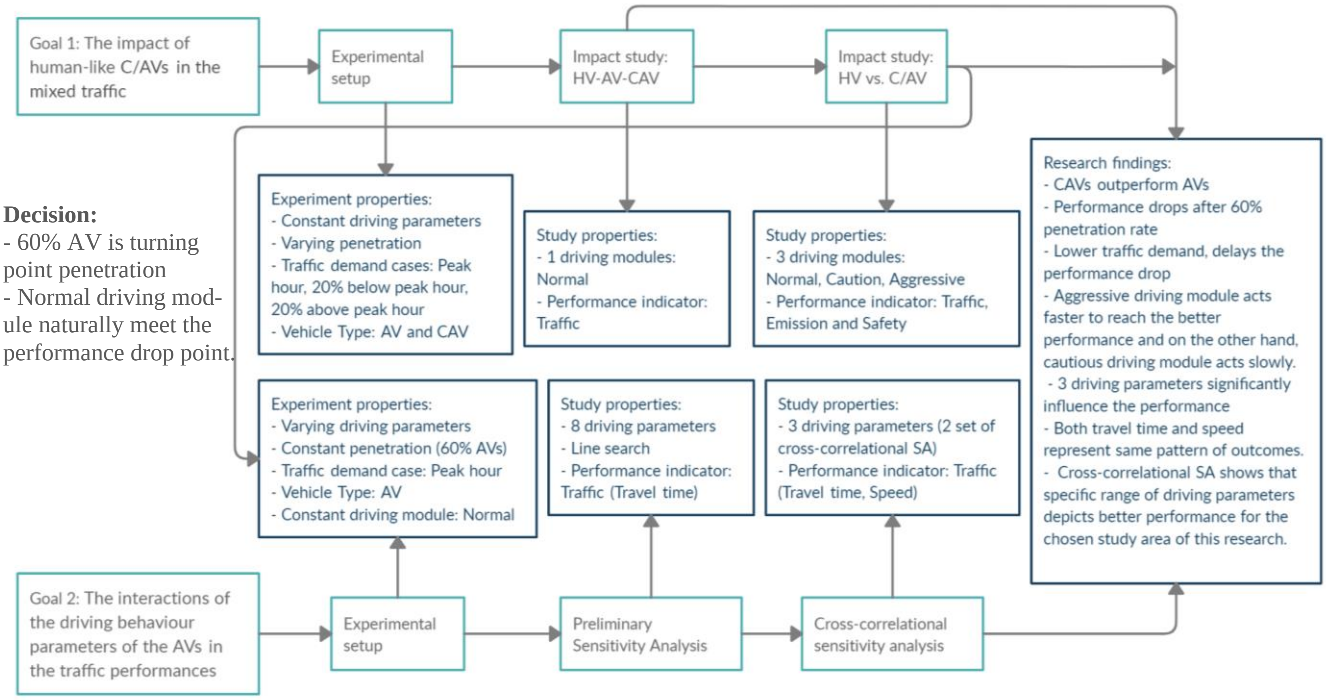


Figure 6.1 Summary of the study

The results, from goal 1: impact study, concerning C/AVs showed improvement for the traffic performance, emission and safety aspect of the study corridor, where CAVs slightly outperform AVs because of V2V and V2I features. Consistent increment of C/AVs share in the study corridor is found to be augmentable upto a certain limit, which displaced for different traffic demand cases. Optimum penetration levels are seen at the penetration of 60%, 50% and 70% for the peak hour demand, 20% below peak hour demand and 20% above peak hour demand, respectively. In general, average travel time and delay time of the study corridor have been decreasing, while speed and connectivity, among C/AVs, have been sharply increasing, for high penetration rates of C/AV, upto the optimum penetration. The bargaining between availability of sufficient C/AVs in the network and allowed number of interacting vehicles exhibits significant impacts in the performance. Even though the traffic demand increases, due to fixed number of interacting vehicles, performance deteriorates. Among three driving modules: normal, cautious and aggressive, significant change of the performance can be seen in the outcome of this study. This change of performances is generated from driving behaviours adopted by these modules. The intensity of the performances is found to be analogous for all scenarios for every indicator: traffic performance, emission and safety. The outcomes of the first part initiated the second part of the experimental setup by providing a choice of penetration and a driving module for further processing in the implementation of goal 2.

The results, from goal 2, concerning AVs showed significant interactions by the driving parameters in the traffic performance. A sensitivity analysis with two parts, which firstly chooses three influential driving parameters, among eight recommended driving parameters, and secondly creates cross-correlational sensitivity analysis for two pairs of combination of driving parameters, based on the substantiality seen in the preliminary stage. Pair 1 consists of minimum clearance (front/ rear) and number of interacting vehicles and pair 2 consists of look back distance and number of interacting vehicles. To obtain lowest region of travel time and highest region of speed in the performance surface of cross-correlational sensitivity heatmap, the pair 1 and 2 outline a range of values for minimum clearance (front/ rear), look back distance, and number of interacting vehicles for 60% AV penetration of normal driving module.

The significance from the impact study and the sensitivity analysis, summarized that negative effects of the presence of the C/AVs evolved from the inability to predict the other vehicles‘ manoeuvres, missing sufficient connectivity with other vehicles and automatic risk avoidance. This scenario becomes significant while traffic demand increases in the network and participation of C/AVs is not significant in the mixed traffic. To get maximum benefits out of C/AVs, the penetration of C/AVs needed to be higher and, at the same time, the technology/ infrastructure should support an increment in the number of interconnected vehicles.

6.2 Limitations and future work

This study tried to visualize and connect the scenarios based on today’s possible technology. Increment of C/AVs in the street will lead it to the properties of fully automated lane, which might have different car following behaviour than now. Such a road condition can utilize other traffic systems apart from current signal control systems i.e. centrally controlled system. C/AVs themselves have a number of different features, which is constantly being improved, which influences the traffic, emission and safety related performances. In this study, some of the V2V and V2I features are investigated. This create an impression of different scenarios that might be faced in the real-world, if other features are implemented. All these variables significantly manipulate the impact of the implementation of C/AVs in the network. The influence of the self-driving associated problems, bottleneck (Van den Berg, V. A.C. and Verhoef 2016) and deadlock (Perronnet et al. 2019) in the traffic performances are not studied, considering their cumulative effects will represent the impact study as a whole. Such decision making related issues (Baiba 2019) cannot be resolved only by time management because in reality scheduling the trips for vast amount of vehicles, especially in the peak hour, can be a huge challenge for the management department.

The continuation and extension of this study will focus on modelling of other C/AV features for the microscopic simulation and implementation of different traffic signals and road types, to cover different aspects of the implementation of the C/AVs for different types of road: urban corridors, motorways, freeways etc. Moreover, exploration by same experimental setup for the networks will reveal the influence of road network in the impact studies. More intersection focused study will be helpful to understand the impact of driving modules into the C/AV associated problems: bottleneck, deadlock, right of way etc. Like previous study

Finally, to obtain detailed and comprehensive knowledge of the interactions of the driving parameters, other optimistic sensitivity analysis approach with better sampling method can be studied. In this case, time management is a crucial part of the implementation. Proper planning from beginning and implementation of parallel simulation will save time as per the need.

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Appendix A: Impact study of C/AVs

Variables	Previous Studies	Study Type	General Findings
Traffic Performance	(Grush et al. 2016)	Review	Performance is increased in the network.
	(ITF 2015)		
	(Friedrich 2016)		
	(Alam and Habib 2018)		
	(Martinez and Viegas 2017)	Simulation	Gradual increment of performance in a peak hour interval.
	(Zhao and Kockelman 2018)		Traffic is decreased in the overall network for integrated public transport and shared autonomous vehicles.
	(Fagnant and Kockelman 2014)		Accident is reduced Emission is decreased
	(Alazzawi et al. 2018)		Performance is decreased in the network.
	(Litman 2018)	Simulation	
	(Lang et al. 2018)	Review	
	(Salazar et al. 2018)	Optimization	Speed is found to be increased.
	(Simoni et al. 2019)	Agent-based	Average speed is found to be decreased for the combination of private autonomous vehicles and shared autonomous vehicles.
	(Teoh and Kidd 2017)	Analytic based	Traffic is found to be decreased while implementing congestion pricing.
Safety	(Arbib and Seba 2017)(Fagnant and Kockelman 2014)	Framework Simulation	Accident and emission are reduced
	(Greenblatt and Saxena 2015)(Arbib and Seba 2017)	Various test procedures of framework	
	(Fagnant and Kockelman 2015)(Greenblatt and Saxena 2015)	Review of various test procedures	
	(Fournier et al. 2017)(Fagnant and Kockelman 2015)	Analytic based review	
	(Fulton et al. 2017)(Fournier et al. 2017)	Analytic based adapted mobility	
	(Martinez and Viegas 2017)(Fulton et al. 2017)	Simulation adapted mobility	Emission is reduced.

	(Bauer et al. 2018)(Martinez and Viegas 2017)	Simulation
		Optimization
	(Lokhandwala and Cai 2018)(Bauer et al. 2018)	
	(Salazar et al. 2018)(Lokhandwala and Cai 2018)	
Emission	(Jones and Leibowicz 2019)(Salazar et al. 2018)	Optimization
	(Vleugel and Bal 2018)(Jones and Leibowicz 2019)	Analytic based
	(Vleugel and Bal 2018)	

Table A.1 Impact study of C/AVs (Narayanan et al. 2020)

Appendix B: Sample Scripts (COM Interface)

```
def SPSA(SPSA_para, Car_fol_para, tt_true_data, traffic_true_data):
    global Vissim
    ## Defining the SPSA variables
    a = SPSA_para["a"]
    c = SPSA_para["c"]
    A = SPSA_para["A"]
    alpha = SPSA_para["alpha"]
    gamma = SPSA_para["gamma"]
    G = SPSA_para["G"]
    N = SPSA_para["N"]

    Car_follow_base = Car_fol_para.copy()
    Car_follow = Car_follow_base.copy()

    print('Simulation 0 started')
    traffic_simulated_data = vissim_sim(Car_fol_para)
    y = gof_eval(tt_true_data,  traffic_true_data, traffic_simulated_data)
    rmsn.append(y)
    print('Starting RMSN = ', y)
    print('======================================')
    Best_Car_follow = Car_fol_para.copy()
    Best_RMSN = 100
    Best_SimulatedCounts = traffic_simulated_data
    #allODVectors = np.zeros((len(OD), N))
    Car_follow_plus = Car_fol_para.copy()
    Car_follow_minus = Car_fol_para.copy()
    Car_follow_min = Car_fol_para.copy()
    # SPSA iterations
    list_ak = []
    list_ck = []
    list_g = []

    for iteration in range(1, N + 1):
    # calculating gain sequence parameters
        print('Current N = ', iteration)
        ak = a / ((iteration + A) ** alpha)
        ck = c / (iteration ** gamma)
        list_ak.append(ak)
        list_ck.append(ck)

        g_hat_it = pd.DataFrame()

        for ga in range(0, G):
            delta = 2*np.random.binomial(n=1, p=0.5, size=len(Car_fol_para))-1 #Berno
            #print(delta)
            # plus perturbation
            i=0
            j=0
            for key in Car_follow:
                Car_follow_plus[key] = float(Car_follow[key]) + float(Car_follow_plus
                if list(Car_follow_range.values())[j]==0:

```

```
                max_1 = max(Car_follow_range.values())
                diff =(max_1)- min(Car_follow_range.values())
                Car_follow_plus[key] = Car_follow_plus[key] + (diff/10)

            elif Car_follow_plus[key] > list(Car_follow_range.values())[j]:
                Car_follow_plus[key] = list(Car_follow_range.values())[j]
            elif Car_follow_plus[key] <= list(Car_follow_range.values())[j+1]:
                Car_follow_plus[key] = list(Car_follow_range.values())[j+1]
            i += 1
            j += 2
        del i, j, key

        #function to assign new perturb parameters
        # tt_simulated_data = vissim_sim(Car_follow_plus)
        traffic_simulated_data = vissim_sim(Car_follow_plus)
        print('Simulation %d . %d . plus perturbation' %(iteration, ga))

        y = gof_eval(tt_true_data,  traffic_true_data, traffic_simulated_data)
        yplus=np.asarray(y)

        # minus perturbation
        i=0
        j=0
        for key in Car_follow:
            Car_follow_minus[key] = float(Car_follow[key]) - float(Car_follow[key
            if list(Car_follow_range.values())[j]==0:
                max_1 = max(Car_follow_range.values())
                diff =(max_1)- min(Car_follow_range.values())
                Car_follow_plus[key] = Car_follow_plus[key] + (diff/10)

            elif Car_follow_minus[key] > list(Car_follow_range.values())[j]:
                Car_follow_minus[key] = list(Car_follow_range.values())[j]
            elif Car_follow_minus[key] <= list(Car_follow_range.values())[j+1]:
                Car_follow_minus[key] = list(Car_follow_range.values())[j+1]
            i += 1
            j += 2
        del i, j, key

        #function to assign new perturb parameters
        traffic_simulated_data = vissim_sim(Car_follow_minus)

        print('Simulation %d . %d . minus perturbation' %(iteration, ga))

        y = gof_eval(tt_true_data, traffic_true_data, traffic_simulated_data)
        yminus=np.asarray(y)

        # Gradient Evaluation
        g_hat_tem = pd.DataFrame((yplus - yminus)/(2*ck*delta))
```

```
            g_hat_it = pd.concat([g_hat_it, g_hat_tem], axis=1)

        g_hat = g_hat_it.mean(axis=1)
        print ('g_hat=',g_hat)


        # Minimization
        i=0
        j=0
        for key in Car_follow:
            Car_follow_min[key] = float(Car_follow[key]) - float(Car_follow[key]) * (
            if list(Car_follow_range.values())[j]==0:
                    max_1 = max(Car_follow_range.values())
                    print("max",max_1)
                    diff =(max_1)- min(Car_follow_range.values())
                    print("min",min(Car_follow_range.values()))
                    Car_follow_plus[key] = Car_follow_plus[key] + (diff/10)

            elif Car_follow_min[key] > list(Car_follow_range.values())[j]:
                Car_follow_min[key] = list(Car_follow_range.values())[j]
            elif Car_follow_min[key] <= list(Car_follow_range.values())[j+1]:
                Car_follow_min[key] = list(Car_follow_range.values())[j+1]
            i += 1
            j += 2
        del i, j, key

        #function to assign new perturb parameters
        traffic_simulated_data = vissim_sim(Car_follow_min)
        print('Simulation %d . %d . minimization' %(iteration, ga))
        y_min = gof_eval(tt_true_data,  traffic_true_data, traffic_simulated_data)
        rmsn.append(y_min)

        Car_follow_base = Car_follow_min.copy()

        print('Iteration NO. %d done' % iteration)
        print('RMSN = ', y_min)
        print('Iterations remaining = %d' % (N-iteration))
        print('========================================')
        if y_min < Best_RMSN:
            Best_Car_fol = Car_follow_min.copy()
            Best_RMSN = y_min
            Best_SimulatedCounts = traffic_simulated_data

        f = open('counts_SPSA.pckl', 'wb') # for counts

        pickle.dump([Best_RMSN, Best_Car_fol, Best_SimulatedCounts, rmsn, list_ak, li
        f.close()

    return rmsn, Best_Car_fol, Best_SimulatedCounts


SPSA_para = dict(       G         = 2,\
                        Min_error = 0.05,\
                        a         = 40,\
                        c         = 0.3,\
                        A         = 1,\
                        alpha     = 0.7,\
                        gamma     = 0.3,\
                        h         = 0.7,\
                        N         = 1)
```

Table B.1 Implementation of SPSA

CAV will acquire the information about the upcoming signal and regulate its speed to appear at green without stopping.

```
def toList(NestedTuple):
    """
    function to convert a nested tuple to a nested list
    """
    return list(map(toList, NestedTuple)) if isinstance(NestedTuple, (list, tuple)) e

def Init():
    """
    Initialization.
    """
    # add global variables
    global minSpeed
    global vehTypesEquipped
    global vehsAttributes
    global vehsAttNames
    # read the minimum Speed from the script UDA
    minSpeed = CurrentScript.AttValue('minSpeed')

    vehsAttributes = []
    vehsAttNames = []

    # read which vehicle types are able to receive the signal information and being al
    vehTypesAttributes = Vissim.Net.VehicleTypes.GetMultipleAttributes(['No', 'Receiv
    vehTypesEquipped = [x[0] for x in vehTypesAttributes if x[1]] # list of vehicle t

def OptimalSpeedMin(minSpeed, desSpeed):
    """
    A minimum speed is required to arrive during the current green.
    """
    if minSpeed < desSpeed: # check if the desired speed is higher then the minimum s
        # keep desired speed because it is faster => the vehicle will arrive at the s
        optimalSpeed = desSpeed
    else:
        optimalSpeed = -1 # no optimal speed in case the desired speed is larger or e
    return optimalSpeed

def OptimalSpeedMax(maxSpeed, desSpeed):
    """
    The vehicle should not drive above the maximum speed in order to arrive just when
    """
    if maxSpeed > desSpeed: # check if the maximum speed is higher then the desired s
        # keep desired speed because the desired speed to lower than the maximum spee
        optimalSpeed = desSpeed
    else:
        optimalSpeed = maxSpeed # optimal speed for arriving at the next green
    return optimalSpeed

def GetVissimDataVehicles():
    """
    this function reads vehicle attributes from PTV Vissim
    """
```

```
    global vehsAttributes
    global vehsAttNames
    vehsAttributesNames = ['No', 'VehType\\No', 'Lane\\Link\\No', 'DesSpeed', 'OrgDes
    vehsAttributes = toList(Vissim.Net.Vehicles.GetMultipleAttributes(vehsAttributesN

    # create dictionary for the attribute names read from PTV Vissim:
    vehsAttNames = {}
    cnt = 0
    for att in vehsAttributesNames:
        vehsAttNames.update({att: cnt})
        cnt += 1

def ChangeSpeed():
    diffSpeed = 2 # keep speed a little smaller so that vehicle arrive shortly before
    GetVissimDataVehicles() # read vehicle attributes from PTV Vissim to global varia

    if len(vehsAttributes) > 1: # if there are any vehicles in the network
        for vehAttributes in vehsAttributes: # loop over all vehicles in the network
            if vehAttributes[vehsAttNames['VehType\\No']] in vehTypesEquipped: # chec
                # set easier variables of the current vehicle:
                DesSpeed = vehAttributes[vehsAttNames['DesSpeed']]
                OrgDesSpeed = vehAttributes[vehsAttNames['OrgDesSpeed']]
                DistanceToSigHead = vehAttributes[vehsAttNames['DistanceToSigHead']]
                SpeedMaxForGreenStart = vehAttributes[vehsAttNames['SpeedMaxForGreenS
                SpeedMinForGreenEnd = vehAttributes[vehsAttNames['SpeedMinForGreenEnd

                if OrgDesSpeed is None: # if the original desired speed has not yet s
                    OrgDesSpeed = DesSpeed
                    vehAttributes[vehsAttNames['OrgDesSpeed']] = DesSpeed # OrgDesSpe

                # if the vehicle does not have a upcoming signal: set original desire
                if DistanceToSigHead <= 0:
                    vehAttributes[vehsAttNames['DesSpeed']] = OrgDesSpeed # DesSpeed
                    continue # jump to next vehicle

                #---------------------------------------
                #  Decide about the optimal speed      |
                #---------------------------------------
                if SpeedMinForGreenEnd > SpeedMaxForGreenStart:
                    # The minimum speed for arriving before the next green end is hig
                    # > there is green ahead!
                    optimalSpeed = OptimalSpeedMin(SpeedMinForGreenEnd, OrgDesSpeed)
                    if optimalSpeed == -1: # check if no optimal speed in case the de
                        optimalSpeed = OptimalSpeedMax(SpeedMaxForGreenStart, OrgDesS
                else:
                    # There is red light ahead!
                    # Use maximum speed:
                    optimalSpeed = max(min(SpeedMaxForGreenStart, OrgDesSpeed) - diff

                vehAttributes[vehsAttNames['DesSpeed']] = optimalSpeed # set optimal

        #-----------------------------------------------------------------------------
        #  After iterating though all vehicles, update the speeds in PTV Vissim     |
        #-----------------------------------------------------------------------------
        vehicleNumDesiredSpeeds = [[x[vehsAttNames['DesSpeed']], x[vehsAttNames['OrgD
        Vissim.Net.Vehicles.SetMultipleAttributes(('DesSpeed', 'OrgDesSpeed'), vehicl
```

Table B.2 V2I communication for adjusting driving speed to arrive at signals at green (PTV AG 2019)

Appendix C: Emission Map (EnViVer)

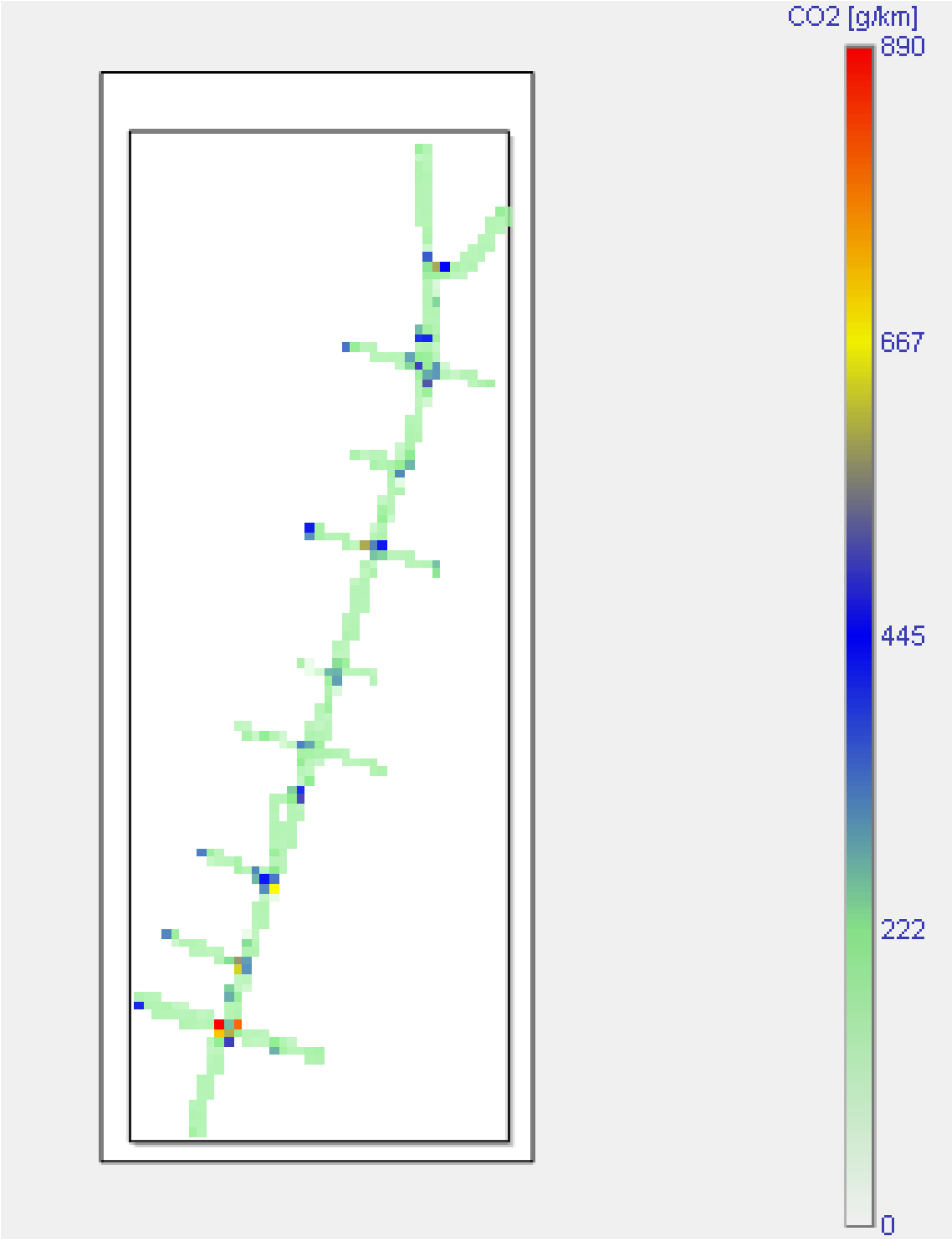

Figure C.1 Emission map for CO_2 (gm/km)

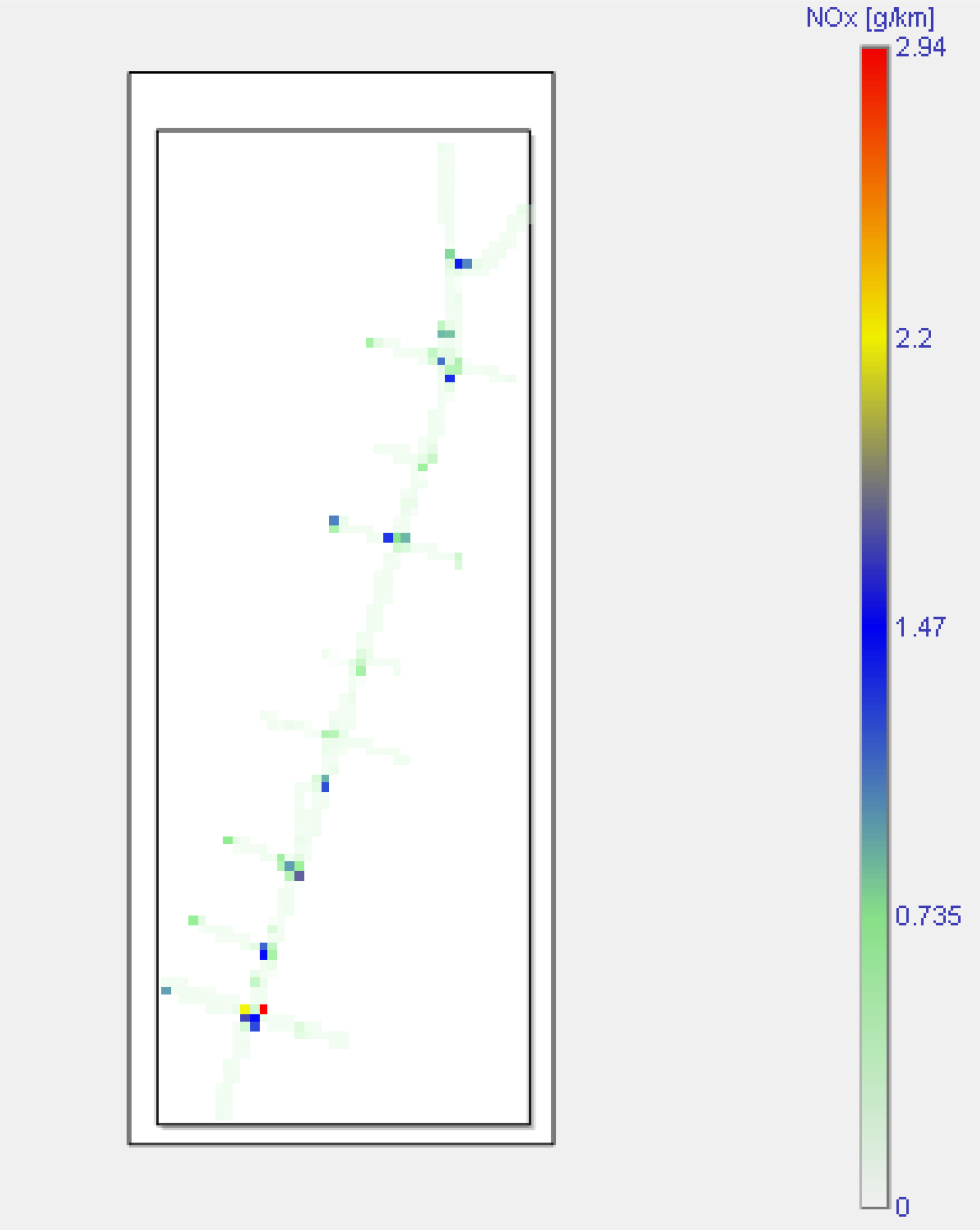

Figure C.2 Emission map for NO_x (gm/km)

Appendix D: Confliction Map (SSAM)

Confliction type	**Colour**
Crossing	Red
Rear end	White
Lane change	Purple

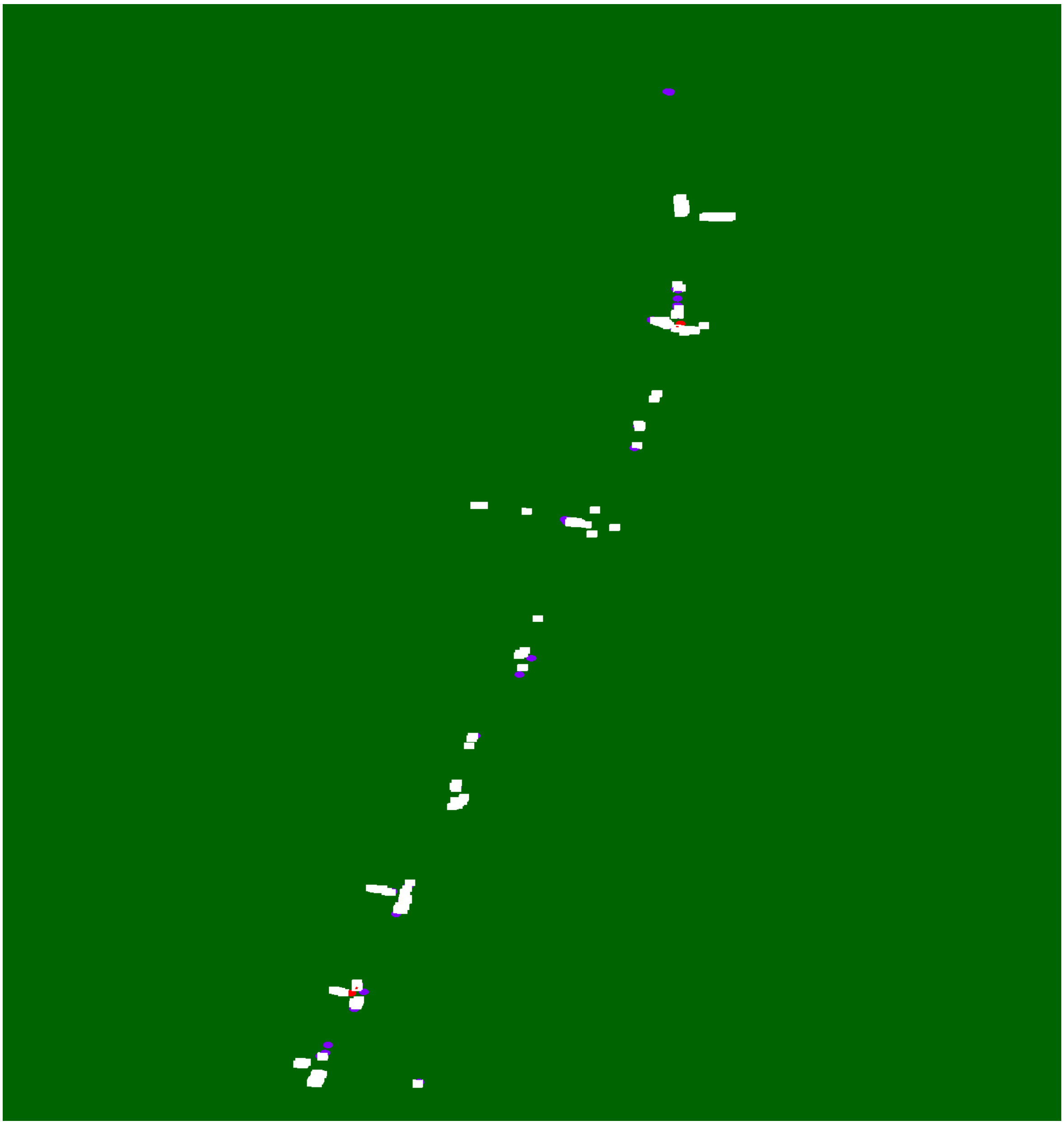

Figure D.1 Locations of different types of confliction

Declaration

I hereby confirm that the presented thesis work has been done independently and using only the sources and resources as are listed. This thesis has not previously been submitted elsewhere for purposes of assessment.

Place, Date, Signature