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Simulation of Automated Vehicles in AIMSUN

Behavioral modeling and design proposals

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Preface

This master thesis was written in the spring of 2021 within the course TBA4945 - Transport Engineering, Master Thesis at the Norwegian University of Science and Technology (NTNU). The study represents the concluding project completing the civil engineering degree in transport.

The authors are Andreas Berge Ims and Haakon Blakstad Pedersen. Associate professor and head of the Traffic Engineering Research Centre Arvid Aakre is the main supervisor. He has provided guidance and help with research questions, finding literature, software installation, and discussing the subject.

We want to thank AIMSUN for enabling and giving access to the academic pro edition of Aimsun Next with microSDK and V2X-SDK. We would also like to acknowledge the support AIMSUN gave through the process, where they answered any inquiries or questions we had. Without the software, extensions, and support, we could have completed none of the presented work.

Both authors have found literature on the thesis' background, future expectations of automated vehicles, and theory. Both authors designed the simulation environment in the software AIMSUN and contributed to the writing of the text body. The cooperation was a success, running smoothly throughout the entire work process.

Norwegian University of Science and Technology

Trondheim, June 2021

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Abstract

Automated vehicles (AVs) are an emerging technology that many foresee will improve transportation systems in relation to delays, safety and efficiency. However, strict regulation and legislation make the testing of AVs on real-world road sections and intersections a challenge. Therefore, the simulation and testing of AVs in a virtual world are increasingly important to validate the technology, study its impacts and predict potential challenges for varying penetration rates representing the transition phase.

This research tested ten different AVs, differentiated by their behavior modeling, based on their longitudinal movement and cautious or assertive parameter settings in the simulation software AIMSUN. The simulation framework contained a merging section to study the AVs cooperation and impact on traffic efficiency. The vehicle composition for each simulation consisted of Human Vehicles and one AV type. Only one AV type was included, as it is considerable uncertainty related to the composition of AVs built on different systems in the future. Two out of the ten AVs improved the overall traffic efficiency in the system and bottleneck.

We conclude that the best way to model and simulate AVs is that using the ACC- and default model with the default lane-changing model provided by AIMSUN and cautious and assertive parameter settings, respectively.

Keywords – AVs, behavior modeling, AIMSUN, simulation

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Nomenclature

Subscripts and superscripts

$n-1$ Preceding vehicle - Leading

n Subject vehicle - Following the preceding vehicle

$n+1$ Succeeding vehicle - Following the subject vehicle

dh Distance headway [m]

dg Distance gap [m]

th Time headway [s]

tg Time gap [s]

v_i Current speed of vehicle i [m/s]

v_{i-1} Current speed of vehicle $i-1$ [m/s]

a_i Acceleration of vehicle i [m/s^2]

L_i Length of vehicle i [m]

Glossary

Aimsun Advanced Interactive Microscopic Simulator for Urban and Non-urban Networks

Downstream Vehicle further ahead subject vehicle on the road in adjacent lanes

Upstream Vehicle further behind subject vehicle on the road in adjacent lanes

Abbreviations

ACC Adaptive Cruise Control

API Application Programming Interface

AV Automated Vehicle

CACC Connected Adaptive Cruise Control

CAV Connected Automated Vehicle

CFM Car Following Model

$EIDM$ Enhanced Intelligent Driver Model

IDM Intelligent Driver Model

LCM Lane Changing Model

OBU Onboard Unit

RSS Responsible-Sensitive Safety

RSU Road Side Unit

SAE Society of Automotive Engineers

SDK Software Development Kit

$V2X$ Vehicle-To-Everything

Part 1:

Article

NTNU | Norwegian University of Science and Technology

Simulation of Automated Vehicles in AIMSUN

Andreas Berge Ims and Haakon Blakstad Pedersen (Supervised by Arvid Aakre)

***Abstract*—Automated vehicles (AVs) are built on an emerging technology that many foresee will improve transportation systems in relation to, e.g, delays, safety and efficiency. However, strict regulation and legislation make it challenging to test AVs on real-world road sections and intersections. Therefore, the simulation and testing of AVs in a virtual world are increasingly important to validate the technology, study its impacts and predict potential challenges for varying penetration rates. This research tested ten different AVs, differentiated by their behavior modeling, based on their longitudinal movement and cautious or assertive parameter settings, in the simulation software AIMSUN. The simulation framework contained a merging section to study the AVs cooperation and impact on traffic efficiency. The vehicle composition in each simulation consisted of human vehicles and one AV-type. Only one AV-type was included in each simulation, as it is considerable uncertainty related to the composition of AVs built on different systems in the future. Two out of the ten AVs improved the overall traffic efficiency in the system and bottleneck. We conclude that the best way to model and simulate AVs is that using the ACC- and default model with the default lane-changing model provided by AIMSUN and cautious and assertive parameter settings, respectively.**

***Index Terms*—AVs, behavior modeling, simulation, AIMSUN**

I. Introduction

Advancements and improvements in technology have enabled automated vehicles' rapid and continuous development over the last couple of decades. The progress is promising, but there is still much uncertainty regarding how the automated systems will affect transportation systems, e.g., safety, efficiency, and traffic flow [1].

Either self-driving or autonomous could refer to automated vehicles. The article will use the term "automated vehicles" and classify them based on the definition given by SAE (Society of Automotive Engineers). SAE [2] divide automated vehicles into six levels of automation. In SAE-levels 0 - 2 there are driver support features, e.g. ACC (Adaptive Cruise Control), lane centering, and emergency braking. SAE-levels 3 - 5 includes automated driving features, e.g., traffic jam chauffeur. In SAE-levels 4 - 5, the automated system will not request the human to drive [2].

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Domonoske [3] argues that vehicles today have SAE-levels 2 - 3 capabilities, e.g., lane centering, ACC, and self-parking. However, as of today there are no companies offering fully automated vehicles (SAE-Levels 4 - 5) [4]. Due to the uncertainty of AVs, access to external data and high external costs, e.g., increased infrastructure cost and traffic problems, AVs need to go through several stages before they can be commercially available. Therefore, they have stricter regulations than other technological innovations [5].

The simulation of AVs mixed with human vehicles is necessary to predict and avert potential challenges and study positive effects. Use of AVs is assumed to reduce reaction time, distance gap between vehicles, and reduce unnecessary accelerations and decelerations exceeding the comfortable level.

The structure of the paper is as follows: Section II presents the literature on what future expectations of automated vehicles are. Section III describes the vehicle behavior modeling of AVs. Section IV presents the implementation-methodology of the car-following models, the parameters chosen, the framework, and the simulation execution. Section V and VI present the results and discussion of these. Section VII will conclude the results and discussion and give the limitations and recommendations of future research.

A. Purpose and Research Questions

This article aimed to add to the existing knowledge pool and academic discussion on modeling automated vehicles in a simulation software.

In Norway, there are no published reports on the modeling of AVs in simulated environments in AIMSUN. However, outside of Norway it exists several reports on the subject. We wanted to explore how to simulate AVs given future expectations and previous research. Furthermore, we wanted to design a suitable simulation environment to test and evaluate the AVs. In this study, we raised the following research questions:

- How to model automated vehicles in AIMSUN?
- How to simulate and evaluate the performance of AVs?

B. *Microsimulation*

The experiment is built in a microscopic traffic simulation to better understand, modify, and model potential AV behavior and analyze their interaction and differences with the default human vehicles.

AIMSUN was chosen as the microsimulation tool due to the software's high credibility globally, with over 7000 professionals in over 90 countries using the software [6]. The software was also mainly chosen due to its extendibility. Extendibility refers to the user being allowed to extend the software using programming tools at five different levels. For the purposes of this article, only two of these levels have been relevant. These two level are;

- microSDK (micro Software Development Kit)
- V2X SDK (Vechicle to Everything Software Development Kit)

These two levels have been the most relevant because they alter behavior and offer a platform to communicate between vehicles and infrastructure. The microSDK allows for a developer to alter and add new behavioral models through programming in C++. The V2X SDK creates communication channels at the level of vehicle, roadside unit, and traffic management center. The model does require the implementation of information-based actions for vehicles. Both the onboard unit (OBU) in the vehicle and the roadside units (RSU) require programming by the user. [7].

II. Future Expectations of AVs

Before modeling automated vehicles and analyzing the results, it was essential to explore and review the literature on the expectations of automated driving systems. E.g., when one expects and predicts the implementation of different technologies and what kind of effects consumers believe they will have on the roads.

A. *Implementation and Effects*

Based on an extensive literature review, Martínez-Díaz and Soriguera [8] assumes that SAE-level 3 and 4 will most likely be available short-term, whereas SAE-level 5 is the longer term. Short-term meaning in 2 years, and longer-term, 20 years.

Calvert et al. [9] is less optimistic, claiming that the vehicle-share of SAE-level 2 will be less than 25% by 2035. The paper bases this on literature and the dependency on regulatory incentives or barriers, technological and economic development. Even if the technology is available, the amount of time it will take before it has achieved a significant share is long [9].

Although researchers expect the in-vehicle technology to be substantial and advanced, it will not necessarily lead to efficient and safe mobility due to the need for a cooperative environment [8], [9]. Calvert et al. [9] support this in their article, saying that vehicle connectivity and cooperation have been rightly hailed as the primary requisite to achieve traffic flow- and safety gains. Nevertheless, due to cooperative capability and the penetration rate of cooperation, effects will initially be too low. Therefore, the article recommends that simulation of vehicle automation do not rely too heavily on cooperation-technology [9].

Despite disagreements on implementation and the effects, one can still argue that the AVs behavior and decisions become harder to interpret as technology advances. Mainly due to the inclusion of additional factors, e.g., communication, which could lead to less trust and potentially less acceptance by the people. [10]

B. *Communication and trust*

How the AV should drive, communicate, and adapt in different situations is difficult. The answer could be subjective, in the same way, manual driving is. The challenge of communication yields both ways due to implicit rules which already exist between the majority of human drivers [11].

The implicit rules refer to the social behavior, e.g., when an AV wants to turn left in a busy non signalized intersection. Getting an acceptable gap for the AV might be challenging. If it were a human driver, it would get the gap through a simple nod, lights, or horn from the other driver in the opposite lane. Not understanding these types of signs might for an AV lead to more delay than necessary [11]. Human drivers could also cause the delay if they are insecure about the actions of the AVs and consequently act more hesitant. Especially in the transition phase as the humans will not be able to know to what extent another vehicle is automated [12].

The multinational corporation and technology company Intel [13] proposes a standardized system for AVs to overcome hurdles as the one mentioned in the previous paragraph. The idea is for the system to be formalized on the human notions of safe driving; thus, a verifiable system exhibits behavior humans might accept. The system will achieve safe and expected behavior with mathematical formulas and logical rules. [13]

C. *Consumer Expectations*

Based on a survey published in a report in 2019, Capgemini [14] found that Chinese consumers are more positive about AVs than consumers from other nations, i.e., Germany, France, Sweden, USA, and UK. The survey showed that acceptance rate is likely to increase over time.

The survey also found that 31% of the over 5500 participating consumers expect reduced traffic congestion due to the implementation of automated vehicles. However, the survey does not elaborate further on why they think it will reduce congestion but focuses more on what they believe AVs could do for them, e.g., shopping and picking up kids from school [14].

A study conducted by Rutgers University in New Jersey claims that automated vehicles can reduce stop-and-go traffic created by human vehicles changing lanes. However, the study also claims that traffic can be worse as AVs will rather drive than stay parked [14]. The worse situation is not due to the behavior, but rather the fact that more vehicles will remain driving in the streets as this is the most economic use of the AV.

Asking consumers what they expect from AVs is essential, as it tells the developers and manufacturers what kind of effects, benefits, and behavior they wish to see. The problem is that the public perception of AVs may be inaccurately displayed in surveys [15]. Only a few participants have perhaps experienced direct interactions with AVs. The lack of experience might lead to over-or underestimation of the effects or consequences AVs may have. Past surveys also had little focus on expectations towards AVs from vulnerable road users, e.g., cyclists and pedestrians. That is whether the behavior will be predictable and understandable [15].

III. Vehicle Behavior Modeling

Car-following and lane-changing models are examples of microscopic models and form the basis of vehicle behavior. Car-following models govern the longitudinal behavior, including acceleration, and deceleration based on the leading vehicle. A lane-changing model describes lateral movement. The model decides how, when, and what kind of approach it will have when changing lanes.

The modeling of proposed AVs utilized five different car-following models and one lane-changing model. Regarding the lateral movement, the default AIMSUN model with enhanced parameters was used. This was done due to time constraints on implementing a new model, limited literature, but also under the assumption that AVs will try to mimic human behavior, in line with previous research [16]–[18].

The rest of this section and article will not refer to any CAVs (Connected Automated Vehicles), even though there is one AV with cooperation capabilities. The CAV term will not be used mainly for simplicity and due to the vehicles *"only"* being able to form platoons, i.e., AVs driving closer together and not having any other CAV capabilities.

The extensions API and V2X-SDK enable to build and implement communication channels between the AVs and possibly infrastructure. Although, we had these tools, it was decided not to explore these extensions further due to time and limited programming experience.

A. Human Vehicle

To model the Human Vehicle behavior, we used the default model provided by AIMSUN, based on the Gipps model. The model implemented in AIMSUN has modifications and additions, e.g., cooperation between vehicles [19]. The model calculates safe speed for subject vehicle n, concerning leading vehicle $n-1$. Two constraints apply to the vehicle's behavior. The first constraint prevents vehicle n from exceeding its desired speed. The second constraint is a safety parameter limiting the braking and making vehicle n gradually brake instead of applying maximum braking.

All vehicles following the model are in either free or restricted driving. Free driving refers to the situation where there are "no" vehicles limiting your desired speed. Restricted driving is based on the "safe" distance to the leading vehicle $n-1$, enabling a safe reaction to avoid a collision. [20]

B. Automated Vehicles

The five different car-following models implemented in the simulation are listed below;

- Gipps Model - Default Model
- Intelligent Driver Model - IDM
- Enhanced Intelligent Driver Model - EIDM
- Adaptive Cruise Control - ACC Model
- Cooperative Adaptive Cruise Control - CACC Model

ACC- and CACC Model refers to the car-following models provided by AIMSUN. The term ACC controller refers to the car-following model corresponding to the principle of which the ACC is built, namely keeping a safe following distance to the vehicle in front.

1) Default Model: Vehicles modeled after the default are based on an assumption similar to the one on lane-changing models. It assumes that AVs want to mimic human behavior with the enhanced parameters, e.g., reaction time. This is also what AIMSUN recommends in a video published on YouTube when simulating a non-equipped AV, meaning with no connective abilities [21].

2) IDM and EIDM Model: IDM and EIDM were the only car-following models which needed implementation via the microSDK in AIMSUN.

IDM: The model was introduced because it was less complex, had no asymmetric accelerations, and did not lose real properties in the deterministic limit [22]. IDM was proposed as an ACC controller due to it being collision-free, corresponding to a natural and smooth manner of driving, and having few parameters that are intuitive [23].

The IDM-formula is shown in equation 1 and 2. Acceleration is determined by the desired speed and time gap in equation 1. The desired gap is a function of the speed and speed difference in equation 2.

$$a_n^t = a_n \left[1 - \left(\frac{V_n^t}{V_n^*} \right)^4 - \left(\frac{s^*(V_n^t, \Delta V_n^t)}{s_n^t} \right)^2 \right] \tag{1}$$

$$s^*(V_n^t, \Delta V_n^t) = s_0 + V_n^t \cdot T + \frac{V_n^t \cdot \Delta V_n^t}{2\sqrt{a_n \cdot b_n}} \tag{2}$$

Where,

a_n^t	Acceleration of the n^{th} vehicle at time t
a_n	Maximum acceleration of the n^{th} vehicle
V_n^t	Actual speed of the n^{th} vehicle at time t
V_n^*	Desired speed of the n^{th} vehicle
s_n^t	Actual gap of the n^{th} vehicle
$s^*(V_n^t, \Delta V_n^t)$	Desired gap for the n^{th} vehicle
s_0	Minimum gap
T	Safe time gap
ΔV_n^t	Difference in speed of n^{th} and $n-1^{th}$
b_n	Desired deceleration

$1 - (V_n^t/V_n^*)^4$ in equation 1 is the accelerating term towards the desired speed V_n^* on a free-flow road, whereas

$(s^*(V_n^t, \Delta V_n^t)/s_n^t)^2$ refers to the braking term. s_0 in equation 2 exists primarily for when the vehicle is traveling with a low velocity.

EIDM: The model was presented due to IDM *"overreacting"* in cut-in situations and in intersections. This happens when the actual gap is smaller than the desired gap and low-velocity differences [24]. EIDM introduces a constant acceleration heuristic (CAH) to avoid potential overreaction. In simple terms, the CAH tells whether a situation requires critical braking or not.

The formula for CAH and EIDM can be seen in equations 3 and 4, respectively.

$$a_{CAH} = \begin{cases} \frac{v^2 \tilde{a}_l}{v_1^2 - 2s\tilde{a}_l}, & \text{if } v_1(v - v_1) \leq -2s\tilde{a}_l \\ \tilde{a}_l - \frac{(v-v_1)^2 \Theta(v-v_1)}{2s}, & \text{otherwise} \end{cases} \tag{3}$$

$$a_{EIDM} = \begin{cases} a_{IDM} \\ (1-c)a_{IDM} + c\left[a_{CAH} + b\tanh(\frac{a_{IDM} - a_{CAH}}{b})\right] \end{cases} \tag{4}$$

Where,

a_{IDM}	See equation 1
s	Gap distance
v	EIDM-vehicle speed
v_1	Leading vehicle speed
a_1	Leading vehicle acceleration
c	Coolness factor. Weight-factor (=0.99)
$\Theta(x)$	Heaviside step function
$\tilde{a}_l$	Maximum of a and a_1

$v_1(v-v_1) \leq -2s\tilde{a}_l$ in equation 3 is true if the vehicles have stopped when they reach the minimum gap. $\Theta(v - v_1)$ is the Heaviside step function which eliminates negative approaching rates in case $v_1(v - v_1) \leq -2s\tilde{a}_l$ is not valid.

Due to the lack of minimum time headways or acceleration to the desired velocity, the CAH is not a complete car-following model. Therefore, the CAH is incorporated with the IDM to make a complete ACC controller, as shown in equation 4. The first condition is fulfilled if $a_{IDM} \geq a_{CAH}$, the second is otherwise.

3) ACC and CACC Models: The controllers were unlike IDM and EIDM, already implemented in AIMSUN thanks to the PATH research group at UC Berkley based on the algorithms developed by Milanés and Shladover [25], [26].

The difference between the ACC- and CACC models is that vehicles equipped with the CACC models can form and join platoons. A platoon comprises vehicles fitted with the CACC model that communicates to drive closer together than vehicles not equipped safely. Platoons are limited to a maximum number of vehicles. A vehicle trying to join a platoon that has reached its maximum capacity will become the new platoon leader.

Dependent on the situation, the model activates one of the following three modes for a vehicle at all times.

- Speed regulation mode
- ACC Gap regulation mode
- CACC Gap regulation mode

Speed regulation mode is active for the subject vehicle n whenever there is no vehicle within range. However, if the leading vehicle $n - 1$ is within range, vehicle n will activate one of the last two regulation modes for "safe" speed adaptation.

TABLE I
OVERVIEW OF VEHICLE FLEET

Vehicle Name	Car-Following Model	Cautious/Assertive
Human Vehicle	Default Model	Human Vehicle
C-Def	Default Model	Cautious
A-Def	Default Model	Assertive
C-IDM	IDM	Cautious
A-IDM	IDM	Assertive
C-EIDM	EIDM	Cautious
A-EIDM	EIDM	Assertive
C-ACC	ACC Model	Cautious
A-ACC	ACC Model	Assertive
C-CACC	CACC Model	Cautious
A-CACC	CACC Model	Assertive

Note: C- and A- are abbreviations for cautious and assertive, respectively.

IV. METHODOLOGY

A. Vehicle Fleet

Changing the parameters that go into a car-following- and lane-changing model can significantly impact how the vehicles perform and affect the system. The changing of these parameters is done in AIMSUN. The decision fell early on that the vehicle fleet should represent cautious and assertive behavior, in line with previous research [18], [27].

Each car-following model has cautious and assertive parameter settings. The motivation was to compare car-following models with different parameter settings. As there were five other car-following models, this meant a total of ten vehicles. Table I shows an overview of the vehicles, their name, car-following model, and whether they have cautious or assertive parameter settings.

Table II shows the parameters and their values for the Human Vehicle, cautious and assertive AVs. The values for the Human Vehicle are mostly default, but some modified to be in line with the recommended values for Norwegian vehicle types [28].

Only the most important and less self-explanatory parameters will be explained in table II.

Reaction time: Is the time it takes for the subject vehicle to react to speed changes, acceleration, and traffic lights. The reaction time of an AV is assumed to be much less than for a Human Vehicle. The reaction time of an AV depends on the processing time, which is assumed to be 0.1 seconds. This is also in line with previous research and assumptions on the car-following models [18], [21], [22], [24], [25], [29].

Safety Margin Factor: Determines when a vehicle can move at a priority junction. A lower value than 1 means more assertive. Therefore, values for cautious and assertive are 2 and 1, respectively. The values are in line with recommendations by AIMSUN [21].

Look Ahead Distance Factor: Value to determine how early a vehicle considers a lane choice. The higher the value, the earlier the lane change. Chose the value of 1.5 for cautious and 1.25 for assertive under the assumption that AVs will make lane changes earlier in line with previous research [18], [21].

TABLE II
VEHICLE PARAMETERS

Input Parameters		Human Vehicle				Cautious AVs	Assertive AVs
		Mean	Dev	Min	Max		
Max Desired Speed	$[km/h]$	110	10	80	120	110.0	110.0
Speed Limit Acceptance	[-]	1.0	0.1	0.9	1.1	1.0	1.0
Max Give Way Time	$[s]$	10.0	2.5	5.0	15.0	12.0	8.0
Clearance	$[m]$	2.0	0.8	0.5	3.5	1.0	1.0
Reaction Time	$[s]$	0.9	-	-	-	0.1	0.1
Reaction Time at Stop	$[s]$	1.2	-	-	-	0.1	0.1
Reaction Time Traffic light	$[s]$	1.35	-	-	-	0.1	0.1
Max Acceleration	$[m/s^2]$	3.0	0.2	2.6	3.4	3.0	3.0
Max Deceleration	$[m/s^2]$	6.0	0.5	5.0	7.0	6.0	6.0
Normal Deceleration	$[m/s^2]$	4.0	0.25	3.5	4.5	2.0	2.0
Safety Margin Factor	[-]	1.0	-	-	-	2.0	1.0
Sensitivity Factor	[-]	1.0	-	-	-	1.5	1.0
Overtake Speed Threshold	$[\%]$	90.0	-	-	-	80.0	90.0
Gap	$[s]$	0.0	-	-	-	2.0	1.0
Look Ahead Distance Factor	$[s]$	-	-	0.8	1.2	1.5	1.25
Aggressiveness Level	[-]	-	-	0.0	1.0	0.0	0.0

Note: Values without deviation, min and max are constant values.

Aggresiveness Level: Controls the gap acceptance model for a lane change. The higher the level, the smaller the gap a vehicle will accept. Set the value of 0, meaning that the AVs will use the “normal” safe gap, in line with previous research and recommendations by AIMSUN [18], [21].

B. Simulation Framework

Testing of AVs in the real world is arguably a safety risk [30], hence AIMSUN was used to facilitate the simulations. The global academic society has a high regard for the software, as mentioned in section I-B. Additionally, the software allows for extracting comprehensive data regarding each simulation with several indicators of choice, e.g., speed, flow, headway, and delay time.

Modeling traffic is challenging, and some scholars argue it is nearly impossible to create an identical replication of a real-world transport system [31]. An actual location requires substantial data collection, and according to Statistician George Box [32], it would still not be correct, as he claimed that *“All models are wrong, but some are useful.”*. The simulation framework used in this article is a fictitious location. Such a location may be suitable to simulate and evaluate AVs performance based on their behavior modeling.

The simulation framework, shown in fig 1, comprises a bi-directional two-lane motorway with ramps leading onto roundabouts that connect to secondary roads. The main area of focus is a bottleneck section on the highway that forces traffic to merge into one lane, built on the zipper-merge principle. Zipper-merge, also known as non-priority merging, is based on the principle of first-come-first-serve [33]. A merge section was chosen over signalized or non-signalized intersections as they would add complexity to the framework, i.e., more factors to assess. That would make it more complicated to evaluate the AVs performance, e.g., green time, yield rules, and design of the intersections.

Each AV has different parameter settings, and a merging section requires the AVs to cooperate to keep a good level of traffic flow. It is challenging to predict how the composition of different types of AVs will be in the future and how to implement multiple car-following models in one simulation. Therefore, the mixed traffic conditions consist of human vehicle and only one AV-type. No other road users present reduces the complexity and make the evaluation process more manageable.

We ran three simulations, called simulation 1.0, 2.0, and 3.0. Simulation 3.0 contained fewer parameters with different values for cautious and assertive AVs than simulation 1.0 and 2.0, making it less complex. Hence, it was easier to evaluate which parameter affected the AVs performance. Section V and VI presents the results from simulation 3.0.

Two types of simulation data were later evaluated; one for the entire system and one for the two detectors placed in the system. Detector A is located 400 meters before the lane drop, and detector B right after. The placement of the detectors is based on a previous study [34]. Fig 1 shows an overview of the simulation framework with the location of both detectors, and fig 2 shows a close-up on the bottleneck and merge sections in focus.

Each vehicle type is simulated several times in what is called replications. Then, the software calculates the average value of these replications, which becomes more representative and resilient to variations with additional replications.

Scholars and consumers expect a gradual introduction of AVs into the traffic system [14]. The simulation of AVs contained different penetration rates to account for this transition phase. Penetration rates imply the amount of AVs present, meaning a simulation with a 10% penetration rate has 10% of that particular AV type and 90% human vehicles present. The simulations contained two replications for each penetration rate of AVs. In that way, one can evaluate the performance of mixed traffic conditions.

Fig 3 shows an overview of the varying travel demand that has been implemented in the simulations to evaluate how the AVs cope with increasing travel demand. Table III lists additional simulation specifications, where the primary road refers to the post-bottleneck section.

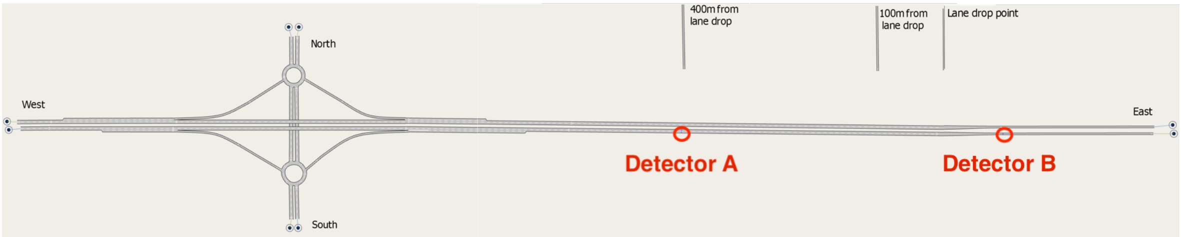


Fig. 1. Location of detector A and B.

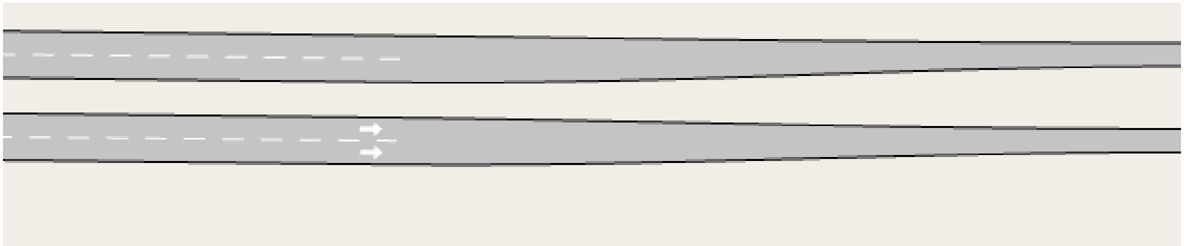


Fig. 2. Bottleneck overview.

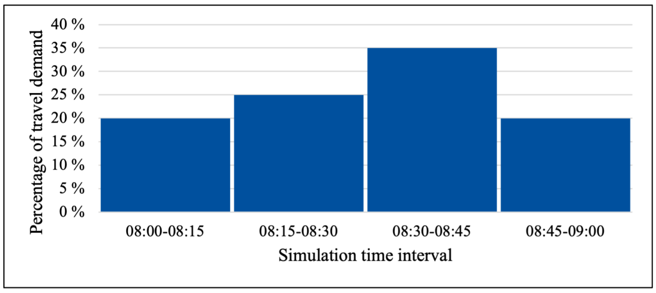


Fig. 3. Percentage of travel demand allocated for each time interval in simulation 3.0.

TABLE III
PARAMETER VALUES FOR SIMULATION 3.0.

Parameter	Item	Value
Speed	Motorway	100
Speed	Primary	80
Capacity	Motorway	2100
Capacity	Primary	1600
Simulation time	Sim 3.0	60
Time of day	Sim 3.0	08:00-09:00

V. RESULTS

Each vehicle type has been assigned distinct colors to distinguish the different car-following models and parameter settings. Cautious AVs are drawn with continuous lines and assertive AVs with dashed lines. A dashed black line will also be shown named the 0% AV-line, representing the situation with 0% AVs present. All AVs are presented with the given vehicle name from table I.

A. Performance of Entire System

1) Difference Between Car-Following Models: Fig 4 shows the delay for the different mixed traffic scenarios in the system. Three cautious AVs stand out with a noticeable higher delay time than other vehicles. C-IDM and C-EIDM see a tremendous increase in 60-80% AV penetration rates, while C-ACC starts increasing in the area of 80-90% penetration rates. The assertive AVs are all following the 0% AV-line, in particular A-Def and A-CACC. Those AVs had a lower delay for all penetration rates than the 0% AV-line, particularly starting at 40% penetration rate.

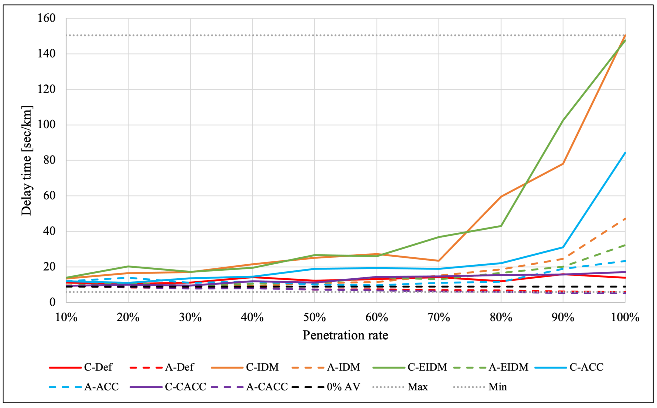


Fig. 4. Delay time for cautious and assertive AVs

2) Assertive AVs: Fig 5 shows the delay times for assertive AVs. The AVs with the highest delay times have the same car-following models as the cautious AVs with the highest delay times, i.e., IDM, EIDM, and ACC car-following models. The increase is noticeable less than for the cautious AVs with the same car-following models. A-Def and A-CACC have lower delay times than the 0% AV-line.

3) Parameter Effects: Fig 6 shows the speed for cautious and assertive AVs. In general, AVs with default and CACC car-following models had higher speeds than all other AVs. Fig 6 indicates that higher penetration rates lead to speeds

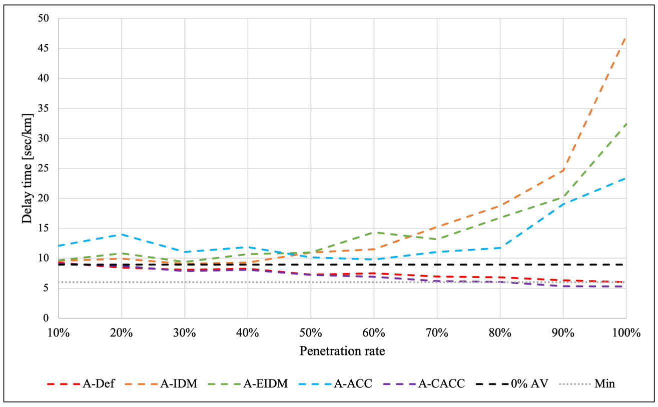


Fig. 5. Delay time for assertive AVs

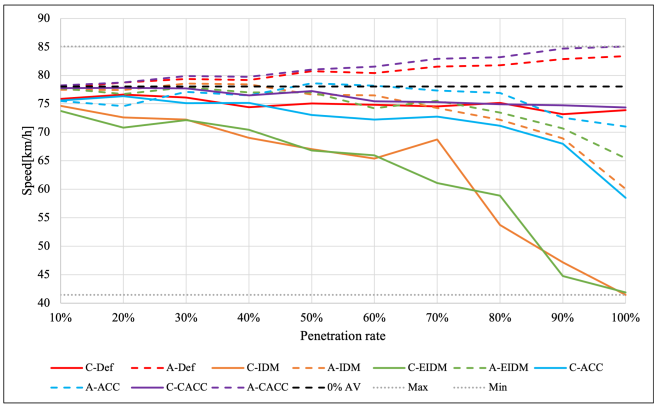


Fig. 6. Speed for cautious and assertive AVs

decreasing for most AVs, except A-Def and A-CACC. Speed indicates the level of flow in the system, and decreasing speeds should indicate a slow-moving queue. Cautious AVs are most prone to lower speeds at high penetration rates, and in general, the assertive AVs decreased less in speed than cautious.

B. Performance through Bottleneck

This section presents the measurements from the two detectors described in section IV-B. The most significant differences between the AVs occur at a penetration rate of 100%. Therefore, it has been chosen to present these results from the detectors and the 0% AV-line.

1) Cautious AVs: The overall system performance of the cautious AVs is not good in terms of delay time and speed. From watching some of the worst cases, i.e., 100% C-IDM and C-EIDM, it was clear that most of the delay traces back to the bottleneck. The delay was noticeable in the graphs for flow and speed from detector A and B shown in figures 7a and 8a, respectively.

C-IDM and C-EIDM had almost a constant flow and speed of 1450 vehicles/hour and 8 km/h, respectively, at detector A. Compared to the 0% AV-line, the average speed decreased by 92%. The low and almost constant value of speed and flow at both detector A and B was due to congestion accumulating in the warm-up period. The warm-up period introduces vehicles into the system prior to simulation start such that there are relative normal traffic conditions when the simulations commences.

The constant flow and speed showed from C-IDM and C-EIDM in fig 8a explain why the congestion was never resolved further upstream at detector A. Unlike C-IDM and C-EIDM, C-Def and C-CACC more or less followed the travel demand, which gave a 33% higher flow on average. The flow was higher, even though the speed was lower during the peak. A similar observation was seen for C-ACC, where again, the speed was lower than C-IDM and C-EIDM even though higher flow.

2) Assertive AVs: Differentiating between the flow performances in fig 7b would be difficult as most assertive AVs followed the 0% AV-line. However, looking at the speed, one can see that the speed of A-IDM, -EIDM, and -ACC dropped to 40 km/h and below during peak. This speed drop means that the congestion during peak reached detector A. However, the congestion quickly resolved for A-EIDM and A-ACC, unlike A-IDM, where the congestion remained the same after the peak period.

In the results from detector B, shown in fig 7b, A-IDM had the highest mean flow during the simulation but the second-lowest speed due to the warm-up period, where congestion before the bottleneck had already begun to form, and it never resolved.

Fig 8b shows that A-CACC and A-Def had the highest mean speed of all the AVs, 24% and 9% higher relative to the 0% AV-line. They both had an almost similar flow value with the 0% AV-line, which means they had a more efficient merging process in the bottleneck.

VI. Discussion

The first research question presented in section I-A encompasses the vehicle behavior modeling, thereunder car-following models, choice of parameters, and what results to expect.

The second research question encompasses how to build the framework should and the simulation completed. This includes the infrastructure design, the modeling of the transition phase, measurement, and performance indicators

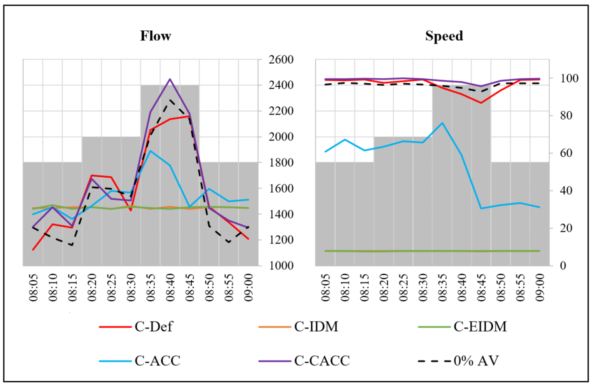
A. How to model automated vehicles in AIMSUN?

It is difficult to suggest the best way to model automated vehicles as the answer rely heavily on assumption and uncertainties regarding the future.

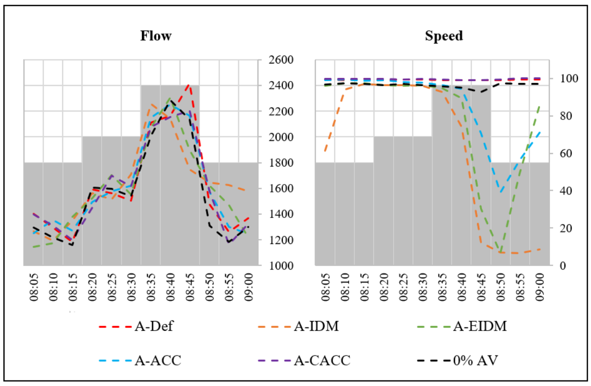
When modeling an automated vehicle, there are three key questions one needs to ask:

1) Which car-following- and lane-changing model should the AV have?
2) Which parameter settings to set for the AV?
3) Should the AV have connective and cooperative capabilities?

The importance of the car-following model can be seen when assessing fig 4 to 8. The difference in performance is especially apparent when comparing the IDM and EIDM to the other models. The performance of IDM and EIDM were

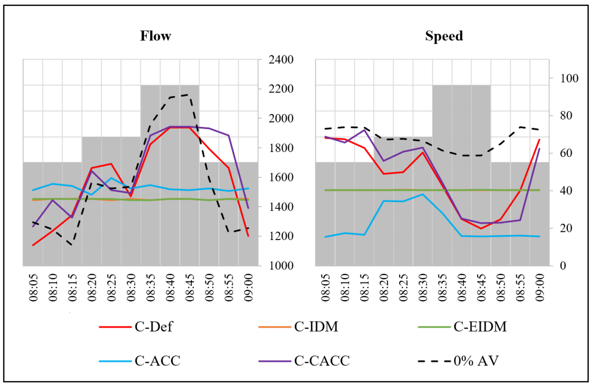


(a) Cautious AVs

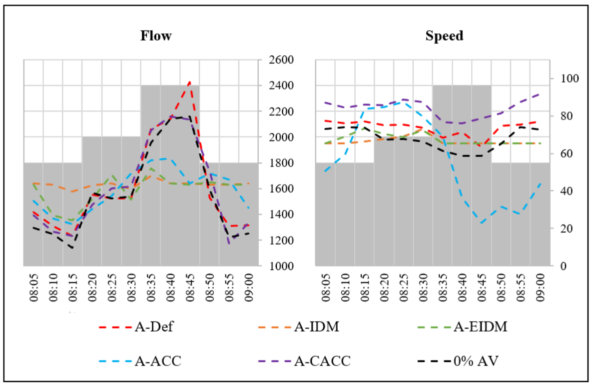


(b) Assertive AVs

Fig. 7. Detector A



(a) Cautious AVs



(b) Assertive AVs

Fig. 8. Detector B

both surprising as previous research indicated that the models improved congestion and overall throughput of traffic [17], [29].

The majority of a delay from IDM and EIDM occurs at the bottleneck described in section V-B. Congestion forms quickly due to sudden deceleration, often to complete stops during merging and cut-in situations before the bottleneck. Based on this performance, it was expected that the EIDM would outperform IDM as the model is designed to not overreact in those types of situations [24], [29].

The CACC contoller and default model gave the best results in reducing delay time and improving the overall traffic flow in the bottleneck with increasing penetration rate. However, these improvements were dependent on the vehicle being modeled with assertive parameters. That said, the cautious types were better than the other assertive vehicles as well. Therefore it can be argued that these models, in terms of performance to a greater extent, resemble what consumers and the majority of research come to expect from automated vehicles in the future (see section II).

The results from the ACC model were worse than expected with both cautious and assertive behavior. It gave the third-lowest performance of all the AVs and the third worst of all the assertive types. The results contradicted previous research, mainly Mesionis et al. [18], who reported higher throughput and average speeds in the motorway mainline.

As with the car-following models, the results showed the importance of parameters and how they affect performance. Some parameters affect the different models more than others. This was seen in preliminary tests where minor adjustments made to, e.g., the distance zone factor and time gap, could either improve or worsen the performance. Some of the delays imposed by the AVs can be attributed to the constant and conservative parameters chosen due to the AVs requiring larger gaps and the acceleration/deceleration capability.

Finding the "correct" car-following model and parameters is no easy task, and the effects may not induce the expected effects on all types of situations and frameworks. The research question is *"How to model automated vehicles?"* but how can the result tell if this has been achieved?

31% of 5500 consumers expect reduced traffic congestion due to the implementation of AVs [14]. However, most of the previous research has to the best of our knowledge, not discussed to a great extent the expectations one could have from AVs, mostly assuming that the AVs will increase efficiency and overall traffic flow [16]–[18].

Many assumptions and claims about the effects are made in the scientific community, often lacking sufficient validation and realism [9]. The slow transition towards partial automation might not be positive for the overall traffic efficiency. Therefore, one should not disregard the AVs that induce adverse effects on the network, as this could be just as realistic. The magnitude of the adverse effects, however, is another topic of discussion.

The degree of connectivity and cooperation capability is hard to estimate and predict, just like the car-following model and parameters. As presented in section II-A, simulation of AVs should be careful not to rely too heavily on cooperation technology. With this in mind, one should not conclude with the CACC model being the best way to model an AV. This is partly based on technology, and the prospects of achieving the vehicle share needed to induce positive non-negligible effects are too far ahead in the future.

Connecting the simulated AVs to specific SAE-levels is very complex and would heavily rely on assumptions made by the authors. Based on the performance in the system and the bottleneck, one could argue that A-Def induced the positive effects one would expect from vehicles classified as SAE-levels 4 - 5 solely based on behavior with no cooperation capability. As the model is based on the Gipps model and already implemented in AIMSUN, it is assumed that it could be used for several types of situations, making the AV more versatile. The C-ACC would characterize an AV in the early stages (SAE-levels 2 - 3) due to the model being extra conservative, as well as being based on existing ACC-technology [25], not necessarily inducing positive effects on the transportation system with a higher penetration rate.

B. How to simulate and evaluate the performance of AVs?

The approach to evaluating AVs performance is to study indicator results from the simulations with varying travel demand through the simulation period. Good flow and high throughput indicate good cooperation and performance. Should the indicator show otherwise, it would imply that either the infrastructure layout or vehicle settings reduce flow or other throughput values. Vehicles with different settings could affect the system's efficiency when all other settings remain the same. That would imply that the settings cause a reduction in traffic efficiency. Hence one could assess the performance of the AVs based on the indicator results.

The simulation framework contains a merging section built on the zipper-merge principle to force cooperation between the vehicles, chosen over signalized and non-signalized intersections, mentioned in section IV. Such a merging section is less complex than intersections, reducing uncertainty and simplifying the evaluation of the AVs performance.

The framework consists of a fictitious location. An actual location requires substantial data collection to achieve a relative realistic replication. Zhou et al. [31] claim a complete replicate of any real-world location is nearly unattainable, making it more complicated to transfer simulation techniques to other locations. The simulation results show significant flow variations and speed when travel demand varies, implying unrealistic behavior, which an actual location could have mitigated. Nonetheless, a fictitious location is transferable to other locations and therefore fitting to test new technologies. In the future, it would be interesting to see simulation studies on AV behavior in actual locations, with both varying travel demand and a merging section.

There will be a transition phase until all vehicles in the transport system are AVs. The simulations are run with set penetration rates of one type of AV and human-driven vehicles present to replicate the transition phase. Only one AV-type is present, as it is great uncertainty related to the composition of AVs built on different systems in the future. Two replications are run for each penetration rate of the AVs, with penetration rate intervals of 10 from 0-100%. Section V shows a positive correlation for nearly all AVs between penetration rates and delay times and a negative correlation with speed. That supports the idea of simulating with varying rates of AVs present to differentiate the AV performance.

The analysis of the results supports the theory that the level of flow is affected by cooperation. To clarify, travel demand exceeding capacity leads to higher delay times and reduced speeds, indicating poor cooperation between AVs. Variation in travel demand during the simulation may affect the indicator results such that AV performance can be evaluated based on the traffic efficiency they showcase.

It is beneficial to place the detectors in the vicinity of the merging section or close to any infrastructure section where the capacity is critical and affects the rest of the system. Flow and speed results indicate how well the traffic efficiency is, as low flow and speed might indicate slow-moving queues and poor cooperation. The higher throughput, the better performance by the AVs, thus increasing the transportation system's efficiency.

The three indicators listed below were used in the evaluation process:

- Delay time
- Speed
- Flow

Additionally, headway, number of lane changes, and number of missed turns were also evaluated in simulations 1.0 and 2.0. Results showed no apparent correlation with traffic efficiency indicators, e.g., flow and speed. Hence they were excluded in simulation 3.0.

Given more time, there could have been conducted additional simulations with fewer variables changed from each simulation. Different travel demand setups could have produced less drastic changes in indicator results. Examples of such setup are longer simulation time, shorter intervals with different travel demand, higher peaks, and more gradual changes, the latter to enable traffic stabilization.

VII. Conclusion

The purpose of the article was to add to the existing knowledge pool and academic discussion on how to model AVs.

The article presented ten different AVs where pairs of two with the same car-following model had different parameter settings. A total of five car-following models were utilized. Three out of five models were implemented in AIMSUN, whereas the remaining two needed to be implemented via the microSDK. A majority of time went into the programming aspect, therein understanding of syntax and functions. The AVs were tested in mixed traffic conditions with different penetration rates.

The ACC- and CACC models provided by AIMSUN are based on real-life experiments from ACC vehicles [25], whereas the default model is envisioned to replicate human behavior [19]. Based on the results, it is assumed that the best way to model AVs is by using the ACC- and default model with cautious and assertive parameter settings, respectively. Furthermore, the default lane-changing model with enhanced parameters should be used for both types of AVs, assuming the lateral behavior to be similar to a Human Vehicle. We assume C-ACC to correspond to the early stages of vehicle automation due to the conservative behavior, the model being based on existing ACC-technology not necessarily imposing, e.g., reduced delay. The A-Def is assumed to correspond to SAE-levels 4 - 5. We assume a higher SAE-level, as the AV is more assertive and can mimic human behavior to a greater degree. Therefore the A-Def can possibly induce positive effects solely based on behavior even though it has no cooperative capabilities.

IDM and EIDM were not chosen due to too high a level of uncertainty in programming. The vehicles equipped with the models displayed unrealistic behavior in cut-in situations and merging. Sudden deceleration to complete stops helped induce significant delays in the system and the bottleneck. The increase in delay got unrealistically higher in correlation with the penetration rate. The CACC was not chosen due to the cooperation-technology being too far ahead in the future. Also, platooning does not, based on our research, induce meaningful positive effects until it has achieved a considerable vehicle share.

To simulate and evaluate the performance of AVs, one must first decide what aspect of the AV to investigate. The simulations in the article studied cooperation between AVs, disregarding other road users. A simplistic framework reduced factors affecting the results and the uncertainty in the evaluation process. In addition, each simulation had varying amounts of AVs to account for the transition phase where only parts of the vehicle fleet are AVs.

The framework was a fictitious highway section with a merging section that created a bottleneck, forcing cooperation between the AVs. Varying travel demand enabled the AVs to showcase how well managed good traffic efficiency. Evaluation of indicator results from the entire system and detectors placed near the bottleneck saw which AV performed the best, mainly based on traffic efficiency through the bottleneck. It was possible to separate the AVs by their performance, enabled by vehicle and simulation set up.

VIII. Future Work

As seen and discussed under sections V and VI, IDM and EIDM, which were implemented via the microSDK, gave the most inadequate performance. As we were the ones who implemented the car-following models, one should question the reliability and whether the correct parameters were set. It is also essential to keep in mind that the performance might depend on the framework in which they were tested. Future potential research could test these models to a greater extent in an actual location with several other road users, e.g., heavy vehicles, cyclists, and pedestrians. The composition and testing of AVs built on different systems should be considered as well, with a gradual transition phase.

Although disregarded due to time constraints, and literature suggesting not relying too heavily on the technology, V2X-capabilities should be explored further. Future research should focus on how the V2X-SDK from AIMSUN can be utilized, be set up, what messages it could send, and how the AVs and infrastructure should use the messages for a limited case-scenario. If possible to successfully implement the V2X, it is assumed that it would reduce delay and improve traffic efficiency even further, partly seen with the CACC model.

Traffic safety could also be investigated. To the best of the author's knowledge, only one article has looked at the safety aspect of AVs with an increasing penetration rate [17]. Future studies could explore the improved safety further, as this is one of the major expected benefits some assume AVs will bring. E.g., calculating collision risk with different mixed scenarios with varying compositions of AVs, human vehicles, and vulnerable road users. In order to not over-complicate the study, it could focus on a single intersection. Additional surveys could map potential fears consumers have towards AVs related to safety, pursuing solutions to cope with such expectations.

Acknowledgment

We want to thank AIMSUN for enabling and giving access to the academic pro edition of Aimsun Next with microSDK and V2X-SDK. We like to acknowledge the support AIMSUN gave through the process, where they answered any inquiries or questions we had. Without the software, extensions, and support, we could have completed none of the presented work. Finally, we would also like to express our sincere gratitude to Arvid Aakre for his guidance and supervision throughout the work process.

Author Contributions

The authors contribution to the article are as follows: programming and implementation of AVs: Pedersen; study design: Ims; analysis and interpretation of results: Ims and Pedersen; draft manuscript preparation: Ims and Pedersen; guidance and supervision: Aakre.

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Part 2:

Process Report

1 Introduction

This chapter will present the theme and the purpose of the simulation of automated vehicles (AVs) in microsimulation software. It will clarify the term “automated vehicles” and why it is essential to simulate these vehicles and briefly introduce the case study. At the end of the chapter, there is a presentation of the chosen research questions, limitations, and experiences with our collaborative writing.

1.1 Purpose

The purpose of this master thesis is to add to the existing knowledge pool and academic discussion on how to model AVs in a computer software. The modeling focuses on utilizing different models governing the longitudinal movement to assess vehicle behavior by analyzing traffic flow through a lane drop in a highway bottleneck. In addition, the thesis focuses on discussing elements of interest for such a simulation to stand out from previous studies. E.g., the car-following models suggested parameters with assigned values, infrastructure elements, and traffic environment.

1.2 Previous Work

This thesis is a continuation of a prestudy report written by the undersigned authors [1]. The prestudy report was a literature review on what theories exist on relevant variables and factors within behavior modeling in AIMSUN and research regarding the simulation of AVs. Purpose of this prestudy report was for the authors to acquire knowledge on AVs and specify research questions. Table 1.1 lists which sections that contain content taken from the prestudy report. Some of which are modified, meaning paragraphs are removed, rewritten, or added.

Table 1.1: Overview of sections retrieved and modified from the prestudy report.

Chapters	Sections
1	1.3
2	2.1 , 2.2
3	3.2, (3.1, 3.3, 3.4, 3.5, 3.6)

Note: Sections in “()” are modified for the thesis

[1] Andreas Berge Ims and Haakon Blakstad Pedersen

1.3 Background

Advancements and improvements in technology have enabled AVs rapid and continuous development over the last couple of decades. Although the growth has been substantial, more research can ensure automated driving systems' reliability. At the 2016 Paris Motor Show, Toyota president Akio Toyoda estimated that it would require approximately 14,2 billion kilometers of testing to accomplish the potential AVs have, including simulations (Ohnsman, 2016).

Self-driving, automated or autonomous vehicles refer to a topic most people have read and heard about or even experienced firsthand. Automation is either viewed as distant in the future or something that already exists on the streets today. The different terms and perceptions could result from the rather vague term and meanings of "Self-driving" and automation. Therefore, this thesis will refer to self-driving vehicles as Automated Vehicles and further sub-categorize them after the definition given by SAE International. They have divided self-driving into six levels of automation (SAE, 2018b). Figure 1.1 shows a visual overview of the levels.

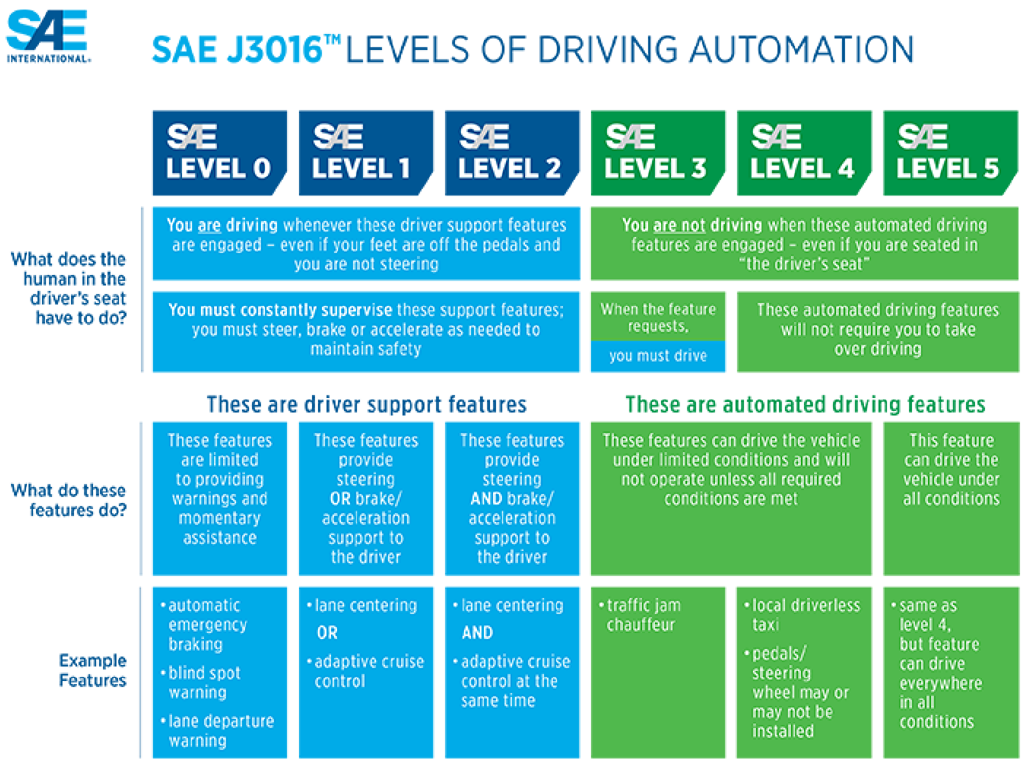


Figure 1.1: SAE-levels of driving automation.

Source: (SAE, 2018a)

To summarize: In SAE-levels 0 - 2, the human monitors the road. In SAE-levels 3 - 5, the automated driving system monitors the road. In level 3, if the system requests, the human has to take control.

The effects of AVs and how they might change mobility systems regarding safety, efficiency, and traffic flow are uncertain (Dennis et al., 2017). The uncertainty is not whether there will be an effect or not, but rather how big or small the effect will be (Dennis et al., 2017). A report published by the Victoria Transport Policy lists some of the external benefits an AV may have (Litman, 2020). A few potential benefits are; increased road capacity, cost savings, reduced parking costs, reduced energy consumption, and increased safety. However, accomplishing all these benefits might seem optimistic, and the report addresses this by saying that most of the benefits require SAE-level 5 automation (Litman, 2020).

Today, current vehicles arguably have SAE-levels 2 - 3 capabilities, e.g., lane centering, adaptive cruise control, and self-parking, among others (Domonoske, 2019). Regarding the current status of development globally, there are currently in the European Union approximately 100 activities, projects, and field trials in the domain of Automated Road Transport (CAD-EU, 2020). Furthermore, prominent car manufacturers are also developing AVs, with Renault and Tesla being some of the most prominent actors (Harris, 2020).

Harris (2020) mentions that no companies are offering fully autonomous vehicles, but the technology is in the works. Based on Litman (2020), AVs need to go through several stages to become widely commercially available due to the vehicles possibly imposing high external costs and, as a result, have stricter regulations than other technological innovations. To emphasize his point, Litman (2020) shows a chart in his article that shows how long it took for automobiles to become the dominant travel mode where saturation was not met until the 1980s, 72 years after automobile production started. Litman (2020) predicts that SAE-level 5 vehicles will not be commercially available before 2030. By 2045, given the availability of buying SAE-level 5 vehicles, it is estimated that 40% of vehicle travel could be autonomous (Litman, 2020).

The prospects of deployment and the potential penetration rates vary from country to country. In Norway, it is possible to apply for testing of self-driving vehicles on public roads (Hansson, 2020). Although it is possible to apply and get a permit to test, only five projects have been accepted (Hansson, 2020). Four out of five projects are self-driving minibusses, limited to only driving on given road sections, in addition to having a human present who monitors at all times. (Valle, 2020)

As for many other countries, Norway's legislation shows the interest of slowly incorporating AVs in its transportation system. The Norwegian Public Road Administration is working on how regulations could be changed to slowly start moving the driver's responsibility to the vehicle itself. Part of this work is first to identify which sections that could qualify for SAE-level 3 automation. (Valle, 2020)

As mentioned in the first paragraph and further supported in the following paragraphs, there will not be an SAE-level 5 AV ready-to-order soon, even though there are reports on tests of SAE-level 4 and 5 projects in the real world. That is why virtual testing is getting more critical. As quoted from Luca Castignani in an article published in the Automotive world about the development and testing of AVs, *"AI is something that lives and breathes in computers. The right place to build, train and validate this technology is the computer."* (Hunsley, 2020)

1.4 Microsimulation

To better understand, modify, and model potential AVs behavior and analyze their interaction and differences with the default human vehicles, it was chosen to build the experiment in a microscopic traffic simulation.

A microsimulation analyzes traffic flow based on the modeling of individual vehicles and their interaction with each other. Individual vehicles mean a detailed description of each vehicle and its driving characteristics. Alternatively, a macroscopic or mesoscopic simulation model could fit, where one would look at traffic streams or groups of vehicles, respectively. In other words, the level of detail is lower. Figure 1.2 shows a visual representation of the difference between microscopic, mesoscopic, and macroscopic models.

1.4.1 Aimsun Next

Aimsun Next enables the modeling of macroscopic, mesoscopic, and microscopic experiments. The software allows the user to assess traffic operations at any scale

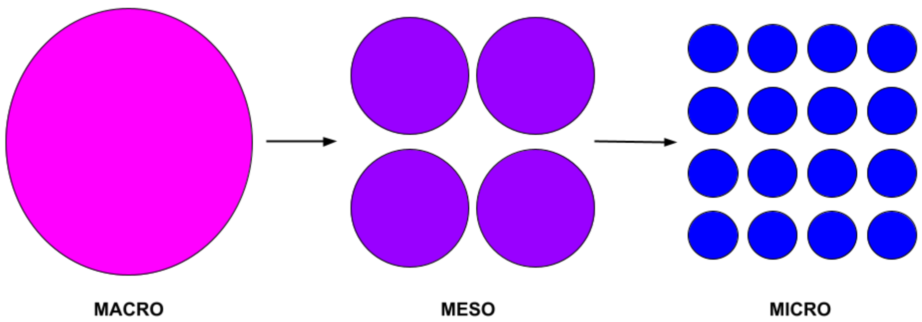


Figure 1.2: Visual representation of macro-, meso and microscopic level.

and complexity, possibly to model anything from a single intersection to an entire region.

AIMSUN was chosen as the microsimulation tool due to the software's high credibility globally, with over 7000 professionals in over 90 countries using the software (Aimsun, 2020c). The software was also mainly chosen due to its extendibility. Extendibility refers to the user being allowed to extend the software using programming tools at five different levels. For the purposes of this article, only two of these levels have been relevant. These two level are;

- microSDK (micro Software Development Kit)
- V2X SDK (Vechicle to Everything Software Development Kit)

These two levels have been the most relevant because they alter behavior and offer a platform to communicate between vehicles and infrastructure.

Aimsun Next 20 was released on June 25, 2020, (Aimsun, 2021b). The new software introduced many new features, e.g., the modeling of pedestrians, cyclists, and the interaction between passengers and public transport vehicles. The new software also enabled non-lane-based microsimulation, which means a new car-following model capable of modeling the movement of vehicles that do not follow lane markings, like cyclists and motorcyclists. The most relevant implementations to this thesis were the ACC and CACC car-following models developed by the PATH research group at UC Berkeley. (Aimsun, 2020d)

1.5 Case Study

A fictitious case study was chosen for the simulation, created in AIMSUN, to avoid unnecessary complexity and uncertainties that come with an actual location. The case study design intends to force merging before a lane-drop, which then provides the opportunity to study the performance of the car-following models and parameter settings. The infrastructure in the case study is a lane drop in a bottleneck at a two-lane highway. Additionally, there are ramps on and off the highway before the lane drop. These ramps connect to roundabouts on each side of the highway. Furthermore, the roundabouts connect to a two-lane secondary road that crosses the highway perpendicularly.

1.6 Research Questions

There is limited experience in Norway with modeling of AVs in a simulated environment, to the best of our knowledge. However, there have been reports on this elsewhere. We want to explore further how to simulate AVs given future expectations and previous research. We want to design a suitable simulation environment in which to test and evaluate the AVs. The following initial research questions are:

1. How to model automated vehicles in AIMSUN?

   The list below includes several sub-questions to help answer and provide structure to the research questions.

   (a) How do the car-following models affect the behavior of AVs and how to implement them?

   (b) How to adjust the parameters of different vehicles to reflect AVs?

   (c) What kind of effect should the AVs induce based on the future expectations?

   (d) How does the SAE-levels of automation reflect the simulated AVs?

2. How to simulate and evaluate the performance of AVs?

   (a) What infrastructure design may be suitable to investigate the performance of simulated AVs?

   (b) How to model the transition phase of AVs?

(c) How to measure the performance of simulated vehicles?

(d) Which indicators are suitable to measure the performance of the system and the bottleneck in particular?

1.7 Limitations

The major limitations of this thesis are listed below.

- Time
- Behaviour prediction
- Programming experience

Behavior prediction is challenging, especially with AVs. Therefore, simulations have been conducted with different types of AVs to account for several possible future scenarios regarding the automated vehicle fleet. The simulations use varying penetration rates of AVs to account for the transition period from most vehicles being human-controlled to automated. Two of the car-following models required programming before implementation in Aimsun Next. The authors have limited programming experience and none regarding the particular programming language used for the car-following models. It turned out to be complex and time-consuming to program other possible applications. Even though AIMSUN provided the V2X Software Development Kit, the simulations had no V2X functionalities due to limited time and complex programming.

1.8 Experiences with Collaborative Writing

We were two authors working together on this thesis, and it is a product of a well-functioning collaboration. The most crucial aspect to consider, to make the collaboration a success, is to consider the other and actively try to make the cooperation work. If both participants facilitate the need of the other part, then the cooperation can be a success. Therefore, it is essential early on to draw out the way forward by stating the ambitions, thoughts on how the work process could be, cooperation strategy, and needs of the participants.

The main advantage of collaboration, as we see it, is to have in-depth discussions on the thesis. It may be challenging to get proper feedback when writing alone, as no one else has in-depth knowledge regarding the thesis. Fellow students of ours wrote alone and expressed frustration about not being able to discuss with anyone daily. Another advantage of being two on a thesis is the efficiency when one can work on separate matters simultaneously and cover more over a shorter period. Finally, regular meetings and updates on the work process help keep the thesis on schedule.

The disadvantages of writing in pairs are that it may be more time-consuming to implement ideas when discussing them with the partner first. The authors may also have different writing styles, which must be dealt with before submission to make the thesis coherent. Finally, a downside to separating the work process is that one author may not acquire a satisfying knowledge base on the other author's matters.

Two of the thesis' main parts were to program the car-following models and design the simulation framework. We chose to focus on one part each but assisting each other when necessary. That way, we developed a deeper understanding of separate matters and combined the knowledge to design the full simulation set up together. We worked collectively for the remainder of the thesis. The author's contributions were as follows: programming and implementation of AVs: Pedersen; study design: Ims; analysis and interpretation of results: Ims and Pedersen; draft manuscript preparation: Ims and Pedersen.

2 Future Expectations of Automated Vehicles

Before answering the questions regarding the modeling of AVs in a simulation environment, it is essential to address and assess what one could expect from AVs both in the long- and short term, potential issues, and the level of uncertainty.

2.1 Predictions of implementation

It is uncertain what effects AVs will induce on the mobility system, as mentioned in section 1.3 on page 16. The uncertainty is partly due to the lack of existing SAE-levels 3 - 5 AVs, but mainly as the exhibit's behavior is unclear and inconclusive. It is essential to understand that there will not be a definitive answer to the behavior as an automated vehicle is not a static thing but rather dynamic, emphasizing the importance of differentiating between the different automation levels as suggested by SAE (2018a).

An article written by Martínez-Díaz and Soriguera (2018) presents theoretical and practical challenges for AVs. The article concludes that SAE-levels 3 and 4 most likely be available in the short term through an extensive literature review, whereas SAE-level 5, for the longer term. Mainly due to the technology, and especially before one can achieve an effective penetration rate (Martínez-Díaz and Soriguera, 2018). Predictions from literature found on AV implementation collected by Martínez-Díaz and Soriguera (2018) can be seen below in table 2.1. (Martínez-Díaz and Soriguera, 2018)

Table 2.1: AV implementation previsions.

Source: (Martínez-Díaz and Soriguera, 2018)

Source	**SAE4-level**	**SAE5-level**	**CAVs environment**
Underwood, 2014	2019-2024	2025-2035	2040-2060
Godsmark, 2015	2020	2020-2025	2020-2030
Shladover, 2016	2020-2030	2075	?
Zmud, 2017	2021	2025-2030	?
Bloomsberg, 2017	2018-2020	2028-2030	2040-2060
Litman, 2018	2020-2030	2020-2040	2060-2080
Kuhnert, 2018	2020-2030	2025-2030	?
Gehrke, 2018	2018-2021	2018-2021	2040-2050
SSCTCC, 2018	2018-2020	2040-2050	2040-2060
Shaheen, 2018	2018-2021	2023-2040	2045-2070

Note: CAVs Environment refer to vehicle cooperation

Calvert et al. (2017) comments on the issue of estimating the uptake of automated technology, referring to the dependency on factors, e.g., technological development, regulatory incentives, or barriers and economic development (Calvert et al., 2017). Even if the technology is available, the amount of time it will take before it has achieved a significant penetration rate is long.

Figure 2.1 shows the predictions of implementation made by Calvert et al. (2017) based on estimates from academia, industry, and government. ACC + LCA (Lane Change Assistant) could correspond to SAE-Level 2, "High Automation", SAE-level 3 - 4, and "Full Automation" as SAE-level 5.

The research article emphasizes that vehicle cooperation most likely will lag, recommending estimation of vehicle automation not to depend too heavily on the presence of cooperative technology (Calvert et al., 2017). However, not having a cooperative environment does not necessarily mean "no communication." Vehicles might communicate with each other and infrastructure. However, they cannot use the information they send or receive due to strict protocols and privacy issues.

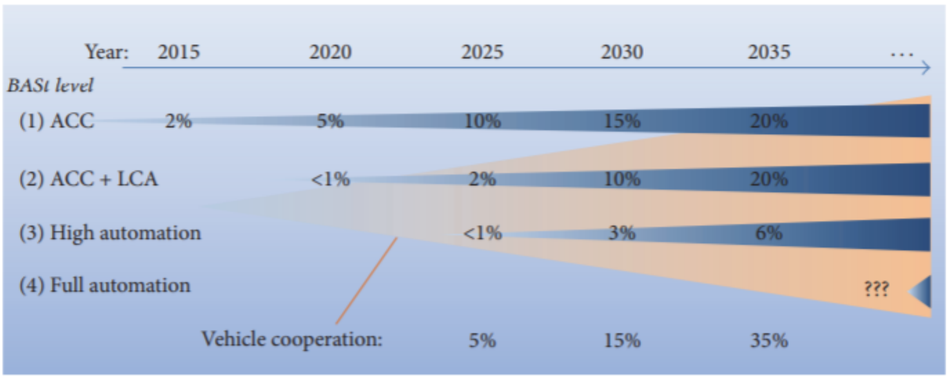


Figure 2.1: Estimated share of AVs on roads.

Source: (Calvert et al., 2017)

2.2 Communication and trust

Although the in-vehicle technology is expected to be substantial, Martínez-Díaz and Soriguera (2018) states that it will not lead to efficient and safe mobility due to the need for a cooperative environment. However, to achieve a cooperative environment is a challenging task as it depends on infrastructure improvements and, maybe most importantly, has to be safe and reliable (Martínez-Díaz and Soriguera, 2018).

Oliveira et al. (2019) points out other challenges with both the in-vehicle technology and the possible exchange of information in a cooperative environment. One of the challenges is the lack of trust and acceptance the vehicle would get because of the occupants not understanding the driving or decisions made (Oliveira et al., 2019). This also yields for human drivers interacting with the AVs. The article further points out that although simulations and real-life experiments have been conducted with AVs in mixed traffic conditions, no research has tested the interaction between AVs built on different systems (Oliveira et al., 2019).

In terms of driving style and behavior, Oliveira et al. (2019) (based on a qualitative study on trust and acceptance for AVs) found that AVs need to control the steering and speed precisely in order for it to achieve a smooth and comfortable ride, similar to when humans drive. It says here *"as humans drive,"* but based on an analysis of preferences for different automated driving styles, it concludes that preferred AV behavior might not correspond to human driving behavior. (Oliveira et al., 2019).

How the AV should act, drive or adapt to situations when implemented in a real-life road environment is complicated. The answer might be subjective in the same way manual driving behavior is. Some want to be aggressive and accept a more uncomfortable ride, while others a smoother ride, accepting a more cautious and conservative behavior.

Müller et al. (2016) mentions in a paper the social dimension of driving (Müller et al., 2016). The dimensions encompass predictions and assessments of the behavior of AVs and other road users. To clarify the problem, Müller et al. (2016) mentions a case where there is a pedestrian crossing. Pedestrians might walk faster if they see the car is waiting, but what will happen if the same car waiting is an AV? Will they walk faster, or will they walk at "normal speed" as the passenger in the vehicle might not be paying attention

(Müller et al., 2016)? Humans being insecure about the behavior of an AV might be a problem in the transition phase, as they will not be able to know to what extent another vehicle is automated. This can lead to pedestrians and human vehicles causing delay and potentially unsafe situations (EUS, 2018).

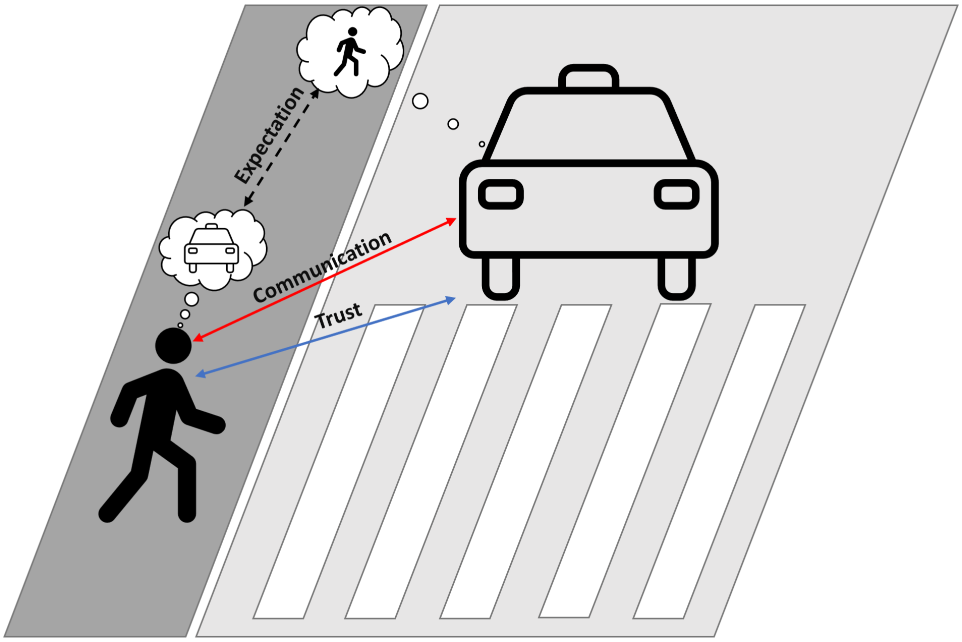


Figure 2.2: Complicated interaction between AV and Pedestrian.

The challenge of communication goes both ways as understanding and adapting to human behavior is challenging for a machine. As Müller et al. (2016) says, this leads to current prototypes being extra careful, as *"it"* is too afraid to make mistakes. Social behavior and understanding might be problems when an AV wants to turn left in a busy non-signalized intersection. To get a gap in which the AV would be allowed to turn can be a challenge, and if it were a human driver, it could get the gap through a simple nod, lights, or horn from the other driver in the opposite lane. How will the AV understand this as being a signal for it being allowed to turn compared to a human driver (Müller et al., 2016)?

2.3 Standardized System

The communication between the AVs and other road users is complex. It can get even more complicated as AVs will not be manufactured or developed by one company, leading to different compositions. In addition, the AVs could have different driving styles and logical rules. Therefore, a suggested standardized system seeks to avoid the possible amount of confusion between AVs and other road users.

Intel (2019) suggests an RSS system (Responsible-Sensitive Safety), a compatible system for any automated driving system. It is formalized on the human notions of safe driving. In other words, a system that is verifiable and exhibits behavior that humans characterize as safe driving. The system's purpose is that humans will accept the AVs and not be annoyed by the potential cautious behavior they could have. (Intel, 2019)

The article lists two types of rules on the road that drivers are taught and, over time, experienced. These are;

1. Explicit rules
2. Implicit rules

Explicit rules usually cannot be misinterpreted and are shown on the road section or intersection with signs, lines, or lights. *Implicit rules* are not shown on any signs but lean on common sense and vary between different cultures. For an AV, explicit rules are *"easy"* unlike implicit which cannot directly be retrieved with technology's help. Why it is so tricky is partly explained in section 2.2 on page 25.

The proposed RSS system is supposed to give a framework for the digitization of these implicit rules. It is meant to formalize safe driving based on human notions with mathematical formulas and logical rules. The keyword is safety, and with an RSS system, the goal is that the AV will not cause any accidents and compensate for the mistakes of others. Intel (2019) says that the system is compatible with any automated driving system, which possibly allows for an AV safety standard. Intel (2019) further states the system can make cautious but assertive maneuvers, unlike decision models based on Artificial Intelligence (AI). These are often too conservative and could lead to increased delay, and therefore the technology is not being accepted by human road users.

To accomplish the goals set, RSS has five safety principles:

1. Do not hit the car in front (longitudinal distance)
2. Do not cut in recklessly (lateral distance)
3. Right of way is given, not taken
4. Be cautious in areas with limited visibility
5. If the vehicle can avoid a crash without causing another one, it must

(Intel, 2019)

2.4 Consumer Expectations

Consulting firm Capgemini published a report in 2019 on a survey they did that investigated what consumers expect from AVs and how well prepared the industry is to cope with these expectations (Buvat, 2019). The survey had 5 500 consumers participating across six nations. Figure 2.3 shows what respondents answered when asked to name emotions invoked in them by the thought of a self-driving car. The figure shows the difference in response from each of the six nationalities represented in the survey.

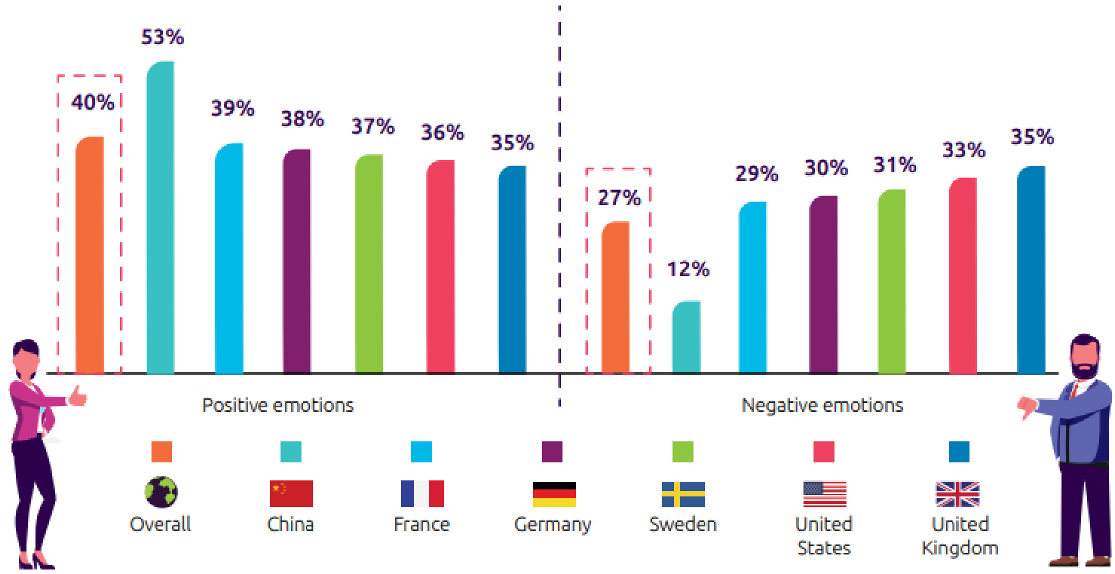


Figure 2.3: Emotions invoked by an automated car – by country.

Source: (Buvat, 2019)

The response shown in figure 2.3 implies that Chinese consumers are more optimistic about AVs. The Head of Autonomous Driving/Connected Car and Services and New Business Models at Volkswagen China Group, Borjana Lambreva, explains why Chinese consumers may, to a greater extent, accept AVs (Buvat, 2019). *"There are cultural and geographic differences that could drive higher adoption for self-driving cars in the Chinese market, (...). (...) In the Chinese market, more consumers prefer not to drive themselves, given the nature of the roads. In other markets, like the US and Continental Europe, many consumers may still enjoy driving."*

Figure 2.4 show that the acceptance for AVs seem to increase over time. Moreover, Chinese consumers claim to be more acceptable today and ten years into the future from 2019, than consumers from the other five nations. Additional findings suggest consumers (31%)

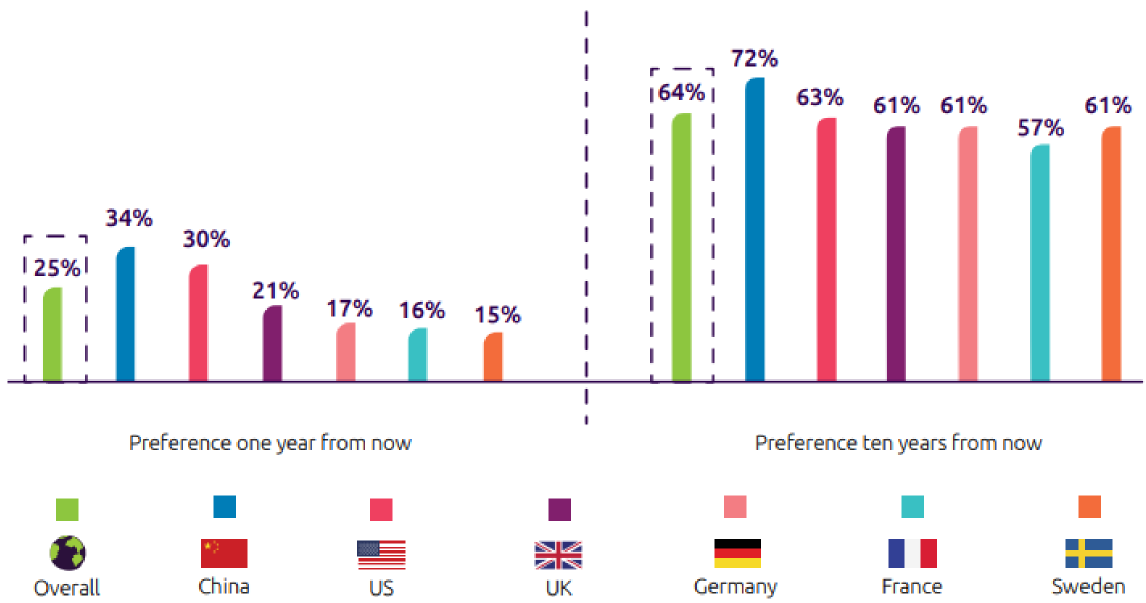


Figure 2.4: Preference of consumers to ride in automated cars over current human-driven vehicles – today and ten years into the future from 2019.

Source: (Buvat, 2019)

expect reduced traffic congestion due to the implementation of self-driving vehicles. A study from Rutgers University found that AVs can reduce stop-and-go traffic created by human drivers changing lanes. Nonetheless, another study suggests that AVs can make traffic worse. That is because it would more economic to have an empty AV drive around without a destination rather than having it parked.(Buvat, 2019). Taking parked AVs onto the road could make traffic worse by increasing the number of vehicles driving.

A study from 2019 highlights the problem that the public perception of AVs may be inaccurately displayed in surveys conducted until today (Penmetsa et al., 2019). The study points out that only a few of the participants of previous surveys have experienced direct interactions with AVs. Such absence of experience may lead to consumers not being prepared for the arrival of the technology and thus over-or underestimate the consequences related to the implementation of AVs. Moreover, past surveys may have ignored the expectations and attitudes towards AVs from vulnerable users, e.g., cyclists and pedestrians.

3 Theory

This chapter presents relevant theories regarding the modeling of different AVs, mainly the implemented car-following models. The first section explains the basic concepts of vehicle behavior in microsimulation models. Then, in the following sections, theory on the relevant car-following models, V2X, and merging will be presented.

3.1 Car-following and lane-changing

Car-following- and lane-changing models are examples of microscopic models. A car-following model explains how the subject vehicle accelerates, decelerates, and controls the gap to the vehicle directly in front of it (longitudinal direction). The following models incorporate several variables and parameters, e.g., vehicle speed, acceleration, and distance to adjacent vehicles. Relevant notations and measurements used in car-following models are illustrated in figure 3.1, and explanations to the notations are provided in the nomenclature. For clarification, the gap is measured front-back and headway front-front, as seen in figure 3.1. The time measurements are th_i and tg_i, for headway and gap, respectively, as shown in table 3.1. (Aakre, 2019b)

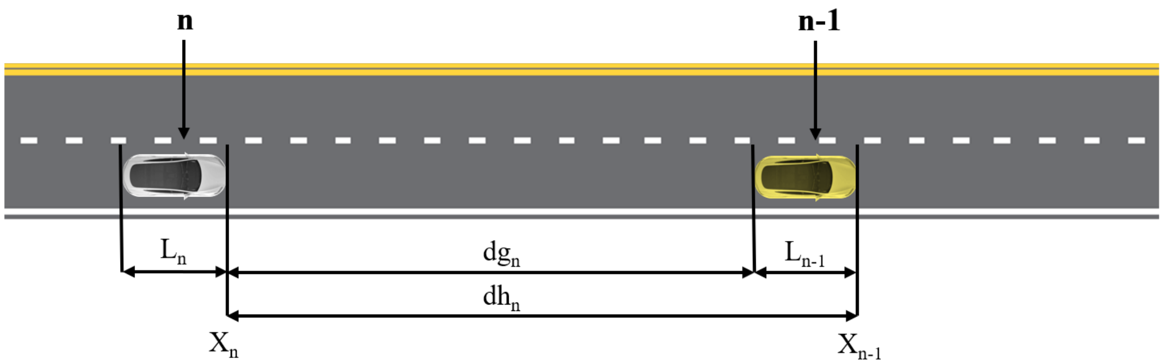


Figure 3.1: Notations for position, distance headway and gap for vehicle n and $n-1$.

A lane-changing model describes the lateral movement of the vehicle. How, when, and what kind of approach it has to choose lanes. Logical rules and assessments tell the lane-changing model if it will change lanes or not depending on the situation. Questions the vehicle could ask itself are; Is the speed difference acceptable? Is it safe and possible to make a lane change?

Table 3.1: "Safe" time headway and gap.

Variable	Formula
Point speed	$u_i = \frac{dx_{i,j}}{dt_i}$
Time headway	$th_i = \frac{dh_i}{u_i}$
Time gap	$tg_i = \frac{dg_i}{u_i}$
"Safe" distance gap	$dg_i \geq$ speed $\cdot$ reaction time
"Safe" time gap	$tg_i \geq$ reaction time

A majority of models classify lane-changing models as either mandatory or discretionary. Mandatory is when one has to change lanes to follow a given route or path. To clarify, it will change lanes because *"it has to."* When discretionary, it will change lanes because the vehicle believes that it will offer an improved traffic condition. An illustration of mandatory- and discretionary lane change is shown i figure 3.2 and 3.3, respectively. (Ben-Akiva et al., 2005)

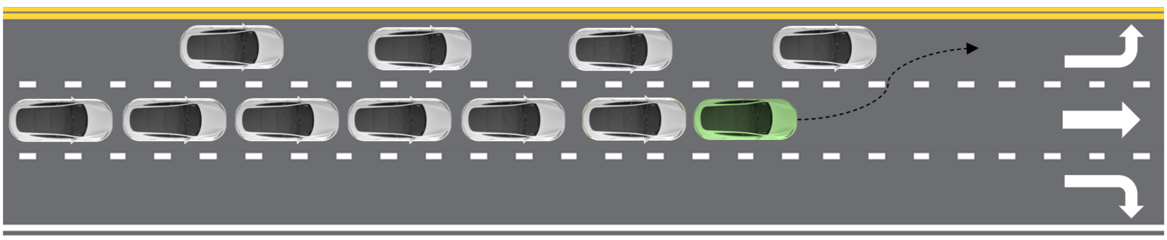


Figure 3.2: Mandatory Lane Change. The green vehicle has to go to the left, so it waits for an acceptable gap.

Within the lane-changing models are gap-acceptance models where available gaps are compared to the minimum gap (critical gap). Lane change is executed if the gap is greater than this minimum value. Figure 3.4 shows a generic structure of lane-changing models. (Ben-Akiva et al., 2005)

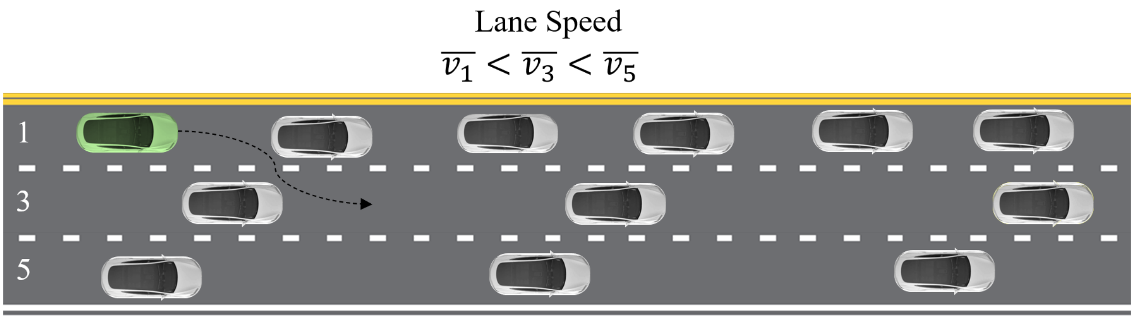


Figure 3.3: Discretionary lane change. The green vehicle wants to change lane due to higher mean speed in lane 3.

3.2 Gipps's model - Default model

AIMSUN bases its car-following behavior on Gipps' model, with modifications and additions, e.g., cooperation between vehicles (Aimsun, 2020a).

The model sets limits to both the driver and the vehicle's performance, and the model calculates the "safe" speed for vehicle n, concerning vehicle $n-1$. The model also applies a set of constraints to the vehicle behavior. The first one prevents vehicle n from exceeding its desired speed, while it also decreases acceleration when approaching desired speed. The model introduces a safety parameter limiting the braking and makes the vehicle n gradually brake to a complete stop instead of applying maximum braking. The model assumes that a driver selects his speed to a desired braking rate but can brake harder if necessary. Two constraints adapt the speed of vehicle n to the flow of traffic, where the degree of congestion determines which constraint is applied. The model design allows disruptive behavior for vehicle n if surrounding vehicles behave aggressively. Examples of disruptive behavior are; vehicle $n-1$ brakes harder than expected, leaves the lane, or another vehicle enters a tight gap. Real-life traffic often displays this kind of behavior. (Gipps, 1981)

All vehicles in the model are in either two modes, free driving or restricted driving. The desired speed (equation 3.1) and vehicle characteristics form the base for the free driving speed (equation 3.2). The vehicle bases its restricted driving speed (equation 3.3) on the "safe" distance to the vehicle $n-1$, enabling vehicle n to react to any typical maneuver without collision safely. The software combines equations 3.1, 3.2, and 3.3 to calculate

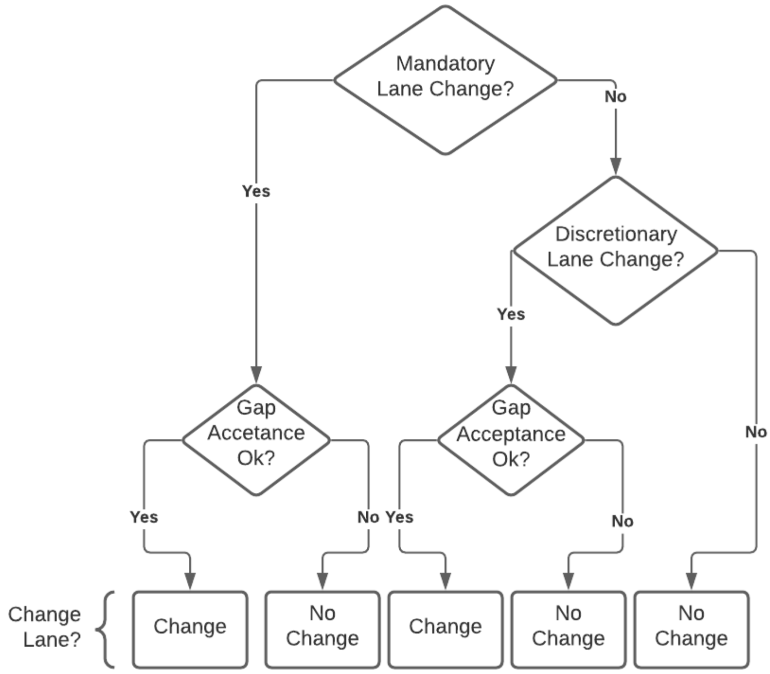


Figure 3.4: Generic structure of lane-changing models.

the vehicle's speed and position using equations 3.4 and 3.5, respectively. All calculations are updated every fixed time interval. (Aakre, 2019a)

Desired speed, v_{des}**:**

$$V_{des}(n,s) = min\Bigg(\Big(v_{lim}(s)\cdot\theta(n)\Big),\ \Big(v_{max}(n)\Big)\Bigg) \tag{3.1}$$

Where,

$v_{lim}(s)$	Speed limit on section s
$\theta(n)$	Acceptance of speed limit for vehicle n
$v_{max}(n)$	Maximum desired speed for vehicle n

The desired speed for the driver of vehicle n is the minimum value of:

- Maximum desired speed
- The product of speed limit and acceptance of speed limit

Figure 3.5 visualizes a possible scenario. A vehicle will drive at desired speed if the product of the speed limit and acceptance for the speed limit is higher than the desired speed.

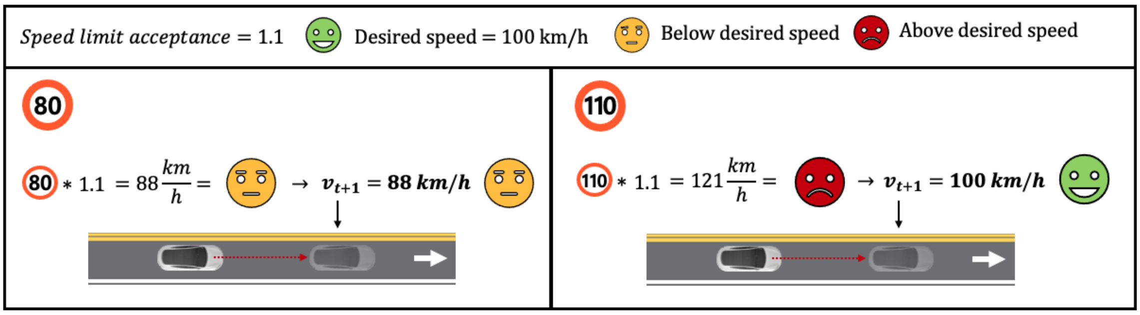


Figure 3.5: Desired speed.

Free Flow Speed, v_a:

$$v_a(n, t+T) = v(n,t) + 2.5 \cdot a(n) \cdot T \cdot \left(1 - \frac{v_n(t)}{v_{des}(n)}\right)\sqrt{0.025 + \frac{v(n,t)}{v_{des}(n)}} \tag{3.2}$$

Where,

$v_a(n, t+T)$	Max speed vehicle n can accelerate to during time interval $(t,t+T)$
$v(n,t)$	Speed for vehicle n at time t
$a(n)$	Max acceleration for vehicle n
T	Reaction time (often equal to simulation step)
$v_{des}(n)$	Desired speed for vehicle n

Equation 3.2 calculates the maximum speed vehicle n may accelerate to during the following time interval, at free-flow conditions shown in figure 3.6a. Such conditions occur when there is freedom to maneuver the car and good traffic flow quality. (Aakre, 2019b)

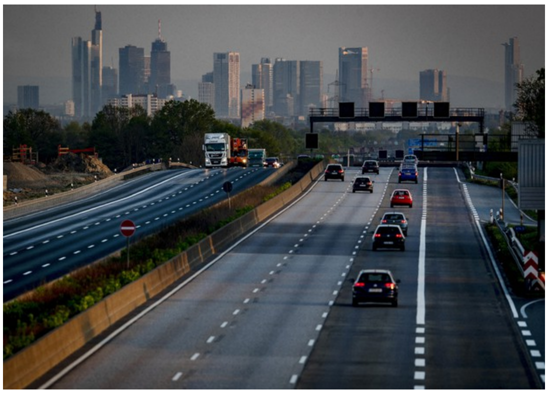
Restricted Speed, v_d:

$$v_d(n, t+T) = d(n) \cdot T \cdot \sqrt{d(n)^2 \cdot T^2 - d(n) \cdot \left[2g(n,t) - v(n,t) \cdot T - \frac{v(n-1,t)^2}{d(n-1)}\right]} \tag{3.3}$$

Where,

$v_d(n, t+T)$	Max safe speed for vehicle n in the next time interval $(t+T)$
$d(n)$	Max deceleration for vehicle n
$d(n-1)$	Max deceleration for vehicle $n-1$
$g(n,t)$	Distance gap between vehicle n and $n-1$
$v(n,t)$	Speed for vehicle n at time t
$v(n-1,t)$	Speed for vehicle $n-1$ at time t

Equation 3.3 calculates the maximum safe speed for vehicle n in the next time interval when the vehicle is not at free-flow conditions. There is limited freedom to maneuver the vehicle at such conditions, and the behavior of any vehicle depends on other vehicles in the traffic stream, as shown in figure 3.6b. The equation depends on the behavior of vehicle $n-1$, e.g., maximum acceleration, distance gap, and speed. To compare, equation 3.2 for free-flow speed only depends on the behavior of vehicle n.



(a) Free traffic flow.

Source: (Manichi, 2020)

(b) Slow moving queue.

Source: (Chen and Rana, 2019)

Figure 3.6: Traffic flow conditions.

From equations 3.1, 3.2 and 3.3, we have;

$v_{des}(n,s)$	Desired speed (Equation 3.1)
$v_a(n,t+T)$	Free flow speed (Equation 3.2) (dependent on desired speed)
$v_d(n,t+T)$	Restricted speed (Equation 3.3)

From this, the speed and position of vehicle n at time $t+T$ is calculated,d.

Speed of vehicle n at time $t+T$:

$$v(n,t+T) = min\Big(v_a(n,t+T),\ v_d(n,t+T)\Big) \tag{3.4}$$

Position of vehicle n at time $t+T$:

$$x(n,t+T) = x(n,t) + v(n,t+T)\cdot T \tag{3.5}$$

The output in equation 3.4 is the minimum value of restricted and free-flow speed. The input in equation 3.5 is position at time t and the product of reaction time and speed of vehicle n at time t+T. Figure 3.7 illustrates the situation that equation 3.5 represents.

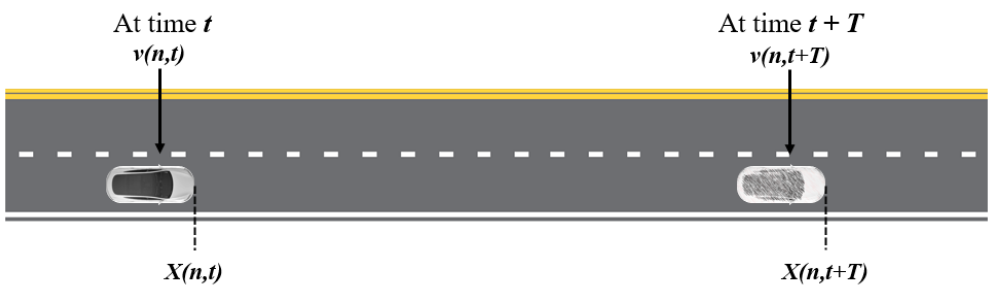


Figure 3.7: Position at time $t+T$.

3.3 Intelligent Driver Model - IDM

The Intelligent Driver Model is a car-following model developed by Treiber et al. and published in year 2000. Treiber et al. (2000) introduced the model because it was less complex than other existing models, had no asymmetric accelerations, and did not lose real properties in the deterministic limit. According to Treiber et al. (2000), the other models showed no traffic instabilities for vanishing fluctuations. There were not any hysteresis effects either, which are delayed effects from an external source (Treiber et al., 2000).

Treiber et al. (2000) listed following advantages of the IDM-model:

- Accident-free behavior because of the dependence on the relative velocity.
- Because of its metastability, the model shows self-organized traffic constants, hysteresis effects, and complex states.
- All model parameters have a reasonable interpretation that is known to be relevant, are empirically measurable and have the expected order of magnitude.
- The fundamental diagram and the stability properties of the model can easily be calibrated to empirical data.
- Allows for fast numerical simulation.
- An equivalent macroscopic model is known, which according to Treiber et al. is not the case for most other microscopic traffic models.

(Treiber et al., 2000)

The formula for the IDM, is shown in equation 3.6 and 3.7. Acceleration is determined by the desired speed and time gap in equation 3.6. The desired gap is a function of the speed and speed difference in equation 3.7.

$$a_n^t = a_n \left[1 - \left(\frac{V_n^t}{V_n^*} \right)^4 - \left(\frac{s^*(V_n^t, \Delta V_n^t)}{s_n^t} \right)^2 \right] \tag{3.6}$$

$$s^*(V_n^t, \Delta V_n^t) = s_0 + V_n^t \cdot T + \frac{V_n^t \cdot \Delta V_n^t}{2\sqrt{a_n \cdot b_n}} \tag{3.7}$$

Where,

a_n^t	Acceleration of the n^{th} vehicle at time t
a_n	Maximum acceleration of the n^{th} vehicle
V_n^t	Actual speed of the n^{th} vehicle at time t
V_n^*	Desired speed of the n^{th} vehicle
s_n^t	Actual gap of the n^{th} vehicle to the $n-1$ vehicle
$s^*(V_n^t, \Delta V_n^t)$	Desired gap for the n^{th} vehicle.
s_0	Minimum gap

$1 - (V_n^t/V_n^*)^4$ in equation 3.6 is the accelerating term towards the desired speed V_n^* on a free-flow road, whereas $-(s^*(V_n^t, \Delta V_n^t)/s_n^t)^2$ refers to the braking term. s_0 in equation 3.7 exists primarily for when the vehicle is traveling with a low velocity.

IDM was proposed as an ACC controller by Kesting et al. (2008) due to the model being collision-free, corresponding to a natural and smooth manner of driving, and few parameters with an intuitive meaning (Kesting et al., 2008). Yu et al. (2019) incorporated the Intelligent Driving Model via the microSDK in AIMSUN. The IDM was incorporated for continuity purposes with previous studies, e.g., the study published by Kesting et al. (2008), as well as for the two main characteristics of AVs:

1. Longitudinal movement of the AV is governed by the predefined desired speed and the time gap, which correlates with how simple ACC-systems work.

2. The movement of AVs should be controlled only using the information it can acquire.

(Yu et al., 2019)

Yu et al. (2019) further supports the choice by saying that the long-range radar, which the ACC-installed vehicles usually have, can only measure the relative speed and distance to the preceding vehicle. Other parameters which the Gipps model has cannot be measured (Yu et al., 2019). Perraki et al. (2018) also used the IDM when assuming the longitudinal behavior of ACC vehicles, mainly due to the same reasons Kesting et al. (2008) listed.

3.4 Ehanced Intelligent Driver Model - EIDM

Kesting et al. (2010) introduced the EIDM (Enhanced Intelligent Driver Mode) due to the IDM "overreacting" in some cases. From equation 3.6, this happens when the desired gap is higher than the actual gap and low-velocity differences. The "overreaction" might, in some cases, be correct. However, as Kesting et al. (2010) claims, a human driver would not initiate a complete stop without reason, as the situation would be considered only mildly critical. This could be in a cut-in situation or braking at an intersection.

Kesting et al. (2010) wanted to introduce the more optimistic view of mildly critical judgments by introducing a constant-acceleration heuristic (CAH). Kesting et al. (2010) bases the CAH on three assumptions:

1. The accelerations of the considered and leading vehicle will not change in the relevant future.
2. No safe time headway or minimum distance is required at any moment.
3. Drivers react without delay (zero reaction time).

(Kesting et al., 2010)

The CAH tells in simple terms whether a situation requires critical braking or not, and EIDM incorporates this in the final formula. The formula for CAH and EIDM can be seen in equations 3.8 and 3.9, respectively.

$$a_{CAH}(s, v, v_1, a_1) = \begin{cases} \frac{v^2 \tilde{a}_l}{v_1^2 - 2s\tilde{a}_l}, & \text{if } v_1(v - v_1) \leq -2s\tilde{a}_l \\ \tilde{a}_l - \frac{(v-v_1)^2 \Theta(v-v_1)}{2s}, & \text{otherwise} \end{cases} \tag{3.8}$$

$$a_{EIDM} = \begin{cases} a_{IDM}, & \text{if } a_{IDM} \geq a_{CAH} \\ (1-c)a_{IDM} + c\left[a_{CAH} + b\tanh(\frac{a_{IDM}-a_{CAH}}{b})\right], & \text{otherwise} \end{cases} \quad (3.9)$$

Where,

a_{IDM}	See equation 3.6
s	Gap distance
v	EIDM-vehicle speed
v_1	Leading vehicle speed
a_1	Leading vehicle acceleration
c	Coolness factor. Determine weihgts placed on CAH and IDM
$\Theta(x)$	Heaviside step function
$\tilde{a}_l$	Maximum of a and a_1

$v_1(v - v_1) \leq -2s\tilde{a}_l$ in equation 3.8 is true if the vehicles have stopped when they reach the minimum gap. $\Theta(v - v_1)$ is the Heaviside step function which eliminates negative approaching rates in case $v_1(v - v_1) \leq -2s\tilde{a}_l$ is not valid.

Due to the lack of minimum time headways or acceleration to the desired velocity, the CAH is not a complete car-following model. Therefore, the CAH is incorporated with the IDM to make a complete ACC controller, as shown in equation 3.9. Kesting et al. (2010) bases the ACC controller on five assumptions:

1. The ACC acceleration is never lower than that of the IDM.
2. If both the IDM and CAH produce the same acceleration; the ACC acceleration is the same as well.
3. If the IDM produces extreme decelerations, while the CAH yields accelerations greater than $-b$ (desired deceleration), the situation is considered as mildly critical. The ACC acceleration equals the comfortable deceleration plus a small fraction of the IDM acceleration due to the coolness factor c.
4. Suppose both the IDM and the CAH result in accelerations significantly below -b. In that case, the situation is seriously critical, and the ACC acceleration must not be higher than the maximum of the IDM and CAH accelerations.

5. The ACC acceleration should be a continuous and differentiable function of the IDM and CAH accelerations.

(Kesting et al., 2010)

Bailey (2016) incorporated the EIDM due to the overreaction of IDM. As well as being an enhanced version of the original IDM, Bailey (2016) claims that the model was being designed for use in semi-autonomous vehicles, and even had been implemented in test vehicles (Bailey, 2016). According to Bailey (2016), the EIDM has been shown to result in increased lane capacity with increased penetration rates, as well as holding string stability. String stability or string instability are disturbances of system states, e.g., a string of vehicles, that are either amplified or not.

3.5 ACC- and CACC Model

One of the many new features provided in Aimsun Next was the possibility of implementing ACC and CACC car-following. The PATH research group implemented these car-following models at UC Berkeley, which were based on the ones developed by Milanés and Shladover (2014) (Aimsun, 2020d; Milanés and Shladover, 2014).

The ACC/CACC model computes a vehicle's acceleration and adjusts the distance from vehicle n to $n-1$. The difference between an ACC and CACC model is that vehicles equipped with the CACC model can form and join platoons. A platoon is a group of vehicles equipped with the CACC model that communicates to safely drive closer together than vehicles not equipped with the CACC model. Figure 3.8 illustrates a platoon. A follower in a platoon is a vehicle that is not at the front of the platoon, while a leader is any other vehicle with CACC installed that is not a follower. Platoons are limited to a maximum number of vehicles. A vehicle trying to join a platoon that has reached its maximum capacity will become a new platoon leader. (Aimsun, 2020a)

A reaction time of 0.1 seconds should be set for all vehicles equipped with the ACC/CACC model. 0.1 seconds is equal to the duration of the simulation steps, suitable for simulating AVs. To compare, the reaction time of a human vehicle is approximately 0.8 seconds. The modeler activates one of the following three modes for a vehicle at all times. (Aimsun, 2020a)

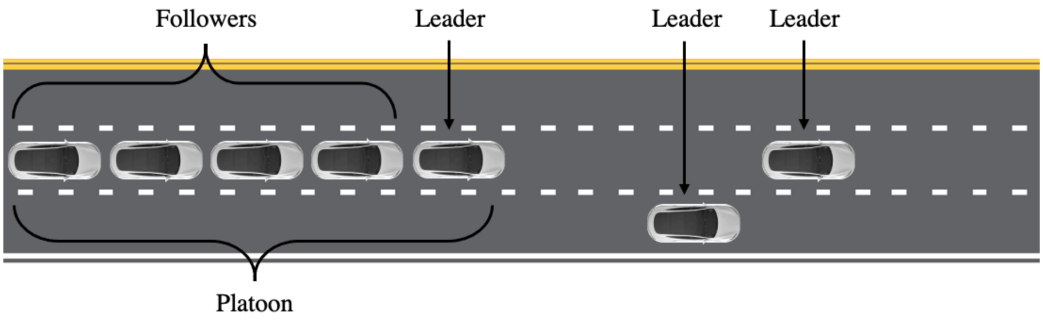


Figure 3.8: A platoon, with leader and followers.

- Speed regulation mode
- ACC Gap regulation mode
- CACC Gap regulation mode

Figures 3.9 to 3.12 illustrate all three regulation modes. Equation 3.10, 3.11, or 3.15 calculates the acceleration of vehicle n. The equations are dependent on the situation downstream. The speed regulation mode is active for vehicle n whenever there is no vehicle within the range, shown in figure 3.9. If vehicle $n-1$ is within the range, vehicle n will activate one of the gap regulation modes for "safe" speed adaptation to the vehicle $n-1$. Either ACC (figure 3.10) or CACC (figure 3.11) gap regulation mode can be activated, depending on which of the models vehicle n have installed. The ACC Gap regulation mode is activated whenever a vehicle is within range of vehicle n, while the CACC gap regulation mode activates for a platoon's followers. (Aimsun, 2020a)

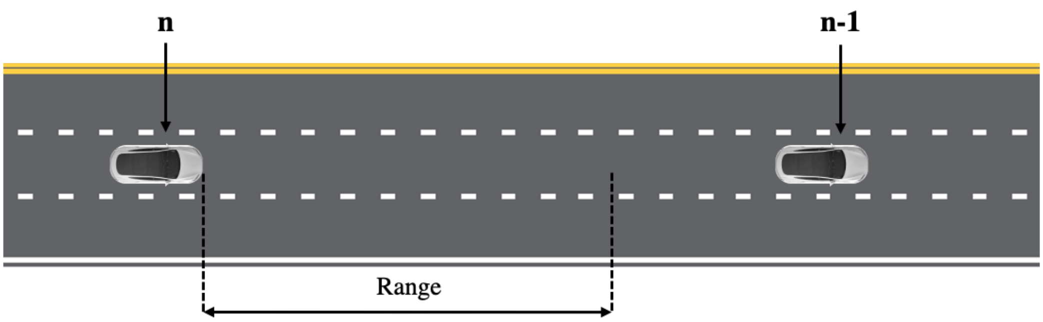


Figure 3.9: Speed regulation mode.

The formulas computing speed and gap regulation are below. Notations AIMSUN uses have been presented earlier, but some are different in equations 3.10 to 3.15. Some index changes are sv (subject vehicle) for n and l (leading vehicle) for $n-1$. (Aimsun, 2020a)

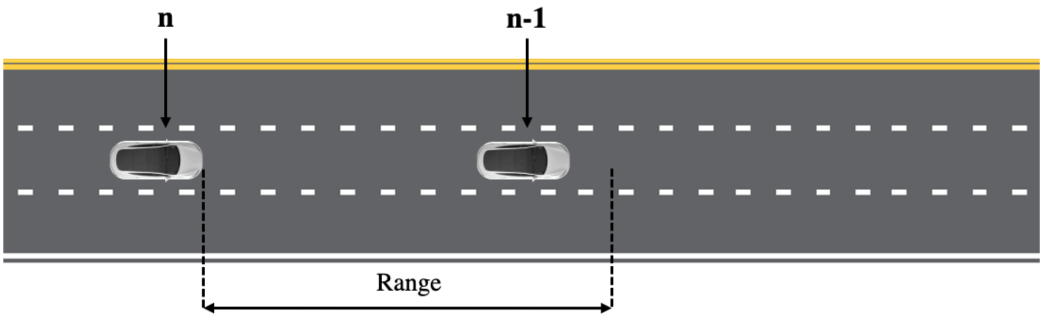


Figure 3.10: ACC Gap regulation mode.

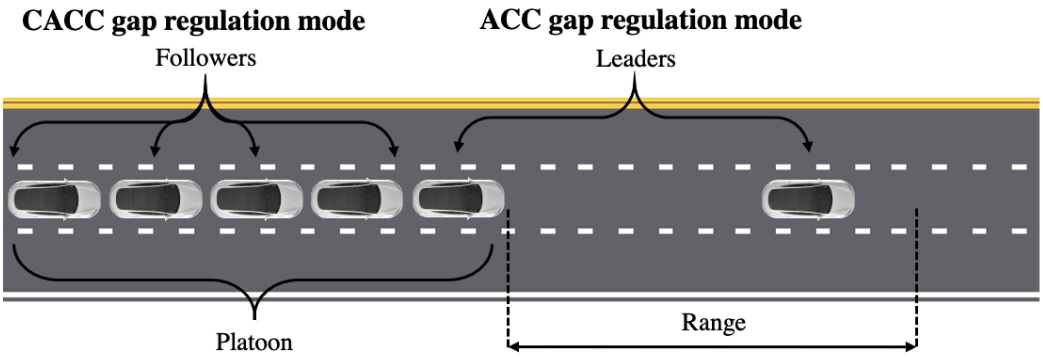


Figure 3.11: CACC Gap regulation mode.

Speed Regulation Mode

$$a_{sv} = k_1 \cdot (v_f - v_{sv}) \tag{3.10}$$

Where,

a_{sv}	Acceleration recommended by ACC controller to vehicle n
k_1	Gain in difference between free flow and current speed of vehicle n
v_f	Free flow speed for vehicle n
v_{sv}	Current speed for vehicle n

If speed regulation mode is applied to vehicle n, it will accelerate to free flow speed v_f at acceleration rate a_{sv}. The parameter k_1 adjusts the difference in free flow speed and current speed v_{sv} of vehicle n to the applied acceleration rate a_{sv}.

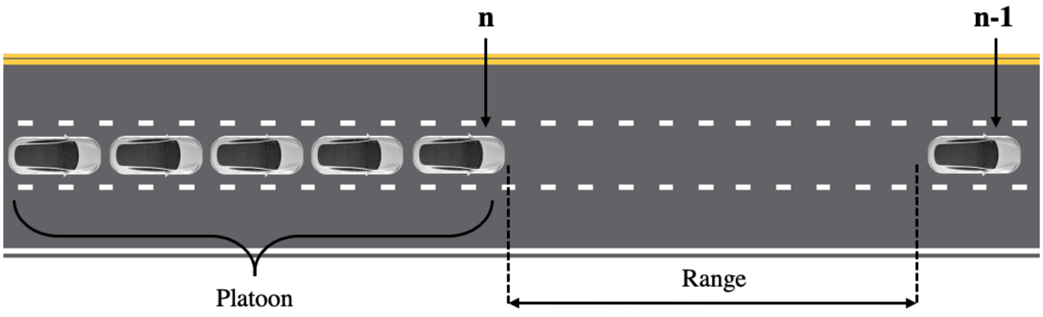


Figure 3.12: CACC Speed regulation mode.

ACC Gap Regulation Mode

$$a_{sv} = k_2 \cdot (d - t_{hw} \cdot v_{sv} - L) + k_3 \cdot (v_l - v_{sv}) \tag{3.11}$$

Where,

- k_2 Gain on position difference between vehicle n and $n-1$
- d Distance headway between vehicle n and $n-1$
- t_{hw} Desired time gap of the ACC controller between vehicle n and $n-1$
- L Length of vehicle $n-1$
- k_3 Gain on speed difference between vehicle n and $n-1$
- v_l Current speed of vehicle $n-1$

Equation 3.11 for a_{sv} is composed of two parts, $(k_2 \cdot (d - t_{hw} \cdot v_{sv} - L))$ and $(k_3 \cdot (v_l - v_{sv}))$. They account for distance and speed differences between vehicle n and $n-1$.

CACC Gap Regulation Mode

Time gap error

$$e_k(t) = d(t - \Delta t) - t_g \cdot v_{sv}(t - \Delta t) - L \tag{3.12}$$

Where,

- $d(t-\Delta t)$ Distance headway at previous time interval
- $v_{sv}(t-\Delta t)$ Speed of vehicle n at previous time step

Time gap error e_k together with k_p contributes to the current speed of vehicle n in equation 3.14, which in turn contributes to the acceleration rate of vehicle n in equation 3.15.

Speed error

$$e'_k(t) = v_l(t - \Delta t) - v_{sv}(t - \Delta t) - t_g \cdot a_{sv}(t - \Delta t) \tag{3.13}$$

Where,

$v_l(t-\Delta t)$	Speed of vehicle $n-1$ at previous time interval
Δt	Time step for each update
k_p and k_d	Gains for adjusting time gap
e_k	Time gap error
t_g	Constant time gap
$a_{sv}(t-\Delta t)$	Acceleration rate of vehicle n at previous time interval

Equation 3.13 for e'_k is composed of three parts. Both $v_l(t-\Delta t)$ and $v_{sv}(t-\Delta t)$ is the speed in the previous time interval, for vehicle $n-1$ and n, respectively. $t_g \cdot a_{sv}(t-\Delta t)$ is the additional speed vehicle n gains during the time interval t_g. e'_k will be positive, if $v_l(t-\Delta t)$ is greater than the sum of $v_{sv}(t-\Delta t)$ and $t_g \cdot a_{sv}(t-\Delta t)$.

Current Speed

$$v_{sv}(t) = v_{sv}(t-\Delta t) + k_p \cdot e_k(t) + k_d \cdot e'_k(t) \tag{3.14}$$

The current speed is greater than the speed at the previous time interval if there is excess distance and time.

Acceleration

$$a_{sv}(t) = \frac{v_{sv}(t) - v_{sv}(t-\Delta t)}{\Delta t} \tag{3.15}$$

Equation 3.15 computes the acceleration or deceleration rate of vehicle n in a platoon, incorporating the outputs from equations 3.12, 3.13, and 3.14.

Mesionis et al. (2020) incorporated the ACC- and CACC car-following models via the microSDK before AIMSUN had it implemented in the software. Mesionis et al. (2020) studied the effects of the model on the motorway M1 near Sheffield in the UK. (Mesionis et al., 2020)

3.6 V2X Software Development Kit

Vehicle-to-Everything (V2X) is a technology that enables communication between vehicles and other parts in the traffic system, both moving and non-moving parts. The V2X technology is resistant to inclement weather (Investopedia, 2020) and may provide vehicles with information to enable several applications. Some of them are listed below:

- Road work warning
- Traffic jam ahead warning
- Approaching the emergency vehicle
- Platooning
- In-vehicle signage
- Traffic info and recommended itinerary
- Green light optimal speed advisory

AIMSUN gives a technical preview of their new V2X software development kit in the newest edition of Aimsun Next (Aimsun, 2018). The kit creates communication channels at the level of vehicle, roadside unit, and traffic management center. The model does require the implementation of information-based actions for vehicles. Both the onboard unit (OBU) in the vehicle and the roadside units (RSU) require programming by the user. (Aimsun, 2021a)

3.7 Merging

National Roads Authority (NRA) on the Cayman Islands defines merging as: *"When two or more upstream lanes are connected to a single downstream lane, a merging area is defined"* (NRA, 2021). There are several types of merging; three of them are listed below.

- Priority merging
- Non-priority merging (zipper merge)
- Congestion merging

Figure 3.13 shows priority merging. One lane must yield to the other lane, as vehicles in the prioritized lane have the right of way. The vehicle yielding can only merge onto the other lane if the projected headway gap is acceptable. There should not be necessary for the prioritized vehicle to slow down. This way of merging may lead to vehicles in the yielding lane coming to a complete stop, resulting in growing queues.

Figure 3.14 shows non-prioritized merge, also called zipper merge. The principal is first-come-first-serve. NRA further explains zipper merge to *"(...) create a high potential for* *sideswipes and rear-end accidents thus careful communication and knowledge of merging practices is essential."* Congestion merging should occur as late merging, close to the lane end, according to NRA. *"Attempting to merge too far upstream during congestion periods is not advisable as it only adds to congestion and increases driver confusion and frustration."*

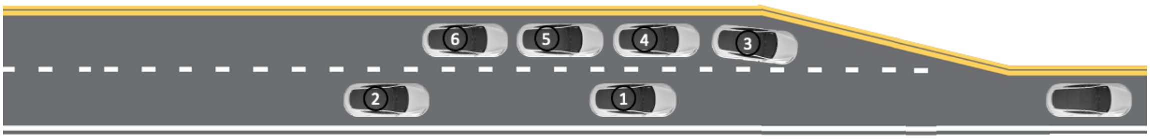


Figure 3.13: Priority merge.

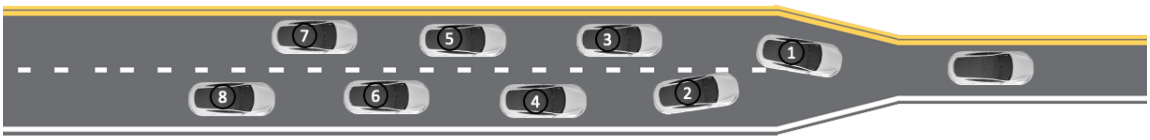


Figure 3.14: Zipper-merge.

4 Methodology

The methodology in this thesis focuses on modeling and implementing the AVs and framework in AIMSUN. A literature review was conducted in the prestudy report, which formed the knowledge base for designing the simulation framework and the vehicle behavior modeling. Nonetheless, additional knowledge is extracted from the theory on microsimulation, future expectations, and car-following models.

4.1 Programming

One of the most challenging tasks the prestudy-report uncovered was understanding and programming in C++ to implement new behavioral models.

AIMSUN enables the building of new behavioral models via the AIMSUN microSDK. The developer must build the behavioral models in Visual Studio 2013, an integrated development environment provided by Microsoft. The environment allows the use of several different programming languages, but as mentioned in the first paragraph, C++ was the language required.

Both authors had limited experience with programming in C++ before the thesis. Therefore, before undertaking the modeling of new car-following models, it was decided to learn the fundamental concepts of C++. The fundamental concepts mainly included understanding the syntax, how classes and objects work, retrieving information, and writing functions.

One of the most important concepts to understand is classes and objects. These two are the main aspects of what is object-oriented programming (OOP). Figure 4.1 illustrates an example to clarify the difference.

The microSDK from AIMSUN provides programming of two C++ classes. The classes include the vehicle and the simulation models used to replace the default vehicle behavior. In addition, AIMSUN also provides the functions required to register new behavior models.

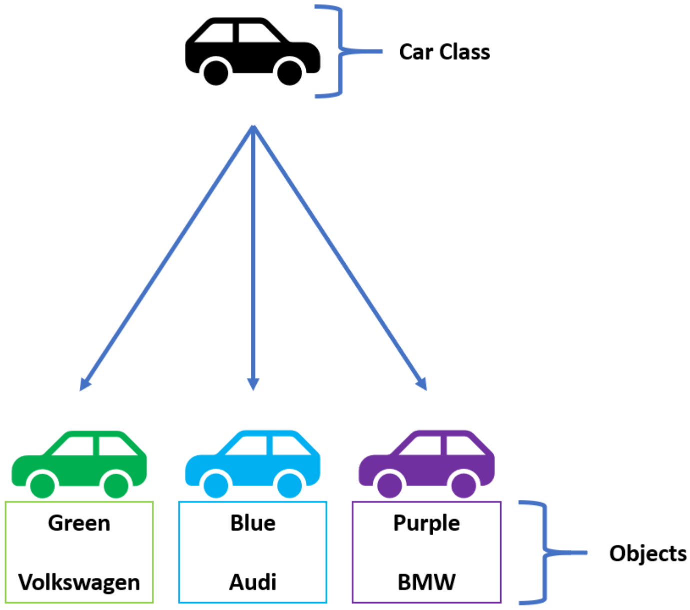


Figure 4.1: Classes and objects in C++.

4.1.1 Car-following models

As with C++, the authors also had limited experience with the car-following models, which chapter 3 describes. Therefore, it was essential to understand the car-following models that needed to be implemented, mainly IDM and EIDM.

To better understand the car-following models, a fictitious speed profile was created for a leader in excel. The functions for the IDM, EIDM and the Gipps car-following model were also implemented in the worksheet. The fictitious speed profile was inspired by the work of Bailey (2016), who looked at the speed profile of EIDM and Gipps (Bailey, 2016). Table 4.1 shows the input parameters for the different followers. Figure 4.2 and 4.3 show the speed profile for the leader and followers and their gap to the leader, respectively.

Looking at figures 4.2 and 4.3, one can see that IDM and EIDM are identical, overlapping each other. There is no difference due to the lack of a possible critical situation where the EIDM is supposed to stand out. The vehicle following Gipps almost overlaps the leader-speed profile, where the acceleration and deceleration are more aggressive than IDM and EIDM.

As written under table 4.1, the reaction time of EIDM/IDM was used as the time interval for the calculations (simulation step). The reaction time was chosen due to the EIDM and

Table 4.1: Input-Parameters for fictitious speed profile.

Parameter	Gipps	IDM/EIDM
Desired speed [km]	110	110
Speed acceptance [-]	1.1	1
Minimum gap [m]	1	1
Reaction time [s]	0.8	0.1
Max acceleration [m/s^2]	3	3
Max deceleration [m/s^2]	6	6
Normal deceleration [m/s^2]	2	2
Safe time gap [s]	1.5	1.5
Effective length leader [m]	3	3
Coolness factor c [-]	-	0.99
Gap $X(n-1,0) - X(n,0)$ [m]	28	28
Speed limit section [km]	80	80

Note: Reaction time for IDM/EIDM is also the time-interval for the calculation

IDM being unstable when having a reaction time and consequently time-interval larger than 0.1 seconds. The unstable behavior can be seen when changing the reaction time, where the curve to IDM and EIDM begins to alternate to a higher degree, trying to adapt to the new speed. In other words, a worsened string stability. The alternating behavior could be connected to the assumptions mentioned in section 3.4 on page 39; drivers react without delay. Therefore as with the ACC/CACC model in AIMSUN, a reaction of 0.1 seconds should be set for IDM and EIDM.

4.1.2 Lane Changing models

As it was described in section 3.1, on page 31 car-following models explain the longitudinal behavior, whereas lane-changing the lateral behavior.

Unlike different car-following models, which are often modeled after ACC and CACC-technology, lane-changing is arguably more complex as it is dependent on several tactical decisions, and therefore, more computationally intensive to solve (Bailey, 2016). Due to its complex nature and a small amount of literature found on the topic, Bailey (2016) assumed that the vehicles could be classified as having SAE-level 2 and 3 automation when following the default lane-changing model.

The implementation of alternative lane-changing models than the default Gipps lane-changing model was investigated. However, as for Bailey (2016) limited literature was

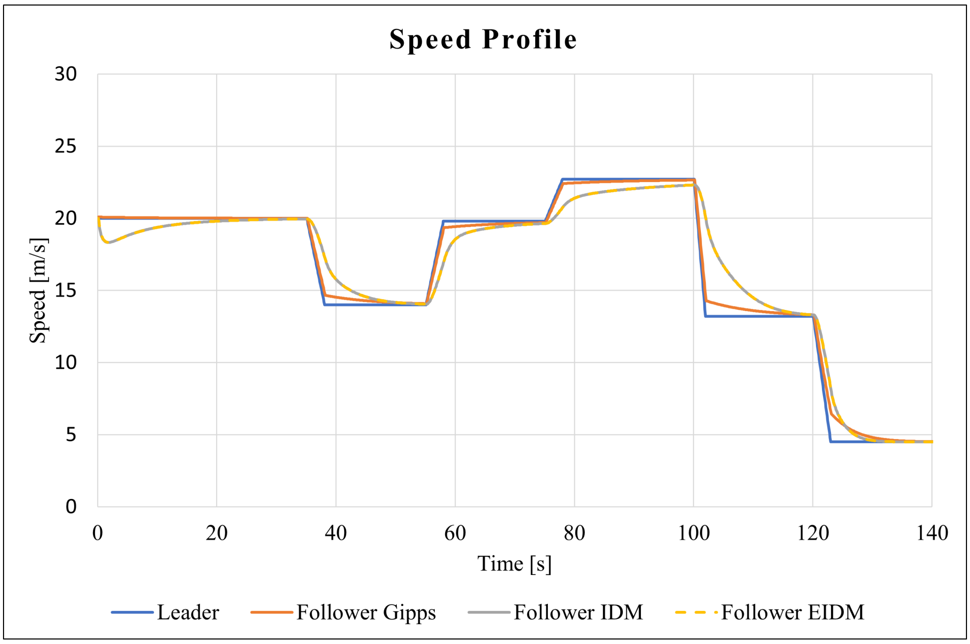


Figure 4.2: Fictitious speed profile.

found on the subject, especially models implemented in AIMSUN via the microSDK. Most of the literature found on the subject had used the default lane-changing model provided by AIMSUN. Mesionis et al. (2020) altered the parameters of the lane-changing model, in order for it to correspond to a more automated behavior (Mesionis et al., 2020). Mattas et al. (2018) had the same approach, assuming AVs and CAVs would try to mimic human behavior. The only thing Mattas et al. (2018) changed in the model was parameters, e.g., reaction time and deceleration capabilities, to coincide with the enhanced technical features an AV and CAV may have (Mattas et al., 2018).

A lane-changing model called for short MOBIL (Minimize Overall Braking Induced by Lane Changes) was studied. The model was developed by Kesting et al. (2007) where the decisions are based on rules of acceleration with IDM as the underlying car-following model (Kesting et al., 2007). Although the model was interesting, it was deemed too complex and time-consuming to implement. Therefore, the decision fell on to rather alter the parameters within the default model, as Mesionis et al. (2020) and Mattas et al. (2018) did.

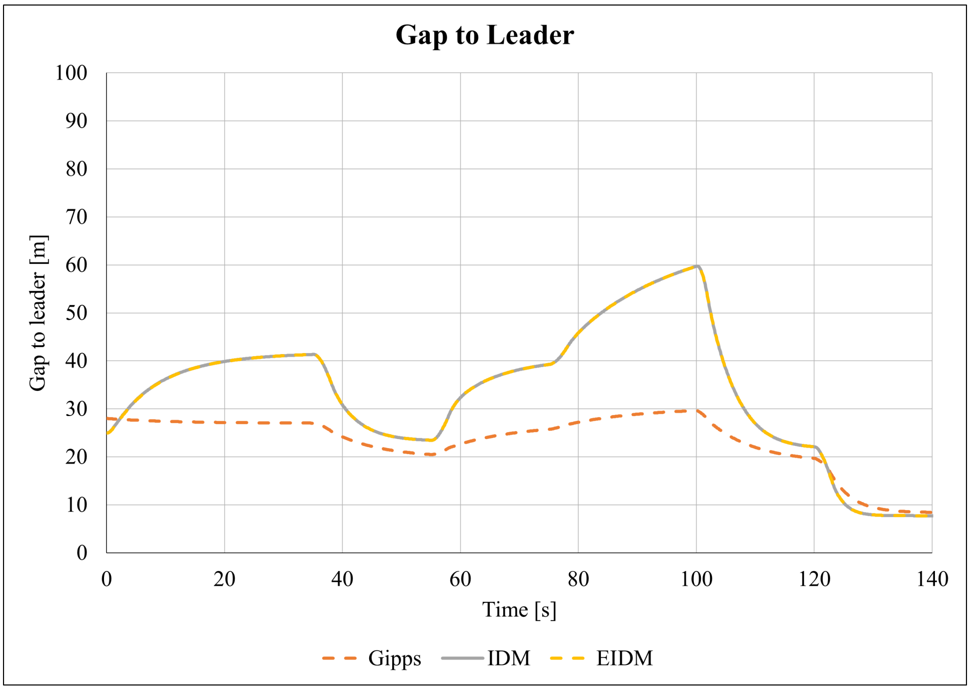


Figure 4.3: Gap to fictitious leader.

The main parameters that could be altered within the lane-changing model are listed below. A further explanation and choice of values to the parameters is given in section 4.2.1 on page 55.

- Overtake Speed Threshold
- Aggressiveness Level
- Look-Ahead Distance Factor
- Cooperation

4.1.3 Implementation

The main challenge faced when building the models in C++ was understanding the objects and their associated values within the classes. Even though AIMSUN offers an overview and explanation of the different parameters, much time went into debugging code when simulating to understand better the parameters and how the functions should be built. Even though no code was written, the debugging was possible due to example files AIMSUN provided with the microSDK.

The example files were used as the basis when implementing the new models, primarily to save time and reduce the potential amount of errors in the code. To build the models in C++, one had to split the formula into an accelerating and decelerating function. In IDM and EIDM, support functions like minimum gap and the constant acceleration heuristic also needed to be built. This primarily for keeping the code simple and straightforward. After the code is built in C++, Visual Studio generates a plug-in that AIMSUN can read through an XML file. One then has to go into AIMSUN and tick the box; Activate external behavior model.

In order to simulate mixed traffic conditions, a logical condition needed to be written in the code. The reason is that when activating the plug-in in AIMSUN, all vehicles follow the code built by the developer. The logical condition checks whether the vehicle has a given value or not, e.g., reaction time. Figure 4.4 shows an example of a logical statement.

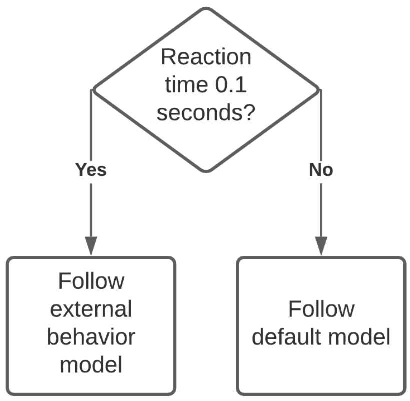


Figure 4.4: Example of logical statement.

4.2 Vehicle fleet

The car-following model governs, as aforementioned, the behavior in the longitudinal direction. The model tells which parameters to use and how they should be calculated to determine an acceleration to the subject vehicle. Changing the parameters that go into a car-following model can significantly impact how the vehicles perform and affect the system.

The changing of these parameters is done in AIMSUN. The decision fell early on that the vehicle fleet should represent cautious and assertive behavior. This aligns with what was discussed and found through the comprehensive literature review in the prestudy report.

Examples here include ATKINS (2016) that divided cautious and assertive behavior into nine different levels compared to Mesionis et al. (2020), which divided it into two.

The discussion of whether an AV should be cautious or assertive is a challenging one, as it was written in section 2.2 on page 25. Moreover, what one can expect is even more difficult. It is strongly related to factors, e.g., the penetration rate, how far the technology has come, the degree of acceptance, and the customization of infrastructure. There are, in other words, many factors with uncertainty, which makes the assumptions challenging.

As it was wished to simulate both cautious and assertive behavior, each car-following model had these two types of behavior. The motivation was to compare car-following models with different parameters. As there were five different car-following models, this meant a total of ten vehicles. Table 4.2 shows an overview of the vehicles, their name, their car-following model, and whether they have cautious or assertive behavior. ACC- and CACC Model in table 4.2 refers to the car-following models provided by AIMSUN. The term ACC controller refers to the car-following model corresponding to the principle of which the ACC is built, namely keeping a safe following distance to the vehicle in front.

In the following sections, the different parameters will be presented. As the only difference between the vehicles is their respective car-following models, the parameters that can be changed in AIMSUN will be presented.

Table 4.2: Overview of vehicle fleet.

Vehicle Name	Car-Following Model	Cautious/Assertive
Human Vehicle	Default Model	Human Vehicle
C-Def	Default Model	Cautious
A-Def	Default Model	Assertive
C-IDM	IDM	Cautious
A-IDM	IDM	Assertive
C-EIDM	EIDM	Cautious
A-EIDM	EIDM	Assertive
C-ACC	ACC Model	Cautious
A-ACC	ACC Model	Assertive
C-CACC	CACC Model	Cautious
A-CACC	CACC Model	Assertive

Note: C- and A- are abbreviations for cautious and assertive, respectively.

4.2.1 Vehicle Parameters

Table 4.3 shows the parameters and their values for the human vehicle, cautious and assertive AVs. Most of the values for the human vehicle are default, but some were changed to be in line with the suggestions published in a manual made by Asplan-Viak (2019) for Norwegian vehicle types. In the bullet-point list below, there is a definition and explanation of the choice of the different parameters. The definitions are retrieved from the user manual for AIMSUN and written in italic to differentiate from the explanation.

Many of the chosen values for AVs are retrieved from various sources of literature. This is due to some articles and research not covering all the parameters presented here; thus, some overlap while others not.

Table 4.3: Vehicle parameters.

Input Parameters		**Human Vehicles**				**Cautious AVs**	**Assertive AVs**
		Mean	Dev	Min	Max		
Max Desired Speed	$[km/h]$	110	10	80	120	110.0	110.0
Speed Limit Acceptance	[-]	1.0	0.1	0.9	1.1	1.0	1.0
Max Give Way Time	$[s]$	10.0	2.5	5.0	15.0	12.0	8.0
Clearance	$[m]$	2.0	0.8	0.5	3.5	1.0	1.0
Reaction Time	$[s]$	0.9	-	-	-	0.1	0.1
Reaction Time at Stop	$[s]$	1.2	-	-	-	0.1	0.1
Reaction Time Traffic light	$[s]$	1.35	-	-	-	0.1	0.1
Max Acceleration	$[m/s^2]$	3.0	0.2	2.6	3.4	3.0	3.0
Max Deceleration	$[m/s^2]$	6.0	0.5	5.0	7.0	6.0	6.0
Normal Deceleration	$[m/s^2]$	4.0	0.25	3.5	4.5	2.0	2.0
Safety Margin Factor	[-]	1.0	-	-	-	2.0	1.0
Sensitivity Factor	[-]	1.0	-	-	-	1.5	1.0
Overtake Speed Threshold	[%]	90.0	-	-	-	80.0	90.0
Gap	$[s]$	0.0	-	-	-	2.0	1.0
Look Ahead Distance Factor	$[s]$	-	-	0.8	1.2	1.5	1.25
Aggressiveness Level	[-]	-	-	0.0	1.0	0.0	0.0

Note: Values without deviation, min and max are constant values.

- **Max Desired Speed**
  - *This is the maximum speed, in km/h, for this type of vehicle when not otherwise constrained by section speed limits.*
  - Assume a constant desired speed for both cautious and assertive vehicles equal to the mean maximum desired speed for human vehicles.
- **Speed Limit Acceptance**
  - *The "level of goodness." The degree of acceptance of speed limits. When greater than 1, means the vehicle will choose a maximum speed greater than the speed limit for that section.*
  - Same for all AVs. Assume a value of 1 because an AV will never go over the speed limit for the given section. This is regardless of the level of assertiveness. The choice of value is in line with previous research (Mesionis et al., 2020).
- **Max Give Way Time**
  - *When a vehicle has been at a standstill for more than this "Give Way Time (In seconds)," it will become more aggressive and reduce the acceptance margins.*
  - Assume the mean value from human vehicles plus the deviation if cautious, and minus if assertive. Assume that assertive vehicles will be more *"impatient"* than cautious Vehicles.
- **Clearance**
  - *This is the distance, in meters, that a vehicle keeps between itself and the preceding vehicle when stopped.*
  - This is used as minimum gap in the car-following models. Set the value of 1 for both cautious and assertive, in line with proposed value from previous research (Bailey, 2016).
- **Reaction Time/-at Stop/-at Traffic Light**
  - *This is the time it takes a driver to react to speed changes in the preceding vehicle.*

  - Assume 0.1 seconds for all, both cautious and assertive, in line with proposed values from previous research (Mesionis et al., 2020; Bailey, 2016).

- **Max Acceleration**
  - *Max acceleration in m/s^2 that the vehicle can achieve under any circumstances.*
  - Set the mean value from human vehicles as constant for both cautious and assertive AVs as the capability of acceleration will be the same. Choice of value is in line with previous research (Bailey, 2016).

- **Max Deceleration**
  - *This is the most severe braking, in m/s^2, that a vehicle can apply under special circumstances, e.g., emergency braking.*
  - Assume a constant value of 6 which is the mean for human vehicles. The choice of value is in line with previous research (Bailey, 2016).

- **Normal Deceleration**
  - *Maximum "comfortable" deceleration, in m/s^2, that the vehicle can use under normal circumstances. This does not include the emergency-braking.*
  - Different suggestions of value, depending on the literature. Chose value of 2, as this was the value used by Yu et al. (2019) when using the IDM (Yu et al., 2019).

- **Safety Margin Factor**
  - *Included in the gap acceptance calculations to determine when a vehicle can move at a priority junction. Higher value than 1 (default value), means more cautious*
  - Chose value of 2 for cautious and 1 for assertive, assuming that the factor for assertive would be the same as for human vehicles. Based on the recommendations for modeling AVs from Aimsun (2020b).

- **Sensitivity Factor**
  - *In the deceleration component of the car-following model, the follower makes*

an estimation of the deceleration of the leader using the sensitivity factor.

 – Set the value of 1.5 for cautious AVs and 1 for assertive. This is in line with the recommended values presented by Aimsun (2020b).

- **Overtake Speed Threshold**
  - *Percentage of speed below which it decides to overtake.*
  - Set the value of 80% for cautious to be in line with previous research (Mesionis et al., 2020; Aimsun, 2020b). A value of 90% was set for assertive, as it is assumed they will wish to overtake as much as the human vehicles.
- **Gap**
  - *Safety gap in seconds between vehicles in the longitudinal direction.*
  - Set the value of 2 and 1 for cautious and assertive AVs, respectively to be in line with recommended values from previous research (Mesionis et al., 2020).
- **Look Ahead Distance Factor**
  - *Used to modify the lookaheads in the lane-changing model to determine where vehicles consider their lane choice for a forthcoming turn. The higher the value, the earlier lane change*
  - Set the value of 1.5 for cautious and 1.25 for assertive, under the assumption, AVs will make strategic lane changes earlier. Values are in line with proposed values from previous research (Mesionis et al., 2020; Aimsun, 2020b).
- **Aggressiveness Level**
  - *Controls the Gap Acceptance model for lane-changing affecting the reduced gap a vehicle will accept to make a lane change. The higher the level, the smaller the gap the vehicle will accept, being a level of 1 the vehicle's own length.*
  - Set the value of 0 for both cautious and assertive AVs. The choice is in line with proposed values from previous research (Mesionis et al., 2020; Aimsun, 2020b).

4.3 Case study - Simulation Framework

This section describes and explains the design choices of the case study simulation framework. Testing of AVs in the real world is arguably a safety risk. Therefore simulation testing has been more and more common in the development of AVs (Bengler et al., 2014). A case study was chosen to simulate AVs because this would, to some extent, mimic how the car-following models function in a real-world traffic situation. The case study is a fictitious location, but it could also have been an actual location. The main focus area in the case study is a bottleneck which creates a merging process; this is based on the zipper-merge principle, which is explained in section 3.7 on page 46. Such a merging process is suitable to study the behavior of AVs and the traffic system as a whole, as the AVs have different parameter settings and will therefore behave differently. Three simulations were conducted and are referred to as "Simulation 1.0", "Simulation 2.0" and "Simulation 3.0". The results from simulation 3.0 are analyzed and discussed in chapter 5 and 6.

Simulation 2.0 was conducted because we felt simulation 1.0 did not reflect a realistic travel demand scenario with different simulation times and travel demand distribution. Furthermore, Simulation 2.0 had, in addition to simulation 1.0, many parameter values that were different for cautious and assertive AVs. That made it challenging to evaluate which parameter affected the different behaviors. On that basis, it was decided to conduct a third simulation, simulation 3.0, which had a reduced number of different parameter values for cautious and assertive AVs.

4.3.1 Comparison Between Actual and Fictitious Location

Table 4.4: Advantages and disadvantages to actual case study location.

Advantages	**Disadvantages**
Relatable to readers	Data collection required
Applicability to similar locations	Uncertainty in location replication
Complexity to be chosen by designers	Reduced applicability to most locations

It is challenging to model traffic. As stated in a study from 2021 on traffic modeling, *"(...) it is difficult, if not impossible, to avoid all detection errors and build an identical replica of the real-world road transport system."* (Zhou et al., 2021). Statistician George

Box claimed that *"All models are wrong, but some are useful."* (Box, 1976). Based on these two statements, one can say that no simulation will ever be a precise replication of the real world. Although, it may be useful for developing and evaluating technology for future scenarios in the real world, e.g., AVs.

An actual location may be more relatable and applicable to existing and similar road networks or intersections. On the other hand, the simulation framework should then be as close to the existing location as possible, which calls for time-consuming data collection. It may also be challenging to replicate the location entirely because several factors influence the traffic behavior, not just the number of vehicles traveling through an intersection. Moreover, such accuracy in the replication makes an actual location unfit to apply to other actual locations that differ in layout.

Table 4.5: Advantages and disadvantages to fictitious case study location.

Advantages	**Disadvantages**
Data collection not needed	Uncertainty in realism of framework
Applicability to other locations	Less relatable to readers
Complexity to be chosen by designers	
Design itself not susceptible to uncertainty	

The advantages of a fictitious location are; no data collection is required, easier to do simplifications, and the network could still be realistic. Comparatively, an actual location may be challenging to simplify because removing infrastructure elements could lead to unrealistic traffic behavior in the network. Furthermore, it means greater flexibility in the infrastructure design. Disadvantages to a fictitious location are the realism of the infrastructure design. In addition, it could be challenging for readers to relate their own experiences with infrastructure to a fictitious design.

4.3.2 Key design elements

Figure 4.5 shows an overview of the simulation framework in AIMSUN and figure 4.6 expands on the bottleneck section, the main focus area for the simulations.

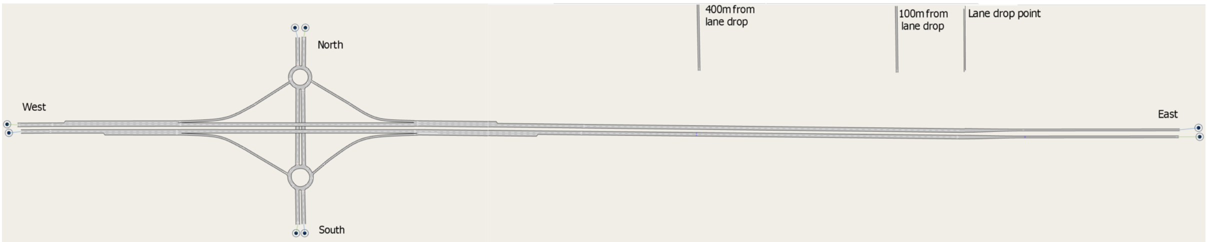


Figure 4.5: Overview of framework in AIMSUN.

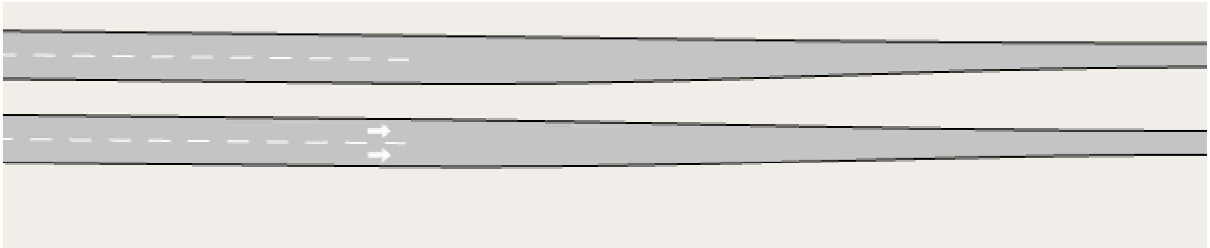


Figure 4.6: Overview of bottleneck section in the framework.

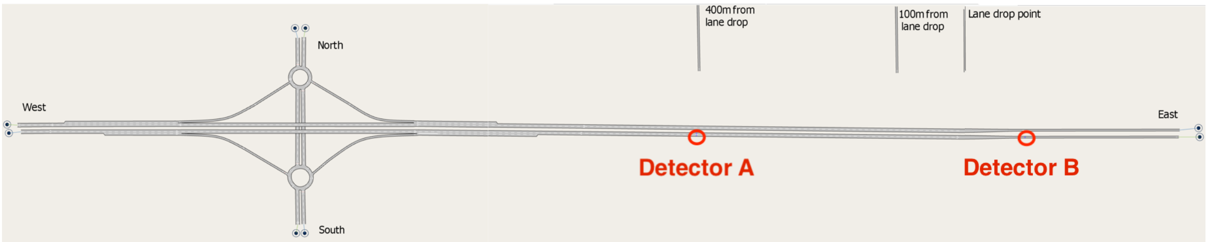


Figure 4.7: Location of detector A and B in the framework.

Figure 4.7 shows the location of the two detectors that capture vehicle behavior at specific time intervals during the simulations. These detectors stores valuable information about indicators that are presented in chapter 5. The location of detector A is 400 meters upstream from lane drop, therefore spanning both lanes of the motorway in the eastbound direction. Detector B is located downstream right after lane drop at the single lane primary road, also in the eastbound direction.

Indicators are helpful to measure cooperation between simulated AVs. In this thesis, several indicators were used, but two of them extracted information about the traffic condition every 5 minutes. Those two are:

- Flow
- Speed

When evaluating the cooperation between simulated vehicles, it is helpful to study simulation data from the system in its entirety and smaller parts. This is to both get an overview of the AVs performance and study particular sections where the entire system's traffic flow is prone to be affected by the vehicle's behavior.

Table 4.6 shows an overview of the design elements that were taken into consideration for the simulation framework.

Table 4.6: Design elements overview.

Design element	Chosen solution	Choice explanation
Merge section	Lane reduction	Implies 50/50 priority in merging process
Road type	Highway	Suitable to force merging
Additional network	Secondary road Ramps Four node clusters	To increase network complexity To increase traffic dynamic on highway To increase traffic dynamic in the network

The merge section ends where the two-lane motorway becomes one lane. The merge process follows the zipper-merge principle, which means that vehicles in both lanes should assert the same amount of attention to the vehicles in the other lane. In contrast, this merge section is not a lane drop, where one lane ends at one point, and the continuing lane gets priority in the merge section. The road type for the merge section is a highway, meaning no disturbance from other road users, apart from motorized vehicles entering or leaving on-ramps. Signalized or non-signalized intersections would add complexity to the framework, complicating the evaluation process. Additional factors could affect the vehicle behavior, e.g., green time in signalized intersections and yield rules.

There is no heavy vehicle traffic in the simulation because it creates a simulation environment with fewer elements that could bring uncertainties into the simulation. Such a sterile road design may be a good testbed for testing AVs. The addition of other road users would arguably make the simulation more realistic and more challenging to evaluate the performance of AVs as there would be more elements to consider.

Additional roads add to the framework complexity, which arguably makes the simulation more realistic. The secondary roads feed vehicles onto the highway through the ramps, with two-node clusters located at each motorway end and two where the secondary roads end. These node clusters feed into attracts vehicles from the network. Two roundabouts in the secondary roads force vehicles to interact with each other as they arrive from different node clusters. This interaction between the vehicles makes the traffic flow in the framework more dynamic.

Figure 4.8 depicts the situation from simulation 2.0, showing vehicles merging at the bottleneck, the main focus area of simulations 1.0, 2.0, and 3.0.

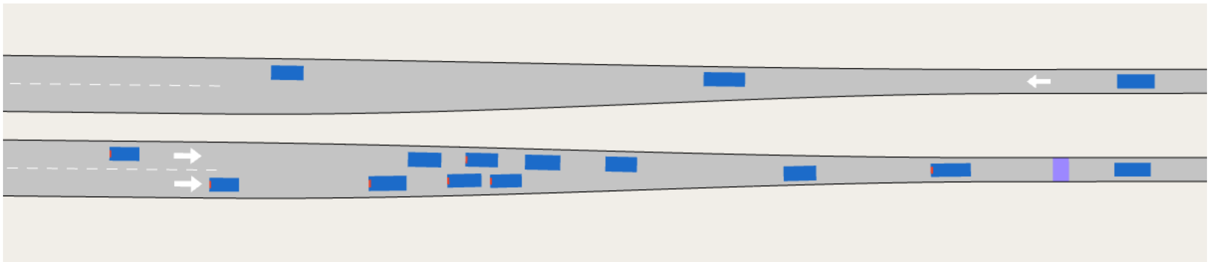


Figure 4.8: Screenshot from bottleneck section in simulation 2.0.

4.3.3 Key parameter values

This paragraph elaborates on table 4.7. The primary road is the bottleneck section, where the two-lane motorway merges into a single-lane primary road. All speed limits match the Norwegian road standards (Vegvesen, 2019). The merge section length is 100 meters, and the early merge is 400 meters. Both section lengths are findings in a study conducted on a similar lane drop, but this merge configuration did not imply 50/50 merge priority (Zhang et al., 2019). The deceleration and acceleration lane lengths were calculated using two excel-sheets from the Norwegian Public Road Authorities. The excel-sheets are available for free, using two links provided in manual V121 on pages 75 and 77 (Vegvesen, 2019). CACC platoon size is zero for secondary roads because the section may not be long enough for platoons to increase traffic flow sufficiently.

Travel demand highly affects the traffic flow in a network, as there exists a theoretical capacity for each lane. This lane capacity limits the number of vehicles that may travel through a network over a given period. A high travel demand that matches or exceeds the lane capacity will provoke a merge situation towards the bottleneck. Varying travel demand helps to create a dynamic traffic situation. Therefore, the travel demand for all simulations, 1.0, 2.0, and 3.0, have peak hours with increased travel demand. Simulation 1.0 differs from simulations 2.0 and 3.0, mainly with replications for the AVs penetration rates, travel demand, and peak period configuration.

Each vehicle is simulated several times in what is called replications. The average value for each indicator, e.g., delay time, is more representative for the vehicle if there are added replications. There are two replications for each penetration rate in simulation 3.0, and penetration rates represent the percentage of AVs implemented in the system. In the future, one can expect AVs to be introduced to traffic gradually. Therefore it is helpful to evaluate the traffic system with varying penetration rates of AVs. Each replication increases the run time for the simulation. Therefore, it was decided to limit the number of replications to two for simulations 3.0 to make the simulations more efficient.

Table 4.7: Framework parameter values overview.

Parameter	**Item**	**Value**	**Note**
Speed $[km/h]$	Motorway	100	[1]
	Primary	80	
	Secondary	50	
	Ramp	100	
Section length $[m]$	Merge	100	[2]
	Early merge	400	
	Acceleration lane	170	[1]
	Deceleration lane	140	
Maximum CACC platoon size $[veh]$	Motorway	20	[1]
	Primary	20	
	Secondary	0	
	Ramp	20	
Capacity $[veh/h/lane]$	Motorway	2100	Default value
	Primary	1600	[3]
	Secondary	1200	[1]
	Ramp	1000	
Simulaton time $[minutes]$	Simulation 1.0	90	
	Simulation 2.0	60	
Time of day $[hr : min]$	Simulation 1.0	08:00-09:30	
	Simulation 2.0	08:00-09:00	
Date		13.05.2019	
Weekday		Wednesday	
Weather conditions		Sunny	
Road conditions		Dry	
Notes	[1] In line with road standards by The Norwegian Public Roads Administration (Vegvesen, 2019) [2] From previous study on lane-changing on motorway conducted in AIMSUN (Zhang et al., 2019) [3] From study by consulting firm Asplan Viak (Asplan-Viak, 2019)		

4.3.4 Simulation 1.0

The idea of replications is that the more there are, the more representative will the average value of all the replications be. Simulation 1.0 contained 1010 replications in total, as shown in table 4.8. The number of replications was reduced to 202 replications in simulation 2.0 because the authors assume this is sufficient to produce a representative enough average value.

Table 4.8: Overview of replications in simulation 1.0.

Element	HV	AVs
Vehicle types	1	10
Penetration rates per vehicle type	1	10
Replications per penetration rate	10	10
Replications in total	10	1000
Total replications in simulation 1.0	1010	

Peak periods create a dynamic traffic flow through the bottleneck, as shown in table 4.9. For example, the travel demand in the peak period, 09:00 to 09:15, is twice that of the other five time periods.

Table 4.9: The percentage of travel demand for each time period of simulation 1.0.

Time period	Percentage of travel demand in each time period
08:00-08:15	14%
08:15-08:30	14%
08:30-08:45	14%
08:45-09:00	14%
09:00-09:15	29%
09:15-09:30	14%

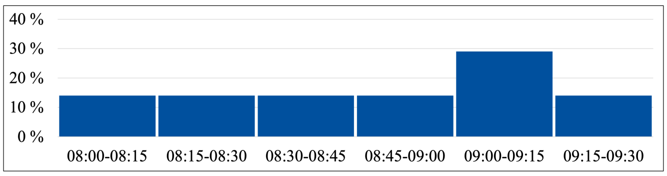


Figure 4.9: The percentage of travel demand for each time period of simulation 1.0.

4.3.5 Simulation 2.0

There are fewer replications in simulation 2.0, which table 4.10 show. The number of replications produces satisfying low standard deviation values for the average. Shorter simulation time in each replication also reduces the time to simulate compared to simulation 1.0. The simulation time is 60 minutes, and the travel demand varies every 15 minutes, as shown in table 4.11 and figure 4.10. The increase in travel demand is smoother in simulation 2.0 to create a more realistic scenario.

Table 4.10: Overview of replications for simulation 2.0.

Element	HV	AVs
Vehicle types	1	10
Penetration rates per vehicle type	1	10
Replications per penetration rate	2	2
Replications in total	2	200
Total replications in simulation 2.0	202	

Table 4.11: Percentage travel demand for each time period of simulation 2.0.

Time period	Percentage of travel demand in each time period
08:00-08:15	20%
08:15-08:30	25%
08:30-08:45	35%
08:45-09:00	20%

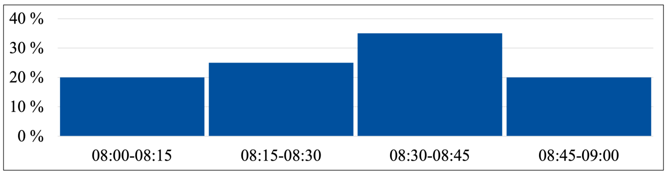


Figure 4.10: Percentage travel demand for each time period of simulation 2.0.

4.3.6 Simulation 3.0

The parameter values for the vehicles are the only settings that are different for simulation 3.0 compared to simulation 2.0. There are fewer parameters with different values for cautious and assertive AVs, which means fewer factors to evaluate when analyzing the results.

5 Results

This chapter presents the simulation results. Each vehicle type has been assigned distinct colors and line types to distinguish the different car-following models and parameter settings. Cautious AVs are drawn with continuous lines and assertive AVs with dashed lines. The situation with 0% AVs present is shown with a dashed black line, named the 0% AV-line. Table 4.2 on page 54 lists the 10 AVs with their name, their connected car-following model and whether they are cautious or assertive. The graphs are from simulation 3.0, and each vehicle was simulated twice for each penetration rate (10%-100%). All AVs have an abbreviation that is either C- or A- depending on whether they are cautious or assertive. The C- and A- abbreviation is then followed by the car-following model. This means that, e.g., C-Def = Cautious Default model.

5.1 Performance - Entire System

AIMSUN calculated the results from vehicle performance in the entire system, presented in this section.

5.1.1 Differences Between Car-Following Models

Figure 5.1 contains the average delay time for each vehicle type and penetration rate. The key findings are listed below.

- C-IDM and C-EIDM had a strong increase in delay time compared to the 0% AV-line.
- Noticeable increase in delay time for C-ACC from 80% to 100% penetration rate.
- All assertive AVs followed the 0% AV-line until the 70% penetration rate.
- A-Def and A-CACC constantly had lower delay time than the 0% AV-line.

C-IDM, C-EIDM, and C-ACC stood out with a noticeable higher delay time than the other vehicles, and those three are all cautious AVs. Delay time for C-IDM and C-EIDM started increasing at 60-70% penetration rate, and at 100% penetration rate, the value was 1544% greater than the 0% AV-line. C-ACC saw an increase later than the two aforementioned,

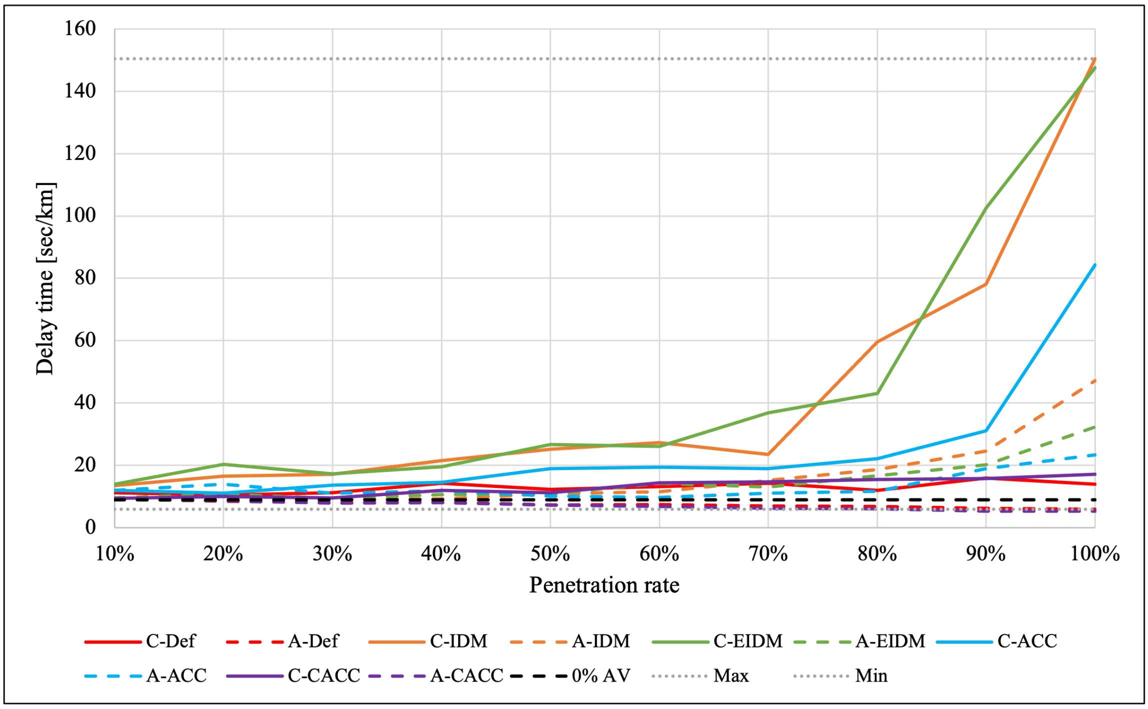


Figure 5.1: Delay time for cautious and assertive AVs.

but the increase had still reached 841% at 100% penetration rate, compared to 0% AV-line. Vehicles equipped with IDM, EIDM, and ACC all had higher delay times than vehicles equipped with default and CACC, regardless of cautious or assertive settings. Vehicles equipped with IDM and EIDM tended to merge one by one, while AVs equipped with CACC used platoons where several vehicles merged at the time from one lane.

5.1.2 Assertive AVs

- A-IDM, A-EIDM, and A-ACC had higher delay time than the 0% AV-line, and increased the difference from 70% penetration rate
- A-Def and A-CACC had lower delay time than the 0% AV-line, and increased the difference from 40% penetration rate

Figure 5.2 shows the delay time for assertive AVs. A-IDM, A-EIDM, and A-ACC had the highest delay time out of the assertive AVs and the 0% AV-line. The increase in delay time for the three aforementioned ranged from 161% to 426% at 100% penetration rate compared to the 0% AV-line. This increase in delay time was still noticeably less than for the three cautious AVs displayed in figure 5.1. Interesting with figure 5.2 is that the three assertive AVs with the highest delay time had the same car-following models like

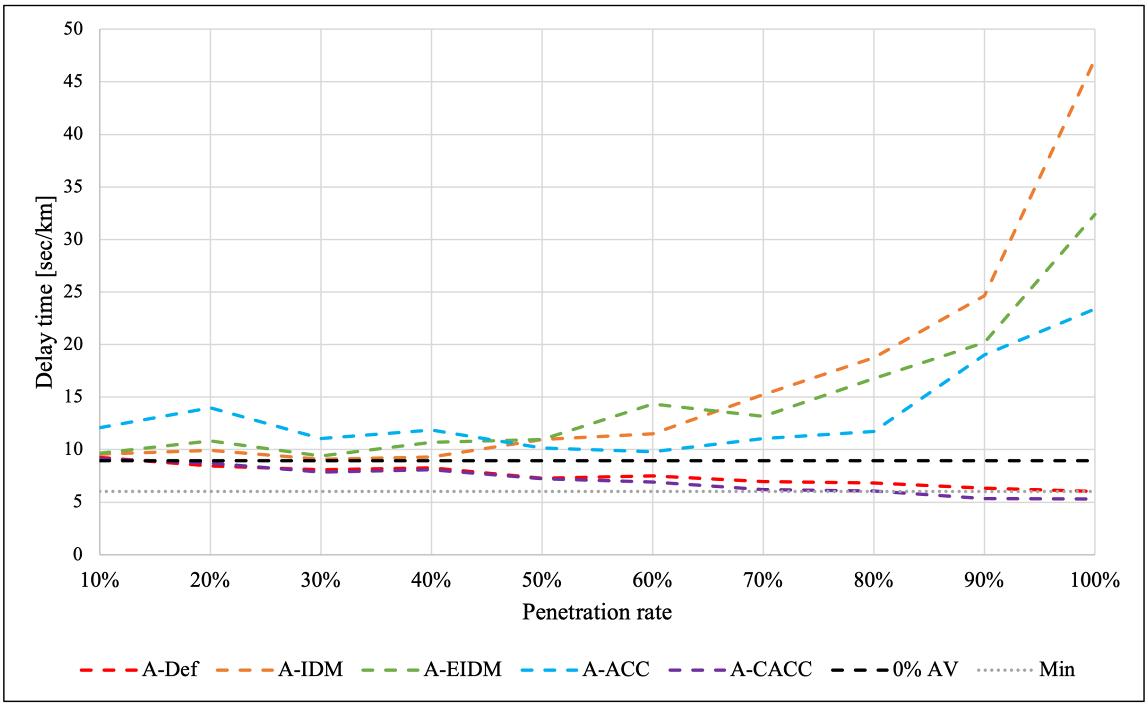


Figure 5.2: Delay time for assertive AVs.

the three cautious AVs with the highest delay time. Those are the IDM, EIDM, and ACC car-following models. On the other hand, A-Def and A-CACC had a continuous decrease in delay time from 0% to 100% penetration rate, constantly with lower delay time than the 0% AV-line.

5.1.3 Parameter Effects

- Difference between assertive and cautious AVs
- C-IDM and C-EIDM decreased the most

Speed indicates the level of flow in the system, and decreasing speeds should indicate a slow-moving queue. Figure 5.3 indicate that high penetration rates lead to slower moving traffic in the entire system. Cautious AVs were most prone to see slower-moving traffic, C-IDM, and C-EIDM in particular. In general, the cautious AVs decreased more in speed than assertive, and the difference between the two were the parameter settings. Again, the A-Def and A-CACC had the highest speeds, higher than the 0% AV-line as well.

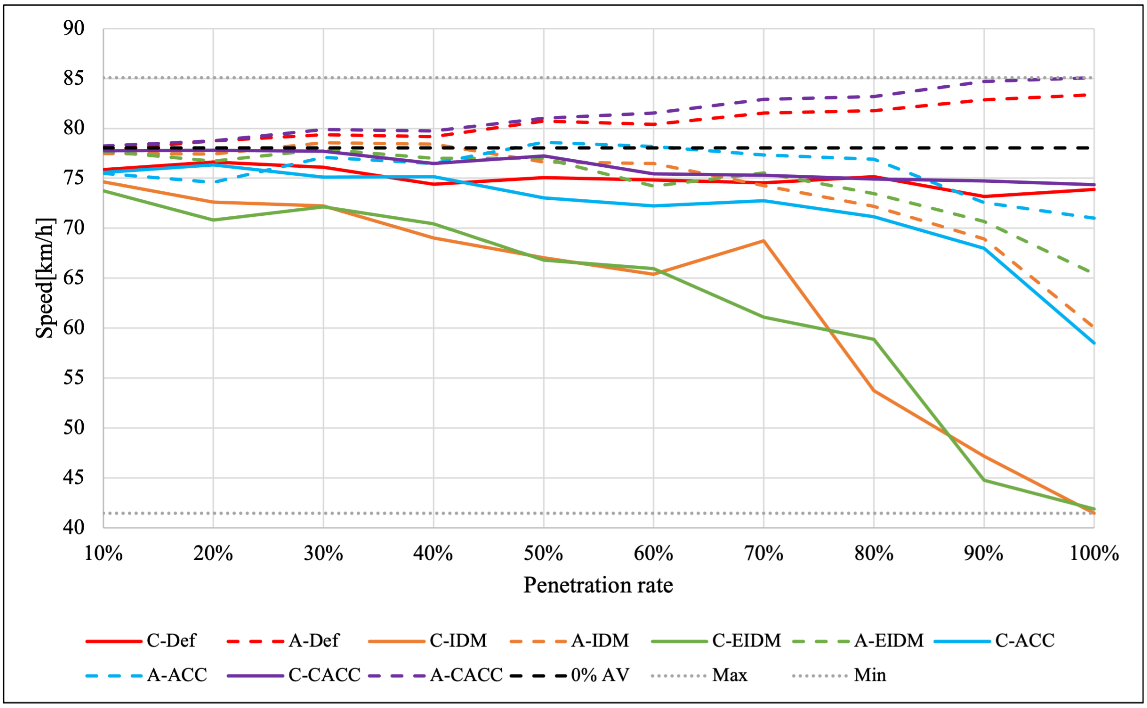


Figure 5.3: Speed for cautious and assertive.

5.2 Performance - Bottleneck

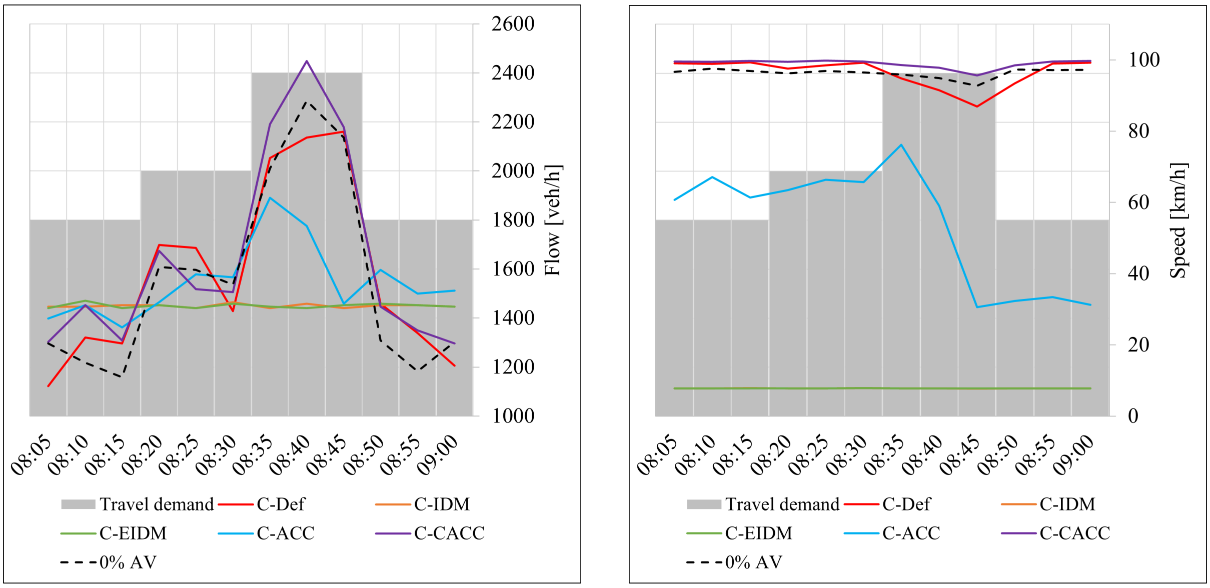
This section presents the measurements from the two detectors before and after the bottleneck. The detectors have measured flow and speed. As it can be seen from the figures in section 5.1 on page 68, the most significant difference between the AVs were at penetration rate 100%. Therefore, it has been chosen to present these results from the detectors to see why the differences are significant.

As described in section 4.3.2 on page 61, detector A is placed 400 m upstream before the bottleneck, and detector B right after downstream.

5.2.1 Cautious AVs

As seen and described in section 5.1 on page 68, the overall performance of the cautious AVs were not good in terms of delay time and speed. Therefore, the performance in the bottleneck is essential, as this can be the cause of the issue.

5.2.1.1 Detector A



(a) Flow - Detector A - Cautious. (b) Speed - Detector A - Cautious.

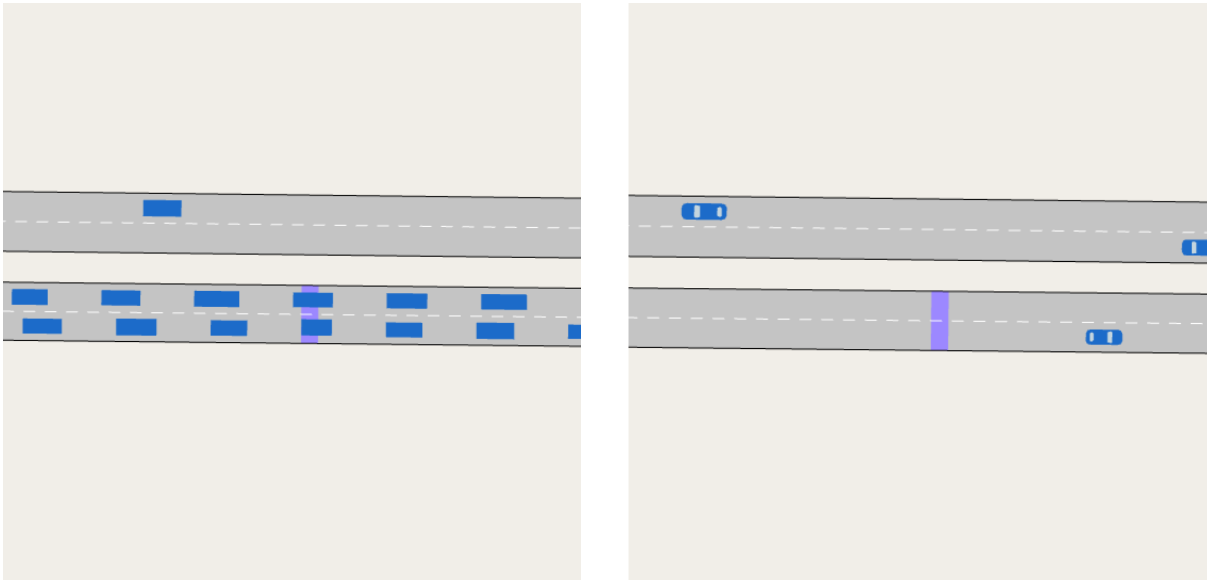
Figure 5.4: Detector A - 100% AVs - Cautious AVs.

The key findings from figure 5.4 are listed below:

- C-IDM and C-EIDM had almost constant flow and speed of 1449 veh/hour and 8 km/h, respectively.
- Speed dropped during the peak period (08:35) for C-ACC.
- C-CACC had a higher flow of traffic compared to the 0% AV-line.
- The speed and flow of C-Def dropped below the 0% AV-line during the peak period.

Only two vehicles had more or less followed the travel demand displayed in the background, whereas C-IDM and C-EIDM gave an almost constant value for flow and speed regardless of increased travel demand. Compared to the 0% AV-line, the average speed throughout the simulation decreased by 92%. The low value of speed at the beginning for IDM and EIDM was due to early system breakdown where queues had already begun to form in the warm-up period. The queue was never resolved; therefore, the value for flow and consequentially the speed remained constant. Figure 5.5 shows how the situation looked by detector A at the beginning of the simulation.

C-ACC had a higher mean speed at the beginning of the simulation compared to C-IDM and C-EIDM with 64 km/h. However, as the travel demand increased, the speed dropped and did not increase, even though the travel demand decreased after the peak period. This means that the congestion was not resolved at the end of the simulation by detector A.



(a) C-EIDM 100% - 08:00. **(b)** Human Vehicle - 08:00.

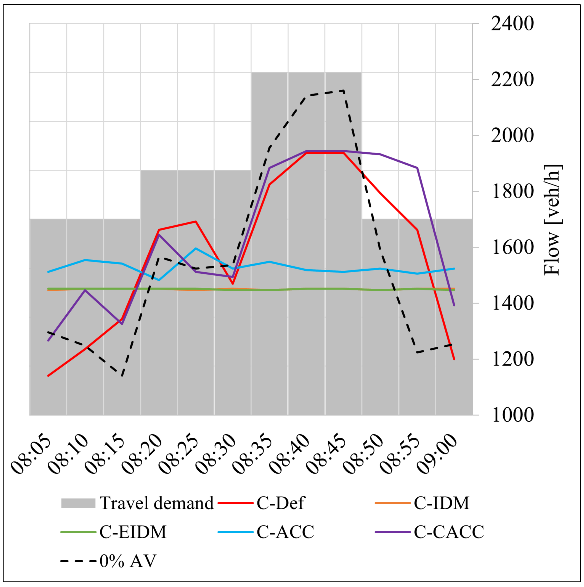
Figure 5.5: Detector A: C-EIDM vs Human Vehicle.

5.2.1.2 Detector B

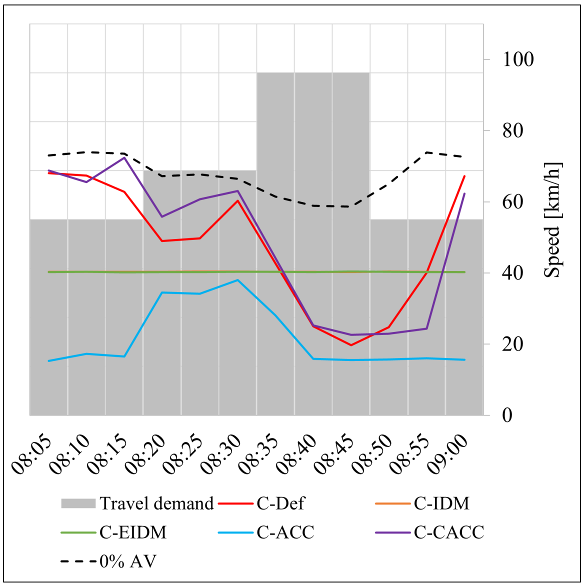
The key findings from figure 5.6 are listed below:

- C-IDM and C-EIDM had an almost constant flow, and speed of 1450 veh/hour and 40 km/h, respectively.
- Flow was lower during the peak-period for C-Def and C-CACC compared to the 0% AV-line.
- Speed of C-Def and C-CACC dropped below the speed of C-IDM/EIDM during peak.
- C-ACC had the lowest speed throughout the simulation.
- No cautious AV outperformed the 0% AV-line.

As in detector A, C-IDM and C-EIDM had constant flow and speed throughout the simulation. The constant value was a result of the merging behavior of C-IDM/EIDM. One vehicle at a time fed the bottleneck with approximately equal headway. Although



(a) Flow - Detector B - Cautious.



(b) Speed - Detector B - Cautious.

Figure 5.6: Detector B - 100% AVs - Cautious AVs.

this gave a constant value of speed through the bottleneck, it does not necessarily mean that it was effective, as seen in figure 5.6a. Although the speed for C-Def and C-CACC dropped below C-IDM/EIDM, the flow was greater, approximately 33% higher. A similar observation was seen for C-ACC, where again the speed was lower than C-IDM/EIDM. However, the flow was greater throughout the simulation, meaning more vehicles entered the bottleneck.

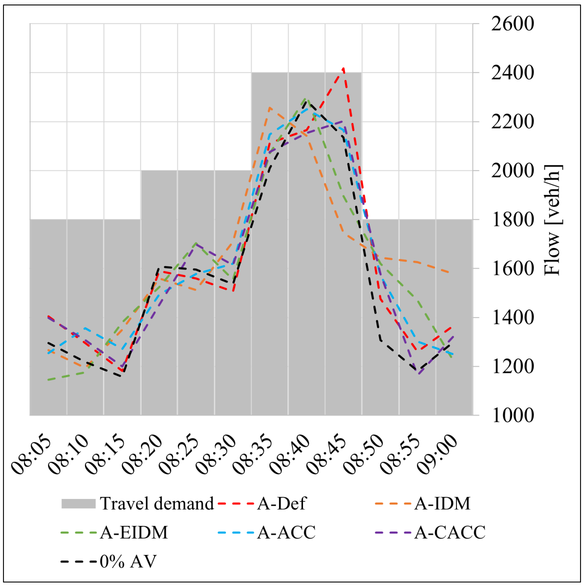
5.2.2 Assertive AVs

Of all the AVs, only two gave a delay time lower than the 0% AV-line for all penetration rates. As for cautious AVs under section 5.2.1 on page 71, results from detector A and B will be presented.

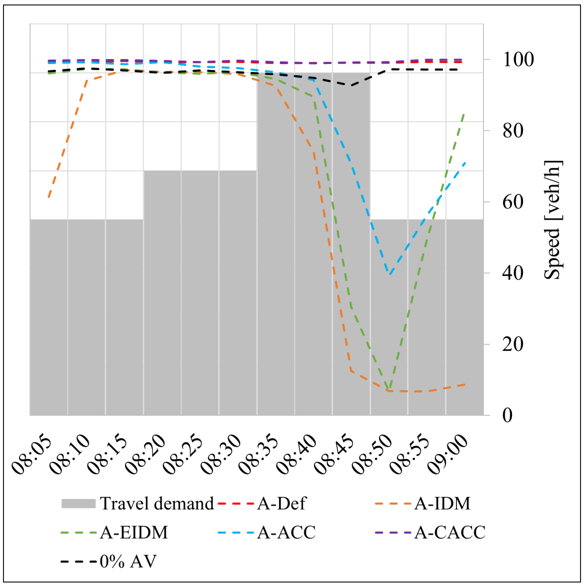
5.2.2.1 Detector A

The key findings from figure 5.7 are listed below:

- All assertive AVs followed to a degree the 0% AV-line for flow.
- A-Def had the highest flow of all the vehicles.
- A-IDM, A-EIDM, and A-ACC dropped in speed during peak.



(a) Flow - Detector A - Assertive.



(b) Speed - Detector A - Assertive.

Figure 5.7: Detector A - 100% AVs - Assertive AVs.

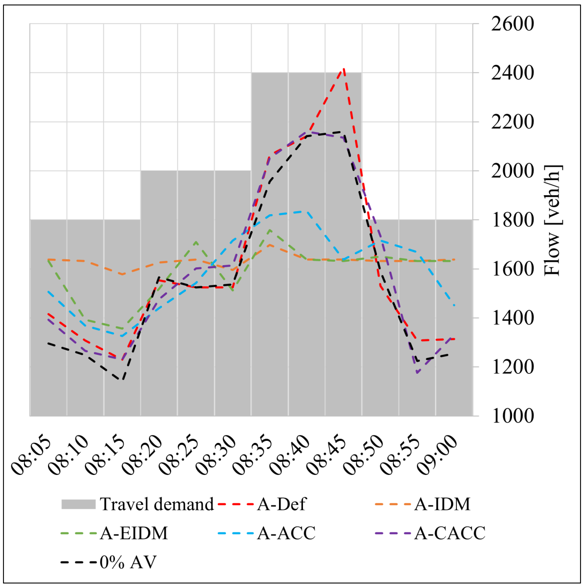
If one only focused on the results from figure 5.7a, differentiating the performance would be difficult as most of the assertive AVs followed the 0% AV-line. Figure 5.7b tells a different story. Here, the speed of A-IDM, A-EIDM, and A-ACC dropped down to 40 km/h and below. This means the queue reached detector A. By looking at the increase of speed from 08:50; it dissolved quicker for A-EIDM and A-CACC. However, the queue for A-IDM was never resolved towards the end of the simulation, as displayed by the horizontal line.

5.2.2.2 Detector B

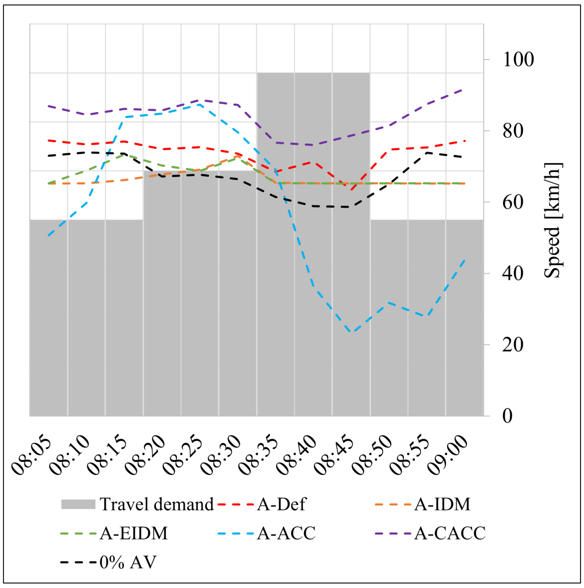
The key findings from figure 5.8 are listed below:

- A-IDM and A-EIDM stabilized during the simulation to an almost constant value (08:40 - 09:00) for flow.
- A-Def and A-CACC almost overlapped the 0% AV-line in flow.
- A-Def achieved the highest flow in peak demand.
- A-ACC dropped in speed as demand peaked.

Looking at the numbers, A-IDM had the highest mean flow during the simulation but the second-lowest speed. The reason is that the simulation, due to the warm-up period began



(a) Flow - Detector B - Assertive.



(b) Speed - Detector B - Assertive.

Figure 5.8: Detector B - 100% AVs - Assertive AVs.

with a queue, resulting in a higher flow entering the bottleneck. The jam before entering the bottleneck was never dissolved. This can be interpreted from the constant value to A-IDM, and A-EIDM displayed to the end of the simulation.

A-CACC had the highest mean speed of all the AVs, 24% higher than the mean of the 0% AV-line. In second came A-Def, which was 9% higher, with an almost similar value to flow with the 0% AV-line for both, which means they had a more effective merging process.

A-ACC followed (08:00-08:30) the flow of the 0% AV-line till demand increased, resulting in a breakdown where flow stopped to increase, and speed dramatically decreased. .

6 Discussion

The purpose of this master thesis was to add to the existing knowledge and academic discussion on the modeling of AVs in a microsimulation with the appropriate framework. The first research question discuss the modeling of the vehicle behavior, thereunder choice of parameters, what one should expect, and how the modeled vehicles could reflect the SAE-levels of automation. The second research question asks how the framework should be built and the simulation completed. The question encompasses the infrastructure design, the modeling of the transition phase, measurement of performance, and which indicators are suitable to measure the performance.

6.1 How to model automated vehicles in Aimsun Next?

The question is strongly dependent on assumptions regarding the future, uncertainties about technology, existing, and what is to come. As it was mentioned in the first paragraph under section 2.1 on page 23, *"The uncertainty is partly due to the lack of existing SAE-levels 3 - 5 AVs"* (...). *"It is essential to understand that there will be no definitive answer to the behavior as an automated vehicle is not a static thing, but rather dynamic."*

The question will be discussed through separate sections, each dealing with a part of the modeling process, what effect it should induce, and how to relate it to a plausible future scenario.

How do the car-following-models affect the behavior of AVs and how to implement them?

The importance of the car-following model can be seen when assessing the result in figures 5.1 to 5.8. The difference is apparent when comparing the cautious vehicles, with IDM and EIDM displaying a constant flow at detectors A and B. The difference is also noticeable when comparing the delay time and speed in the system, where the cautious vehicles of IDM and EIDM had the highest and lowest values.

The results shown from the IDM and EIDM were both surprising as previous research indicated that the models improved congestion and the overall throughput of traffic (Yu et al., 2019; Bailey, 2016). Both the cautious and assertive vehicle-types gave a "worse" traffic situation as the penetration rate increased in the system. The majority of the delay occurs traces back to the bottleneck where the queue begins to form during the peak period in the travel demand. From analyzing the simulation, the queue forms due to sudden deceleration during the merging and cut-in-situations. Based on this behavior, one would expect that the EIDM-vehicles would outperform the IDM, as the EIDM is modeled to not overreact in those types of situations (see section 3.4 on page 39). Nevertheless, the results coincide with what the simple Excel-test showed in section 4.1.1 on page 49. I.e., the models give a more or less equal performance.

On the other hand, the CACC and Default model gave a more expecting result where it almost overlapped the 0% AV situation for all penetration rates. They gave the lowest delay time and high traffic throughput in the bottleneck for cautious and assertive vehicle types of all the AVs. The assertive ones even surpassed the 0% AV situation, slightly improving the traffic situation in the entire system and bottleneck as the penetration rate increased.

The results from the ACC model were more unsatisfactory than expected with both cautious and assertive behavior. It gave the third-lowest performance of all the AVs and the third worst of all the assertive types. The results contradicted previous research, mainly Mesionis et al. (2020), who reported higher throughput and average speeds in the motorway mainline. However Mesionis et al. (2020) acknowledged that if junctions existed, the results could vary widely (Mesionis et al., 2020).

Based on the results, the CACC and Default model gave the best result in reducing the delay time and improving throughput in the bottleneck with increasing penetration rate. The improvements, however, are dependent on whether it is modeled as cautious or assertive. Worth mentioning is that the cautious vehicle types gave a better performance than the other AVs, even when they were modeled as assertive. Therefore, one can with a good level of certainty claim that these car-following model to a greater extent resembles what most consumers and researchers come to expect from AVs in the future (see chapter 2).

The car-following models that gave the more unsatisfactory results, EIDM and IDM, were implemented via the microSDK. Thus, these models have the highest level of uncertainty compared to models that AIMSUN already provides in their software. As it was mentioned at the beginning of the section, the poor results were surprising. The models have correctly been implemented after rigorous testing and debugging to the best of the authors' knowledge. Previous research found on the model, have as mentioned, been mostly positive. Milanés and Shladover (2014) concluded after comparing ACC to the IDM model that the IDM showed smooth behavior but had a slow response and significant variations in Gap (Milanés and Shladover, 2014). Watching the animated simulations for IDM and EIDM, two of these claims were experienced. These are smooth behavior and slow response. The smooth behavior, in that, when congestion, the queue moved at a constant pace as clearly seen in figures 5.4 to 5.6. The slow response was seen when free-moving vehicles approached congestion with the normal deceleration. An unrealistic deceleration was applied when the vehicles came closer than the desired gap.

It is beyond the scope of this thesis to conclude which car-following models resemble the future of AVs. The level of uncertainty, especially for IDM and EIDM, cannot be disregarded. The uncertainty lies primarily in the programming, therein algorithms, and the parameters that go within. Based on previous research, the ACC and CACC model implemented in AIMSUN has the most credibility as the behavior is based on real-life experiments (Milanés and Shladover, 2014; Mesionis et al., 2020; Mattas et al., 2018).

AVs equipped with the CACC model can only communicate with each other in the simulation, forming platoons. Although forming platoons in the system gives an additional reduction in delay and increase in speed, simulations should be careful not to rely too heavily on cooperation technology as presented in section 4.1.3 on page 52. With this in mind, one should not conclude with the CACC model being the best car-following model to use when simulating AVs. This is partly based on technology, and the prospects of achieving the vehicle share needed to induce positive non-negligible effects are too far ahead in the future.

Further research is needed to establish the reliability of the implementation of IDM and EIDM in microSDK. Additional research should also consider the connectivity and how this can be incorporated and affect the car-following models to a greater degree. Even though the CACC model introduces some connectivity, it is limited to gather vehicles in platoons. A suggestion is incorporating a driving strategy for EIDM-vehicles proposed by Kesting et al. (2010). The strategy includes having the vehicle dynamically adapt its parameters based on the situation downstream. With a bottleneck case, changes could, as the article mentions, be a reduction of the time gap and increasing maximum acceleration (Kesting et al., 2010). Another suggestion is to delve deeper into the V2X-capabilities of AIMSUN through the V2X-SDK.

How to adjust the parameters of different vehicles to reflect AVs?

The importance of the parameters is apparent when comparing assertive and cautious AVs. E.g., the speed is reduced by 30% when the IDM has cautious parameter settings instead of assertive at 100% penetration rate. This is shown in section 5.1.3 on page 70.

Similar to the car-following models, the results contradict previous research (Mesionis et al., 2020; Yu et al., 2019; Bailey, 2016). Worth mentioning is that the parameters used for cautious and assertive vehicle types have been retrieved from various literature sources and the recommended values from AIMSUN. Various sources were used as no article covered all the parameters that can be changed, not as extensive as presented in this thesis.

The results contribute a clearer understanding of parameters and how some might induce a greater effect on the performance of the AVs than others. Preliminary tests of the car-following models showed a significantly improved performance when adjusting the sensitivity factor or the distance zone factor. While previous research has focused on the AVs giving the most noticeable performance, which often is the assertive type. These results demonstrate that the system's performance, the car-following- and lane-changing models with different compositions of parameters, should not be overlooked.

The generalizability of the results and conclusions is limited by the amount of testing, sensitivity analysis, and different frameworks, further elaborated upon in section 6.2 on page 82. Future research should take this into account, focusing more on the parameters, with more research into what the values should be and to which extent they affect different car-following- and lane-changing models. The adjustment itself is not complicated as AIMSUN offers a straightforward user interface on how to do this. The difficulty is the values themselves and how to fine-tune them to give the best representation. Unlike fine-tuning the parameters in a model to represent the observed traffic situation, the same cannot be done for AVs.

What kind of effect should the AV induce based on the future expectations?

Up until now, the discussion has mainly been on the car-following models and the different parameters. What kind of effects they give and how they should be adjusted. It was mentioned under the first sub-question that *"It is beyond the scope of this thesis to conclude which car-following models resemble the future of AVs."*

Finding the correct car-following model and correct parameters is no easy task, and the effects may not induce the expected outcomes in all types of situations. The main question of the thesis is *"How to model automated vehicles?"* but how does one know that one has been able to do this based on the results? Under section 2.4 on page 28, it is presented based on a survey published by Buvat (2019) that 31% of 5 500 consumers expect reduced traffic congestion due to the implementation of AVs. Whether AVs will induce positive or negative changes is still debated (Buvat, 2019). Many assumptions and claims about the effects made in the scientific community often lack sufficient validation and realism (Calvert et al., 2017). The slow transition towards partial automation might not be positive for the overall traffic efficiency. Therefore, one should not disregard AVs that induce adverse effects on the network, as this could be just as realistic.

Research conducted by Rutgers University in New Jersey claims that AVs could mitigate stop-and-go traffic. However, traffic could worsen as more cars will circulate on streets rather than stay parked (Buvat, 2019). Another concern is the difference in systems that can be deployed on the streets. Some systems can be more advanced and assertive, whereas others might be not fully developed, and therefore be more cautious. The potential amount of different systems might result in a worse situation, which is why some call for a standardized system which is elaborated upon in section 2.3 on page 27.

Based on the literature, most are expecting positive effects. However, few discuss the implications and possible acceptance or denial by the people who will interact with the AVs and how the development of the AVs should have them in mind. As mentioned in section 2.2 on page 25, the preferences might be different. Some wish for a cautious system, while others an assertive or even aggressive one.

How does the SAE-levels of automation reflect the simulated AVs?

The SAE-levels were briefly introduced in chapter 1. In the literature, the levels have been used to indicate which automated vehicle has been simulated. Mesionis et al. (2020) assumed for its AVs, SAE-level 5 behavior and Bailey (2016), SAE-level 3 (Mesionis et al., 2020; Bailey, 2016). The main difference between these levels is that the SAE-level 3 can drive under limited conditions and if the vehicle request, the human has to take control. SAE-level 5 vehicles can drive under all conditions and will not require humans to take control (SAE, 2018a).

Connecting the simulated AVs to specific SAE-levels is very complex and relies heavily on the authors' assumptions. Based on the performance in the system and the bottleneck, one could argue that A-Def induced the positive effects one could expect from vehicles classified as SAE-levels 4 - 5, solely based on behavior with no cooperation capabilities. The vehicle implements the default (Gipps) model; it is versatile and fitting to test for several other types of situations. The C-ACC could characterize an AV in the early stages at the beginning of a transition phase (SAE-levels 2 - 3). Due to the extra conservative model, the model is based on today's ACC technology, not necessarily inducing positive effects on the transportation system with higher penetration rates.

6.2 How to simulate and evaluate the performance of AVs?

What infrastructure design may be suitable to investigate the performance of simulated AVs?

The simulation framework is a fictitious one, with a highway and a merging section. It is designed to evaluate the cooperation between AVs and human vehicles when the travel demand varies, and cooperation becomes necessary to maintain good traffic efficiency. We assume the degree of cooperation between AVs indicates their performance in the system and may therefore be used to evaluate the AVs. The approach is to study indicator results during a simulation and evaluate the AVs performance based on these results, e.g., flow and speed. High values of flow and speed indicate high throughput and good traffic efficiency, i.e., it could be helpful to force congestion to make the AVs cooperate. The thought is then to include an infrastructure element that would force such cooperation. If the AVs were to perform differently, that result could be explained with the AV car-following models or parameter settings.

A merging section was chosen as the infrastructure element that forces cooperation between vehicles. It is less complex than both signalized and non-signalized intersections. Less complexity in the design reduces uncertainty factors, which makes it easier to evaluate. Moreover, a merging section has a lower capacity than the adjacent road network, making it possible to see different flow results in the system simultaneously. All vehicles entering the merging section into the bottleneck have the same destination, which means one can rule out different destinations as a reason for lane-changing behavior. This particular merging section implies "zipper-merge," which means both lanes have equal priority, so the vehicles must assert the same amount of care to one another. Based on the literature, we assume zipper merge to be the most efficient approach, given good cooperation between the AVs (NRA, 2021).

Whether the case study should be based on a realistic or fictitious location is essential to assess. Extensive data collection forms the foundation for an actual location, which means uncertainty in the collected data's representativeness. For an actual location to realistically be replicated, the simulation environment should be as similar as possible. Zhou et al. (2021) have claimed identical replications of real locations to be a nearly unattainable task. Therefore, it is challenging to transfer the simulation techniques to other locations that differ in layout and traffic conditions. Figure 5.4a shows variations in flow as travel demand varies and possible irregularities with some AVs as the flow is constant throughout the simulations. With extensive data collection, an actual location could have better represented the reality with smoother variations in flow and fewer irregularities. That being said, simulations may never replicate the reality entirely, as Box (1976) mentioned in chapter 4. Modeling is a tool, and fictitious locations could then befitting for a simple case, e.g., a merging section entering a bottleneck. In the future, it would be interesting to see more studies on the simulation of AVs at an actual location, with travel demand variations and a merging section.

How to model the transition phase of AVs?

The transition phase of AVs mixed with human vehicles is designed with ten different penetration rates, from 0% to 100%. Only one AV-type is present in the simulation, as it is great uncertainty related to the composition of AVs built on different systems in the future. No other road users were incorporated into the simulations to simplify the evaluation of the AVs further. The results in chapter 5 show that nearly all AVs see an increase in delay times in the entire system with increasing penetration rates, indicating worse traffic throughput late in the transition phase. These additions could be considered for future research.

How to measure performance of simulated vehicles?

The analysis of the results supports that the level of flow is affected by the degree of cooperation. Travel demand exceeding capacity leads to higher delay times and reduced speeds for all AVs, indicating poor cooperation. Variation in travel demand during the simulation creates dynamicity and provides the AVs with an opportunity to show how well they can cooperate to cope with the increased travel demand. The travel demand variations may be visible in indicator results, e.g., flow and speed, and it could make it easier to distinguish the performance of the AVs.

It is helpful to look at information from these detectors located in the vicinity of the bottleneck or any location where the traffic flow could be affected. Flow and speed at each time interval may be helpful to assess the traffic situation. Low flow may indicate poor cooperation between vehicles, and low speeds may indicate slower-moving queues. The higher throughput, the better performance by the AVs, and the transport system become more efficient.

Which indicators are suitable to measure the performance of the system and the bottleneck in particular?

Three indicators were chosen for the simulation evaluation, listed below;

- Delay time
- Speed
- Flow

The detectors capturing the indicator results are located close to the bottleneck, but it could have been interesting to place some detectors elsewhere in the system. For example, that could have been close to the ramps, where entering vehicles must merge onto the motorway. Additionally, headway, number of lane changes, and number of missed turns were also evaluated in simulations 1.0 and 2.0. Results showed no apparent correlation with traffic efficiency indicators, e.g., flow and speed. Hence they were excluded in simulation 3.0.

7 Conclusion

The purpose of the master thesis was to add to the existing knowledge pool and academic discussion on how to model AVs. In order to do this, the following research questions were set:

- How to model automated vehicles in Aimsun Next?
- How to simulate and evaluate the performance of AVs?

The thesis presented ten different AVs where pairs of two, each with different parameter settings, followed the same car-following model. Five car-following models were used, either available in the software or implemented via the microSDK provided by AIMSUN. A majority of time went into understanding the programming aspect, therein syntax, and functions. The vehicles were tested in a fictitious infrastructure framework that aimed to look at cooperation through a bottleneck, on- and off-ramps, and roundabouts.

Based on the results, if measuring performance relative to no AVs present, the A-Def and A-CACC gave the lowest delay time and highest average speed overall in the system for all penetration rates. The bottleneck in the framework was the main contributor to the existing delay in the system. This could be seen from the simulated delay time for the different sections. As the A-Def and A-CACC gave the best performance, they improved the bottleneck's efficiency and throughput.

The ACC model provided by AIMSUN is based on real-life experiments from ACC-vehicles conducted by Milanés and Shladover (2014), whereas the default model was envisioned to replicate human behavior. Based on the results, it is assumed that the ACC model with cautious parameter settings and the default model with assertive parameter settings could potentially correspond to SAE-levels 2 - 3 and SAE-levels 4 - 5, respectively. Therefore it could be argued that the best way to model and simulate AVs in AIMSUN is by doing the following: Using the ACC model with cautious parameters for AVs in early stages and the default model with assertive parameters for AVs in later stages. Both AVs can be modeled with the default lane-changing model for simplicity and assume that the AVs will mimic the human lateral behavior with the enhanced parameter settings.

IDM and EIDM were not chosen due to too high a level of uncertainty in programming. The vehicles equipped also displayed unrealistic behavior in cut-in situations and merging. The vehicles had sudden decelerations to complete stops which helped increase the delay in the system and bottleneck. Delay also had an unrealistic increase in positive correlation with a higher penetration rate. The CACC model was not chosen due to the technology possibly being too far ahead in the future. Platooning does not induce significant reductions in delay till it has achieved a penetration rate of 40% and higher.

The simulation framework allows differentiating the AVs based on their performance. The merging section included in the framework enables the simulation to force AVs and human vehicles to merge and cooperate. Detectors near the bottleneck made it possible to study AVs performance based on indicator results that implied traffic efficiency. Varying travel demand further differentiated AV performance and penetration rates simulating the transition phase from all human vehicles to AVs in the vehicle fleet.

7.1 Future Work

Under discussion, some proposals for future research have been presented. In this section, only the key elements will be mentioned. As seen and discussed under section 5.1 and 6.2 on page 68 and 82, respectively, IDM and EIDM which were implemented via the microSDK, gave the most unsatisfactory performance. As we were the ones who implemented car-following models, one should question the reliability and if the correct parameters were set. It is also essential to keep in mind that the performance might depend on the framework in which they were tested. Therefore, future potential research should test these models to a greater extent, ensuring reliability and uncover specific challenges with the models.

Another vital aspect of AVs is their connective abilities, which will become more critical through intelligent transportation systems (ITS). Although given access to the V2X-SDK in AIMSUN, it proved too challenging and time-consuming to pursue further. Further research could be put into what messages it should send and how the vehicles and infrastructure should use the messages. If possible, to successfully implement the V2X, it is assumed that it will reduce delay and improve traffic efficiency even further, as seen with the CACC-model, which only had cooperation between vehicles.

Future research could also focus on the framework in which the AVs have been tested. The one used in this thesis was fictitious. However, it would be interesting to evaluate simulated AVs in an actual location with other road users, e.g., heavy vehicles, cyclists, and pedestrians. That could make the simulation more realistic, although more challenging to evaluate the AVs as well. Additional research could look at different simulation setups for travel demand, e.g., extended periods with equal demand, greater variations, and more gradual changes. Future work could also apply different compositions of AVs in a mixed traffic scenario to a real-life location and measure the effects using several detectors placed around the system.

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