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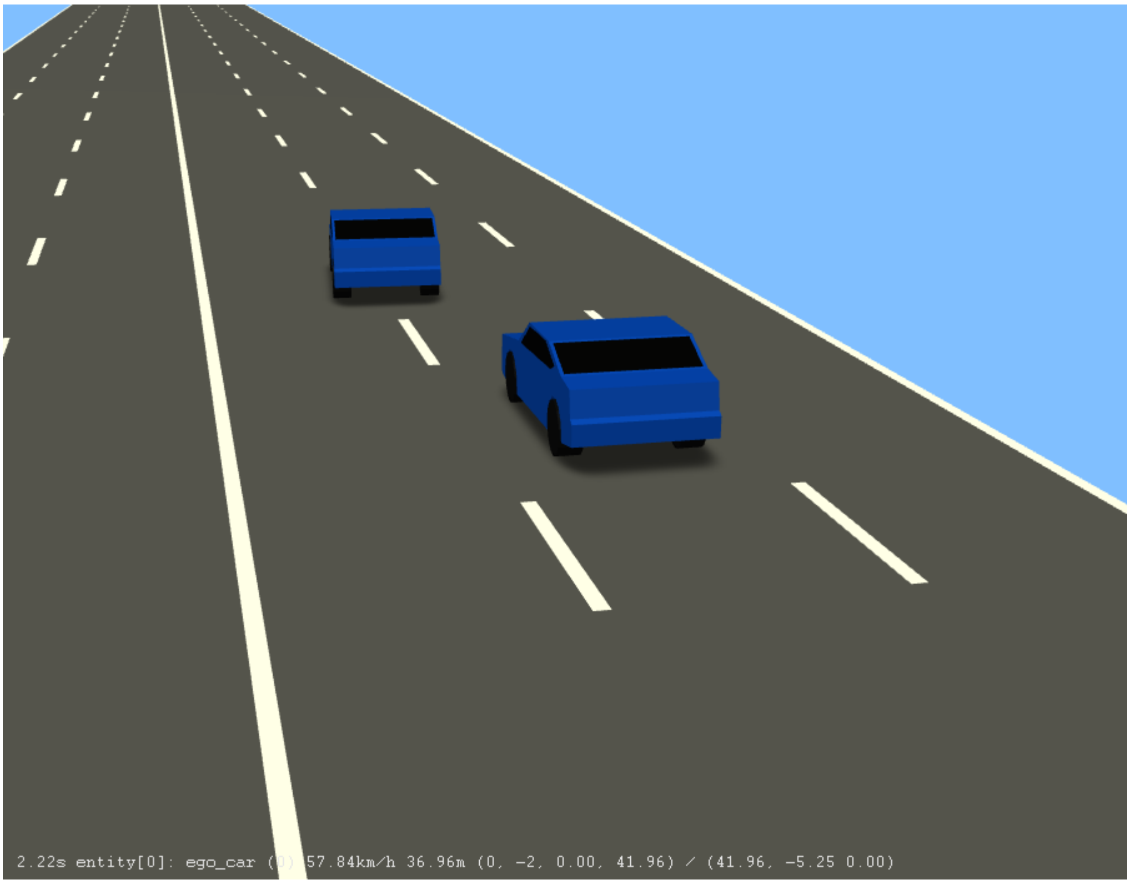

Method development for evaluation of Automated Driving Systems:

Investigating the performance of two reference driver models

Master's thesis in Complex Adaptive Systems

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CHALMERS UNIVERSITY OF TECHNOLOGY
Gothenburg, Sweden 2022
www.chalmers.se

Master's thesis 2022

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Master's Thesis 2022:56
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Cover: Visualisation of the cut-in scenario in esmini, simulated in OPENScenario with the ALKS reference driver model.

Typeset in LaTeX
Printed by Chalmers Reproservice
Gothenburg, Sweden 2022

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Abstract

This work deals with the subject of safety verification and validation of automated driving systems with a high level of automation, in this particular case, SAE level three. The method investigated is scenario based simulation, with the use of reference driver models as performance comparison. The operational design domain is a traffic jam at a highway, and the response is evaluated. Specifically, the simulated scenarios are the cut-in and cut-out scenarios. The two investigated reference driver models are: the ALKS UNECE models and the FSM, which is a proposed performance model by the UNECE. A parameter sweep was done for the two scenario types, where the parameter limits were chosen to target difficult or unavoidable scenarios. Time to collision (no crash) and impact speed (crash) were analysed. First, results from the ALKS model is presented by itself. Then, the performance of the FSM is compared to the ALKS model in the cut-in scenarios. Results show that the ALKS model crashes more than twice as many times as the FSM. Also, the FSM has a more spread out distribution of impact speeds, while the ALKS model is sharply peaked at the initial velocity. This suggests that, for SAE level tree automation systems, the FSM is a more challenging performance target than the ALKS model, in the analysed scenarios.

Keywords: traffic safety, simulation, avoidance, driving model, automated driving system.

Acknowledgements

I would like to thank my advisors at Chalmers University of Technology, Jonas Bärgman and Giulio Bianchi Piccinini. For their guidance and ideas about the analysis that was performed.

I would also like to thank Volvo Cars, and the people and my advisors at Safe Vehicle Automation, Mian Zain Zubair and David Kastö. For their knowledge in automated driving systems validation and verification, their assistance in using and developing the simulation architecture, and as working colleges during the thesis project.

I would also like to thank Chalmers University of Technology for excellent education during my university studies.

Dennis Kristiansson, Gothenburg, June 2022

List of Acronyms

Below is the list of acronyms that have been used throughout this thesis listed in alphabetical order:

ADS	Automated Driving System
AEB	Automatic Emergency Braking
ALKS	Advance Lane Keeping System
CI	Crash Index
CFS	Critical Fuzzy Surrogate Safety Metric
DAS	Driving Automation Systems
DDT	Dynamical Driving Task
ECV	Ego Crash Velocity
ego vehicle	vehicle that is navigated by the driving system/ model
FO	Fail-Operational
FS	Fail-Safe
FSM	Fuzzy Safety Model
H	Headway
KPI	Key Performance Indicator
LD	Lateral Deviation
lidar	Light Detection and Ranging
M&S	Modeling and Simulation
MTTC	Modified Time To Collision
ODD	Operational Design Domain
OEDR	Object and Event Detection and Response
passed scenario	Scenario in which the ego vehicle does not crash
PFS	Proactive Fuzzy Surrogate Safety Metric
RCV	Relative Crash Velocity
RT	Reaction Time
TET	Time Exposed Time to collision
TTC	Time To Collision
UNECE	United Nations Economic Commission for Europe
V&V	Verification and Validation

Contents

List of Figures

List of Tables

1

Introduction

1.1 Background

Vehicle transportation is experiencing a transition from vehicles being operated by the driver to vehicles being controlled more and more by driving automation systems (DAS). The reason for this development is that DAS is believed to lead to increased safety. In recent commercially available cars, there are usually multiple different functional DAS. These have been DAS that can partially function with the support of the driver (supervises automation). These are level one and two automation, using the SAE J3016 levels of driving automation [1]. Examples of such systems are pilot assistance functions, supporting for example lane keeping and vehicle following. In these DAS the human driver is responsible for the object and event detection, and the response (OEDR). [2][3]
The next step in the automation transition is to implement SAE level three automated driving systems (ADS's). These are different in the sense that here, the ADS is responsible for the OEDR while it is active. However, the human driver needs to be ready to take over the driving task (fallback) if the ADS requests this [2]. This level of automation requires the ADS to be able to react to a wide number of different scenarios in a safe way. There is therefore an extensive need for validation of the ADS, ensuring that it operates in a way that leads to sufficient safety for the people inside and outside the vehicle. The ADS is designed to function in a specific operational design domain (ODD). [1]

1.1.1 Operational design domain (ODD)

In the level three of ADS's, the ADS is designed to function in a specific environment, and should not operate outside of this. This environment is called the operational design domain (ODD). The ADS that this work concerns is designed to function in a traffic jam on a highway. It is restricted to function on a highway with lane markings, where the highway needs to be approved in advance. The ADS requires daylight with sufficient sunlight, and dry conditions. The speed of the ego vehicle may not exceed 60 km/h.

1.1.2 Dynamical driving task (DDT)

For level three and higher levels of automation, the ADS is in charge of the full OEDR. For level three automation, the ADS is also required to detect if it has left its ODD, and in that case navigate safely until fallback has been made to the human

driver. An example of this is when the lead vehicle exceeds the 60 km/h threshold, and thus leaving the ADS's ODD. [1]
The ADS also needs to handle possible system failure. Depending on the situation, the ADS will either perform this navigation in fail-operational (FO) or fail-safe (FS) mode. FO mode is used when the failure is not critical and the ADS can still function. Depending on the failure, it might operate at a reduced mode of operation (e.g., reduced speed), and might re-weight data from failing sensors (e.g., rely more on camera data if lidar fails). Under FO, the ADS can still navigate the car safely. FS mode, however, is used when the failure is so severe that the ADS can no longer operate safely. The ADS then needs to transition control back to the fallback-ready driver, but must navigate until this is done. Maneuvers could include stopping in lane or moving out off the travel lane. [2]

1.1.3 Verification and Validation

The ADS needs to operate safely. Thus, the ADS needs to navigate the trip while avoiding crashing. Then, there is another dimension, which is comfort (e.g., an ADS that is not crashing but braking hard all the time would be perceived in a negative way from the user). There are different approaches to perform Verification and Validation (V&V). Modeling and Simulation (M&S) consists of modelling the environments (scenarios) and the ADS functionality. Then, the scenarios are simulated (including the ego vehicle and any included surrounding traffic participants), and the behaviour of the ADS is observed. M&S has the advantages of being highly controllable and predictable. It is also scalable, repeatable and efficient. Other ways to perform V&V are closed-track testing and open-road testing. These provide high fidelity, however they are subject to high costs, time constraints, less controllability and potential injuries. [2]
A question that is central to V&V is what operate safely means. The ADS can not be expected to avoid a crash in all situations. One approach is to compare the performance of the ADS to an attentive human driver. If the ADS outperforms the attentive human driver with regards to safety, completeness of trip and following the rules, it can be argued that the ADS is operating safely. [3][4]

1.1.4 Reference driver model

Comparing the performance of the ADS to an attentive human driver is a complex task. One approach to doing this is using a reference driver model. There are many different driver models. Driver models typically model how an average human driver behaves and reacts in different situations, and some models include variability in human driver behaviour. Most driver models only handles either safety critical or normal driving. For collision avoidance (safety critical driving), most driver models react by either braking or steering, while some models reacts with a combination of the two. [5]
While there are many different driver models, there is only a few reference driver models. A reference driver model is used as a standard for something, and may thus be used as a safety target for an ADS. The UNECE reference driver model

[6] is built to approximate the behaviour of a skilled and attentive human driver in different safety critical situations. This model does not include variability in human driver behaviour, and reacts by braking. Since the UNECE reference driver model describes how the model should react in different situations, it can be used in simulations in a wide range of scenario setups (parameter settings). Waymo has another scenario-based reference driver model [3]. This model is based on naturalistic driving data, in other words human performance in real-life driving. The model reacts by steering and/ or braking. Volvo Car Company has a third reference driver model (ADEST) [4] which may be used on real-world traffic near-crashes and crashes for specific conflict situations. It is a mathematical model of an attentive, skilled and experienced driver.

1.1.5 Societal, ethical and ecological aspects

The ADS of interest in this thesis (level 3) will be functional in a specific ODD, and can not operate a vehicle during the entire trip. No workers (e.g., taxi drivers) should therefore lose their jobs. The ADS can offer time saving (in the regard that the driver can perform other tasks) and increased safety during certain parts of the trip, which is desirable. However, the work could build a foundation for future V&V of more advanced ADS, that might render e.g. taxi drivers obsolete. When this becomes a reality, this matter needs to be addressed.

The thesis is performed as part of the effort to validate the safety of ADS. It is essential to ensure the ADS is safe enough before launch. The validation process has a responsibility to not accept flawed functionality. When an ADS is brought into commercial products, unwanted behaviours from the ADS would hold developers and V&V accountable. Since these could in worst case scenario cause unnecessary human injuries, the V&V coverage and reliability is of utmost importance. The M&S process of the V&V that this work entails is however not dangerous, therefore, no safety regards needs to be taken during the M&S.

ADS's will, just as humans drivers do, face difficult scenarios where difficult decisions needs to be made. An illustration of this is the trolley problem [7], where a worker needs to decide whether or not to change the direction of a train heading towards five people, into the direction of one person. Similar situations can be imagined for ADS's, where a vehicle only have two available trajectories. The current trajectory has two persons on it, while the other trajectory has only one. Other difficult questions is if the ADS should discriminate between different pedestrian. Should the ADS rather drive into an adult than a child, or should it treat them the same? These questions lie outside the scope of this thesis, but needs to be addressed by developers and possibly also in V&V. Also note that the trolley problem is highly theoretical, rather than a practical problem, as the ADS practically making split second decisions in critical situations are not "programmed" in the way that the problem statement alludes to it being. The M&S is performed in a virtual environment. The only ecological influence will be with regards to energy consumption. That is there will be no direct pollution from physical vehicles from this part of the V&V.

1.2 Aim

This works main aim is to investigate the parameterization of two specific reference driver models as safety targets for ADS of SAE automation level three, as part of the V&V of such systems. The ODD is highway traffic jams daytime with good weather and road conditions, and the two models the UNECE [6] ALKS model and the FSM [8]. The assessed V&V approach is in the form of M&S, which using computer representations of traffic scenarios, where simulations using reference driver models act on the presence of other road users in the simulation (here cut-ins and cut-outs). Scenarios for simulation are found and created, and suitable parameter values will be chosen to cover safety critical scenarios. The two reference driver models are investigated with respect to their suitability as safety performance targets. Key performance indicators (KPIs) are identified and compared.

1.3 Scope

This work only deals with M&S (virtual simulations). Closed-track testing and open-road testing are not regarded. The study perform M&S in the form off virtually simulating different scenarios with different combinations of model and scenario parameter values, *without* considering the probability of the combination of scenario parameters occurring in the real-world. That is, the study does not aim to estimate the impact of safety that the reference models would have, if they were drivers in the real worlds. Only the responses of the reference driver models to the unfolding of the situation are investigated (no ADS system is evaluated). ODD detection is not analysed. That is; the ego vehicle is always assumed to be within its ODD. All sensors are assumed to be functional and ideal. That is, FO and FS are not regarded. The hardware of the vehicle, object detection software and the ability to detect errors of these are not addressed. The chosen reference driver models are only assessed for a specific set of base scenarios.

1.4 Specification of issue under investigation

1. How does the chosen scenario and model parameters impact safety KPIs for the investigated reference driver models for the specific scenario types?
2. How do the safety KPI outcome differ between the two reference driver models, and what are the implications of those differences on their use as safety performance targets?

2

Theory

2.1 Simulation

The simulations in this work will not test the object detection, and will therefore always assume that the objects present in the simulation has been detected properly. In this way, the event detection and response of the reference driver may be analysed. Examples of events are lead vehicle braking or a vehicle in the adjacent lane cutting into the ego-vehicle's lane. Examples of ego-vehicle responses are acceleration and steering.

There are different approaches to defining suitable scenarios for validation. One approach is trying to use naturalistic driving data for generation of scenarios – either data from normal driving, near-crashes or crashes [9]. Another is using reconstructed crashes from in-depth crash databases [10]. A third is defining a set of scenarios that are likely (may) to happen in the real world, but without taking the probability of the individual events occurring in the real-world into account [3]. This work will be based on the latter.

2.1.1 ALKS scenarios

Using a set of scenarios that the ego vehicle is likely to face within its ODD during a drive can give an indication of its performance. Two of these are the cut-in and cut-out scenarios. [6]

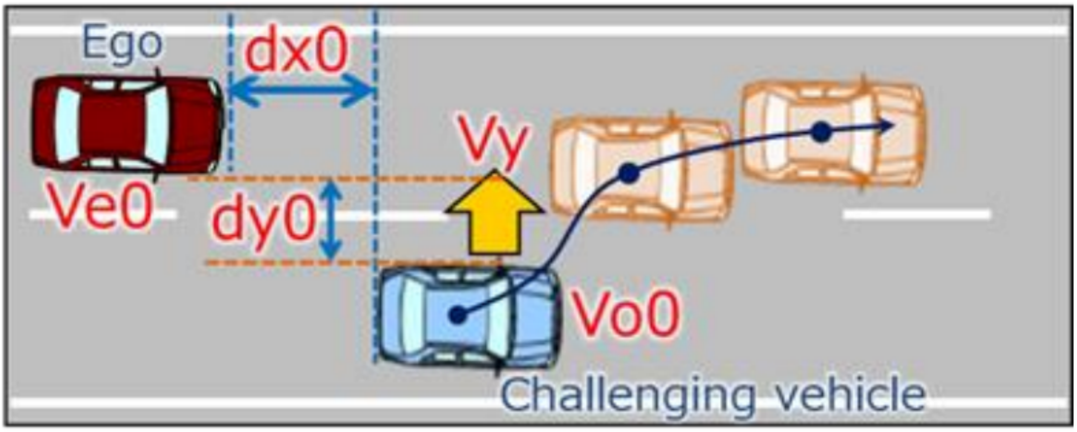

Figure 2.1: The cut-in scenario. A challenging vehicle in the adjacent lane enters into the ego vehicle lane. Parameters of the scenario are the ego velocity Ve0, challenging vehicle velocity Vo0, lateral velocity Vy of the challenging vehicle, and longitudinal distance dx0 between the ego vehicle front end to the challenging vehicle rear end. Figure source: Picture from [6] with written permission.

2.1.1.1 Cut-in

The cut-in scenario can be seen in figure 2.1. Here, a challenging vehicle in the adjacent lane enters into the ego vehicle lane. All parameters are specified at the start of the scenario. In the start of the scenario, both the ego vehicle and the challenging vehicle are in the centre of their lanes. Therefore, the distance dy0 in the figure depends on the vehicle's widths and the lane width. dx0 is the distance from the front end of the ego to the back end of the challenging vehicle. Ve0 and Vo0 is the speed of the ego and challenging vehicle respectively. Vy is the lateral speed of the challenging vehicle during the lane change (Vy is zero after the lane change).

2.1.1.2 Cut-out

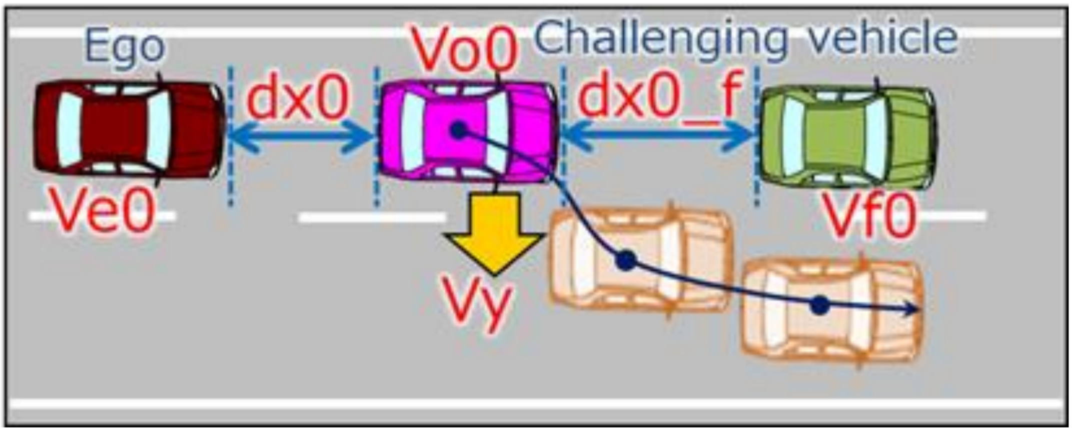

Figure 2.2: The cut-out scenario. A challenging vehicle in the ego lane leaves the ego lane, while another vehicle up ahead in the ego lane remains in the ego lane. Parameters of the scenario are ego velocity Ve0, velocity Vo0 and Vf0 of the challenging and other vehicle respectively, longitudinal distance dx0 and dxo_f, and lateral velocity Vy of the challenging vehicle. Figure source: Picture from [6] with written permission.

The cut-out scenario can be seen in figure 2.2. Here, a challenging vehicle in the ego lane leaves the ego lane into an adjacent lane. Further on in the ego lane there is another vehicle that stays in the ego lane. All parameters are specified at the start of the scenario. At the start of the scenario, all vehicles are in the centre of the ego lane. Ve0 ,Vo0 and Vf0 is the speed of the ego, challenging and other vehicle respectively. dx0 is the distance from the front end of the ego vehicle to the back end of the challenging vehicle. dx0_f is the distance from the back end of the other vehicle to the front end of the challenging vehicle. Vy is the lateral speed of the challenging vehicle during the lane change (Vy is zero after the lane change). The time headway of the ego vehicle to the challenging vehicle is denoted by TH, and is given by

$$\mathrm{TH} = \frac{\mathrm{dx0}}{\mathrm{Ve0}}. \tag{2.1}$$

2.2 Reference driver models

In this study, two reference driver models from the UNECE will be used. The ALKS reference driver model [6], and the by the UNECE proposed performance model, the FSM [8], that will be treated as a reference driver model in this work. They are both defined in the three traffic critical disturbance scenarios: cut-in, cut-out, and lead vehicle decelerating into a stop (deceleration).

2.2.1 The ALKS driver model

For the cut-in and cut-out scenario, the driver model is defined as follows. First, the risk perception is determined. It is taken to be at the point of the challenging vehicle (the vehicle in the adjacent lane, cutting into the ego-vehicle's lane) deviating 0.375 m from its starting lane center position. This parameter will be called lateral deviation. When the driver has perceived the risk, there is a reaction time between the risk perception and the point where the braking starts. This includes the ego-vehicle's drivers risk evaluation, decision on braking and physical movement of the foot. The reaction time is set to 1.15 s. The deceleration increases linearly with 12.65 m/s^3 (jerk) to $0.774g$ (maximum deceleration) After that it stays at $0.774g$ until the ego-vehicle is at stand-still. Here, $g = 9.81$ m/s^2.
This model is equipped with an automatic emergency braking (AEB), that if triggered overrides the previous behaviour. That is, the AEB is basically seen as an integral part of the driver (model), but implemented as an AEB. The AEB is triggered if a TTC value lower than 2.0 s is observed in longitudinal direction. Further, it will only trigger for a vehicle that at least partly occupies the future path of the ego vehicle. The deceleration of the AEB begins instantly when triggered, and instantly makes the braking become $0.85g$. Note that this is different from the reference, where the braking increases linearly with 13.90 m/s^3 to $0.85g$, and then stays at $0.85g$. [6]

2.2.2 The Fuzzy Safety Model (FSM)

The following text describes the driver model in the cut-in scenario. The behaviour of this model is made up by three parts. A lateral and longitudinal safety check, and a reaction. A reaction happens only in the event of a safety risk in both the lateral and longitudinal direction. Values of the driver model parameters are given in section 2.2.2.4. [11]

2.2.2.1 Lateral safety check

A lateral safety risk is perceived if and only if all of the following conditions are true:

1. The back of the challenging vehicle is in front of the ego vehicle front.
2. The challenging vehicle is moving towards the ego.
3. The longitudinal speed of the ego is larger than the longitudinal speed of the challenging vehicle.
4. $$\frac{dist_{lat}}{u_{cut-in,lat}} < \frac{dist_{lon} + length_{ego} + length_{cut-in}}{u_{ego,lon} - u_{cut-in,lon}} + 0.1, \tag{2.2}$$

where $dist_{lat}$ is the lateral distance between the vehicles ($dist_{lat}$ = dy0 at t = 0), $dist_{lon}$ is the longitudinal distance between the vehicles ($dist_{lon}$ = dx0 at t = 0), $length_{ego}$ and $length_{cut-in}$ are the length of the ego and challenging vehicles respectively (= 5 m), $u_{cut-in,lat}$ = Vy during the lane change, else zero, $u_{ego,lon}$ is the ego longitudinal velocity (= Ve0 at $t = 0$), and $u_{cut-in,lon}$ = Vo0.

2.2.2.2 Longitudinal safety check

The longitudinal safety check uses two fuzzy metrics, proactive fuzzy surrogate safety metric (PFS) and critical fuzzy surrogate safety metric (CFS). A longitudinal safety risk is perceived for an instance if PFS or CFS are greater than zero, in an intermittent fashion. The PFS is the anticipatory measure, that may sense a possible future collision and will cause a mild deceleration. The CFS on the other hand is the safety critical measure, and will cause larger deceleration. [8]
The PFS is given by

$$\mathrm{PFS}(dist_{lon}) = \begin{cases} 1, & \text{if } 0 < dist_{lon} - d_1 < d_{unsafe} \\ 0, & \text{if } dist_{lon} - d_1 > d_{safe} \\ \dfrac{dist_{lon} - d_{safe} - d_1}{d_{unsafe} - d_{safe}}, & \text{if } d_{unsafe} < dist_{lon} - d_1 < d_{safe} \end{cases} \tag{2.3}$$

where d_1 is the safe distance when both vehicles have stopped,

$$d_{safe} = u_{ego,lon}\tau + \frac{u^2_{ego,lon}}{2b_{ego,comf}} - \frac{u^2_{cut-in,lon}}{2b_{cut-in,max}} + d_1, \tag{2.4}$$

$$d_{unsafe} = u_{ego,lon}\tau + \frac{u^2_{ego,lon}}{2b_{ego,max}} - \frac{u^2_{cut-in,lon}}{2b_{cut-in,max}}, \tag{2.5}$$

where τ is the reaction time, $b_{ego,comf}$ is the comfortable deceleration threshold, $b_{ego,max}$ is the maximum deceleration, and $b_{cut-in,max}$ is the maximum deceleration of the challenging vehicle.
The CFS is calculated by

$$\mathrm{CFS}(dist_{lon}) = \begin{cases} 1, & \text{if } 0 < dist_{lon} < d_{unsafe} \\ 0, & \text{if } dist_{lon} \geq d_{safe} \\ \dfrac{dist_{lon} - d_{safe}}{d_{unsafe} - d_{safe}}, & \text{if } d_{unsafe} \leq dist_{lon} < d_{safe} \end{cases} \tag{2.6}$$

where

$$d_{safe} = \begin{cases} \dfrac{(u_{ego,lon} - u_{cut-in,lon})^2}{2a'_{ego}}, & \text{if } u_{ego,lon,NEXT} \leq u_{cut-in,lon} \\ d_{new} + \dfrac{(u_{ego,lon,NEXT} - u_{cut-in,lon})^2}{2b_{ego,comf}}, & \text{if } u_{ego,lon,NEXT} > u_{cut-in,lon} \end{cases} \tag{2.7}$$

$$d_{unsafe} = \begin{cases} \dfrac{(u_{ego,lon} - u_{cut-in,lon})^2}{2a'_{ego}}, & \text{if } u_{ego,lon,NEXT} \leq u_{cut-in,lon} \\ d_{new} + \dfrac{(u_{ego,lon,NEXT} - u_{cut-in,lon})^2}{2b_{ego,max}}, & \text{if } u_{ego,lon,NEXT} > u_{cut-in,lon} \end{cases}. \tag{2.8}$$

The new variables is given by

$$a'_{ego} = \max(a_{ego}, -b_{ego,comf}) \tag{2.9}$$

$$u_{ego,lon,NEXT} = u_{ego,lon} + a'_{ego}\tau \tag{2.10}$$

$$d_{new} = (\frac{u_{ego,lon} + u_{ego,lon,NEXT}}{2} - u_{cut-in,lon})\tau \tag{2.11}$$

where a_{ego} is the acceleration of the ego, a'_{ego} is a modified acceleration of the ego, $u_{ego,lon,NEXT}$ is the expected ego speed after the reaction time (assuming constant acceleration), and d_{new} is the longitudinal distance change between the vehicles after the reaction time.

2.2.2.3 Reaction

The deceleration happens after the reaction time τ, after both the lateral and longitudinal safety checks are identifying a safety risk, and is given by

$$b_{reaction} = \begin{cases} \text{CFS} \cdot (\text{b}_{\text{ego,max}} - \text{b}_{\text{ego,comf}}) + \text{b}_{\text{ego,comf}}, & \text{if CFS} > 0 \\ \text{PFS} \cdot b_{ego,comf}, & \text{if CFS} = 0 \end{cases}. \tag{2.12}$$

The applied deceleration is not instantaneous, but increases with a constant rate, given by the maximal jerk (see table 2.1).

2.2.2.4 Driver model parameter values

The values for the different parameters presented above are shown in table 2.1.

Table 2.1: The FSM parameter settings.

reaction time	$\tau = 0.75$ s
maximal jerk	12.65 m/s^3
safety distance for stopped vehicles	$d_1 = 2$ m
comfortable ego deceleration	$b_{ego,comf} = 4$ m/s^2
maximum ego deceleration	$b_{ego,max} = 6$ m/s^2
maximum deceleration of challenging vehicle	$b_{cut-in,max} = 7$ m/s^2

2.3 Verification and Validation (V&V)

The purpose of the reference driver models in the V&V in this work is attempting to validate if the ADS is driving in a safe way. This is a complex task, since it not always possible for the ADS to keep sufficient distance to other vehicles and to avoid crashes. One approach is to identify key performance indicators (KPI's) that quantifies the momentary safety of the vehicle [12]. Subjecting the ADS and reference driver models to a scenario and measuring the KPI's can give an indication of the safety performance.

2.3.1 Safety KPI's

The most significant (safety) performance indicator is if the ego vehicle avoids a crash or not. If the vehicle avoids crashing, it is of interest of how close the ego vehicle came to crashing. However, if the vehicle has crashed, the magnitude of the crash is instead of interest. Therefore, safety KPI's are divided into crash KPI metrics and non-crash KPI metrics.
If a crash has happened, the severity of the crash is relevant. Therefore the speed of the ego vehicle is measured at time of impact, and referred to as ego crash velocity (ECV). Also, the relative velocity of the crashing vehicles is recorded (in longitudinal direction only), and will be called relative crash velocity (RCV). It is given by

$$\mathrm{RCV} = v_{\mathrm{lon,ego}} - v_{\mathrm{lon,target}} \tag{2.13}$$

where v_{lon} is the longitudinal velocity of the vehicle. The target denotes the vehicle of interest in the scenarios (challenging vehicle for cut-in, other vehicle for cut-out). This definition may seem like the more commonly used term impact speed. However, in this thesis the term relative crash velocity is used because in some simulations its value is negative, where negative means that the target vehicle has crashed into the ego vehicle ($v_{\mathrm{lon,target}} > v_{\mathrm{lon,ego}}$). Note that the absolute value of the RCV is the (longitudinal) impact speed. The injury risk of a crash may also be analysed [13], but have not been done in this work.
If the ego vehicle has managed to avoid a crash, the minimum time to collision (TTC) may be of interest. At every moment, the TTC gives the time until a crash would happen, if the vehicles velocities would not change. Note that if a crash has happened, the minimum TTC is 0 seconds. The TTC is given by

$$\mathrm{TTC}_{\mathrm{lon}} = \begin{cases} 0 & \text{if } x_{\mathrm{target}} - x_{\mathrm{ego}} - l < 0 \\ \dfrac{x_{\mathrm{target}} - x_{\mathrm{ego}} - l}{v_{\mathrm{lon,\ ego}} - v_{\mathrm{lon,\ target}}} & \text{else if } v_{\mathrm{lon,\ ego}} > v_{\mathrm{lon,\ target}} \\ \infty & \text{else} \end{cases} \tag{2.14}$$

$$\mathrm{TTC}_{\mathrm{lat}} = \begin{cases} 0 & \text{if } y_{\mathrm{target}} - y_{\mathrm{ego}} - w < 0 \\ \dfrac{y_{\mathrm{target}} - y_{\mathrm{ego}} - w}{v_{\mathrm{lat,\ ego}} - v_{\mathrm{lat,\ target}}} & \text{else if } v_{\mathrm{lat,\ ego}} > v_{\mathrm{lat,\ target}} \\ \infty & \text{else} \end{cases} \tag{2.15}$$

$$\mathrm{TTC} = \max(\mathrm{TTC}_{\mathrm{lon}}, \mathrm{TTC}_{\mathrm{lat}}) \tag{2.16}$$

where x denotes the longitudinal centre position of the vehicle (forward direction), y is the lateral centre position of the vehicle (the y axis direction is down in figure 2.1), l is the length of the vehicles, w is the width of the vehicles, and v_{lon} and v_{lat} is the respective longitudinal and lateral velocity of the vehicle. Note that in this work, vehicles of same dimensions are used. If this is not the case, $l = l_{\mathrm{ego}}/2 + l_{\mathrm{target}}/2$ is used, and similarly for w.

3 Methods

3.1 Simulation

The scenarios cut-in and cut-out are simulated. For the simulation of the ALKS driver model, the scenarios are built with OpenDrive [14] and OpenSCENARIO [15]. The behaviour of the ALKS model is implemented in OpenSCENARIO. The scenarios are executed with esmini [16]. For the FSM driver model, the scenarios and driver model behaviour are implemented and executed purely in Python. For the latter, [17] was used as a base, upon wish some functionality was added.

3.1.1 Reference driver models

The implementation of the ALKS model differs somewhat from the reference literature that is presented in section 2.2.1. The jerk time for both braking responses are different. The braking with a reaction time (jerk 12.65 m/s^3) is altered to 30 m/s^3. The AEB (with jerk 13.90 m/s^3) is altered to infinite jerk, thus the full braking force is applied instantly.

Table 3.1: The different parameter settings for the ALKS driver model are shown in the table. The different parameter settings are referred to by different names, where the top one is called ALKS driver model, because it has the unchanged parameter values specified in section 2.2.1.

	lateral deviation	reaction time
ALKS model	0.375	1.15
slow model	0.375	1.55
fast model	0.375	0.75
very attentive model	0.2	1.15
inattentive model	0.55	1.15

The ALKS and FSM driver models are used in the simulations. For the ALKS driver model, the driver model parameters of the reference driver model are altered, creating new versions of the ALKS model for each combination of parameter values. That is, the lateral deviation for risk perception and the reaction time are changed, to study the impact the changes has on the safety outcome (KPIs). The settings are shown in table 3.1. The different parameter settings are referred to by different names, where the top one is called ALKS driver model, because it has the unchanged parameter values specified in section 2.2.1. The reaction time is varied keeping the lateral deviation unchanged, producing two new models. The model with longer reaction time is the slow model. The model with shorter reaction time is the fast model. Also, the lateral deviation is varied, with unchanged reaction time. The model with a short lateral deviation is called the very attentive model. The model with a large lateral deviation is the inattentive model.

3.1.2 Scenarios

In all scenarios, the width of the lanes is set to 3.5 meters. The length 5.0 meters and width 2.0 meters are used for the vehicles.
For the two scenario types cut-in and cut-out, a parameter space is defined, where every possible permutation of parameters is simulated. The parameters are chosen to asses challenging scenarios. Note that this all-permutation simulation setup does not consider the probability of the individual parameter combinations occurring in the real world, and any analysis must bare that in mind (see discussion).
Parameter values for the cut-in scenario is shown in table 3.2. The definition of the parameters can be seen in figure 2.1. Here, Ve0 is fixed to 60 km/h. Note that dy0 is set by the lane width and vehicle width, since the vehicles are initialized in the centre of their lanes.

Table 3.2: The different parameter settings for the cut-in scenario can be seen in the table. For definition of the parameters, see figure 2.1. Each permutation of these parameters is simulated. Consequently, 17x9x20 = 3060 events are simulated.

dx0 [m]	Vy [m/s]	Ve0−Vo0 [km/h]
1	0.25	1
3	0.5	2
5	0.75	3
7	1	4
9	1.25	5
11	1.5	6
13	2	7
15	2.5	8
17	3	9
19		10
21		11
23		13
25		15
27		17.5
30		20
35		22.5
40		25
		30
		35
		40

Parameter values for the cut-out scenario is shown in table 3.3. The definition of the parameters can be seen in figure 2.2. Vo0 = Ve0 is chosen, and Vf0 is fixed to 0, i.e. the other vehicle is stationary. Vy = 1.5 m/s is chosen.

Table 3.3: The different parameter settings for the cut-out scenario can be seen in the table. For definition of the parameters, see figure 2.2. Each permutation of these parameters are simulated. A total of 30x10x17 = 5100 simulations were consequently run.

dx0_f [m]	TH [s]	Ve0 [km/h]
6	0.2	20
7	0.4	22.5
8	0.6	25
9	0.8	27.5
10	1.0	30
11	1.2	32.5
12	1.4	35
13	1.6	37.5
14	1.8	40
15	2.0	42.5
16		45
17		47.5
18		50
19		52.5
20		55
21		57.5
22		60
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3.2 Verification and Validation

The data from the scenarios are analysed to extract KPIs. This includes crash or no crash, ego crash velocity, relative crash velocity and TTC. The KPI outcome for the different driver models (and different driver model parameter settings) are visualized and compared to validate their performance.

3.2.1 Cut-in: ALKS and FSM driver model comparison

In the ALKS and FSM driver model comparison, some parameter settings were removed from the analysis. In the cut-in scenario, some of the scenario parameter settings leads to the challenging vehicle entering the ego lane behind the ego vehicle, if the ego vehicle does not brake. The FSM model can account for this and may not brake thus avoiding a crash, while the ALKS model always brakes. Therefore, when comparing the models, these scenarios have been removed. The condition for the scenario to be removed from consideration is if and only if

$$\frac{\mathrm{LW} - \mathrm{VW}}{\mathrm{Vy}} \frac{\mathrm{Ve0} - \mathrm{Vo0}}{3.6} > \mathrm{dx0} + 2 \cdot \mathrm{VL} \tag{3.1}$$

holds. LW is the lane width, VW is the vehicle width and VL is the vehicle length. These scenarios are the ones where if no response comes from the ego vehicle, the cutting in vehicle will end up behind the ego vehicle without a crash. Thus it can be beneficial to not brake in these scenarios. Note that the scalar 3.6 is added to convert km/h to m/s.

3.2.2 Cut-out

For some combinations of dx0_f and Ve0, the challenging vehicle crashes into the stationary vehicle. This happens when the challenging vehicle has not moved enough laterally before it reaches the stationary vehicle, i.e. for short dx0_f values and high Ve0 values. These scenarios were removed from the analysis.

4
Results

When a TTC value for a scenario is given, what is meant is always the minimum TTC. In this chapter, the results of the study are presented. For each section, there is a corresponding section in the discussion that discusses the outcome of the result and reflects on the results.

4.1 ALKS driver model

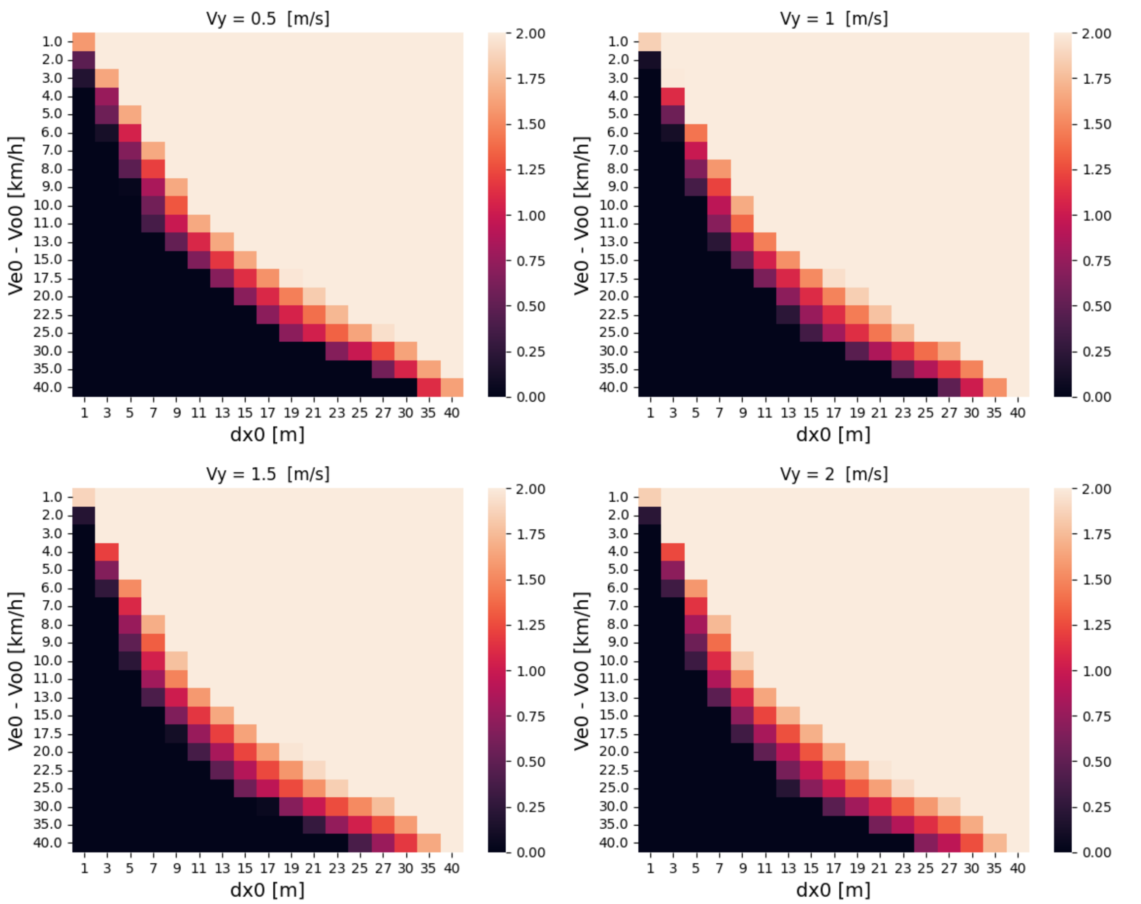

Figure 4.1: For the cut-in scenario, minimum TTC values (in seconds) are shown for different Vy values.

An analysis of the ALKS driver model is presented, with plots of minimum TTC and relative crash velocity values. First, the cut-in scenarios are analyzed. The minimum TTC for different scenario parameters is analysed. TTC values that are larger than 2 s are shown as 2 s in the heat maps in this section. Note that in the case of a crash, TTC = 0 s.

4.1.1 Cut-in: TTC analysis

The parameter influence on the line TTC = 0 s is not mentioned in this section, since it is the same as the line between crash or no crash in section 4.1.2 and is addressed there.
In figure 4.1, minimum TTC's in seconds are shown as a function of the relative velocity between the vehicles and the longitudinal distance. Each subfigure shows the behaviour for different lateral velocities. It can be seen that lines TTC = 0 s and TTC = 2 s are quite close to each other, and that the distance (in the figure) between them seem to increase with larger Vy.

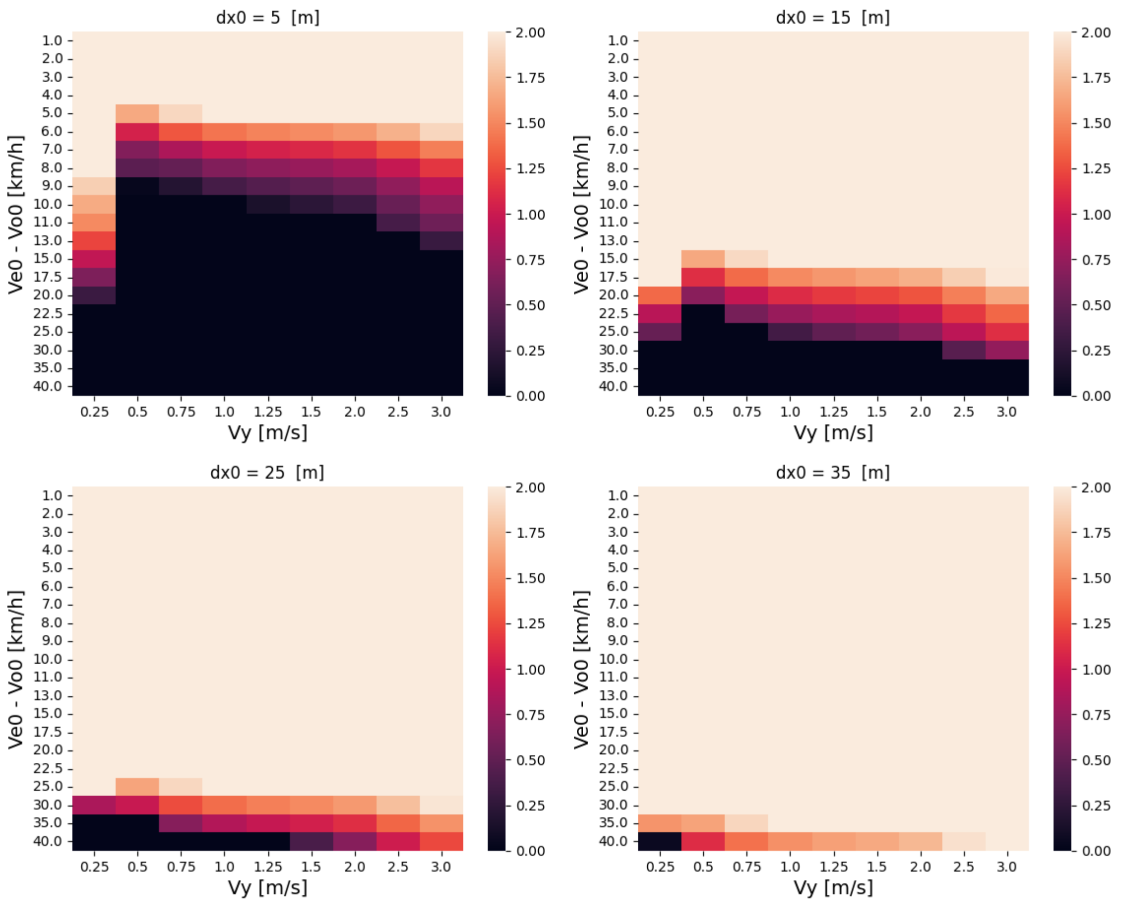

Figure 4.2: For the cut-in scenario, minimum TTC values (in seconds) are shown for different dx0 values.

In figure 4.2, minimum TTC values are shown in seconds. The subfigures show different values of longitudinal distance, with relative velocities and lateral velocities on the y and x axis respectively. For dx0 = 5 m the lines TTC = 0 s and TTC = 2 s have a larger separation, and this separation becomes smaller with increasing dx0, except for at Vy = 0.25 m/s. One can see that Vy = 0.25 m/s stands out, leading to larger TTC's than for Vy = 0.5 m/s, for all shown longitudinal distances except dx0 = 35 m.

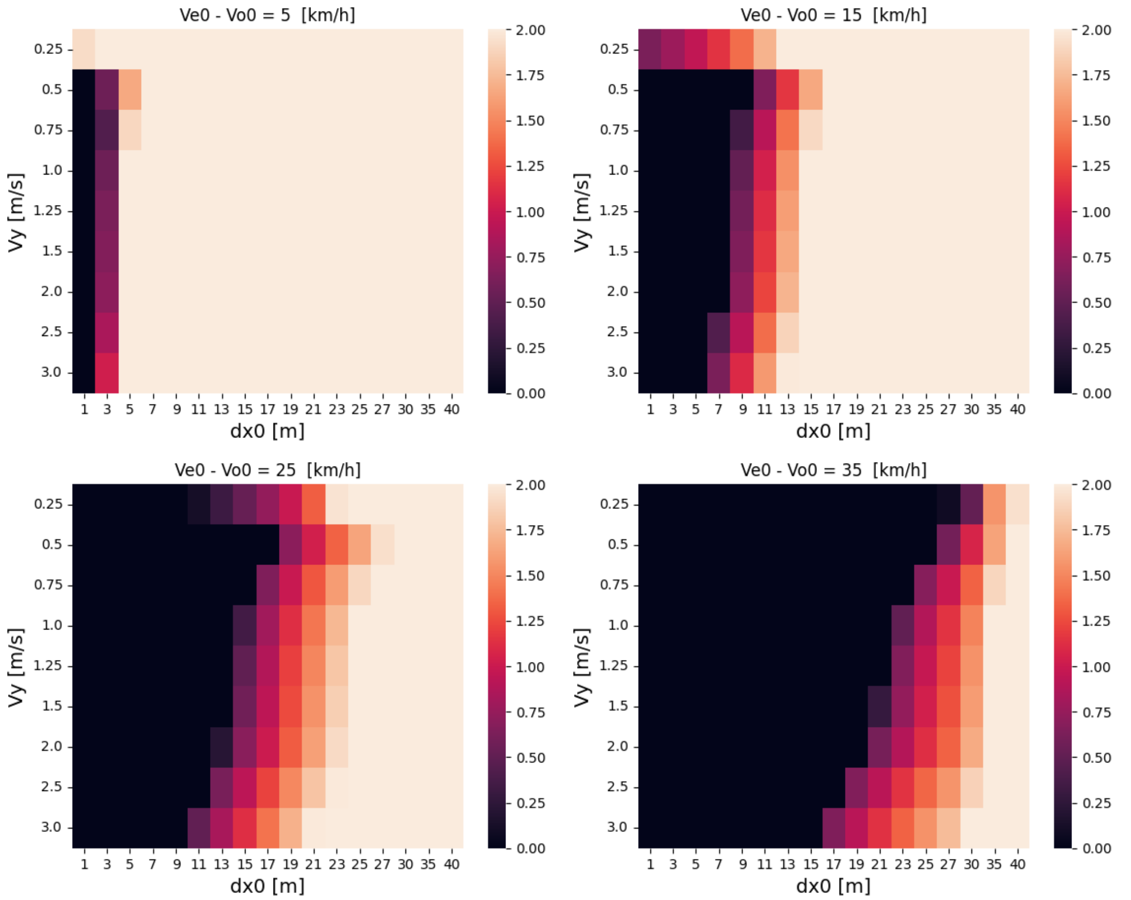

Figure 4.3: For the cut-in scenario, different minimum TTC values (in seconds) are shown for different Ve0 -Vo0 values.

In figure 4.3, minimum TTC's are shown in seconds. The subfigures show different relative velocities as a function of the lateral velocity and the longitudinal distance. One can see that the area between TTC = 0 s and TTC = 2 s grows with increasing relative velocity, if Vy = 0.25 m/s is excluded.

4.1.2 Cut-in: Relative crash velocity analysis

Relative crash velocity (in km/h) is shown such that a positive value means that the ego vehicle had a greater speed than the challenging vehicle, thus the ego crashed into the challenging vehicle. A negative value means that the challenging vehicle had a lower speed than the ego vehicle, thus the challenging vehicle crashed into the ego vehicle. For further explanation of this, see section 5.2.2. White space indicates that no crash has happened.

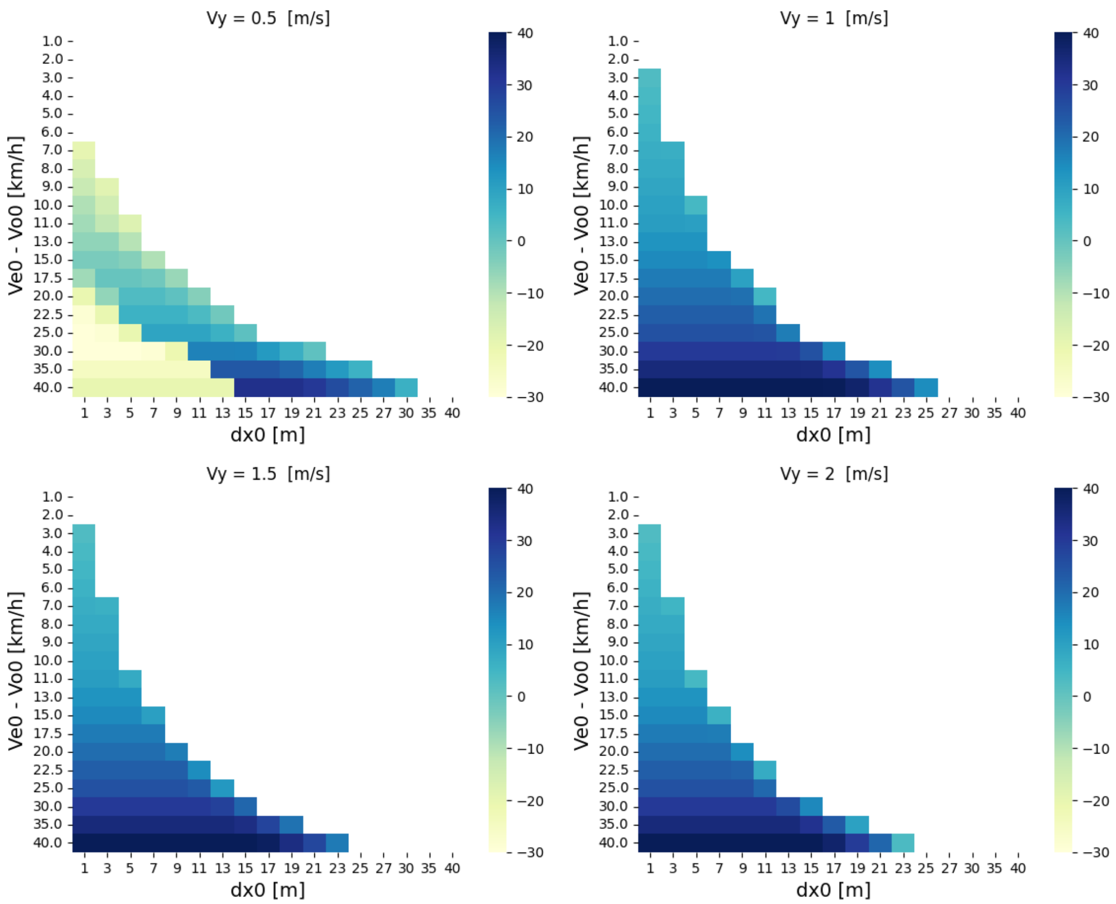

Figure 4.4: For the cut-in scenario, relative crash velocity (in km/h) is shown for different Vy values. A positive velocity means the ego vehicle has higher velocity than the challenging vehicle at the time of impact. No crash is shown in white.

In figure 4.4, relative crash velocities are shown (in km/h) for four lateral velocities, as a function of relative velocity and longitudinal distance. One can see that the line that separates crash and no crash moves towards the southwest corner with increasing lateral velocities, except for Vy = 0.5 m/s. Note that this is the same line as the line TTC = 0 s seen in figure 4.1. For Vy = 0.5 m/s there are negative values.

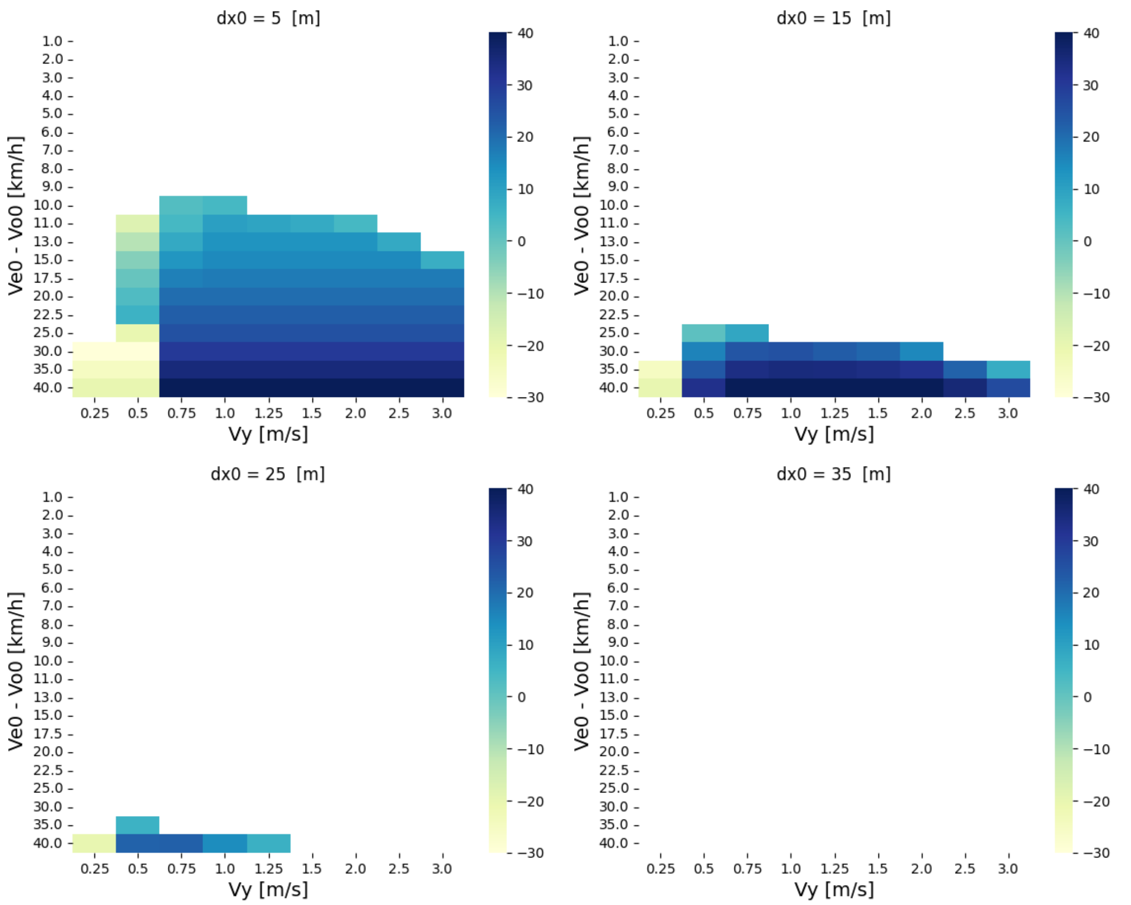

Figure 4.5: For the cut-in scenario, relative crash velocity (in km/h) is shown for different dx0 values. A positive velocity means the ego vehicle has higher velocity than the challenging vehicle at the time of impact. No crash is shown in white.

In figure 4.5, different longitudinal distances are shown. In general, the line between crash and no crash moves towards the southwest corner with increasing dx0. One can see that this line moves more for the different dx0 values than for the different lateral velocity values, see figure 4.4. Lateral velocities stand out (Vy $\in [0.25, 0.5]$ m/s), leading to fewer collisions, as was observed in figure 4.2 also.

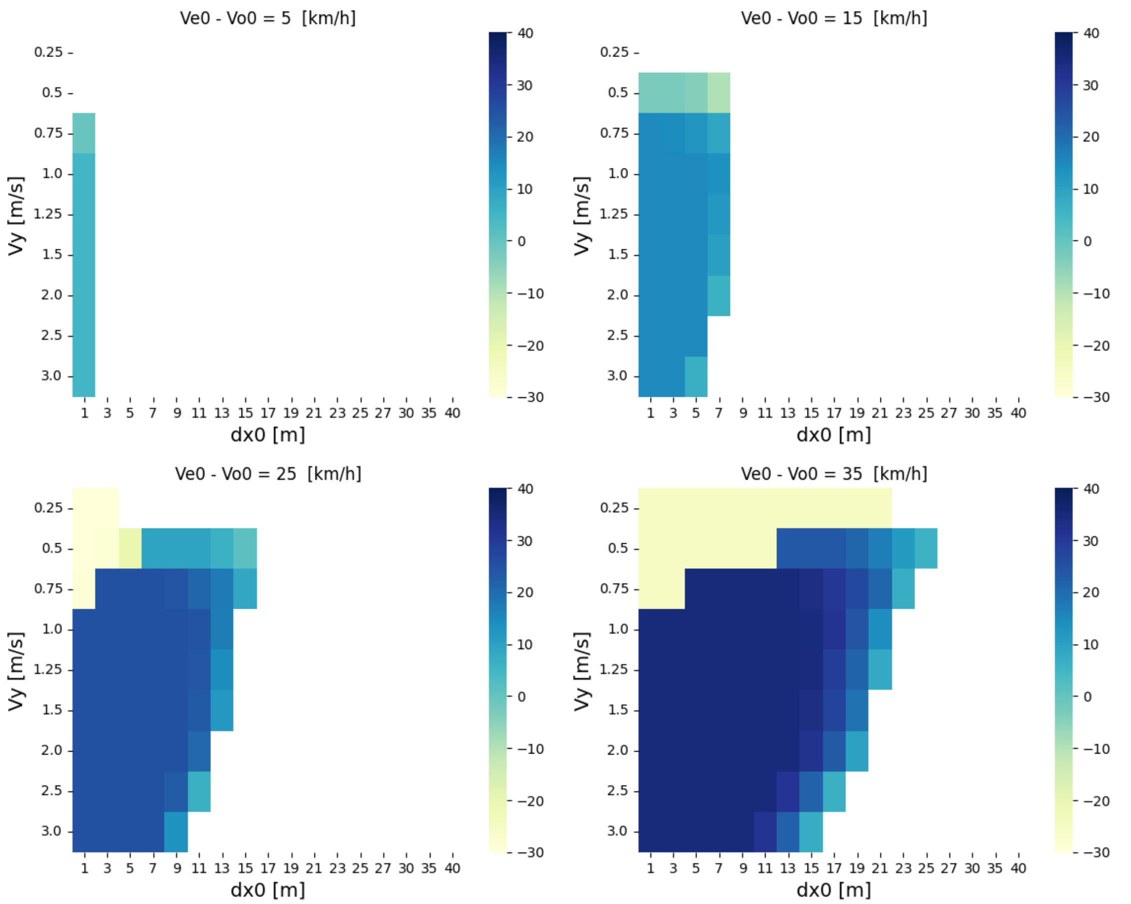

Figure 4.6: For the cut-in scenario, relative crash velocity (in km/h) is shown for different Ve0 -Vo0 values. A positive velocity means the ego vehicle has higher velocity than the challenging vehicle at the time of impact. No crash is shown in white.

In figure 4.6, subfigures of relative velocities are shown. The relative velocity impacts the position of the line between crash and no crash much, moving it to the right for increasing relative velocities. Also here, Vy $\in [0.25, 0.5]$ m/s stands out when it comes to if the ego crashed or not.

In the figures for relative crash velocity, one can see that for the most crashes that happens, the relative crash velocity is either equal to the relative velocity or negative.

4.1.3 Cut-out: TTC analysis

In the cut-out scenario, TTC values are analysed for the ALKS driver model. For every varied parameter, the TTC distribution for four values are shown as a function of the other parameters. Also here, TTC values of more than 2 s are shown as 2 s in the plots, and a crash means the TTC is 0 s. The white pixels in the plot indicates scenarios where the challenging vehicle crashes into the stationary vehicle, as described in section 3.2.2.

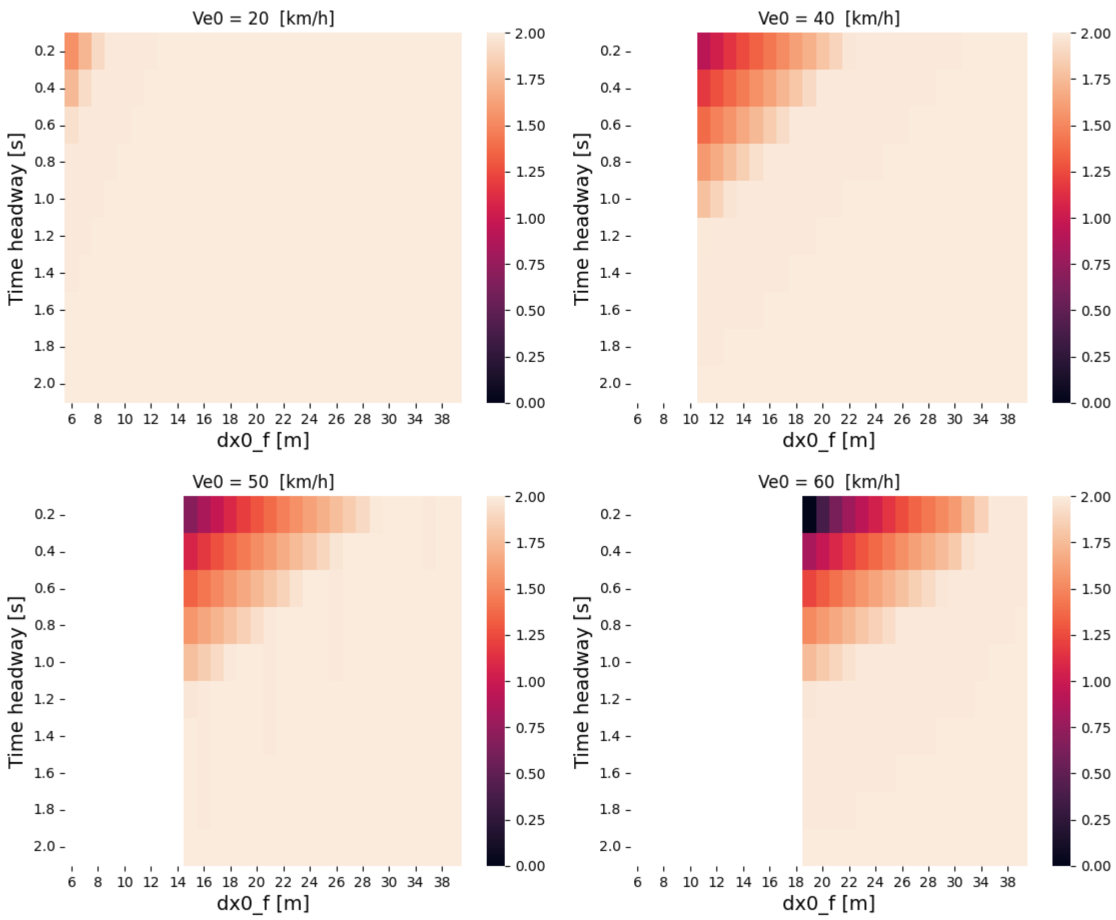

Figure 4.7: For the cut-out scenario, different minimum TTC values (in seconds) are shown for different Ve0 velocities. A white pixels indicates the case of the challenging vehicle crashing into the stationary vehicle. (section 3.2.2).

In figure 4.7, minimum TTC's (in seconds) are shown for ego vehicle velocity as a function of time headway and front longitudinal distance. One can see that the ego velocity impacts the minimum TTC. For Ve0 = 20 km/h all TTC's are greater than 1.25 s, while Ve0 = 60 km/h gives one TTC of 0.0 s.

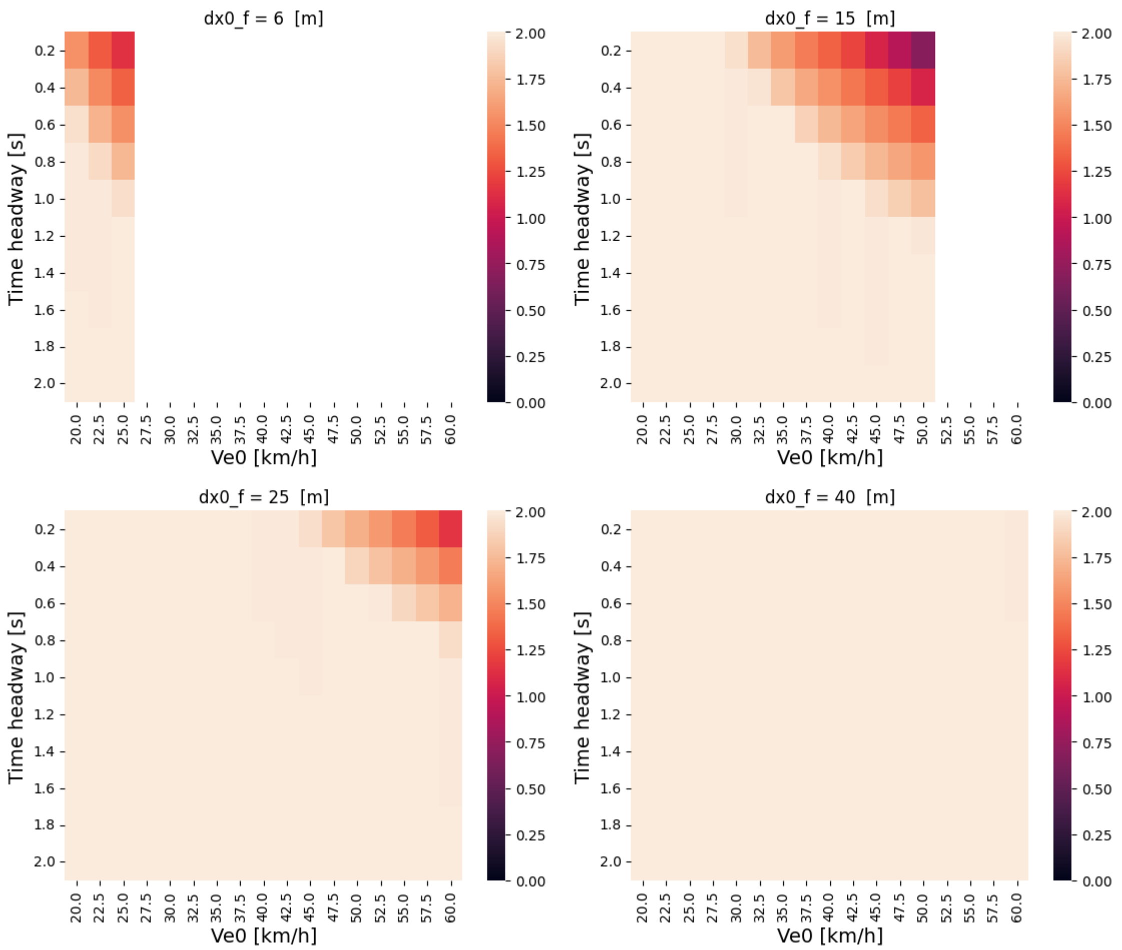

Figure 4.8: For the cut-out scenario, different minimum TTC values (in seconds) are shown for different dx0_f distances. A white pixels indicates the case of the challenging vehicle crashing into the stationary vehicle. (section 3.2.2).

In figure 4.8, minimum TTC values are shown in seconds for different front longitudinal distances. Here the smallest TTC value happens for dx0_f = 15 m, giving a minimum TTC of 0.7 s. For dx0_f = 6 m and dx0_f = 25 m the smallest TTC is 1.1 s and 1.2 s, while for dx0_f = 40 m it is larger.

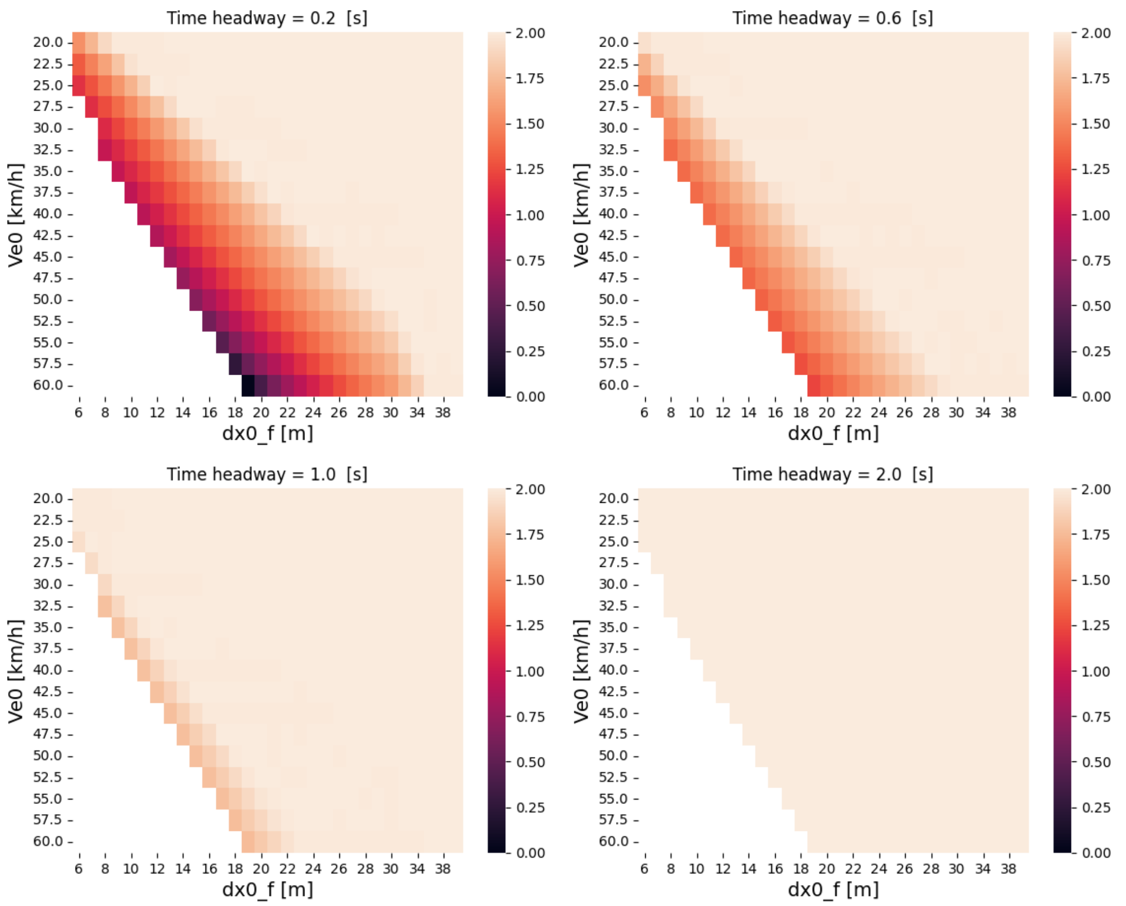

Figure 4.9: For the cut-out scenario, minimum TTC values (in seconds) are shown for different time headways. A white pixels indicates the case of the challenging vehicle crashing into the stationary vehicle. (section 3.2.2).

In figure 4.9, minimum TTC's (in seconds) are plotted for four time headways, with front longitudinal distance and ego velocity on the x- and y-axis respectively. One can see that the time headway influences the TTC's significantly. For TH = 0.2 s, the minimum TTC is 0.0 s. Increasing TH to 0.6 s increases the minimum to 1.2 s, while the other two larger TH values gives larger TTC's.

For the used scenario parameters, the ego vehicle only crashes in one of the cut-out scenarios. The parameters for this scenario is Ve0 = 60 km/h, dx0_f = 19 m and TH = 0.2 s. Since the ego vehicle only crashes once, crash velocity is not visualized.

4.2 ALKS Model: Driver model parameters

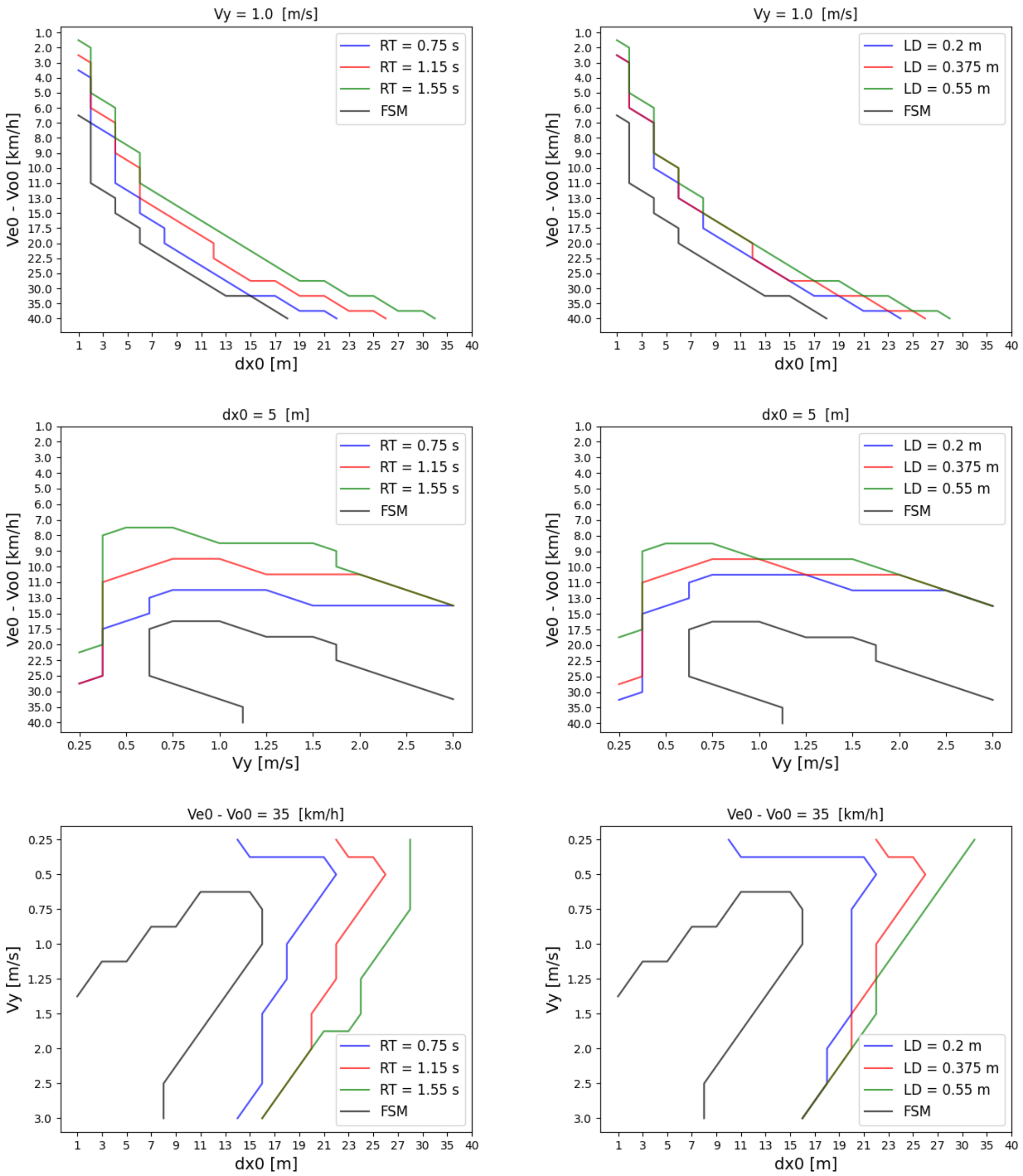

Figure 4.10: For the cut-in scenario, the line between crash and no crash is shown for different ALKS model parameters (as shown in table 3.1) and the FSM. Here, RT is the reaction time driver model parameter and LD is the lateral deviation driver model parameter.

To investigate how sensitive the ALKS model parameters are, the line between crash and no crash are shown for different driver model parameter settings (as shown in table 3.1). The FSM is also included as a comparison. Only the cut-in scenario is shown. reaction time = 1.15s and lateral deviation = 0.375m is the unaltered ALKS model settings. These lines can be seen in the relative crash velocity plots (figure 4.4, 4.5, 4.6), as the line separating the white and the non-white areas (no crash and crash).

The result is shown in figure 4.10. The FSM outperforms (avoids more collisions) all of the ALKS model parameter settings, for all visualised parameters. In general, the change in performance is larger for the reaction time (RT) parameter variation than the lateral deviation (LD) parameter variation. The FSM line shows different behaviour compared to the ALKS model for $dx0 = 5$ m and $ve0 - Vo0 = 35$ km/h. This different behaviour is seen for large relative velocities and low lateral velocities.

4.3 FSM: comparison to ALKS model

The FSM is compared to the performance of the ALKS model. For this comparison, only the cut-in setup is evaluated. A passed scenario means the ego vehicle does not crash in this scenario. The scenario parameters that leads to the challenging vehicle possibly driving into the lane behind the ego are removed, as described in section 3.2.1. All other scenario parameters are included in the analysis in this chapter.

4.3.1 Fraction of passed scenarios

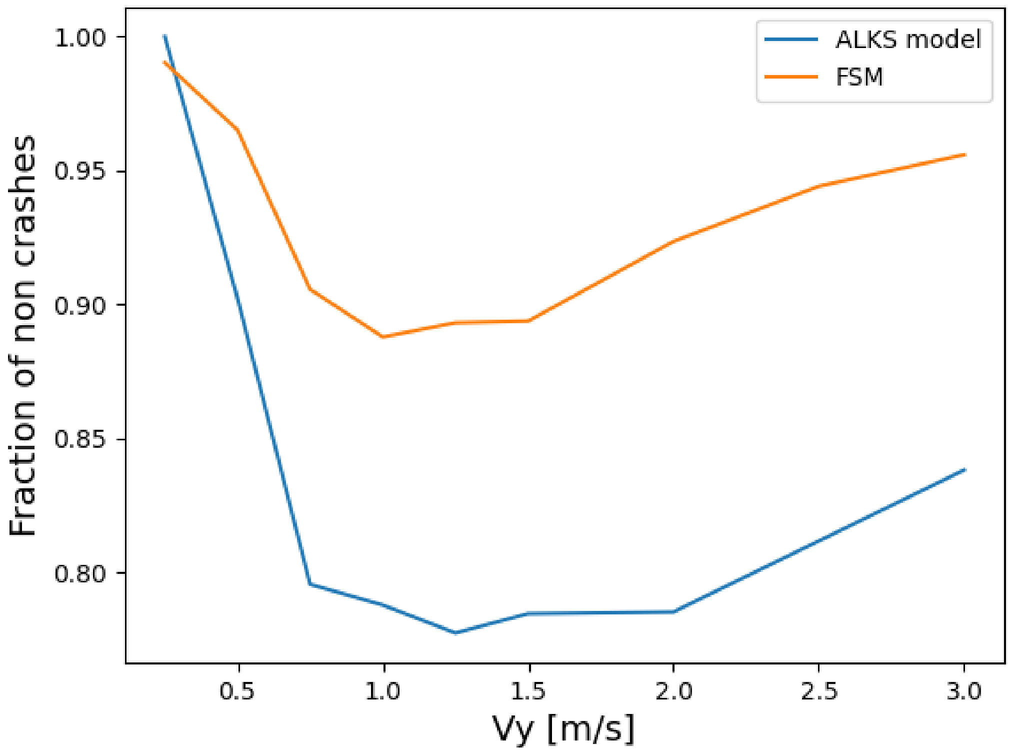

Figure 4.11: Here, the fraction of passed scenarios is visualised for the cut-in scenario. For every value of Vy, the fraction of passes scenarios is shown for the different driver models. Note that here all the parameters (dx0,Vy,Ve0-Vo0) are varied according to table 3.2. Consequently, every value of Vy consists of 17x20 = 340 simulations, without any consideration to the probability the individual combinations of parameters have in the real-world.

The FSM avoids a crash in 92.7% of the scenarios, while the ALKS model avoids in 82.3% of the scenarios. The following figures in this section shows how the fraction of crashes depends on the different parameters. For each parameter value, the fraction of passed scenarios of all permutations containing that value is shown. That is, again, these are scenarios generated by simulating all combinations of parameter values in table 3.2, without probability weighting.

In figure 4.11, the fraction of passed scenarios can be seen for the ALKS model and FSM, for different lateral velocities. Note that the FSM avoids crashing in more scenarios than the ALKS model for most lateral velocities, except Vy = 0.25 s. Both models have a similar dependence of the lateral velocity, performing well for small lateral velocities (Vy = 0.25 s), performing the worst at the lateral velocities 1.0 s and 1.25 s (FSM and ALKS model respectively), and then increasing the performance for larger lateral velocities.

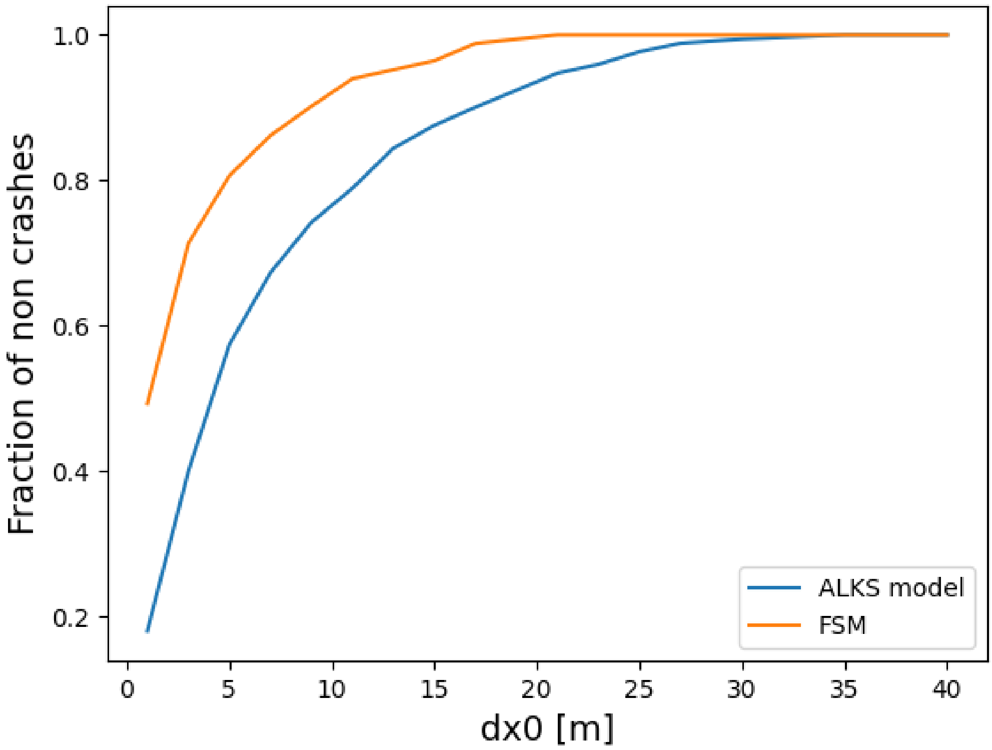

Figure 4.12: Here, all of the cut-in scenarios simulated are included. For every value of dx0, the fraction of passes scenarios is shown for the different driver models.

In figure 4.12, the fraction of passed scenarios is plotted as a function of the longitudinal distance. The FSM performs better than the ALKS model for all longitudinal distances. One can see that the longitudinal distance has a big impact on the outcome of the scenarios, for both models. The performance of the FSM seems to be close to constant for about dx0 > 20 m, while the decline in performance of the ALKS model starts already at about dx0 = 35 m.

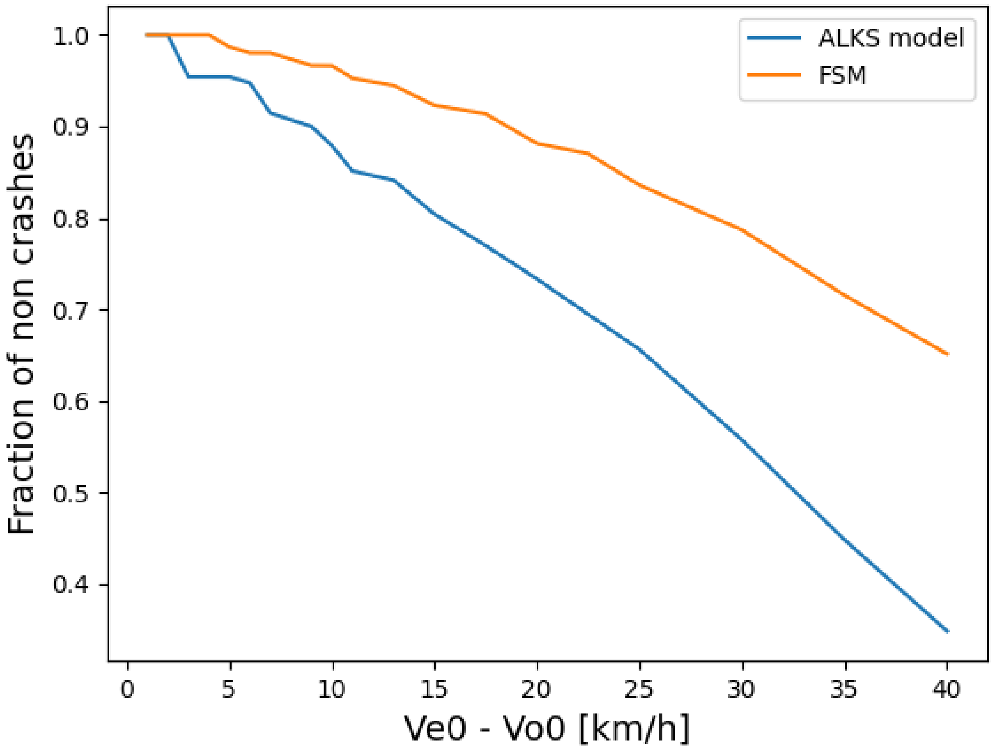

Figure 4.13: Here, all of the cut-in scenarios simulated are included. For every value of Ve0-Vo0, the fraction of passes scenarios is shown for the different driver models.

Figure 4.13 shows the fraction of passed scenarios as a function of the relative velocity. The relative velocity impacts the fraction of collisions much. The FSM performs similarly or better than the ALKS model for all simulated relative velocities. Both the ALKS model and the FSM shows an approximately linear decrease in performance, after an initial constant segment. This constant segment is longer for the FSM (about 5 km/h) than the ALKS model (about 2 km/h).

4.3.2 Minimum TTC distributions

In the following TTC plots, the lower TTC values are plotted and analysed, to focus on the safety critical scenarios. Crashes (TTC = 0) are not included.

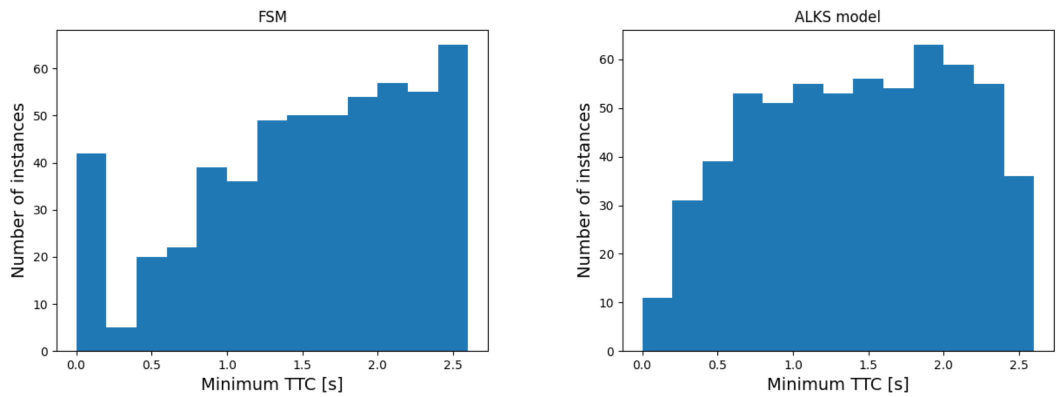

Figure 4.14: For the cut-in scenario, for all scenarios where a collision is avoided, minimum TTC's are plotted in a histogram.

In figure 4.14, the TTC distribution in between 0 and 2.6 s is shown for the two models - again for all permutations of the parameters in table 3.2 and without probability weighting (in relation to the probability of the combination occurring in the real world). The distributions have some differences. The FSM has a peak for low TTC's, while the ALKS model seems to have a minimum there. If the TCC values below 0.2 s are disregarded, the distribution is increasing for low TTC's (TTC $<$ 0.75 s). For higher TTC's, the ALKS model seems to have an approximately constant distribution (with outliers). The FSM distribution however seems to increase with larger TTC's. The increase is larger for lower TTC's, i.e. the distribution does not seem to increase linearly.

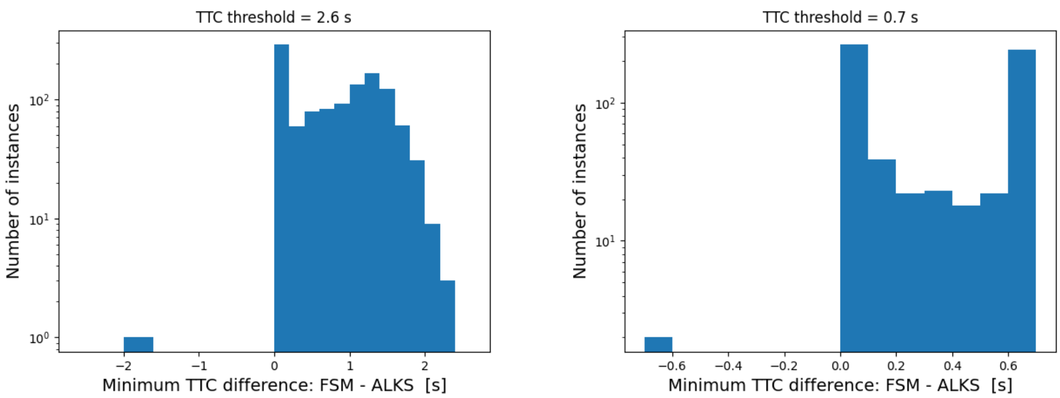

Figure 4.15: For the cut-in scenario, the difference in TTC between the FSM and ALKS model is plotted in the histogram. The TTC values are capped at 2.6 s and 0.7 s, since larger TTC values are of less safety concern. Note that the y-axis is in logarithmic scale.

In figure 4.15, the difference in TTC between the two models is calculated for each simulation, and plotted in a histogram with logarithmic y-axis. The TTC's are capped, i.e. $\text{TTC} = \max(\text{TTC}, \text{TTC threshold})$. The simulation is not included in the analysis if both TTC's are greater than this limit. The difference is given by

$$\text{minimum TTC difference} = \text{TTC(FSM)} - \text{TTC(ALKS model)} \tag{4.1}$$

for each simulated scenario. In some of the scenarios, the TTC values are the same (or very similar). However, in the majority of the scenarios, the FSM has a higher TTC than the ALKS model. Only in a few instances, the ALKS model has a lower TTC. For TTC threshold 0.7 s, one can see that there is a large number of scenarios where the FSM keeps a TTC larger than or close to 0.7 s, while the ALKS model has TTC = 0 s.

4.3.3 Ego crash velocity distributions

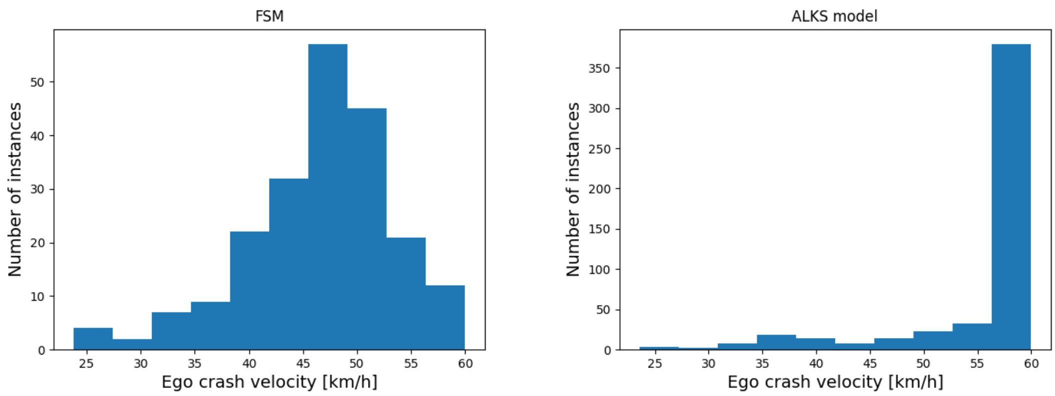

Figure 4.16: For the cut-in scenario, for all crashes, the ego crash velocities are plotted in a histogram for the two models.

In figure 4.16, ego crash velocity distributions are shown for the two models. The FSM has in most cases crashed around 57 km/h, while for the ALKS model crashes are most frequent close to 60 km/h. One can clearly see that the FSM ego crash velocities are more spread out, while the ALKS model is sharply peaked at 60 km/h.

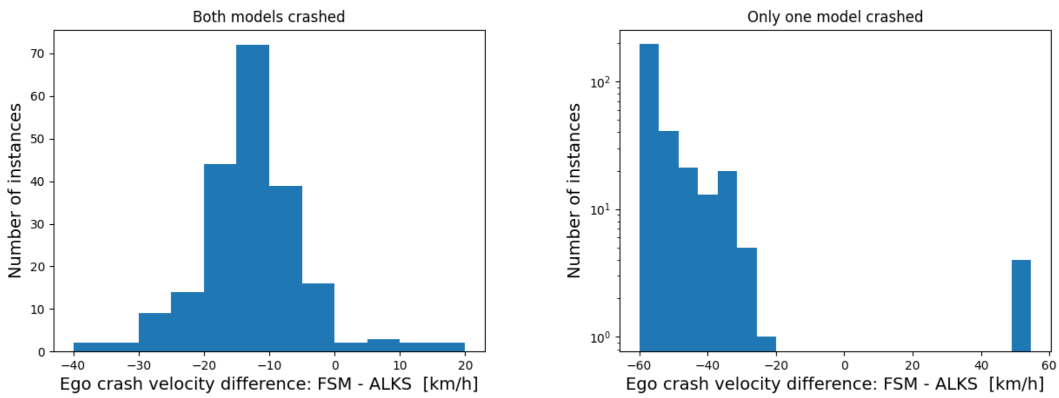

Figure 4.17: In the cut-in scenario, for crashes that happens the difference between ego crash velocities of the FSM and ALKS model are plotted. The scenarios where both models crashes are separated from scenarios where only one model crash. Ego crash velocity is 0 km/h if the model has not crashed. Note that the only one vehicle crashed plot has a logarithmic y-axis.

Figure 4.17 shows the difference in ego crash velocity in each scenario. The plots are dividing the two cases where both models crashes, and when only one of the models crash. If the model does not crash, it is assigned the ego crash velocity 0 km/h. The ego crash velocity difference is given by

$$\text{ECV difference} = \text{ECV(FSM)} - \text{ECV(ALKS model)} \tag{4.2}$$

in each simulated scenario. Here, ECV denotes ego crash velocity. In the case where both models crash, in the majority of scenarios the ALKS model has a higher ego crash velocity than the FSM. Only in a few scenarios the FSM ego crash velocity is higher. In the case of only one vehicle crashing, it is mainly the ALKS model that crashes, in only four scenarios the FSM crashes when the ALKS model does not. Both models crash in 207 of the scenarios, while only one of the models crash in 300 of the scenarios.

5
Discussion

5.1 Method

The ALKS model and the FSM were simulated in different programming architectures. It might have been more robust to implement them in the same architecture, such as using OpenDrive and OpenSCENARIO in the esmini [16] simulation environment. For time constraint reasons, this was not done. To my knowledge, there is no substantial bias between the two architectures used.

For the scenarios, some parameters were fixed to simplify the analysis of the performance. In the cut-in scenario, the velocity of the ego vehicle was fixed to 60 km/h. This is because the ego vehicle velocity does not influence the scenario much, what matters is the relative velocity between the cars. For the ALKS model, the ego velocity does not influence the performance in any way.

In the cut-out scenario, the velocity of the challenging vehicle was set to the ego velocity. This was done because it is common that following vehicles have similar velocities. The other vehicle was fixed to be standing still. This was done since it illustrates the situation of a car having stopped in the lane for some reason, and is more challenging than if the car had had a non zero velocity. For the ALKS model, and also for seeing the stationary vehicle up ahead (at least for straight roads), it matters at what point the challenging vehicle has moved out of the centre of the lane enough to observe the stationary vehicle, thus registering a potential danger. At which point this happens is influenced by both the front longitudinal distance and the lateral velocity. For this reason, the lateral velocity was fixed to 1.5 m/s, which seemed like a reasonable cut-out velocity in the given situation.

The values of the varied parameters were chosen to access a challenging parameter space for the scenarios. This was successful, however a lot of the scenarios simulated were impossible (unavoidable crash) or easy (easily unavoidable crash). One could have tried targeting the challenging (avoidable but not easy) scenarios more precisely, and this might have given a more precise performance evaluation. However, simulating the full parameter space, as was done in this case, provides one perspective of the understanding of the overall performance. The chosen scenario distribution is not representing the distribution of cut-ins [18] and cut-outs in real world traffic. That is, importantly and as noted several times, the probability of the individual combinations of parameters occurring in the real world was not considered, and therefore the outcomes must not be assessed as absolute risks, but can still help developers and evaluators to understand the impact of the two reference driver models behaviors on the KPIs.

In the cut-out scenario, if the challenging vehicle crashes into the stationary vehicle, these scenarios are removed from the analysis. This is due to the fact that if these scenarios would be implemented in a feasible way, one would need to take into account the crash dynamics to determine the kinematics of the challenging and stationary vehicle after the crash. This was not considered in this work.

5.2 ALKS driver model performance

That the threshold TTC = 2.0 s was used as higher limit for visualisation, was to make the interesting regions of smaller TTCs more visible. The value 2.0 s was chosen as a point where if the vehicle did not reach a TTC lower than this, it does not appear to have been subjected to a safety risk, and is thus concluded to have been operating safely in the scenario. The value of 2.0 s could have been chosen differently, but was used in this work.

5.2.1 Cut-in: TTC analysis

In the figures showing these TTC's (figure 4.1, 4.2, 4.3), one can see that the parameter values influence the area between the lines TTC = 0 s and TTC = 2 s. This area is the part of the parameter space where the model did not crash but was subjected to a safety risk. This area is in general not big, compared to the area of TTC = 0 and/ or TTC $\geq$ 2 s. This means that in most scenarios, the vehicle is either always safe or crashes. This might be explained by the nature of the model, since as soon as it detects the lane change, breaks with full force.

5.2.2 Cut-in: Relative crash velocity analysis

The results of this section are shown in figure 4.4, 4.5, 4.6. For low lateral velocities and longitudinal distances, and high relative velocities, the relative crash velocity becomes negative. This means the ego has detected the lane change and brakes, until it comes to a stop. For these parameter values however, the challenging vehicle has ended up on the side or behind of the ego, and since the challenging vehicle does not brake, it crashes into the ego. In a real scenario, the challenging vehicle might have braked. Also, a real driver would probably not brake until standing completely still, if the challenging vehicle is behind the ego. The ALKS driver model and the modelling of the challenging vehicle is therefore not well suited for these parameter settings.

For most crashes that happen, the relative crash velocity is either equal to the relative velocity or negative. This means that for most scenarios, the vehicle either does not start braking before the crash, or has already decelerated to a stop. Only in a small number of scenarios, the ego starts braking and then crashes into the challenging vehicle.

As seen in the figures above, both TTC and relative crash velocity has a non-linear dependence of the lateral velocity. The ALKS model perform better for low and high lateral velocities, than it does for lateral velocities around $(0.5 \text{ m/s}, 0.75 \text{ m/s}, 1.0 \text{ m/s})$.

This can be explained that for large lateral velocities (Vy > 1.0 m/s), the challenging vehicle enters the ego lane soon after the cut-in begins (< 1.5 s). In these scenarios, the ego vehicle needs to react as fast as possible to avoid the challenging vehicle. The ego reacts faster for higher later velocities, because for higher lateral velocities, the lateral deviation is crossed earlier, and thus the cut-in is registered faster. Also, the cutting-in vehicle reaches the future path of the ego vehicle faster, thus triggering the AEB system faster, making the ego vehicle brake harder earlier. For lower lateral velocities (e.g., 0.25 m/s), it take some time until the cutting-in vehicle reaches the future path of the ego vehicle (about 6 seconds). Here, it does not matter that the ego vehicle does not register the cut-in fast, since the ego vehicle reacts and has already braked for some time before the cutting-in vehicle reaches the path of the ego. This is likely the reason for the difference between 0.25 m/s and the higher lateral velocities in figures 4.4, 4.5, 4.6. It would be interesting to analyse the behaviour for lower lateral velocities with higher resolution, to get a more precise idea of the lateral dependence in the lower range, however, that is for future studies to address.

5.2.3 Cut-out: TTC analysis

In figure 4.7 TTC's for different ego velocities are shown. One can see that the ego vehicle velocity affects the TTC's, giving lower TTC's for larger velocities. It is interesting from a safety aspect that for the velocity 20 km/h the model is (quite) safe for all scenarios, while for 60 km/h it crashes in one scenario.

In figure 4.8 subfigures showing front longitudinal distances (dx0_f, distance between challenging vehicle and stationary vehicle) can be seen. This parameter affects the TTC, and with fixed time headway and ego velocity a decrease in longitudinal distance decreases the TTC, as is expected. The minimal TTC found in the plotted scenarios however is not found in the shortest longitudinal distance, but instead for dx0_f = 15 m. This is due to that the ego velocity also impacts the TTC's, and for low longitudinal distances, the challenging vehicle crashes into the stationary vehicle for higher velocities, and thus higher velocities are not analysed.

In figure 4.9, TTC's for different time headways are shown. It is clear that the time headway has a big impact on the TTC's. For 2.0 s the model is safe in all scenarios, while for 0.2 s it crashes in a scenario. This matches that headway has a significant safety impact for human drivers. Note that the headway matters here not because of that the ego vehicle crashes into the challenging vehicle, because they do not, but due to that the time headway affects the distance to the stationary vehicle when the cut-out starts (shorter time headway gives a shorter distance).

In all three figures, one can see the (white) region that causes the challenging vehicle to drive into the stationary vehicle. This region is determined by the front longitudinal distance and ego velocity only, as is expected.

That the ego vehicle only crashes once in the simulated scenarios was a bit unexpected. This has to do with the chosen parameters, including larger ego velocities or lower time headways might have caused more crashes. The ODD however is restricted to not go over 60 km/h, and a time headway of 0.2 s is already very low. For the cut-out, this implies that in the given ODD, human attentive drivers seems to be able to avoid crashing in most cases, if the model is reliable.

5.3 ALKS Model: Driver model parameters

The results from the analysis is shown in figure 4.10. The changed parameters for the ALKS model does not lead to any new behaviours, the results are similar but improved ("driving" safer) for lower reaction times and lower lateral deviations. The larger increase in performance for the reaction time than the lateral deviation is interesting. This implies that the reaction time parameter is more important than the attentiveness parameter for the ALKS model, since the lateral deviation distance was changed more than the reaction time (in relative magnitude). Although the two metrics are in two different units (distance and time), the relative magnitude changes can be compared. Care should be taken when interpreting such comparisons, as it is unclear what the impact of the relative differences are in practice.
0.75 s was chosen as the lower reaction time. This is substantially lower than the reaction time found in some studies [19], but still higher than other studies (if urgency is taken into account, where, in urgent situations, the rection time was shown to be around 0.5 s in [20]). 0.75 s was chosen to compare with the FSM, that has this reaction time. The reaction time of 1.55 s is quite long compared to the literature [19]. The lateral deviation was varied with a somewhat larger relative magnitude (than the reaction time), to access the importance of the parameter.
That the FSM outperforms (drives safer) all chosen parameter settings of the ALKS model, shows that the single driver parameter settings can not explain the enhanced performance of the FSM. Both the faster reaction time and the ability to detect potential dangers without any lateral deviation (trajectory/ relative velocity based) are important reasons for the FSM higher performance. For low lateral velocities and high relative velocities, a different behaviour for the FSM is observed (compared to the ALKS model). This difference is because of the lateral check of the FSM, which makes it not brake if the challenging vehicle is either beside or behind the ego vehicle. This lets the FSM avoid a crash by not braking and the challenging vehicle enters the lane behind the ego vehicle, whilst the ALKS model starts braking and makes a crash happen. For these scenario parameters, it is suggested that the FSM better describes how an attentive human driver would react, since few human drivers would be prone to braking because of a vehicle entering behind the ego vehicle – it is simply unrealistic.

5.4 FSM: comparison to ALKS model

When comparing the two models, it needs to be taken into account that they have different conditions. The FSM have a lateral safety check, and also checks if the challenging vehicle is in front of it (if the rear of the challenging vehicle is in front of the front of the ego vehicle) before braking. The ALKS model does not have this check, and might brake even if the challenging vehicle is behind the ego, which could lead to a crash. It was therefore decided to remove these scenarios in the comparison, as described in section 3.2.1. This was done to avoid a bias for the

FSM in the comparison. With these scenarios being removed, no advantage can be gained by not braking in the cut-in scenarios. One could however argue that this is advantageous for the ALKS model, since the FSM might in some cases defer from braking, when it would be better to brake.

One might have considered other conditions for removing scenarios, e.g. not allowing potential side-swipes, i.e. only allowing scenarios where the cutting-in vehicle always enters the future path of the ego vehicle in front of the ego vehicle. It would be interesting to investigate how this would change the performance comparison between the two models. One might guess that the ALKS model would at least slightly improve its performance in this comparison, due to the instant braking reaction of the AEB system. The chosen parameter space also affects the comparison, and one could look into how sensitive the results are to parameter space changes.

5.4.1 Fraction of passed scenarios

The FSM seems to overall perform substantially better than the ALKS model on the simulated cut-in scenarios. This might be due to that FSM can identify the threat faster than the ALKS (since it can see the threat before 0.375 m lateral deviation), and that the reaction time is shorter. That the ALKS model has a higher maximum deceleration does not seem to play an important role.

Figure 4.11 shows how lateral velocities influence fraction of crashes. The shapes for both models contains a minimum inside the plotted range, and thus shows non-linear behaviour. This might have been expected, since this result was already observed and discussed for the ALKS model (see section 5.2.2). Also, here some of the scenarios have been removed (see section 3.2.1), and the removed scenarios are many for lower lateral velocities. The remaining scenarios, where the challenging vehicle can not enter behind the ego, seems to be handled well by the models for low lateral velocities. That the models perform well on very low lateral velocities seems reasonable, since this could be expected from a human driver. The increase in performance for larger lateral velocities (around $Vy > 1$ m/s) was a bit surprising. This behaviour was however observed for the ALKS model (section 4.1). It is a bit harder to motivate why this should also be the case for the FSM. The ALKS model performs the worst for $Vy = 1.0$ m/s. This is a higher velocity than what was observed in section 4.1, where the worst performance was at around 0.5 - 0.75 m/s. This difference might be due to another aspect that can affect the result – the chosen parameter space for this study. For higher lateral velocities, there is a lower fraction of scenarios that might result in a potential side-swipe, and this might affect the lateral velocity dependence. The FSM outperforms the ALKS model for all lateral velocities except $Vy = 0.25$ m/s. The reason FSM performs worse for this lateral velocity might be due to the fact that the FSM does not brake if the challenging vehicle is not ahead of the ego, but it might have avoided the crash if this had not been the case. The ALKS model however always brakes. This might give the ALKS model an unfair advantage here, since all scenarios where not braking could be advantageous are removed, as discussed previously.

In figure 4.12, the fraction of non-crashes is seen for different longitudinal distances. It is expected that the longitudinal distance is an important parameter for the model performance, which the result shows clearly. It is interesting that the FSM performs similarly for dx0 > 20 m, showing that its performance is robust for dx0 > 20 m with the chosen lateral velocities and relative velocities. This ALKS model shows similar properties, but for dx0 > 35 m, which is a notable distance difference.

Figure 4.13 shows the fraction of passed scenarios for relative velocities. One can see that the relative velocity impacts the performance of both models drastically, as expected. It is interesting that both models show an approximately linear performance. That the performance of the FSM does not change for relative velocities below 5 km/h is interesting, and means that the model is resilient against these cut-ins with the used lateral velocities and longitudinal distances. The same is observed for the ALKS model but with 2 km/h, which might seem like a small difference, but could have a big impact in reality.

5.4.2 Minimum TTC distributions

In figure 4.14 the two models TTC distribution is shown. That the FSM has its distribution peak close to 0 s, while the ALKS model has the least amount of TTC's here, is interesting. Disregarding this region (TTC < 0.2 s), the FSM TTC distribution is increasing, and increases more for the lower TTC values. This behaviour could be expected from a human driver, since one tries to avoid low TTC's. The ALKS model distribution has a similar shape for low TTC's only, for TTC > 0.75 s it is close to constant. This difference could be explained due to that the FSM reacts in a continuous way and can brake with different deceleration's, while the ALKS model always brakes with full force (with a buildup phase).

Figure 4.15 shows the difference between the TTC values of the two models. If in the scenario, both TTC values are larger than the TTC threshold, the scenario is not included in the plot. This because if both models would have been able to keep a high TTC, both models would have been able to drive safely, and the scenario is then not of interest in the comparison. A common outcome is that the TTC's are similar, this is because when the models both crash, the difference is zero. That the FSM in most cases drives with a larger TTC, agrees with the result that it avoids crashing in a larger extent than the ALKS model, since a larger TTC implies safer driving. For the threshold 2.6 s, the shape of the distribution and why it declines for about TTC > 1.4 s, and increases before, is however not clear. That the plot only contains scenarios where at least one of the models has a TTC below 0.7 s, can be seen as it only containing safety critical scenarios. Here, the FSM manages to keep a higher TTC (in most cases), and in many instances this TTC is larger than 0.7 s, which is a notable performance difference. Here, the distribution is instead declining, apart from at the threshold TTC = 0.7 s. The ALKS has a higher TTC in only a (very) small number of the simulated scenarios.

5.4.3 Ego crash velocity distributions

In figure 4.16, the ego crash velocity distributions are shown for the two models. It is interesting that they show such different shapes. As was also observed in section 4.1.2, the ALKS does not start braking before it crashes in many scenarios, thus the

ego crash velocity is sharply peaked at 60 km/h. This is however not seen for the FSM, as the crash velocities are spread out more. The FSM thus responds to the challenging vehicle before a crash happens in most cases. This difference might be due to that FSM can identify the threat faster than the ALKS (since it can see the threat before 0.375 m lateral deviation), and that the reaction time is shorter. This could lead to the FSM being able to respond in time when the ALKS model does not.
Figure 4.17 shows the difference in ego crash velocities are shown. For the scenarios where both models crash, one can again see the result discussed above, that the FSM manages to react in many cases where the ALKS model does not. There are however, if so a minority, but multiple instances where the ALKS performs better than the FSM. In a majority of the scenarios where a crash happens, only the ALKS model crashes. This illustrates the enhanced performance of the FSM. In only four of the scenarios, the ALKS model avoids a crash when the FSM crashes.

5.5 KPI's

The analysed KPI's were chosen to measure safety level (and collision severity magnitude) of the ego vehicle. Both KPI's (TTC and impact speed) agrees well on the safety of the two models. Other KPI's were considered, but were not used. These includes modified time to collision (MTTC), space headway (H), crash index (CI), and time exposed time to collision (TET) [12]. The MTTC did not differ much from the TTC, therefore it was excluded. For H and CI, it was difficult to see clear patterns and draw safety conclusions. TET was not tested due to lack of time.
For the TTC, a two dimensional TTC was used. Originally, only a longitudinal TTC was considered. This proved to be suboptimal in the cut-in scenario, since the challenging vehicle sometimes ends up on the side of or behind the ego vehicle, giving TTC = 0 s when no crash had happened.

5.6 Driver models

The ALKS model and the FSM models shows different performance in the analysed cut-in scenarios. Except for very low lateral velocities Vy = 0.25 m/s, the FSM seems to perform better, avoiding a crash in a larger extent, than the ALKS model. Thus, the FSM has a higher safety performance in the cut-in scenarios. The FSM might be a good performance target for an ADS, but this does not necessarily mean that it represents an attentive human driver well in all cases. The ALKS model, on the other hand, has a lower safety performance (drives less safe), and could be seen as a more realistic model of which scenarios an attentive human driver is able to avoid on an average. This has not been proven in any way, and have not been investigated in dept either, but might be argue due to a longer reaction time (that is found in some studies [19]) and a non-instant event detection, that is not feasible in reality. That the ALKS model might be a more realistic model is however only valid as long as the cutting-in vehicle stays in front of the ego, since the ALKS model will react in the same way if the cutting-in vehicle is to the side or behind the ego, which is not a good model for a human driver. The ALKS model might not be a good model for a human driver in non safety critical scenarios, since it always brake with full force. In these scenarios, the behaviour of the FSM might be a better model of a human driver, since it has continuous ways of acting. It could therefore be useful to use both models as ADS performance comparison, where the FSM is seen as a desired "perfect" behaviour, and the ALKS model seen as the performance of an average attentive human driver, which might be regarded as good enough. For non-safety critical scenarios however, the FSM model seems like a better performance target, and may be more close to how an attentive human driver would react.

In some scenarios with low lateral velocities (Vy = 0.25 m/s), the ALKS model does better than the FSM. This is due to that in the scenarios (that are not removed before the analysis), it is always beneficial to brake, which the ALKS model always does. However, the lateral check of the FSM sometimes makes the FSM refrain from braking, making it crash into the ego. For these low lateral velocity scenarios, the best performance of the ALKS model and FSM could be a target to classify scenarios as avoidable or not. For the scenarios that were removed from the model comparison, where the challenging vehicle would enter behind the ego if the ego does not change its velocity, the FSM is probably performing better and is more close to human driving behaviour. This performance was not analysed though, but the FSM model seems more suited to handle these kinds of scenarios.

The used ALKS model differs somewhat from the one in the reference [6], see section 3.1.1. This was due to a limitation in the used architecture, that was not solved in time. This difference has an impact on the ALKS model, and makes it perform better (driving safer) than the one in the reference. The difference is largest in situations where the braking of the AEB happens before the other braking starts. This is because here, the deceleration jumps from 0 to 8.34 m/s^2 in one time step, which is different from the literature, where it increases linearly. This difference however should not affect the qualitative performance in a major way, since the maximal difference in distance between the two models (from [6] and the one used in this work) is 1.0 m (difference in distance travelled at initial velocity of 60 km/h, for AEB happening before other braking). The difference is smaller when the other ("human") braking happens before the AEB, since here there (initial) increase in deceleration is linear and not instant, and the fraction that was found to determine the distance difference is smaller for the other ("human") braking. A derivation of this can be found in the appendix, section A.1.

For both of the reference driver models, the response of the models is solely braking. Other driver models reacts by steering, and some reacts by a combination of braking and steering [5]. Since only braking is quite limiting in some scenarios, and might not be how a human driver reacts, the models with different reaction tools would be interesting to evaluate and compare to analysed reference driver models. Neither the FSM nor the ALKS model considers conflict avoidance actions laterally, such as the ego vehicle moving laterally in its own lane when the adjacent vehicle starts moving laterally.

5.7 Limitations and outlook

A comparison between the ALKS model and the FSM was not done for the cut-out scenario. This was mainly due to lack of time, but it seemed a bit more difficult to analyse due to the low amount of crashes for the used parameters. For a crash to happen, very low time headways of the ego vehicle was needed (since Ve0 $\leq$ 60 km/h), and these time headways is not expected to be common in real world driving. However, an analysis of the TTC's could be done, to give an indication of the safety performance of the models. Of course, the few crashes that do happen could also be analysed.
This work focused on driving speeds less than or equal to 60 km/h. It would be interesting to see if the model performance of the models are similar for larger velocities, or if different results emerge.
To get a better understanding of how well the driver models represent (attentive) human drivers, it would be interesting to look into cut-ins from real world data and compare the outcomes. Actually, the simple parameter sweeping that was done in this study is only a way to get a "feeling for" the model performance, and does in no way quantify the models actual safety performance (what the safety impact would be in the real world). This is due to each combination of scenario parameters being treated with equal "weight". Consequently, if information about parameters combination probabilities were available from, for example naturalistic driving data, that could be used to quantitaively estimate the safety performance. It would, however, be extremely hard and time consuming to actually get the probabilities for all parameter combinations. Future work should investigate combinations of crash data with naturalistic driving data to create models of scenarios. Actually, there is today much research on scenario generation that aims to create realistic and representative scenarios sets. If such scenario sets were available, a study such as this thesis work could apply the models to those sets, and study the outcomes with a more real-world-impact perspective.
This work might help to understand the differences between the two analysed reference driver models, and how these differences might impact their suitability as performance targets for ADSs. Also, the comparison between the two reference drive models might give some insight in how an ADS and a reference driver model could be compared for safety evaluation.

6
Conclusion

In order to investigate safety performance of a driver model, the KPI's crash or no crash, crash velocity and minimum TTC seem like suitable safety indicators. The minimum TTC gives an indication of safety level when a crash has not happened, where a low TTC (less than $\sim [1, 2]$ s) indicating that the ego vehicle might have been subjected to a safety risk. When a crash happens, the impact speed gives an indication of how severe the crash is and if the driver had started braking to avoid the crash.

In the cut-in, the ALKS model drives safer (lower impact speeds and larger TTCs) for long longitudinal distances (longitudinal distance between the two vehicles) and small relative velocities (relative velocity between the two cars), compared to shorter distances and higher relative velocities, as expected from a human driver. For the lateral velocity, on the other hand, it performs better (drives safer) for low values (about Vy < 0.5 s), and higher values (about Vy ≥ 1.0 s), but performs the worst around Vy $= 0.75$ s.

The FSM shows the same tendencies with regard to safety performance as the ALKS model. It does however substantially outperforms (drives safer than) the ALKS model in the analysed cut-in scenarios, in terms of number of avoided crashes, lower impact speeds and higher minimum TTC's. The FSM avoids a crash in 92.7% of the generated scenarios, while the ALKS model avoids crashes in 82.3% of the scenarios. This makes the FSM a harder performance target for an ADS than the ALKS model. The only scenarios where the ALKS model sometimes performs better is in the low lateral velocity range (about Vy < 0.5 s). The FSM might be seen as a performance target ("perfect driving behaviour"), while the ALKS model might be seen as closer to an attentive human driver performance. This has however not been proven in this work, and just a reflection from my side. Analysing minimum TTC's and crash velocities, it is concluded that the FSM has a broader distribution of crash velocities, and a more separated minimum TTC distribution (higher values favored over small values) compared to the ALKS model. This could have been expected due to the fact that the FSM has a continuous spectrum of reactions (braking forces) and because it can react to the event faster (lower reaction time and no lateral deviation threshold). This could make the FSM a more accurate model of an attentive human driver in general, even thought its reaction time is very low.

In the cut-out scenario, the ALKS model is analysed. The most important scenario parameter is the time headway. For TH $= 0.2$ s the ego vehicle crashes, while it does not crash for higher time headways. Larger ego velocities and lower front longitudinal distances also gives a higher crash velocity (where crashes occur) and lower TTC's, as is expected. Due to that if the challenging vehicle crashes or not

depends on dx0_f and Ve0, the lowest TTC's are not found for the lowest front longitudinal distances, since these only allows small ego velocities (since challenging vehicle crashes for larger ego velocities).
For the ALKS model, the reaction time and lateral deviation were varied. The change in reaction time impacts the safety performance more than the change in lateral deviation, when they are altered by a similar (relative) amount. The FSM however outperforms (drives safer than) all ALKS models (all parameter combinations), thus neither of the reaction time and lateral deviation can fully explain the improved performance of the FSM by themselves. The importance of the lateral safety check, that checks if the vehicle is in front of the ego vehicle or not, is clearly seen and improves the safety performance for small relative velocities. small longitudinal distances and high relative velocities.

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A

Appendix 1

A.1 Distance calculation

Here follows a calculation of the maximal distance difference Δd_{max} between the ALKS model used in this work and the ALKS model from the reference literature [6]. The maximal distance difference happens when the AEB braking is starting before the other braking starts. First the distance d_1 for the ALKS model in the reference literature is calculated. The deceleration here is increasing linearly from 0, $a_1 = t \cdot J$, where $J = 13.90\text{m/s}^3$ is the jerk, and t is the time ($t = 0$ is at the start time of braking). The time until maximum deceleration ($a_f = 8.34\text{m/s}^2$) is reached, t_f, is given by

$$t_f = \frac{a_f}{J}. \tag{A.1}$$

The velocity at time t is given by

$$v(t) = v_0 - \int_0^t Jt'\, dt' = v_0 - \frac{J}{2}t^2 \tag{A.2}$$

where v_0 is the initial velocity. The distance travelled is given by

$$d_1 = \int_0^{t_f} (v_0 - \frac{J}{2}t^2)\, dt = v_0 t_f - \frac{J}{6}t_f^3. \tag{A.3}$$

Then, the distance d_2 for the ALKS model used in this work is calculated. The deceleration here is constant, $a_2 = 8.34\text{m/s}^2$. Thus, the velocity at time t is

$$v(t) = v_0 - \int_0^t a_2\, dt = v_0 - a_2 t. \tag{A.4}$$

d_2 is given by

$$d_2 = \int_0^{t_f} (v_0 - a_2 t)\, dt = v_0 t_f - \frac{a_2}{2}t_f^2. \tag{A.5}$$

Thus, Δd_{max} is given by

$$\Delta d_{\text{max}} = d_1 - d_2 = \frac{a_2}{2}t_f^2 - \frac{J}{6}t_f^3 = \frac{a_f^3}{3J^2}. \tag{A.6}$$

Thus, $\Delta d_{\text{max}} = 1.0$ m. Note that the initial velocity (v_0) does not impact the distance (as long as it is high enough so that the vehicle does not stop before t_f).

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