A method to assess safety implications during authority transitions in automated driving

Omiros Athanasiadis

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Committee

Chair:	B. (Bart) van Arem	TU Delft, CiTG
Supervisors:	S.C. (Simeon) Calvert	TU Delft, CiTG
	E. (Eleonora) Papadimitriou	TU Delft, TPM
	Gerdien Klunder	TNO

Preface

This thesis is the final fulfillment for obtaining the Master of Science in Transport, Infrastructure and Logistics from Delft University of Technology. For the purposes of this project, the research has been conducted in association with TNO (department of Sustainable Urban Mobility and Safety).

I would like to express my gratitude to all those who helped me in this process and contributed to my research. Firstly, I would like to thank my supervisors from TU Delft and TNO, Dr. Simeon Calvert, Dr. Eleonora Papadimitriou and Ir. Gerdien Klunder respectively, for their guidance and supervision. Furthermore, I would like to thank Prof. Bart van Arem for his support and for giving valuable insights in critical moments throughout the entire time. In addition, I would like to thank a colleague and scientist from TU Delft and TNO, Xiao Lin, who helped me by providing me with her guidance and the results from her studies in a critical moment. Finally, I would like to give special thanks to my parents, for their invaluable support throughout this demanding scientific journey. Also, my sincere appreciation to my partner Archontia for her patience and motivation, my friend Antonios for his endless courage and support, and my friends and colleagues Marios and Mesay for their invaluable feedback and positive energy.

Hopefully, this research can contribute to the future implementation of automated vehicles, by bringing insight into the possible safety effects during authority transitions. I hope it will also inspire and work as a structure for other students who are interested in autonomous vehicles.

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Abstract

The question of how well in terms of safety can a driver take over control of an automated vehicle in response to an emergency situation is of crucial importance. Several studies have been performed in that direction with noteworthy but also ambiguous results. Most of them focus on the drivers' reaction times and the mechanisms behind the transition. In this study, an effort is made to incorporate the braking times that are required in order to finalize a safety maneuver, with the aim to assess the safety implications of the entire transition in control. For this purpose, a new methodology was developed and a simulation model was used in order to simulate platoons of CACC equipped vehicles. Two new KPIs for Take Over performance were defined: the Time to Control and the Safe Time Budget. The results suggest that higher number of critical events and crashes are associated with higher market penetration rates. This reveals that despite the fact that AV can in general increase traffic efficiency and safety, when it comes to emergency situations where safety is inextricably linked to the combination of AV and driver performance, overall safety may be compromised under certain conditions. In addition, the results revealed a strong connection of the above-mentioned action times with the initial speed of the vehicles involved in a conflict. The proposed new methodology for safety evaluation is more sensitive compared to previous approaches and estimates more accurately the remaining available time for a driver to react. It is therefore a more conservative method that leads to higher number of critical conflicts. The findings of this research, point to new directions particularly in concern to the extension of the operational design domain of automated vehicles in order to minimize system deactivations, and also with regard to the need for better prediction models and safety assessment tools.

1 Introduction

1.1 Background

The development of automated driving is growing rapidly over the last years. This has mainly occurred due to the high demand for safer roads, better travel times and comfort in the driving experience. According to van Arem et al., (2006), enhanced driving strategies can allow for larger traffic volumes and safer operations. Based on Milanés & Shladover (2014), the Cooperative Adaptive Cruise Control function (CACC), has shown positive results when tested in controllable environments. Based on that, platoons of CACC vehicles can operate safely and efficiently under various traffic conditions by minimizing time headways and eliminating possible human errors. However, fully automated vehicles are far from mass production and implementation on today's roads. While the concept of self-driving cars promises to enhance the overall performance of road traffic, the impacts on traffic safety are not yet well understood (Shladover et al., 2013; Flemisch et al., 2017).

One of the main challenges for scientists and car manufactures is to make sure, that the operators of such vehicles are capable of perceiving not only the capabilities but also the limitations of the automated systems (Flemisch et al., 2017). That said, it is clear that until the automated systems become capable of performing all kinds of driving tasks in all kinds of road conditions, human drivers will bear the responsibility to take back control when the system is no longer able to perform due to failure or because it reaches its operational limits. In that sense, Damböck et al. (2012b) state that the more the level of automation increases, the more the role of the driver is about to change. In addition, Merat et al. (2012) draw the conclusion that traffic safety is increasingly dependable on the combination of the performance of the human driver and the automation. As a result, it seems that driver's behavior is crucial, as it determines to a great extent the safety performance during the transitions of control (Peterman & Kiss, 2009).

A control transition can occur for various reasons. During system failure, it is important that enough time is given to the driver to become aware of the request for takeover control, in order to prevent hazardous situations and to guarantee the smoothness of the transition process (Damböck et al., 2012a). As Son et al. (2017) state, the time that is necessary for a transition, is a function of the time that the driver needs to collect information from the environment and the time to build sufficient situational awareness. By the time the driver is able to have a comprehensive view of the current situation, s/he is then capable of safely regaining back control from the system.

A critical question in that sense, is how effectively in terms of safety, can a driver take over control of the vehicle when the latter fails or reaches its boundaries. To understand that, the impacts in terms of safety of an authority transition have to be determined. A lot of studies have been performed in this field, trying to explain the factors that influence this transition and the driver's behavior during an authority transition. A scientific gap in the eventual safety impacts of that process has been identified and an effort is made to fill it by literature review and post processing data analysis of an existing simulation study.

1.2 Problem definition

In this section a brief description of the key principles of an authority transition is given, and the formulation of the problem is described.

A transition in control from an automated system to a human driver is necessary under the occasions that the system is not capable of addressing the situation by itself. By the time the automation system identifies a situation that lies outside its operational design domain, it initially sends a warning to the human driver (Take Over stimulus), who is responsible for taking over the control of the vehicle. The driver has to take over within a certain time budget to ensure safe operations. Such a time sequence can be seen in Figure 1, as described by Zhang et al. (2019).

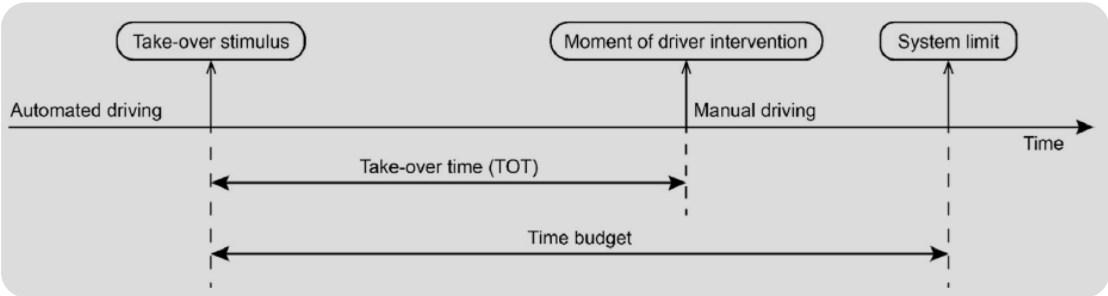


Figure 1: Take Over sequence (Zhang et al., 2019)

The time from the moment of the warning, till the moment of driver's first intervention (first action of braking or steering), is called Take Over Time (TOT). The last moment at which the driver can take action is called system limit (last moment of driver's first intervention). The time between a warning and the system limit is called Time Budget (or Required Time to Take Over). Any effort of taking over after that point would likely result in a collision (TOT has to be smaller than TB to ensure safe operations). (Zhang et al., 2019)

Based on the above, one can make the assumption that if the Take Over Time is smaller than the Time Budget during an authority transition, then the situation is considered to be safe. However, this is not entirely true as both times refer to perception and reaction times. For instance, if from a simulation study both TOT and TB are measured and they reveal the aforementioned desired inequality (TOT < TB), that does not necessarily mean that a critical situation will be evaded. It might be the case that after the driver took over (first moment of intervention) the deceleration force that he applied, or the maneuver he tried to perform did not suffice to avoid a collision (automation levels which do not have full stop capabilities). Although a simulation does not allow in general for such "poor" driver behavior, in reality drivers quite often do not behave in an optimal way (misconception of the situation, bad cognitive process of the available information or simply poor execution etc.). Both Take Over Time and Time Budget metrics, are not designed for capturing that "poor" driver behavior which is critical in terms of safety as the driver is responsible for acting in a potentially hazardous scenario.

Towards that direction, it seems that reliable Key Performance Indicators which can adequately interpret the safety attributes of such a transition in control of AV, are lacking. Therefore, in this study the functionality of such innovative KPIs is explored.

1.3 Research Questions

Several studies have been carried out regarding the effects of car automation with respect to traffic efficiency as well as traffic safety. However, the majority of the studies that focus on the safety impacts, take into account only drivers' perception/reaction times. In this way they only partially address the human factor when planning for AV operations. In order to further investigate that, a number of knowledge gaps need identification. After reviewing the existing literature, the gap of safety implications during authority transitions was identified. The research focuses specifically on braking driver action in order to address the above limitation. The below research questions were formulated. A complete review of the literature is presented in Chapter 2.

Research question:

- What are the safety implications on network level, during an authority transition due to collision warning in CACC platoons of SAE level 2, when the automation system cannot handle an emergency situation?

Sub Questions:

1. Under which conditions is there a Take Over request and what are the mechanisms behind it?

2. What are the basic principles that govern a Take Over design (Human-machine interface) and what are the factors that influence driver behavior and thus affect Take Over performance?

3. How is a Take Over Request related to safety and how can the Take Over performance be translated into safety effects?

4. What are the limitations of the methods used so far for safety evaluation and what can be done to address them?

5. Which safety metrics can define the criticality of an authority transition; of those who are found to be critical, what is the relation among them (followed pattern?

1.4 Approach

In order to determine the impacts of automated driving, and more specifically during an authority transition to a broader extent, simulation is necessary since real world experiments are hazardous and uneconomical. With simulation tools, several scenarios can be tested with different driving strategies and under various traffic conditions. In this way, a representation of real-world situations can be made in a safe and cost-effective way.

This research aims to explore the effects of a transition in control, and an effort is made to translate its mechanisms into safety implications. In order to do that, a number of relevant studies had to be explored, and data analysis had to be performed to derive safety metrics such as Time to Collision, Deceleration rates etc.. This evaluation will likely bring insight into the authority transition process and might work as a start for future research that will shed light on the automation-human interaction.

For this project, a simulation experiment performed by Xiao et al. (2018) was used to obtain the necessary data for the purpose of answering the research questions formulated above. The software used for this simulation was MOTUS and the impacts in terms of traffic efficiency during system failure were measured. In that study, an effort was made to bring insights into the effects of CACC systems on highways and merging situations with the usage of a CACC model that incorporates human-system interactions (authority transitions). For the purposes of this thesis, the dataset from Xiao's study was used, in order to assess the impacts of CACC platoons in reference to safety. In order to do that, an algorithm was created in MATLAB so that safety measures can be derived from the existing dataset as the available metrics were exclusively related to traffic efficiency.

For the first sub-question (1), literature review was necessary to investigate the reasons that a Take Over request takes place in the first place. In addition, the structure and mechanisms of the transition were reviewed. This is important so that a more comprehensive scope of a TOR is attained.

The second sub-question (2), needs to be addressed to get a better insight into the factors that influence driver behavior (in different levels of automation) and thus, affect the performance of the transition. This was done by literature review of experiments in high-fidelity driving simulators. In that sense, the principles behind Take Over design (Human-machine interface) had to be reviewed.

For sub-question three (3), regarding the conditions under which a transition in control can be characterized as safe or hazardous, an extensive review of existing experimental designs in several studies had to be performed. In this way, a more comprehensive view of the typical driver related and traffic-related characteristics and their impact on safety could be given. Furthermore, in this part a framework was created with regard to the safety metrics that are used in this study, by means of marginal conditions.

The purpose of sub-questions four (4) and five (5), is to understand how time affects a transition in control and which are the appropriate key performance indicators to use in such cases. To do that, data analysis was performed in order to try to understand the marginal conditions of the system. This is critical so that a framework can be built around authority transition safety. Also, the data analysis revealed the differences in the new approach compared to older methods by comparing various Key Performance Indicators. Finally, the potentially followed pattern between critical incidents (system deactivation output) is captured by isolation and statistical analysis of their characteristics.

2 Literature review on Authority transitions

Automation in driving is expected to positively influence traffic efficiency as well as safety in driving operations. Vehicles in particular that are capable of cooperative behavior, are expected to dissolve congestion faster, increase network capacity and guarantee safety by anticipating traffic conditions downstream. However, current automated driving systems are not capable of addressing every situation under all traffic conditions. Thus, the human driver is expected to resume back control of the driving tasks to deal with the limitations of the system. The alteration in control of the driving tasks is called authority transition (Varotto et al., 2015).

2.1 Automation Levels

The introduction of self-driving cars is expected to gradually occur over the next years. The Society of Automotive Engineers International defines the different levels of automation as follows (Table 1, SAE Standard J3016):

Level of automation	Description
0	Manual driving
1	Driving assistance
2	Partial automation
3	Conditional automation
4	High automation
5	Full automation

Table 1: Automation Levels (SAE Standard J3016)

A system with driving assistance (*SAE level 1*) is capable of taking over either the longitudinal or lateral control. Adaptive Cruise Control is one of these systems providing support by handling the longitudinal control. Such a system can maintain the desired speed and a time headway predefined by the driver. SAE level 1 has limited capabilities in terms of car automation.

Vehicles equipped with partial automation (*SAE level 2*), can handle both longitudinal and lateral control. However, the driver is responsible for monitoring the system at all times and is expected to resume back control anytime he is asked for, as the automation operational design domain has limitations. Current automated vehicles are mainly equipped with such a level of automation. The main purpose of this automation level is to bring safety and comfort in the driving experience.

In Conditional automation (*SAE level 3*), the system can take over both longitudinal and lateral control while it is not expected from the driver to fully monitor the system at all times. The driver can be out of the loop and engage with non-driving activities, but he is still expected to regain back control in case of an emergency. This level of automation is the next step to the existing technology, trying to let the driver get out of the loop for finite time intervals. However, the challenge here lies in the fact that automation systems with such capabilities have limited ODD and for that reason drivers need to have an adequate level of readiness in case of emergencies.

In high and full automation (*SAE levels 4&5*), the driver is completely out of the loop as the system is capable of addressing any situation. The difference lies in the operational design domain of these two categories; Level 4 has a limited ODD, where Level 5 can operate under all road and environmental conditions.

As we can see, the automation industry seems promising when it comes to improving traffic safety and efficiency, but until higher automation levels become available, drivers will bear the responsibility of taking over control in case of emergencies. In the sections below, the mechanisms of authority transitions are described.

2.2 Transition types

Nowadays transitions in automated driving are becoming increasingly important since vehicles are equipped with automation to an ever greater extent. Driving states can be defined depending on the allocation of the driving tasks such as longitudinal and lateral control, and monitoring of the driving process. Lu et al., (2016) define the transition in control as the alteration of the above states between the human and the automation system (Figure 2).

Based on the fundamental questions, (1) who initiates the transition and (2) who is in control after the transition, Lu et al., (2016) defined six (6) categories of authority transitions:

a) Optional Driver-Initiated Driver-in-Control

b) Mandatory Driver-Initiated Driver-in-Control

c) Optional Driver-Initiated Automation-in-Control

d) Mandatory Driver-Initiated Automation-in-Control

e) Automation-Initiated Driver-in-Control

f) Automation-Initiated Automation-in-Control

In a more simplified version, Lu & de Winter (2015), categorized the control types as follows:

a) Driver-Initiated Driver Control (DIDC)

b) Driver-Initiated Automation Control (DIAC)

c) Automation-Initiated Driver Control (AIDC)

d) Automation-Initiated Automation Control (AIAC)

A Driver Initiated Driver in Control state, occurs when the driver voluntarily selects to deactivate the automated system and resume back control. This is the case for example when a driver wants to overtake a preceding vehicle, or when a driver wants to take over control of his vehicle as he approaches the limits of the ODD of the system.

Similarly, a Driver Initiated Automation in Control state, can be defined as the situation where the driver activates the system, as for example he exits an urban area and enters a highway.

Authority transitions can be defined as AIDC (Automation-Initiated Driver Control) and AIAC (Automation-Initiated Automation Control) when the automated system initiates the transition. In the first case, the driver is in control after the transition, when in the latter one the automation takes over (Varotto et al., 2015). Such transitions occur for example when the automation senses that either the driver, or itself cannot handle the upfront situation.

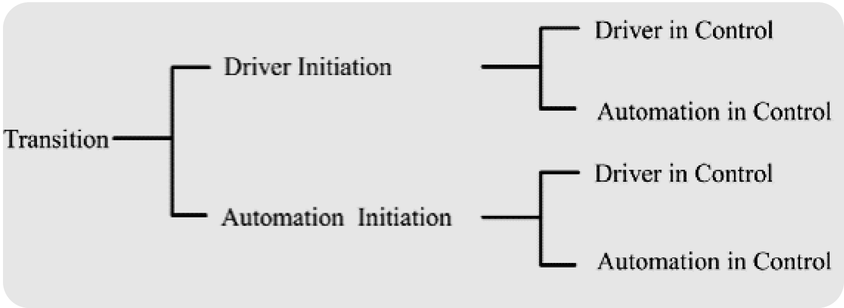


Figure 2: Categorization tree of authority transitions (Lu et al., 2015)

We can see how various system deactivations can occur depending on traffic conditions and driver preferences. This research focuses on the third category: Automation Initiated Driver in Control (AIDC), as an effort is made to assess the safety implications during a collision warning. This category is characterized by great complexity as it involves mechanisms that are critical in terms of safety and require human adaptation in emergency scenarios under limited time. In order to take car automation to the next level to a broader extent, it is important to capture the characteristics of the transition that need to be improved so that the upgrade will take place in a smooth and safe manner.

2.3 Time sequence of an authority transition

While driving with an active automation system, the driver receives a warning (Take Over request/Take Over stimulus) as the automation cannot handle the upfront situation (system failure or end of operational design domain). The time from the moment of the warning (first boundary), till the moment that the driver resumes control (first action of braking or steering), is called Take Over Time (TOT). The same time interval can be called reaction time (RT) (Borojeni et al., 2017).

The last boundary in the time sequence is the system limit and it is the last moment at which the driver can take over control of the vehicle. After that point, the situation can be characterized as critical, as it is likely that a collision will occur. The system limit is often associated with a critical Time to Collision or an inverse Time to Collision (Kiefer et al., 2005). The time between a warning and the system limit is called Time Budget (or Required Time to Take Over), and

TOT has to be smaller than that to avoid potential collisions (Zhang et al., 2019). Figure 1 represents the chronological order of an authority transition.

For a widespread embracement and acceptance of automated systems, Take Over Time should allow for safe and successful control transitions (Gold et al., 2016). This is basically the time that is necessary for a driver to realize the warning and build enough situation awareness (driving state and condition wised) in order to perform a safety maneuver.

It is worth mentioning that the time that is available for the driver to take over, has the limitation by the range of the sensors that a system carries, and their ability to identify system boundaries. As a result, the reaction time of the driver is essential for gaining back control of the vehicle, especially in higher levels of automation where the desired time gaps are significantly lower, leaving less available time for the driver to react. The transition shown below (Figure 3) is performed from a highly automated system to manual driving.

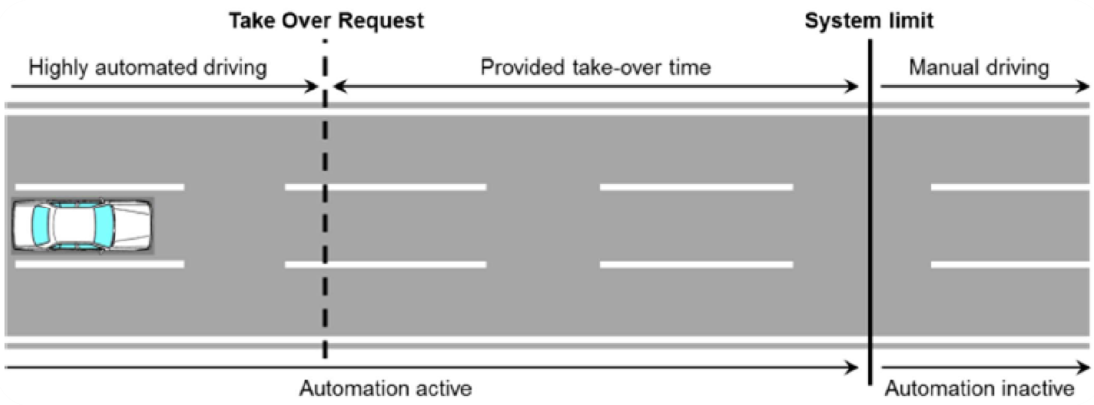


Figure 3: Sequence of an authority transition (Damböck et al., 2012a)

2.4 When is an authority transition necessary

Before going into the effects of authority transitions, the possible reasons that trigger them had to be explored. In this section, the reasons that initiate a Take Over request between an automated system and particularly Cooperative Adaptive Cruise Control and manual driving, are reviewed based on the existing literature.

It seems that the characteristics of the driver support system strongly influence authority transitions which can be either initiated by the driver or by the system (functioning limitations) (Varotto et al., 2015).

As described in the previous section, in this study, the effects of authority transitions when the automation fails are explored. That said, there are two occasions when by the time the transition is over, the control is given back to the driver; the DIDC and the AIDC.

Below, the most possible motivations for both states are given. Table 2 summarizes the following information:

1) Driver Initiated Driver in Control (DIDC) (Viti et al., 2008, Pauwelussen et al., 2010):

a) Speed adaptation before lane change or overtake:

When the driver wants to change lane while the current acceleration of the vehicle does not suffice, the driver takes over in order to adjust vehicle's speed to an adequate level for a smooth and safe overtaking.

b) Defensive or Offensive behavior:

When the driver decides to brake or accelerate in order to build (or remove) a merging gap for other vehicles. This can happen either to encourage other vehicles to merge between the automated vehicle and the preceding one, or to discourage other vehicles of such an attempt.

c) Left lane speed adjustment:

When the driver decides to brake in order to avoid an illegal Overtake on the right lane.

2) Automation Initiated Driver in Control (AIDC) (Klunder et al., 2009, Pauwelussen et al., 2010):

a) Sensor failure:

When the sensors of the automation stopped working in a proper way, the automation system initiates a TOR for the driver to take over to ensure safety. This can happen for instance in case of bad weather, fade of road markings, etc.

b) System boundaries are reached:

When the system boundaries in terms of safety have been reached, and the driver has to exceed system limits (speed, acceleration/deceleration) to such an extent to avoid a possible collision (or overtake a stopped vehicle)

c) ODD exit:

When a vehicle approaches an off-ramp, and the automation system is not capable of addressing the driving tasks outside its predesigned operational design domain.

d) Driver awareness:

When the system identifies lack of awareness so it intends to alert the driver to resume control. In this case the automation deliberately initiates an authority transition in order to ensure traffic alertness.

DIDC	AIDC
Speed adaptation before lane change	Sensor failure
Defensive/Offensive behavior of other vehicles	System boundaries are reached
Left lane speed adjustment	ODD exit
	Driver awareness

Table 2: Possible reasons for an authority transition initiation

2.5 Take Over Request design

Higher levels of automation can improve road safety by eliminating human errors, and also bring comfort in the driving experience by taking over driving tasks (Shladover et al., 2013). This control transition from the driver to the system encourages people to engage in non-driving tasks (NDT) such as reading, phone calls, surfing the internet, etc., giving the in-vehicle environment more complexity. Due to the high complexity in transitions in control process (visual processing demand and time limitation), the human-machine interface (HMI) has to be designed appropriately (Borojeni et al., 2017).

During an authority transition initiated by the automation, the driver needs to switch his attention from the secondary task that he is occupied with, to the driving task (SAE level 3). But even in lower levels of automation where the driver is supposed to always be aware, studies revealed reduced cognitive awareness (Lu et al., 2015). Borojeni et al. (2017), state that this shift in attention "requires perceiving the state of the driving environment, making decisions and acting accordingly". Merat et al. (2012), mention that when a driver tries to get back in the driving task while he is occupied in secondary tasks, he becomes vulnerable to errors and delays. This can have a negative effect and might provoke hazardous situations as it negatively affects the reaction times of the human drivers. Therefore, in order to ensure smooth transitions from the non-driving tasks to manual driving, an appropriate type of take over request (TOR) has to be designed. In the section below, several types of warnings are reviewed based on existing literature.

2.5.1 Type of warning

One key aspect related to the above issue is to appropriately schedule the process of information. In a multi-tasked and complex driving environment, it is essential to determine methodologies to communicate the information effectively to the driver so that he is well prepared in case of an emergency.

Take Over Request designs have been researched widely over the last years. Koo et al. (2015) explored the effectiveness of verbal messages. The results revealed that "why messages" (describing reasons) were better and led to better driving performance compared to "how messages" (describing action) when the automation takes over. Naujoks et al. (2014) studied TOR designs in auditory and visual modalities. The results showed that the simultaneous usage of visual and auditory messages can lead to shorter reaction times and better performance in both longitudinal and lateral control compared to visual messages only. Another study by Baldwin et al. (2014) tested the use of various phrases to indicate the different levels of urgency to drivers. In particular, the word "danger" resulted in higher urgency compared to the words "caution" or "warning". Based on the above, we can see how a combined modality can influence Take Over performance. In this way the warning can be perceived by different driver senses resulting in a possible faster reaction. However, it is of crucial importance to maintain a low level of warning complexity to an already complex and dynamic environment.

In that sense, Politis et al. (2015) focused their research on multi-modal language-based warnings to design Take Over requests. Different combinations of visual, auditory and tactile warnings were tested to measure the perceived urgency, the level of annoyance and the effectiveness of the warning. They found that shorter transition times can be achieved with higher urgency warnings, while single visual warnings led to low driving performance. In addition, the usage of multiple modalities for the warning process (visual, auditory and tactile) resulted in a higher level of annoyance. This reveals the importance of a balance between the different modalities so that a driver is sufficiently alerted but at the same time not being annoyed and thus distracted from his main functions.

In another study by Borojeni et al. (2017), a peripheral light display was proposed for informing drivers about a TOR. They revealed that contextual messages through ambient displays resulted in shorter reaction times (and thus longer times to collision) without significant raise of the workload. This finding enhances the idea of a simple and balanced warning approach to achieve shorter and better reactions.

A noteworthy research by Petermeijer et al. (2017), initially hypothesized that when the non-driving task and the Take Over request share the same modality, there is an increase in reaction times (TOTs are larger). This was based on Wickens' et al. (2012) statement that "presenting a warning signal via a 'free' modality increases sensitivity, probably resulting in faster reaction times and fewer misses." For instance, in cases where the driver is talking on the phone, it is expected that informing him with an auditory warning would be relatively ineffective. In the same way, when a driver is engaged in a visual activity, a TOR with visual information would have little to no effect. The results of this study showed that a combination of audio and tactile TORs led to faster Take Over Times compared to visual-only requests.

From the above review in the literature we can draw the conclusion that during a transition initiated by the system, a combination of visual and auditory warnings can significantly decrease reaction times and increase overall performance. In addition, peripheral visual information and type of audio warnings can add positively in that sense. However, different modalities of warnings did not manage to affect the authority transition performance significantly. Last but not least, it seems that maintaining a plain warning design in an already complex environment, and a balance among the different modalities, play an important role in terms of sufficient information and level of annoyance.

2.5.2 Time of warning and driver role

A critical question in automated driving is how long does it take for the driver to regain back control after he received a Take Over request or in case of a critical event. In the same way, it is important to understand the factors that determine this TOT (moment of stimulus till first steering/braking action). However, the performance of the transition is not only dependent on time. Take Over performance is also correlated to the readiness of the driver and his cognitive awareness of the situation (Zhang et al., 2019).

The driver Take Over process comprises several information-processing stages (Gold & Bengler, 2014; Gold, Damböck, Lorenz, & Bengler, 2013; Petermeijer, De Winter, & Bengler, 2016):

1) perception of visual, auditory, and/or vibrotactile stimuli
2) cognitive processing of the information
3) response selection (decision making)
4) resuming motor readiness (hands and feet on steering wheel and pedals)
5) initial action (e.g., first steering and braking input to the vehicle)

These stages require corresponding time intervals to be executed, which are represented below (Table 3):

a) warning perception time:
   time needed for the driver to perceive the warning and realize that something occurred and the automation system cannot handle it

b) information process time:
   time needed for the driver to understand what the situation is about and how vital his intervention is

c) selection of response time:
   required time for the decision making; driver decides to steer, brake etc.

d) readiness time (SAE level 3):
   time required for the driver to get ready by putting hands on the wheel and feet on the pedals

e) initial action time:
   time that lapses from the previous step, till a significant deceleration rate or angle is achieved in the vehicle dynamics

Task	Corresponding Time
Stimulus perception	Perception time
Information process	Process time
Decision making	Selection of response time
Readiness	Reposition time
Initial Action	Actual action time

Table 3: Corresponding time per necessary task during an authority transition

The summation of the above five (5) mentioned times, consists the Take Over Time. Various studies state reaction times of approximately 0.7sec to 1sec for the first road fixation and 1.2sec to 1.8sec for the first contact with the steering wheel (SAE level 3) (Gold et al., 2013; Zeeb et al., 2015). Such times are quite large compared to the desired time gaps that an advanced CACC system can achieve (0.6 to 0.9 seconds). This means that in a hypothetical immediate full stop of the front vehicle a collision would be inevitable as the available time for a driver to react does not suffice.

Despite the fact that all five categories can be measured in seconds, and faster is better, the third category (selection of response time) does not necessarily comply with that rule as cognitive processing of information is deteriorated by driver distraction. For example, if a driver devotes 2 seconds instead of 1 second in the decision-making process, it is likely that his selection of response would be more rational by means of effective interaction. Having more time to think would most probably lead to a better decision (e.g. braking instead of steering to avoid a collision in case that adjacent lanes are occupied) (Buchner et al., 2016).

In the same way, Gold et al. (2013), define four response times as seen below:

i) gaze response time

ii) eyes-on-road time

iii) hands-on-wheel response time

iv) Take Over time (i.e., intervention time)

Although there are various response time measures available, Take Over Time (TOT) seems to be the most commonly used in literature. TOT strongly varies between SAE level 2 and SAE level 3. This is because, in SAE level 2, human drivers have to monitor the road at all times, while in SAE level 3 they can engage in secondary tasks. Current technology has allowed some car manufacturers to build cars with partial automation (SAE level 2), which requires drivers to remain aware of the road conditions and be prepared for immediate intervention. This “limitation” in drivers’ freedom to perform non-driving tasks, seems to achieve better results (compared to SAE level 3) when measuring TOT and driver awareness.

In that direction, a meta-analysis of 129 studies was performed by Zhang et al. (2019). The review of the literature mentions a great variety of Take Over Times as revealed in Figure 4. Mean TOT values of 0.87sec (SD=0.24) were reported in situations where the driver had to brake when warned by a salient red stop sign (Winter et al., 2016). However, in Politis et al. (2018), when the driver had to take over after a 60 seconds TOR countdown, mean values of 19.8sec were measured (SD=9.3). It is clear that the longer the time given to a driver to take over, the more he is going to delay the process. This is mainly done because the driver either takes more time for the decision making or consciously delays as the situation does not seem critical to him. Particularly, in higher levels of automation drivers might want to “finish” their secondary task before taking over control of the vehicle.

In that matter, Radlmayr et al. (2015) states that longer time budgets lead to longer TOT and better transition performance. Based on their study, time budgets which are smaller than 7sec are inadequate for a driver who is out of the loop to take over control. In general, if more time is given to the drivers to make a decision, they tend to use more time to take over. In addition, if there is no sufficient time to make a decision or perform a maneuver, the driver tends to reduce vehicle speed in order to create more time to act respectively. In that way, they try to alter the automation desire time gap to the one that they are comfortable driving with.

In a similar study by Walch et al. (2017), a satisfactory Time Budget was concluded to be 10 seconds. In their research, the authors point out the importance of the driver state and the traffic conditions in the driver’s capacity to resume control. Eriksson and Stanton (2017) made a review of 25 relevant to Take Over Time studies. They draw the conclusion that the most frequent time budget times used were 3sec, 4sec, 6sec, and 7sec. The TOTs corresponding to these time budgets were 1.14sec, 2.05sec, 2.69sec, and 3.04sec. These times are also used for the purpose of this study, since they are comparable to the KPIs used in the simulation.

2.5.3 Factors determining Take Over Time

Regarding the factors that determine the Take Over Time, it seems that the environment, driver, human-machine interface and the vehicle itself, play an important role (Vogepohl et al., (2016). That said, the high complexity of an authority transition, the Take Over modality as well as the secondary task that the driver is engaged with, are important factors influencing Take Over Time and Take Over Performance. Take Over Times and Take Over Performance can be improved by multimodal TORs while single modalities and high complex non-driving tasks can lead to deterioration of the transition quality.

Gold, Happee, and Bengler (2018) created a model to predict TOTs based on driving simulators. The results showed that the time budget, the traffic density and the prior experience of the driver in authority transitions played a significant role in determining drivers’ Take Over Times. On the other hand, factors such as age, cognitive load, and driving lane revealed insignificant effect. What can be observed here, is the role of driver’s mental work load and the fact that it does not seem capable of affecting significantly Take-Over Times. This is the case as in this research, only the speed of taking over control was measured and not the quality of the transition, meaning that a driver can still react fast enough (by braking or steering reflexively) without processing and evaluating the situation.

Relevant studies have tested several TOR strategies incorporating visual and acoustic warnings, or haptic feedback. A research by Petermann and Stock (2013) showed that a transition time of 8,8 seconds is adequate (from the moment that the warning appeared till full control is gained back) in a scenario involving traffic jams. In a similar way, Dambock (2012) mentioned a time interval of 8 seconds for a smooth transition of control. However, such time budgets can suffice in non-critical situations where the driver has more time to react. In more complicated scenarios where limited time is available to the driver, Take Over mechanisms should allow from greater time budgets (warning initiated to the driver sooner).

Based on the meta-analysis of 129 studies realized by Zhang et al. (2019), Figure 4 aggregates the mean TOT found in the literature. Take Over Time variated from 0.69 seconds to 19.79 seconds. The mean TOT was 2.72 seconds with a standard variation of 1.45 seconds. It can be seen that the majority of the studies were performed using the specific key performance indicators, as these can appropriately represent the time used by the driver as well as the remaining time left for the driver to react. The results greatly vary depending on several driver and other factors, such as prior experience and time budget magnitude.

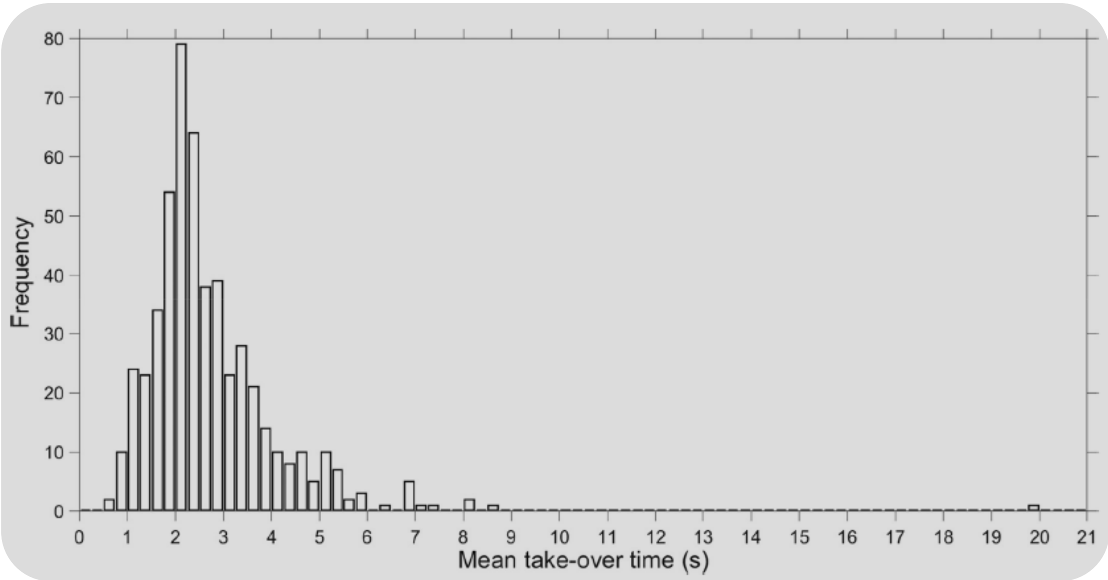


Figure 4: Distribution of 520 mean TOTs reported in 129 studies. (Bin width of 0.25s) (Zhang et al., 2019)

The main conclusions drawn from this extensive literature study are aggregated below:

- Time Budget strongly affects TOT, resulting in a difference of D= +1.35 seconds
- The prior experience strongly influenced TOT (drivers showed much lower TOT when they tried taking over for a second time). D= -1.00 seconds
- Using a handheld device increased TOT of D= +1.33 seconds
- When a driver was involved in a visual non-driving task (no handheld device though), TOT slightly increased (D= +0.29 seconds)
- Presenting a TOR decreased TOT by an average of D= -0.58 seconds

In addition, below there are some additional conclusions drawn. However, they are only based on a few studies.

- When a driver had his eyes closed before an authority transition, TOT was significantly increased (D= +1.19 seconds)

- A strong positive effect was found when auditory or tactile TOR was used (D= -1.41 seconds)

- TOT was reduced by D= -0.54 seconds when the driver was able to identify a potential TOR before its actual initiation (due to traffic conditions)

- Higher traffic had a minor effect (D= +0.49 seconds)

The above conclusions are summed up in tables 4 and 5.

Reasons for TOT increase	**Effect**
Time budget increase	D= +1.35 seconds
Handheld device	D= +1.33 seconds
Closed eyes	D= +1.19 seconds
High traffic density	D= +0.49 seconds
Visual NDT	D= +0.29 seconds

Table 4: Main reasons for increased TOT

Reasons for TOT decrease	**Effect**
Auditory-Tactile stimulus	D= -1.41 seconds
Prior experience	D= -1.00 seconds
TOR existence	D= -0.58 seconds
Priori identification	D= -0.54 seconds

Table 5: Main reasons for decreased TOT

Based on the above mentioned, it is concluded that the most important factors affecting the Take Over Time, and thus Take Over Performance, are:

- Driver occupation (what is the driver doing, NDT book, phone, etc.)
- Prior experience (how experienced is the driver in taking over)
- Time budget **-** Urgency (how critical and complex is the situation)
- Type of warning (visual, auditory, vibrotactile stimuli)

These are the factors that importance needs to be attached to when designing and evaluating authority transition mechanisms. More specifically, for SAE level 2 which is the main focus of this study, time budget availability and prior driver experience seem to have a major impact on Take Over Time. The other two factors (driver occupation and type of warning) played an important role in higher levels of automation as they are related to alerting a distracted driver and in SAE level 2 drivers always monitor traffic conditions.

2.6 Safety in authority transitions

Current driving automation is able to enhance traffic safety by eliminating human errors which cause up to 90% of road accidents (Chiellino et al., 2007). But as long as a system has boundaries, a driver is necessary for the redirection of the driving tasks. Since a boundary is detected (faded lanes, extreme weather conditions, etc.), the system initiates a Take Over Request and the driver has to take over control of the vehicle within a certain time interval (Time Budget).

Time Budget influences Take Over quality to a great extent (Zeeb et al., 2016). But Take Over quality, and thus safety is found to be influenced by other factors as well. For instance, high complexity of a driving situation and involvement in non-driving tasks were found to negatively influence the performance of the transition (Merat et al., 2012; Radlmayr et al., 2014). Also, the intensity and modality of the TOR play an important role during a control transition (Naujoks et al., 2014).

In addition, Take Over Time has received a lot of interest regarding safety evaluation. However, as described by Zeeb et al. (2016), TOT is not the most important element when assessing the performance of an authority transition. Studies have shown that shorter Take Over Times reveal faster driver responses but that generally comes with worse quality. As described in Papadimitriou et al., (2020), Take Over Quality (TQ) was found to be better in terms of lateral control and number of steering corrections, in non-emergency transitions, whereas other indicators (Take Over Time) could not reveal different values for emergency and non-emergency situations. Also, a study by Ruscio et al. (2015), revealed that a driver’s perceiving and cognitive awareness affects his ability to mentally process a TOR thus the Take Over performance. Therefore, an approach that uses reaction times (TOT and TB) seems to be inefficient to ensure the safety of a transition, despite the fact that it is, in general, a good estimate regarding the criticality of incidents.

A critical question arises regarding the above-mentioned statements: How is a TOR related to safety and how can the overall performance be translated into safety effects?

Neubauer et al. (2012) report that engaging in a demanding visual task during manual driving can raise mental workload. On the other hand, driving automation seems to decrease cognitive workload (Ma and Kaber, 2005). Young et al. (2002) mention that both overload and underload can prove to be hazardous in driving. Based on that, they claim that during an automation failure, a driver's confined maximum capacity might lead to inappropriate ways of dealing with the situation resulting in performance deterioration.

In that sense, Neubauer et al. (2012), studied the effects of secondary tasks on both manual and automated driving. The results showed that although secondary tasks increased braking times when driving manually, in automated mode they led to faster reactions. This seems to be due to the compensation of workload difference. For instance, engaging in non-driving tasks when driving in manual mode can increase workload (overload) and thus negatively affect the performance during an emergency. On the other hand, when driving with an active automation system, the workload of the driver is considered to decrease, thus leading to delayed reaction times. However, secondary tasks compensate for that by increasing the mental workload of the driver and thus balancing the performance.

Whether a control transition is safe or unsafe, depends on various conditions and it is characterized by high complexity. During the chronological sequence described by Damböck et al. (2012a), there are three phases that can be identified:

1) Automation in control: Right before the Take Over Request

2) In between period (automation in control): After TOR and before driver intervention

3) Driver in control: After driver intervention

Many TOR algorithms have been designed in a way that when a request is initiated the dynamic states of the vehicle (longitudinal and lateral) do not change. That means that during the Take Over Time, the automation controls the vehicle in the exact same way as it did before the warning stimulus as studies have shown that there are situations where steering might be preferable instead of braking (most emergency algorithms are designed to brake) (Radlmayr et al., 2014). More specifically, during an event that a collision occurred upfront and there is not enough time to come to a full stop, a steering maneuver might opt for. However, the lane that the maneuver needs to take place might be occupied by another vehicle. In that case, after the transition, the driver needs to accelerate to avoid the stopped vehicle in front, as well as prevent a collision with vehicles on the adjacent lane.

Table 6 presents the road conditions under which the above-mentioned categories are considered to be safe. The consideration has been done based on the available Time Budget provided by the system to the driver as this is the only element that can be influenced by the system (since there is no emergency state). In addition, as in this research the explored level of automation is SAE level 2, it is assumed that the driver is always in the loop and monitors the road.

Road Conditions	Safe	Unsafe
Off-ramp	√	
Collision		√
Faded markings	√	
Extreme weather conditions		√
Congestion	√	
Road works	√	
Sensor failure		√

Table 6: Safety consideration for various road conditions

During a collision, sensor failure, or extreme weather conditions, the required Take Over Time is low, and the event is considered to be an emergency. All the other situations can be characterized as safe, as either the required TOT is sufficient (congestion, off-ramp) or the driver can identify potential reasons to take over before the initiation of a TOR (faded markings, road works) as long as he is always kept inside the control loop.

The study performed by Radlmayr et al. (2014) explored how traffic situations influence Take Over quality in high automated driving. Their experiment included traffic situations where drivers drove in a three-lane highway under regular traffic conditions. When the TOR was initiated, a mandatory lane change had to be performed due to limited time for a full stop. The time budget was in all cases above 7 seconds, and drivers were told to primarily engage with the non-driving task they were given. The tested scenarios simulated road works, congestion, or collision upfront cases. The results of this research showed a great influence of non-driving tasks on the transition quality. For a safe and comfortable handle of the situation, drivers need to replenish potential decreased mental awareness. The analysis of the Time To Collision (TTC), longitudinal acceleration and occurred collisions indicated that manual drivers that are always inside the control loop, had lower TOT and better Take Over quality. Also, from that study, it can be said that eyes on road (monitoring the system) do not necessarily ensure high mental awareness compared to visual non-driving tasks. That means that even if the driver is inside the loop (hands and feet on the steering wheel and pedals, eyes on road) if he is not actively involved in the driving process it is possible that his mental awareness is low. However, except for road conditions, the driver state is crucial and affects the performance of a transition.

Several studies revealed that engagement in demanding secondary tasks that require high cognitive awareness can degenerate the way that the driver responds to a warning stimulus. Although the reaction time to readiness remains at the same levels, the decision-making process which consists perhaps the most critical aspect in a control transition and cannot be measured in seconds, is deteriorated (Zhang et al., (2019). Being involved in authority transitions and automated driving in the past (prior experience) showed that it can decrease TOT and raise quality. On the other hand, age did not seem to significantly affect any of these metrics (Gold et al., 2013).

What is worth noting, is well described in research by Zeeb et al. (2016). In their study they refer to the complexity of assessing the Take Over performance due to the high complexity of the characteristics that govern it. Zeeb et al. (2016) found no influence on the readiness time (time to return hands and feet at driving position) due to non-driving task engagement. In the same way, they revealed little to no influence on the time needed from drivers to control the vehicle (steer, brake). However, the performance was deteriorated due to the distraction of the drivers. It seems that although motor readiness can be ensured reflexively, cognitive processing of the critical situation is highly deteriorated when drivers are engaged in non-driving tasks. From this study we can conclude that not only response times, but also Take Over quality should be considered important factors that affect safety.

2.7 Safety Key Performance Indicators

Over the years, safety has been difficult to evaluate for new traffic solutions and ITS systems. This mainly happens as good predictive models of accident potential are missing. In addition, a general agreement on what is considered to be safe or not is missing. Gettman and Head (2003) worked on the investigation of potential surrogate measures that could help deal with the above issue. They claim that each surrogate metric can be measured during a conflict event. A conflict can be defined as a state where two or more road users (in that case vehicles) approach each other in time and space for such an extent that there is risk of collision if their movements remain unchanged. The measures proposed in that research field were the Time to Collision, post encroachment time, deceleration rate, maximum speed, and speed differential (Gettman et al., 2003). The first three can be used to assess the conflict likelihood while the other two can be used to assess the severity of a potential collision. These measures can be used to evaluate traffic solutions and ITS systems with respect to safety without the need for costly accident studies. Moreover, the results can be more detailed and can cover broader scenarios compared to the subjective measures derived by human observations.

In several researches, the elemental conflict severity measure that has been proposed is the Time to Collision (TTC). However, this measure is not adequate to capture the severity of an incident (system initiated deactivation) as speed is not taken into account. For instance, when traveling with 50 km/h or 120 km/h, a TTC of 1 second is considered to be the same, and counts as a critical event. In reality this is not true as traveling at higher speeds will result in more critical situations (Horst et al., 1993). Thus, a lower TTC can, of course, lead to a higher probability of collision, but is not quite enough to define the severity of the collision. It seems that the deceleration rate is a measure that can be used to capture the severity and compensate for TTC limitation. These two metrics are described in the following sections in more detail, as they were mostly used in this research for the derivation of other KPIs (Time to Control and Safe Time Budget).

Other proposed measures capable to define a conflict are the gap time, encroachment time, proportion of stopping distance. In similar studies, other measures found are delay, travel time, approach speed, speed and deceleration distribution (Sultan & Mcdonald, 2003). In their study, Mullakkal et al. (2017) provided a quantitative and qualitative comparison between different safety KPIs by means of risk measurement. The KPIs used in their research were the “inverse time to collision (iTTC), post-encroachment time (PET), potential indicator of collision with urgent deceleration (PICUD), warning index and safety field force. The results showed that all KPIs were able to delineate risk in cases of one-dimensional interaction (car following). However, the findings revealed the limitations of selected safety indexes (discontinuity on the operational space, omission of uncertainty in vehicle state assumption, and the inability to account for crash severity).

2.7.1 Time to Collision

The Time to Collision value at a specific time *t*, can be defined as the remaining time until a collision of two vehicles would have occurred if the course and speed of the vehicles are maintained (Hyden, 1996). The higher the TTC the safer a situation is. The lower the TTC the more hazardous the situation can be (Sultan & Mcdonald, 2003).

The Time-To-Collision of a vehicle *i* and a leading vehicle *i-1* can be calculated as:

$$\boldsymbol{TTC_i} = \frac{\boldsymbol{X_{i-1} - X_i - l_i}}{\boldsymbol{v_i - v_{i-1}}} \qquad \forall\, v_i > v_{i-1}\ \&\ TTC_i < TTC_{Threshold} \tag{1}$$

x_i: Position of vehicle *i* (m)

v_i: Speed of vehicle *i* (m/s)

l_i: length of vehicle *i* (m)

A critical value (threshold) is often selected to differentiate safe from unsafe situations. Van der Horst (1991) as well as Hirst and Graham (1997), state a TTC of 4s to distinguish between cases where drivers face dangerous situations and cases where they remain in control. However, laboratory experiments showed that these values result in too many false alarms (Nilsson et al., 1991). Hogema and Janssen (1996) studied the behavior of drivers while approaching a queue and they reported values of 3.5s and 2.6s for non-supported and supported drivers accordingly. The value of 2.6 seconds is considered to be a safe concern. In addition, Sultan et al. (2002) analyzed driver behavior and concluded that a decrease in the speed can provoke a decrease in the observed minimum TTC.

2.7.2 Deceleration Rate

The number of strong deceleration is calculated from the vehicle's i acceleration (a_i), as long as it surpasses a predefined threshold ($a_{threshold}$). It can be measured in km/h or gravitational power.

The Deceleration Rate can be formulated as follows:

$$\boldsymbol{DR_i = a_i} \ \forall\, a_i < a_{threshold} \tag{2}$$

A warning algorithm was formulated by Burgett et al. (1998), in which the maximum braking level (DRmax) was used to provoke a warning of a critical event. A test of this algorithm realized by Richard and Daniel (2001), reports a value of 0.75g (7,35 m/s^2) deceleration rate which led to a warning for an average of 2,5% of deceleration events. The theory suggested by Burgett et al. (1998), uses parameters like spacing, speed, and acceleration or deceleration from all vehicles involved (leading and following vehicles).

The deceleration rate is a good indicator to capture the severity of a potential impact as TTC does not consider speed in the calculations. The combination of these two metrics is used quite often in similar studies.

In this chapter a comprehensive overview of the literature was given. First, a synopsis was presented on the automation levels followed by the possible transition types which is the main focus of this study. Next, an analysis was given on the time sequence of a transition for a better understanding of the examined concept. In addition, a description of the causes of a transition in control was given, together with the principles behind the design of take-over requests. This was essential so that an impression is created regarding the several stages involved in the process. After that, a deeper analysis of the Take-Over Time indicator was provided and associated with safety attributes explored in several studies. The chapter concludes with a summary of well-known key performance indicators used in literature to investigate safety impacts.

3 Methodology

To fulfill the purpose of this project, a specific use case is necessary in order to investigate the safety effects of CACC platoons during authority transitions. In this case, the platoons are equipped with Cooperative Adaptive Cruise Control of SAE level 2 automation. Every authority transition initiated by the system is isolated and the incident is explored in order to assess its safety implications. This system initiated deactivation is basically the process of switching the control from the automation to the human driver, while the incident is the output of this process. The behavior of the vehicles in the platoon is analyzed by means of critical KPIs, and the safety impacts are evaluated.

The dataset that is used includes redundant information that needs to be cleared in order to create a more manageable dataset. In addition, as the data are in a raw format, some calculations are necessary so that the data can take the appropriate form to fit the requirements of this study. For instance, clearance is necessary with respect to the data related to authority transitions initiated by the drivers, as the focus of this assignment lies in the system initiated transitions. Also, the Time Budget and the Take Over Time have to be calculated as a function of other parameters, etc..

As described earlier, drivers, especially in higher levels of automation, may appear to respond "poorly" when asked to take back control, resulting in safety deterioration. Thus, it is of high importance to take that error margin into account when planning towards safe operations of automated vehicles. Braking times are an important factor to consider. The longer it takes the driver to react (cognitive awareness), the shorter the available braking time (Zhang et al., 2019). What could possibly guarantee safe operations and deal with that limitation is the usage of action times (perception/reaction + execution) instead of just reaction times when planning or programming the automated system. The exploration of the braking times instead of reaction times can not only predict but they can also conclude on the safety implications of an authority transition. An alteration of the time sequence given by Zhang et al. (2019) is given in Figure 5.

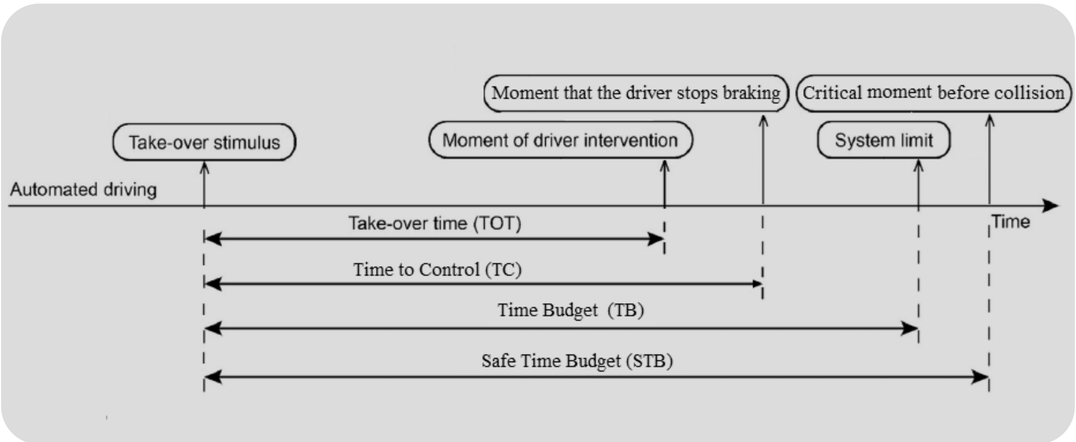


Figure 5: Take Over sequence after execution stages implementation

In the original concept created by Zhang, two additional times are added in the time sequence. These two metrics are aimed to address the limitation of Take Over Time and Time Budget, by taking into consideration the time that is required for the driver to perform the required action for the collision avoidance. These two metrics are:

- the Time to Control (TC), and
- the Safe Time Budget (STB)

For the purposes of this study, these two metrics are created for the first time, in order to better represent the execution stages of an authority transition. Compared to the Take-Over Time which only captures the first moment of action (braking/steering) and thus cannot guarantee collision avoidance, the Time to Control indicates the moment at which no more deceleration force is required to avoid a potential collision with the vehicle upfront.

In accordance with that, a measure that captures the last "safe" moment right before a collision is necessary. Compared to the Time Budget, which shows the last moment that the driver starts taking action (steering/braking), the Safe Time Budget defines the moment just before the collision under the driving dynamics that the collision is evaded and includes the action that needs to be taken by the driver in order to perform the collision avoidance action.

With the combination of the Time to Control and the Safe Time Budget, we can safely assume that a ratio of these two metrics smaller or equal to 1, entails a collision-free situation. However, the difference of these two metrics is preferable to conclude not only on the critical incident possibility, but on the severity of the incident as well, compared to the ratio, as the latter one might have the same values for quite different circumstances. For example, a Time to Control of 2 seconds with a Safe Time Budget of 4 seconds has the same ratio with a Time to Control of 5 seconds and a Safe Time Budget of 10 seconds. The actual difference though is 3 seconds (2/4=0,5 and 5/10=0,5 but 4-2=2 seconds and 10-5=5seconds) between those two scenarios.

For the purposes of this study, the above metrics have to be calculated. Both measures can be calculated from the existing dataset derived by Xiao et al. (2018). In order to present the applicability of the performance assessment framework, the above mentioned Key Performance Indicators were applied to a case study. It seems that microsimulation software promises to collect surrogate measures with respect to safety. However, all simulation packages assume that drivers drive in a safe way according to certain characteristics, for instance how aggressive a driver will be regarding lane change or gap acceptance. Due to that fact, the process of deriving the surrogate measures should take that into consideration.

3.1 Time to Control

For the purposes of this project, and the necessity to incorporate braking times into the transition in control, the Time to Control had to be determined. The TC is defined as the time from the warning stimulus until the moment that the driver stopped decelerating at a certain rate. After this point the driver can either maintain a constant speed, accelerate, or switch control back to the system again. Only when these actions are fully performed we can safely assume that an authority transition took place in a safe manner.

The Time to Control indicator, compared to the traditional Take Over Time, includes the actual braking time that the driver needs in order to complete his safety maneuver. In the simulation model, for every scenario, the time elapsing from the moment of the warning till the moment that the driver stopped applying deceleration force greater than -2 m/s^2 was measured. The specific threshold is the value at which the automation is able to automatically activate again after an authority transition. This time interval is called Time to Control, and it represents the time that the driver needs in order to perceive the warning stimulus, get cognitive awareness of the situation, get readiness actions and perform the desired action. This time equals the summation of the TOT and the action time. Its calculation derives directly from the simulation algorithm.

3.2 Safe Time Budget

In accordance with the previous metric, an additional indicator that represents the last “safe” moment right before a collision is necessary. Compared to the Time Budget, the Safe Time Budget spots the moment before the collision under the driving dynamics that the collision is evaded. For a better understanding of this indicator, the STB is the total available time for the driver to actually take control of the vehicle. It is thus, the time from the warning, till the last moment before a potential collision, and it is based on the dynamic states of both vehicles. In that time (STB) the driver has to perform all the actions necessary to avoid a collision.

The Safe Time Budget can be estimated as follows:

The moment before the potential collision, the following kinematic equation is valid:

$$x_2 - x_1 - l > 0 \tag{3}$$

x_1: position of rear vehicle (front edge) (m)

x_2: position of preceding vehicle (front edge) (m)

l: vehicle length (m)

The STB is the result of the above equation, divided by the speed difference of the two vehicles. It is basically a safe Time to Collision (sTTC), which captures the last safe moment right before a collision, in such a way that a collision is evaded. This time is the summation of the TB and the action time. Its calculation derives directly from the simulation algorithm.

$$STB = (x_2 - x_1 - l)/(v_1 - v_2) \tag{4}$$

x_1: position of rear vehicle (front edge) (m)

x_2: position of preceding vehicle (front edge) (m)

l: vehicle length (m)

v_1: speed of rear vehicle (m/s)

v_2: speed of preceding vehicle (m/s)

3.3 Time to Control with Safe Time Budget difference (Dif)

In this study, another innovative Key Performance Indicator is created. This metric derives from the difference of the Time to Control and the Safe Time Budget and tries to capture the risk of a critical event occurrence and the importance of the transition.

$$Dif = Safe\ Time\ Budget - Time\ to\ Control \tag{5}$$

When the difference is smaller than 0.9 seconds, it means that the system limit has been exceeded, and a collision is likely to occur. In addition, the closer the KPI Dif gets to the value 0, the more likely it is that an accident will happen. The larger the difference, the safer the situation and the authority transition. The criticality of these incidents (0.9 seconds value) is estimated based on the research performed by Ayres et al. (2001), Taieb-Maimon & Shinar (2001), and Eriksson & Stanton, (2017). According to this literature, the required time gap between vehicles both in terms of safety and comfort, is approximately 1 car length for every 16 km per hour (4.44 meters per second) of speed of the following vehicle. By dividing the car length (4 meters) with the 4.44 m/s speed, we derive the 0.9 seconds that are required for a vehicle to cover one car length.

In a similar way, a threshold for the difference of the Take Over Time and Time Budget (Dif_2) has to be determined. The purpose of this threshold is to determine which incidents are critical based on the old approach. As mentioned previously, the critical Time To Collision selected for this study is 2.6 seconds. However, this time is characterized as critical in terms of remaining available time for a driver to handle a situation. Thus, it refers to a combined time of reaction and action. For the purposes of this study the braking times have been calculated for every scenario. The mean value of these times is subtracted from the above critical TTC to determine the critical threshold for the Dif_2 KPI. The mean actual braking time is found to be 1.02 seconds, so the threshold for the Dif_2 is found to be 1.58 seconds. In this way, a comparison of the new method compared to previous approaches is possible.

3.4 Safety Evaluation Thresholds

At this point, it is worth mentioning some of the evaluation thresholds as well as some factors that might affect the calculation of the above mentioned key performance indicators.

To begin with, the turning speed of vehicles might affect the estimation of the surrogate measures. Also, another factor that can influence the metrics calculation, is the variable driver reaction time which is highly dependent on several characteristics of the driver (age, experience, etc.). Another important factor is the variation of vehicle's capabilities with respect to acceleration and deceleration rate distributions. Other aspects that need to be included in the modeling process are the friendly merging (vehicles create gap so that other vehicles can merge), variable time steps (models that allow for tunable time step lengths), gap acceptance criteria variation depending on delay (several drivers change their behavior regarding gap creation depending on how long they have been waiting), vehicle length, etc.. Thus, it is important that the chosen simulation model can take into account the above-mentioned characteristics so that the calculation of the surrogate measures can be realized in a comprehensive way.

Finally, in order to evaluate the results derived from the simulation, an isolation of the critical incidents was necessary. The criticality of these incidents is estimated based on the research performed by Ayres et al. (2001), Taieb-Maimon & Shinar (2001), and Eriksson & Stanton, (2017). According to this literature, the required time gap between vehicles both in terms of safety and comfort, is approximately 1 car length for every 16 km per hour of speed of the following vehicle. This is the threshold that was used for the purposes of this research in order to characterize every incident. By isolating each case, we can then conclude on whether they reveal any particular pattern and if they share any similar characteristics.

In this chapter the methodology was described in a comprehensive way. First, a description of the new Key Performance Indicators that are used in this study was given and a comparison was made in relation to the previous approaches. The innovative metrics are the Time to Control and the Safe Time Budget and their main difference with the Take-Over Time and the Time Budget, is that they incorporate the actual behavior (braking action) of the driver after his first reaction during an authority transition. Next, an overview was given regarding the calculation of these metrics together with their meaning. Finally, in the last section the thresholds for these metrics were defined for the purpose of critical conflicts identification after the simulation. This is important not only for concluding if an incident is critical in terms of safety or not, but also for the comparison of the two methodologies.

4 Experimental Setup

The experimental setup as used in Xiao, Wang, Schakel, & van Arem (2018), is described in this chapter together with the algorithm that has been used for the purposes of this study. Here, the car following model together with the lane changing model of CACC vehicles are described. Next, the basic assumptions for system deactivation in CACC mode are mentioned. In addition, the conditions and the vehicle behavior during authority transitions are explained. In the end, a description of the model implementation is given together with a brief analysis of the dataset.

Other CACC traffic flow models also exist, but a realistic reproduction of CACC vehicle behavior is lacking. The choice of the specific traffic flow model has been made mainly for two reasons. Firstly, in this model the attention on the influence of system deactivations on traffic flow on bottlenecks was highlighted. This resulted in one of the few datasets which includes all these authority transitions. Also, the CACC model manages to capture driver-system interactions in a realistic way, and the scenario is simple enough to avoid result 'noise', so that emphasis can be given on the already complex translation of traffic flow impacts to safety impacts. Another factor that played an important role in the model selection, was the simultaneous access to both the model and its creator. In this way, a deeper understanding of the model, its limitations and its adaptability capabilities were possible. Our collaboration with the model creator resolved various issues that would have led to vague assumptions otherwise. Therefore, the CACC model created by Xiao et al., (2018) was found to be an appropriate model to work with.

4.1 Car following model

As elaborated in Xiao et al. (2017), the car following model is based on two parallel control loops. Three stages namely, perception, decision making, and actuation, govern the human driver as well as the (C)ACC control loop. These three stages are a representation of the sequential process for the physics of vehicle behavior in discrete time steps (Milanes et al., 2014). At every time step the preceding vehicle's as well as the subject vehicle's position, speed, desired time gap and cruising speed are used as an input by the CACC model (or human driver) in order to provide a speed or acceleration output to the vehicle (Xiao, Wang, Schakel, & van Arem, 2018).

The vehicles have three possibilities in terms of operation system: a) manual driving, b) ACC operation and c) CACC operation. The automated operations (ACC and CACC) integrate controllers for 3 control purposes (Milanes and Shladover, 2015):

- Cruising controller (desired speed maintenance if there is no preceding vehicle)
- Gap regulating controller (desired time gap maintenance when there is a preceding vehicle)
- Gap closing controller (transition from cruising controller to gap regulating controller when a preceding vehicle is identified)

When it comes to manual driving, the car following model is based on a modification of the IDM (intelligent driver model) (Treiber et al., 2000, Schakel et al., 2010), the IDM+. In this model, the desired acceleration is given by the minimum acceleration of driving towards the desired speed and the desired headway. With the implementation of the IDM+ instead of the IDM, more logical values in terms of capacity can be achieved.

4.2 Lane changing model

The LMRS (lane change model with relaxation and synchronization) by Schakel et al., (2012) is the base for the lane change model designed by Xiao et al., (2018). In this model, a decision model is used for the prediction of the lane changing behavior, where it calculates the desire for lane change and determines if a lane change is necessary. In addition, the type of lane change is also investigated. In order to obtain the desired lane change, a weighted summation of multiple-lane change motivations, gaining speeds and traffic rules (keep right instructions) is required.

In reference to the interaction amongst lateral and longitudinal behavior of the vehicle, it is modeled with the expression of the desired gap and acceleration as a function of the desired lane change.

4.3 Deactivation of CACC

Authority transitions in CACC systems refer to deactivation and reactivation of the automated system. As described in previous chapters, a system can be deactivated for several reasons (system failure, speed adaptation, operational design domain issues). When the system is deactivated, the driver has to take over control of the vehicle and increase the time gap from CACC to manual driving. This situation can have a great impact when it comes to safe operations.

4.3.1 Assumptions

As any model, the simulation study performed by Xiao et al., (2018) incorporated some assumptions. One important assumption regarding the usage of the automation system for instance, was that the drivers intended to drive with an active system (ACC/CACC) as much as possible. In addition, during active system operation, there were three scenarios under which the deactivation process could take place. These scenarios are:

- Safety-related (collision warning – critical approaching)
- Lane change related (synchronization for a lane change)
- Route related (exits, merging scenarios, lane drop)

Another assumption made is that the automated system cannot be reactivated when the deceleration rate overpass the margin of (-) 2 m/s^2 or during a lane change (Xiao et al., 2018). For that reason, the Time to Control is measured based on that margin. This basically means that the Time to Control is measured from the moment of the warning till the moment that the driver keeps decelerating with a rate higher than the above-mentioned threshold, as below that threshold the automation system can automatically jump back in, ending the deactivation process.

Additionally, drivers' attention is considered to always be continuous during the activation-deactivation of the system as they are kept in the control loop constantly (SAE Standard J3016).

Next, in the main reference study (Xiao et al., 2018), the reaction of the driver is considered to be equal to zero (0) seconds. In reality, even if the driver is constantly kept inside the loop, a reaction time of at least one (1) second applies. For that reason, and for the calculation of the Time to Control, four different Take Over Times have been used based on the research performed by Eriksson and Stanton (2017). The values for the TOTs are 1.14, 2.05, 2.69, and 3.04 seconds and the corresponding Time Budgets are 3 sec, 4 sec, 6 sec and 7 sec (Table 7). The Time Budget times were selected based on the Safe Time Budget ranges calculated from the simulation model, and the Take Over Times were selected based on the Time Budgets. This means, that if a Safe Time Budget was calculated to be approximately 5 seconds, the respective range that the Time budget falls in is the 4 seconds one, and thus the TOT is 2.05 seconds.

Take Over Time (s)	Time Budget (s)
1.14	3
2.05	4
2.69	6
3.04	7

Table 7: TOT and TB values (Eriksson et al., 2017)

In reference to the first possible reason of system deactivation (system initiated), a warning is issued for a potential collision, the system will be deactivated and the control will be switched back to the driver. The warning for the collision is based on an indicator called inverse time to collision (iTTC) (Kiefer et al., 2005). The rest of the reasons for system deactivation are related to the drivers' purpose to adjust vehicle dynamics (driver initiated). Thus, they are not going to be explored in this study.

For the system deactivation, both ACC and CACC systems can be deactivated directly to manual driving, since it is essential that drivers are capable to resume control from any automation system (SAE level 1&2). The model used by Xiao et al. (2018), assumes that since vehicle dynamics are highly associated with acceleration capabilities, driving comfort and safety, a gradual transition from an active system to manual driving is necessary. One important alteration in CACC behavior has to do with the main advantage it comes with; the reduced time gap. Thus, when there is an authority transition, there is need to adapt from one desired time gap to another. CACC time gaps range from 0.6s to 1.1s (CACC and ACC) when the corresponding time gap for manual driving is 1.4s (Xiao et al., 2016).

Last but not least, in reference to the deceleration forces that apply in this study, by the time the driver takes over control of the vehicle, the deceleration force that he applies starts at $-6m/s^2$. Depending on the time gap with the front vehicle the deceleration force is gradually reduced in a smooth way so that the desired time gap of 1,4s is reached. Such a policy was implemented by Xiao et al., (2018) for the purpose of addressing the maximum deceleration capabilities of the vehicle.

4.4 Experiment design

In order to investigate the implications of CACC systems, Xiao et al., (2018) simulated a merging bottleneck where traffic jams occurred on highways and there was a drop in capacity. In the simulation, there is a four-lane highway section, with an on-ramp (single lane). The entire network is 11 kilometers long and the on-ramp is located 8 kilometers downstream from the initial start point (acceleration lane 250m). The first 3 kilometers are used as a warm-up period in order to generate CACC strings through the join maneuver. Figure 6 shows the network used.

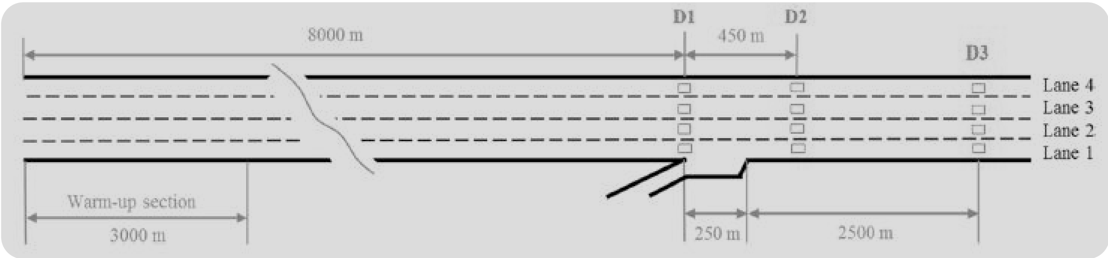


Figure 6: Merging network (Xiao et al., 2018)

Xiao et al., (2018) tested 6 different market penetration rates for CACC operations, starting from 0% to 100% with a 20% increment. The on-ramp demand was set to 400 vehicles per hour. There is a total of 6 scenarios, each run for 5 times with different random seeds (vehicle class, desired speed, arriving interval between 2 vehicles at the generator). The entire simulation lasted for one hour (0.1s time step) with the first 10 minutes used as a warm-up period. The main demand was set to 80% of the capacity of the corresponding CACC market penetration rates in a pipeline section.

Table 8 lists the parameters of the car following model as well as the simulation settings (Xiao et al., 2016, Shladover et al., 2012):

Parameters	Value	Units
Max acceleration (conventional vehicles)	1.25	m/s^2
Max deceleration (conventional vehicles)	6	m/s^2
Stopping distance	3	m
Desired time gap (manual driving)	1.4	s
Vehicle length	4	m
Free flow speeds	N (125, 8.75)	km/h
V2V communication range	300	m
Sensor range	120	m
Desired time gap (ACC)	1.1	s
Desired time gap (CACC)	0.6	s
ACC-CACC lower acceleration limit	-4	m/s^2
ACC-CACC upper acceleration limit	2	m/s^2

Table 8: Parameters and values used in the simulation

4.5 Dataset description

There are two main categories of data in Xiao's results; a) detector data and b) trajectory data. For the purposes of this study, the data derived from the trajectories are used for the evaluation. The reason for that selection is that an investigation of each vehicle characteristics is preferable, and then based on each individual, an aggregation is made to assess the overall network safety.

In the study of Xiao et al. (2018), the measures that are calculated per vehicle were:

- **Time step** (0.1s)
- **Location** (m)
- **Speed** (m/s)
- **Acceleration** (m/s^2)
- **Lane** (current lane)
- **Class ID** (=1 then normal vehicle, 7-10 then CACC)
- **Mode** (Cruising / gap regulating / gap closing)
- **Operation system** (manual=0 / ACC=1 / CACC=2)
- **Distance headway** (m)
- **Deactivation type** (0 means no deactivation, 1 means collision warning)

The dataset that is used includes redundant information that needed to be cleared in order to create a more manageable dataset. In addition, as the data are in a raw format, some calculations are necessary so that the data can take the required form to fit the requirements of this study. For instance, clearance is necessary with respect to the data related to authority transitions initiated by the drivers, as the focus of this assignment lies in the system initiated transitions. Figure 7 shows the format of the raw data gathered from MOTUS.

Variables - out.trajectories

out | out.trajectories

out.trajectories

Fields	t	x	v	a	lane	classID	vFree	mode	operation	lcProgress	gap	deactType
1	1943x1 dou...	1943x1 dou...	1943x1 dou...	1943x1 dou...	1943x1 dou...	1	148.7818	[]	[]	1943x1 doub...	1943x1 dou...	[]
2	2158x1 dou...	2158x1 dou...	2158x1 dou...	2158x1 dou...	2158x1 dou...	1	133.2741	[]	[]	2158x1 doub...	2158x1 dou...	[]
3	2456x1 dou...	2456x1 dou...	2456x1 dou...	2456x1 dou...	2456x1 dou...	1	115.7165	[]	[]	2456x1 doub...	2456x1 dou...	[]
4	2475x1 dou...	2475x1 dou...	2475x1 dou...	2475x1 dou...	2475x1 dou...	1	114.8241	[]	[]	2475x1 doub...	2475x1 dou...	[]
5	2488x1 dou...	2488x1 dou...	2488x1 dou...	2488x1 dou...	2488x1 dou...	1	114.2097	[]	[]	2488x1 doub...	2488x1 dou...	[]
6	2444x1 dou...	2444x1 dou...	2444x1 dou...	2444x1 dou...	2444x1 dou...	1	116.3401	[]	[]	2444x1 doub...	2444x1 dou...	[]
7	2232x1 dou...	2232x1 dou...	2232x1 dou...	2232x1 dou...	2232x1 dou...	1	131.3998	[]	[]	2232x1 doub...	2232x1 dou...	[]
8	2232x1 dou...	2232x1 dou...	2232x1 dou...	2232x1 dou...	2232x1 dou...	1	131.0540	[]	[]	2232x1 doub...	2232x1 dou...	[]
9	2253x1 dou...	2253x1 dou...	2253x1 dou...	2253x1 dou...	2253x1 dou...	1	126.1360	[]	[]	2253x1 doub...	2253x1 dou...	[]
10	2209x1 dou...	2209x1 dou...	2209x1 dou...	2209x1 dou...	2209x1 dou...	1	128.7146	[]	[]	2209x1 doub...	2209x1 dou...	[]
11	2164x1 dou...	2164x1 dou...	2164x1 dou...	2164x1 dou...	2164x1 dou...	1	131.3262	[]	[]	2164x1 doub...	2164x1 dou...	[]
12	2431x1 dou...	2431x1 dou...	2431x1 dou...	2431x1 dou...	2431x1 dou...	1	116.8927	[]	[]	2431x1 doub...	2431x1 dou...	[]
13	2395x1 dou...	2395x1 dou...	2395x1 dou...	2395x1 dou...	2395x1 dou...	1	131.2348	[]	[]	2395x1 doub...	2395x1 dou...	[]
14	2311x1 dou...	2311x1 dou...	2311x1 dou...	2311x1 dou...	2311x1 dou...	1	122.9480	[]	[]	2311x1 doub...	2311x1 dou...	[]
15	2113x1 dou...	2113x1 dou...	2113x1 dou...	2113x1 dou...	2113x1 dou...	1	134.4518	[]	[]	2113x1 doub...	2113x1 dou...	[]

Figure 7: Table with parameters, Xiao et al., (2018)

4.5.1 Time to Control calculation (TC)

In this section, the algorithm that has been used to calculate the Time to Control is explained. As mentioned previously, the Time to Control is the time from the moment the warning stimulus goes off, till the moment that the driver stopped decelerating with a deceleration force smaller than -2 m/s^2. This is when the automation activates again. In order to calculate that time from the dataset, the following steps had to be made.

- First, the table that contains the Time to Control per vehicle and per deactivation needed to be created. To do that, a table with zero values was first created, so that the correct values could be stored later on during the simulation.

- Next, the simulation run a loop through all the vehicles, and a second loop for all the time steps that the specific vehicle was inside the network.

- Next, for the purpose of minimizing the number of loops for the sake of time efficiency, an 'if' function checked whether there is a deactivation or not.

- Then, in order to separate the different deactivation types, and isolate the ones that occurred due to collision warnings only, while at the same time the deceleration force on the vehicle specified before is less than the deceleration threshold, an 'if' statement was necessary.

- After that, and if the previous functions were satisfied, the corresponding cell of the initial table was filled with the Time to Control value, which derived from the difference of the timestep where the deceleration force became smaller (absolute value) than the threshold, minus the timestep where the warning appeared, plus the driver reaction time.

4.5.2 Safe Time Budget calculation (STB)

In this section, the algorithm that has been used for the calculation of the Safe Time Budget is explained. The Safe Time Budget is the total hypothetical time from the moment of the warning stimulus till the time right before the potential collision. It is thus, the total available time that the driver has in order to hear the warning stimulus, get cognitive awareness of the situation, get readiness actions and perform the desired action.

In order to calculate the STB, the following steps were necessary:

- First, the table that contains the Safe Time Budget per vehicle and per deactivation needed to be created. To do that, a table with zero values was first created, so that the correct values could be stored later on during the simulation.

- After that, all the vehicles found before (TC calculation), had to be checked with all the other vehicles in the network as the exact sequence of the vehicles is unknown.

- Then, in order to save time and make the algorithm more efficient, the total number of vehicles was reduced based on the next 'if' functions' satisfaction:

a) If the vehicle to be checked has been in the network at the same time step with the vehicle under consideration.

b) If both vehicles were on the same lane at the specific time step.

c) If the vehicle to be checked was in front of the vehicle under consideration.

d) If the speed of the rear vehicle was larger.

- Next, a check was necessary to find out if the two found vehicles are consecutive.
- Finally, if the previous functions are satisfied, the corresponding cell of the initial table was filled with the Safe Time Budget value, which derived from the equation 4 (paragraph 3.2):

$$STB = (x_2 - x_1 - l)/(v_1 - v_2) \tag{4}$$

x_1: position of rear vehicle (front edge) (m)
x_2: position of preceding vehicle (front edge) (m)
l: vehicle length (m)
v_1: speed of rear vehicle (m/s)
v_2: speed of preceding vehicle (m/s)

In this chapter, the experimental setup of this study was given. First, the car following model together with the lane changing model as designed by Xiao et al., (2018) and Schakel et al., (2012) are described. Then, the main assumptions for both the reference study by Xiao et al., (2018) and this study are mentioned, with the most important ones being the point of automation reactivation and the reaction times. Next, the experiment design in which the simulation took place was presented, followed by a description of the data used in the experiment. Finally, the chapter concludes with an analytical calculation of the Time to Control and Safe Time Budget indicators.

5 Results

In this chapter, the results of the simulation are presented. The data derived from the simulation model are analyzed and described in the sections below. The data used for this experiment were derived from the trajectory data (input) used from Xiao et. al. (2018). The results are trying to address quantitively the following topics and correspond to the research questions formulated in chapter 1:

- What is the impact of the AV introduction with respect to safety?
- What is the ability of the proposed method to capture incidents (critical), compared to previous methodologies used so far?
- Do the critical incidents reveal any pattern (Market Penetration Rate, initial speed, operation, class ID)?

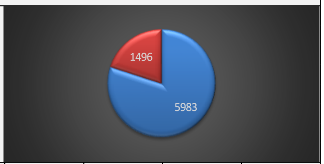
5.1 Format explanation

In order to be able to present a more comprehensive picture, there is a need to first explain the format of the results. All the results are generated from the simulation model performed in MATLAB software. The format of the results is shown in Figure 8.

Repetition 1

Total vehicles =	7479
Manual =	5983
AV =	1496
Incidents =	5
Critical incidents =	0
HMM =	1

Manual % of total =	80
AV % of total =	20
incidents % of total =	0.07
incidents % of AV =	0.33
critical incidents % of total =	0.00
critical incidents % of AV =	0.00



vehicleID	vehicleID2	classID	classID2	operation	v0 [m/s]	v02 [m/s]	Act. Br.	TC [s]	STB [s]	Dif [s]	TOT [s]	TB [s]	Dif2 [s]
926	951	8	7	2	37.06	33.20	0.60	3.29	7.92	4.63	2.69	6.00	3.31
1470	1463	7	7	2	34.23	30.37	1.10	3.15	5.98	2.83	2.05	4.00	1.95
1689	1727	7	7	2	28.97	23.31	0.90	2.95	5.18	2.23	2.05	4.00	1.95
1703	1694	7	1	1	33.66	27.16	1.90	4.59	6.13	1.54	2.69	6.00	3.31
4511	4527	8	8	2	29.22	24.89	1.20	3.25	5.29	2.04	2.05	4.00	1.95

Figure 8: Format of the results (example: MPR=20%, repetition 1)

There are 5 different market penetration rates, and each one is simulated for 5 times (5 repetitions) to capture different seeds and get a representative idea of likely performance. As seen in the picture above, the results are categorized per MPR and per repetition. For each set, the following data are stored:

- Vehicle ID (identity of the AV under examination (rear vehicle))
- Vehicle ID_2 (identity of the AV that caused the collision warning (front vehicle))
- Class ID (class of AV depending on its desired time gap (0.6s, 0.7s, 0.9s, 1.1s)
- Class ID_2 (class of AV depending on its desired time gap (0.6s, 0.7s, 0.9s, 1.1s)
- Operation (0,1,2 – Manual, ACC, CACC)
- v_0 (initial speed of the AV under examination (rear vehicle))
- v_{02} (initial speed of the AV that caused the collision warning (front vehicle))
- Act. Br. (actual action of braking)
- TC (Time to Control)
- STB (Safe Time Budget)
- Dif (Difference of Safe Time Budget with Time to Control)
- TOT (Take Over Time)
- TB (Time Budget)

- Dif_2 (Difference of Time Budget with Take Over Time)

All of the aforementioned data were derived from a post processing data analysis of the existing simulation study, apart from TOT and TB which were produced through calculations (derivation explained in section 4.5).

The measures that were calculated manually were the following:

- Act. Braking
- Dif
- Dif_2

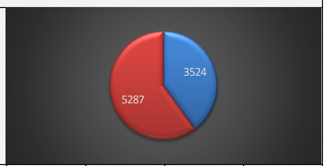
For the calculation of the Dif and the Dif_2, the difference between the Safe Time Budget with the Time to Control, as well as the difference of the Time Budget with the Take Over Time were used. The results of the metrics show the remaining available time for the driver to perform any action, in both the new and the old methodology. The Act. Br. (actual braking) data were calculated by subtracting the Take Over Time from the Time to Control.

For the sake of simplicity, an example is given in Figure 9 for one market penetration rate and one repetition. The results for the MPR=60% and repetition 1 for the first forty (40) AV are shown below. The critical Differences of Safe Time Budget and Time to Control are noted with red color, based on the 0.9 seconds threshold explained in section 3.3 (and 1.58 seconds for Dif_2 respectively). Negative values indicate crashes.

Repetition 1

Total vehicles =	8811
Manual =	3524
AV =	5287
Incidents =	145
Critical incidents =	8
HMM =	8

Manual % of total =	40
AV % of total =	60
incidents % of total =	1.65
incidents % of AV =	2.74
critical incidents % of total =	0.09
critical incidents % of AV =	0.15



vehicleID	vehicleID2	classID	classID2	operation	v0 [m/s]	v02 [m/s]	Act. Br.	TC [s]	STB [s]	Dif [s]	TOT [s]	TB [s]	Dif2 [s]
555	550	8	9	2	31.12	26.70	1.00	3.05	5.61	2.56	2.05	4.00	1.95
587	638	7	8	2	31.57	28.10	0.80	2.85	5.98	3.13	2.05	4.00	1.95
653	651	7	7	2	26.33	22.80	1.00	3.05	5.02	1.97	2.05	4.00	1.95
721	717	7	10	2	26.72	21.67	1.10	3.15	5.02	1.87	2.05	4.00	1.95
726	723	7	7	2	33.32	29.80	0.60	3.29	6.82	3.53	2.69	6.00	3.31
742	740	7	7	2	31.35	27.66	1.10	3.15	5.78	2.63	2.05	4.00	1.95
744	739	7	1	1	23.87	19.79	2.00	3.14	4.61	1.47	1.14	3.00	1.86
753	748	8	1	1	22.51	17.38	1.80	2.94	4.39	1.45	1.14	3.00	1.86
754	773	7	1	1	29.16	24.25	1.90	3.95	5.35	1.40	2.05	4.00	1.95
762	757	10	7	2	31.60	24.60	2.00	4.05	5.33	1.28	2.05	4.00	1.95
763	794	7	8	2	28.27	24.93	2.50	3.64	4.94	1.30	1.14	3.00	1.86
781	777	7	1	1	29.44	24.09	3.00	5.05	5.24	0.19	2.05	4.00	1.95
794	790	8	1	1	29.03	23.84	2.70	4.75	5.22	0.47	2.05	4.00	1.95
797	793	10	1	1	29.51	24.49	1.70	3.75	5.31	1.56	2.05	4.00	1.95
820	804	10	1	1	27.68	22.83	2.00	4.05	5.07	1.02	2.05	4.00	1.95
830	840	8	1	1	28.67	23.75	1.80	3.85	5.21	1.36	2.05	4.00	1.95
839	834	10	1	1	25.80	21.50	2.00	3.14	4.91	1.77	1.14	3.00	1.86
841	852	7	7	2	33.14	28.16	2.20	4.25	5.43	1.18	2.05	4.00	1.95
847	844	8	7	2	30.76	24.16	2.00	4.05	5.32	1.27	2.05	4.00	1.95
848	843	8	1	1	28.74	23.58	2.60	4.65	5.13	0.48	2.05	4.00	1.95
852	838	7	7	2	31.65	28.29	2.10	4.15	5.72	1.57	2.05	4.00	1.95
868	891	7	7	2	28.08	21.06	4.30	5.44	4.98	-0.46	1.14	3.00	1.86
872	870	8	8	2	29.21	25.11	2.60	4.65	5.33	0.68	2.05	4.00	1.95
883	880	8	7	2	29.18	23.20	0.90	2.95	5.01	2.06	2.05	4.00	1.95
884	882	7	1	1	25.48	20.94	1.60	2.74	4.73	1.99	1.14	3.00	1.86
886	884	7	7	2	25.12	21.91	1.60	2.74	4.50	1.76	1.14	3.00	1.86
900	841	7	7	2	32.37	29.08	2.00	4.05	5.72	1.67	2.05	4.00	1.95
903	850	8	10	2	33.96	29.66	0.90	3.59	6.14	2.55	2.69	6.00	3.31
910	908	7	7	2	34.37	29.80	1.50	4.19	6.46	2.27	2.69	6.00	3.31
928	952	7	1	1	25.91	21.60	1.30	2.44	4.95	2.51	1.14	3.00	1.86
954	950	7	1	1	28.74	23.57	1.60	3.65	5.17	1.52	2.05	4.00	1.95
993	992	7	8	2	30.56	26.45	1.60	3.65	5.74	2.09	2.05	4.00	1.95
994	993	7	7	2	32.83	28.39	2.00	4.05	5.28	1.23	2.05	4.00	1.95
997	996	8	7	2	32.70	28.41	1.70	3.75	5.56	1.81	2.05	4.00	1.95
1040	1036	7	10	2	29.23	24.67	0.60	2.65	5.10	2.45	2.05	4.00	1.95
1295	1310	7	7	2	29.39	24.97	1.10	3.15	5.25	2.10	2.05	4.00	1.95
1295	1310	7	7	2	28.91	24.54	0.80	1.94	4.83	2.89	1.14	3.00	1.86
1395	1417	7	7	2	35.55	31.75	1.00	3.69	6.93	3.24	2.69	6.00	3.31
1444	1441	7	7	2	27.18	23.97	0.80	1.94	4.98	3.04	1.14	3.00	1.86
1457	1455	8	7	2	32.05	27.90	1.00	3.05	5.98	2.93	2.05	4.00	1.95

Figure 9: Example for the first 40 AV (MPR=60%, repetition 1)

For each of the 25 scenarios, the following graphs are presented:

- TC with initial speed, operation and class ID :

  These graphs reveal the patterns that the Time to Control follows in relation to the initial speed, the operation and the class ID of the examined (rear) vehicle. In other words, with this graph we can see how different characteristics affect the time that a driver requires to perform a safety maneuver.

- Dif with v_0-v_{02} :

  This graph reveals how the speed difference (v_0-v_{02}) between the two vehicles involved in a potential collision affects the remaining available time (STB-TC) that the driver has in order to finalize the safety maneuver.

- Dif with Dif_2 :

  This graph clearly shows the difference between the innovative indicators (Time to Control, Safe Time Budget) that are introduced in this research and the old indicators (Take-Over Time, Time Budget), by revealing the additional or the fewer incidents that were captured.

5.2 Key Performance Indicators per Market Penetration Rate

In this chapter, the results of the indicators used in this study are presented in the format of graphs with the aim of better visualization and understanding of their fluctuation through the different market penetration rates. After a statistical analysis of the results (t-test statistical significance, mean and standard variation values), the most converging results were found on the first repetition of each market penetration rate. As a result, only this repetition is selected for the MPRs of 60%, 80% and 100%. The 20% and 40% include a very small number of incidents (5 and 24 respectively) and definite conclusions are not possible from such small samples.

From the five graphs presented below, the first four graphs include scatter (X, Y) points which represent all incidents that are taken into consideration. Each point belongs to a different equation and does not reveal any relation with regard to the graph they are gathered. Their collection and appearance on the same graph was made in order to evaluate whether they reveal any potential pattern in relation to the initial speed, the operation mode, the class ID and the speed difference of the vehicles.

5.2.1 Market Penetration Rate 60%

The first graph (Figure 10), represents the Time to Control (TC) in relation to the initial speed of the rear vehicle (v_0). The linear regression line ($y = 0.0558x + 1.58$, $R^2 = 0.0855$) is also shown in the diagram for a better visualization of the increase in the Time to Control. The R-squared value is approximately 0.086 which reveals that the data are not very close to the fitted regression line. However, this study attempts to capture human behavior and humans are simply harder to predict than physical processes. This R-squared value is basically an estimate of the strength of the relationship between the model and the response variable (Time to Control), but it does not provide a formal hypothesis test for this relationship. An F-test of overall significance could possibly determine the statistical significance of this relationship.

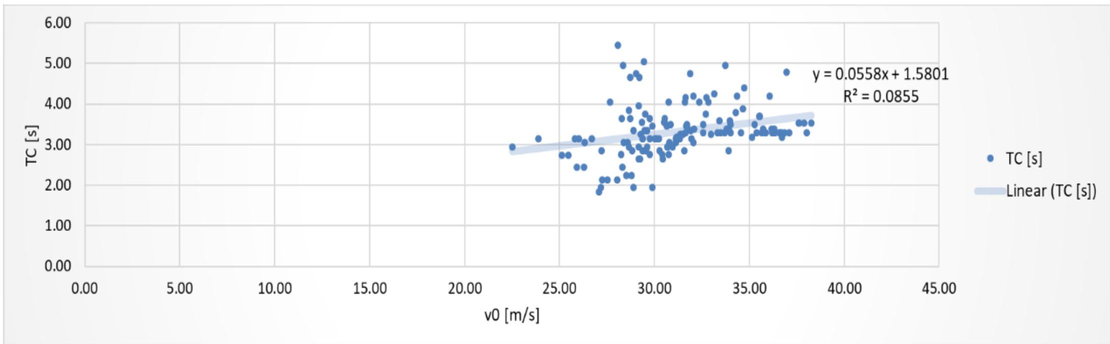


Figure 10: Time to Control with Initial speed (60% MPR, repetition 1)

From this graph, a great variability is visible and a clear systematic regression pattern is missing. One idea of handling such a variability could have been to analyze the data based on the average Time to Control per speed value, since for each speed there are many cases of different Times to Control. However, by taking the average values, the outliers would not have been considered which would result in a tampering of the actual representation making the evaluation unrealistically flattered.

In a similar way, in Figure 11 the relation of the Time to Control with the operation mode of the examined vehicle is captured. It seems that the amount of conflicts that occurred to vehicles equipped with CACC is higher than the ones that were equipped with ACC.

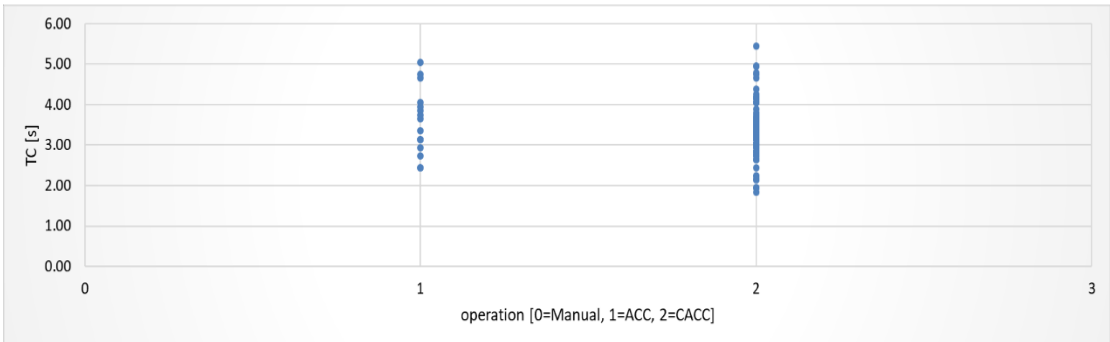


Figure 11: Time to Control with operation (60% MPR, repetition 1)

In order to answer the question if any of the two operation modes reveal higher or lower Time to Control values, a hypothesis test for the two means is performed. For a 5% significance the following data are valid (Table 9):

	Variable 1	*Variable 2*
Mean	3.593	3.306
Variance	0.664	0.365
Observations	15	130
Hypothesized Mean Difference	0	
df	16	
t-Stat	1.320	
P(T<=t) one-tail	0.103	
t Critical one-tail	1.746	
P(T<=t) two-tail	0.205	
t Critical two-tail	2.120	

Table 9: Two-Sample test for operation mode significance (60% MPR)

As we can observe, the t-statistic value is t-Stat=1.32 which is smaller than the t critical values. In addition, the P(T<=t) is greater than the 0.05 value. As a result, the two means are not significantly different. Thus, it is concluded that there is not enough evidence of specific preference related to the operation mode of the automated vehicle and its influence on the Time required to Control the vehicle.

In Figure 12 we can see the relation of the Time to Control with the class ID, which shows how the desired time gap affects the Time to Control. The graph reveals that the majority of the vehicles captured in this scenario were operated with a desired gap of 0.6 seconds.

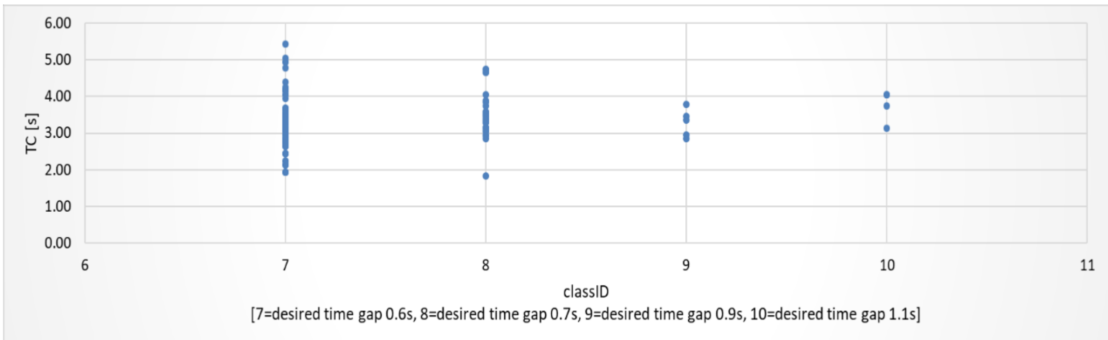


Figure 12: Time to Control with class ID (60% MPR, repetition 1)

In order to conclude on any potential significant difference in the Mean values over the four different class ID values, an analysis of the variances was made, which reveals the following (Table 10):

SUMMARY

Groups	*Count*	*Sum*	*Average*	*Variance*
class ID 7	108	354.10	3.28	0.40
Class ID 8	28	98.23	3.51	0.41
Class ID 9	5	16.39	3.28	0.15
Class ID 10	4	14.99	3.75	0.18

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	1.88	3.00	0.63	1.59	0.19	2.67
Within Groups	55.57	141.00	0.39			
Total	57.4497	144				

Table 10: Analysis of the variances for class ID significance (60%)

As we can see from the analysis of the variances, vehicles equipped with CACC system capable of achieving desired gaps of 1.1 seconds, demonstrate higher Mean values (Mean=3.75, St. Deviation=0.37) than the rest class IDs. However, the difference is not statistically significant.

The following graph (Figure 13) shows how the Dif KPI (STB-TC) is related to the difference in the initial speeds of the vehicles involved in a conflict. The higher the Dif KPI, the safer the situation can be as high Difference between Safe Time Budget and Time to Control means that the driver took over with plenty of time remaining until a potential collision. This graph could potentially show that small speed differences are associated with safer situations ($y = -0.5373x + 4.8376$, $R^2 = 0.2136$). For the analysis of the statistical significance a t-test was performed.

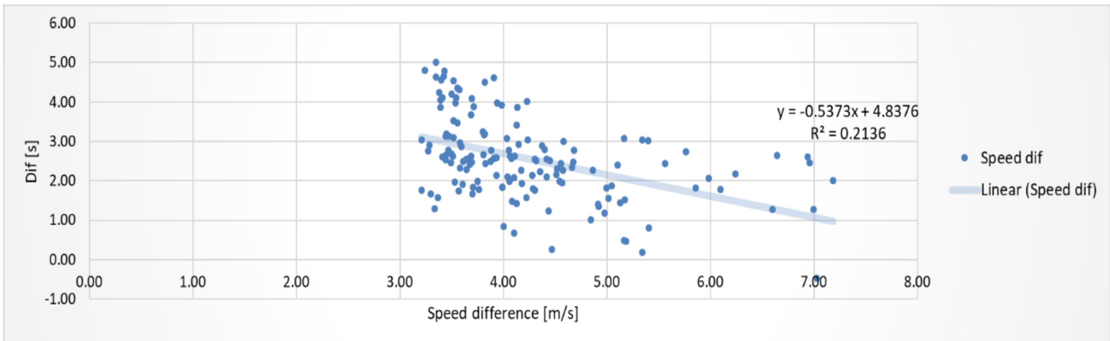


Figure 13: Dif with speed difference (60% MPR, repetition 1)

For the two-sided, 5% significant slope test, the t-statistic is:

$$t = \frac{b_1}{SE_{b_1}} = \frac{-0.537}{0.086} = -6.233 \quad (6)$$

When compared with the critical value of 1.976, it appears that the slope of the regression line is again statistically significant, revealing that indeed small speed differences in the initial speed of the vehicles involved in a conflict are associated with higher Dif values and thus more spare time left after the finalization of the safety maneuver.

$$\pm t_{1-\frac{a}{2},n-2} = \pm t_{0.975,143} = 1.976 \quad (7)$$

The final graphs (Figures 14 and 15) depict Dif and Dif_2 values (STB - TC, TB - TOT). The two horizontal lines (green/purple) represent the threshold of each indicator. If the values of Dif and Dif_2 surpass their threshold, then the corresponding incident is considered to be critical. The thresholds for each KPI are determined in section 3.3.

What is noteworthy here, is that with the old key performance indicators (Take-Over Time, Time Budget) there are no critical incidents captured, while with the new approach there were 8 critical incidents. This has to do with the fact that this set of KPIs sets up a hypothetical framework around impact investigation, based on optimally performed safety maneuvers. This verifies our initial hypothesis that these metrics are not capable of capturing poor driver behavior which is common in real-world situations.

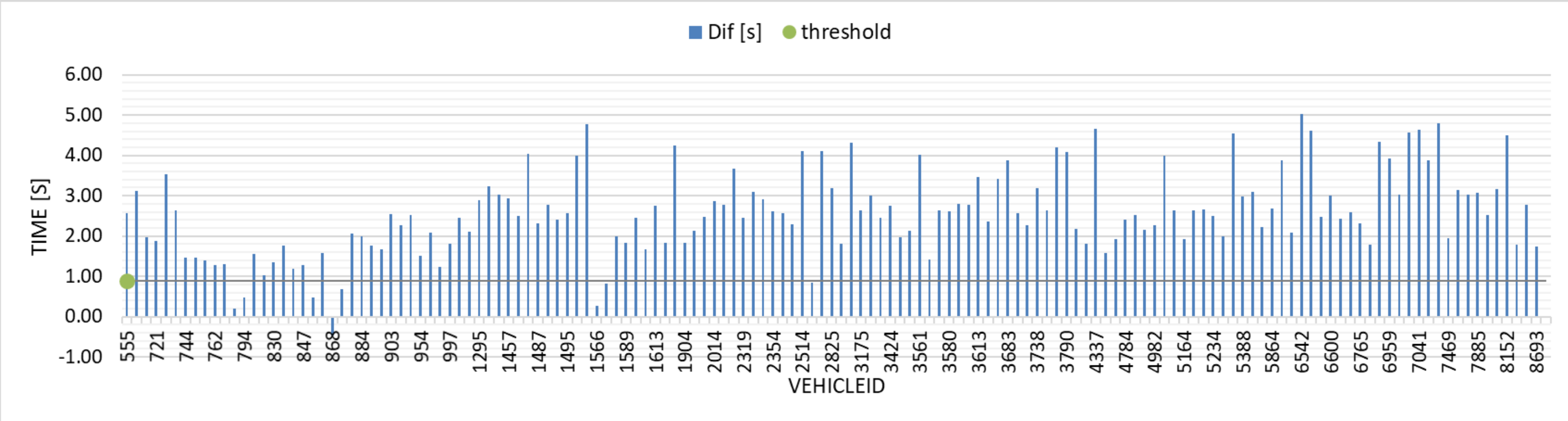


Figure 14: Dif values (60% MPR, repetition 1)

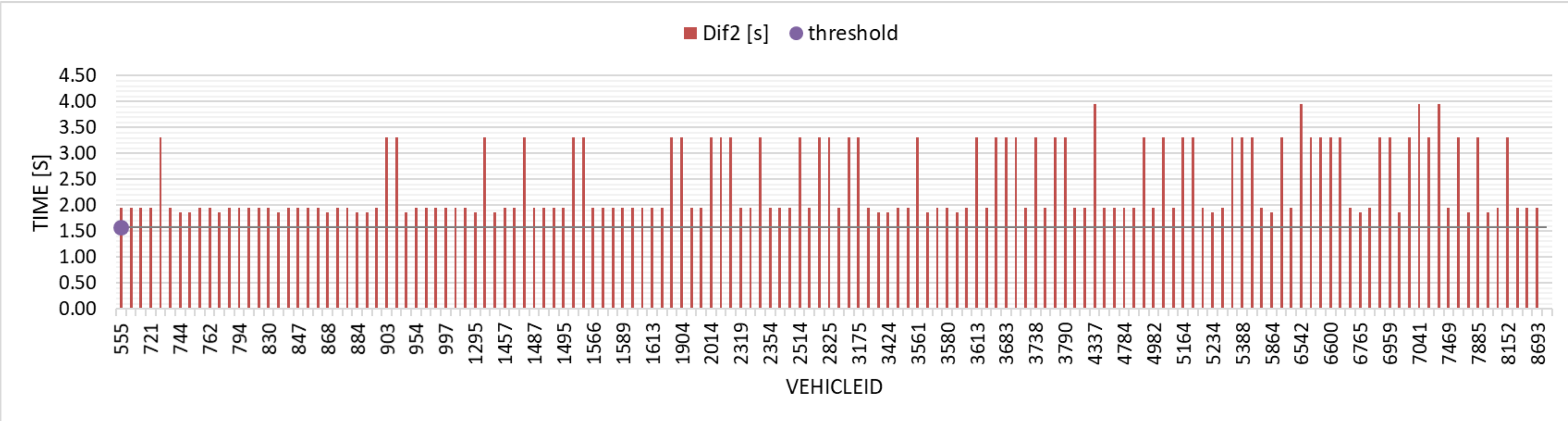


Figure 15: Dif2 values (60% MPR, repetition 1)

5.2.2 Market Penetration Rate 80%

The 80% MPR graph (Figure 16) of the Time to Control in relation to the initial speed reveals more or less the same pattern with the 60% MPR. The sample is quite larger at 313 incidents and we can assume that higher initial speeds result in longer Times to Control the vehicle. The linear regression line ($y = 0.0951x + 0.17$, $R^2 = 0.2465$) is visible to better visualize the increase in the Time to Control. The R-squared value is approximately 0.25, revealing a stronger relationship between the model and the response variable (Time to Control) compared to the 60% MPR.

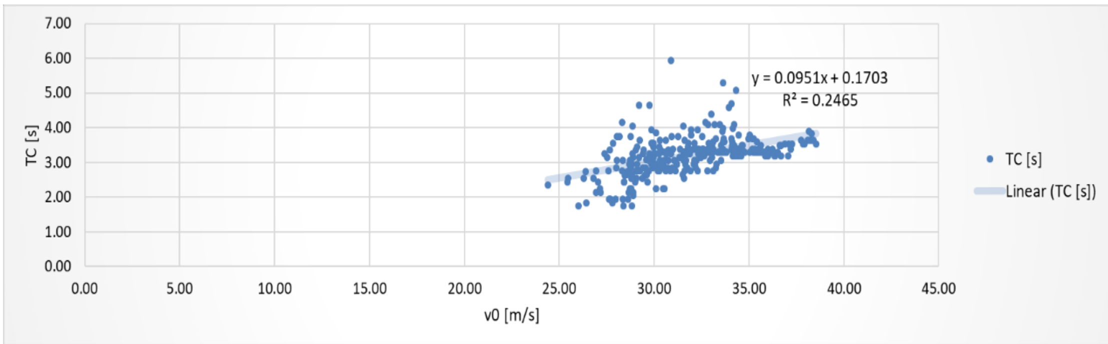


Figure 16: Time to Control with Initial speed (80% MPR, repetition 1)

For the two-sided, 5% significant slope test, the t-statistic is:

$$t = \frac{b_1}{SE_{b_1}} = \frac{0.095}{0.009} = 10.086 \tag{8}$$

When compared with the critical value of 1.96, it seems that the slope of the regression line is statistically significant which further supports the assumption that initial speeds are associated with higher Times to Control.

$$\pm t_{1-\frac{a}{2},n-2} = \pm t_{0.975,311} = 1.968 \tag{9}$$

The trend (Figure 17) that seems to continue while we increase the MPR from 60% to 80% is that CACC vehicles are more likely to phase an incident (conflict) mainly due to the smaller desired gaps. Only a few automated vehicles were found to be equipped with Adaptive Cruise Control system. However, we cannot safely draw a clear conclusion as the algorithm controlling the vehicles was designed in a way to keep CACC system active as much as possible.

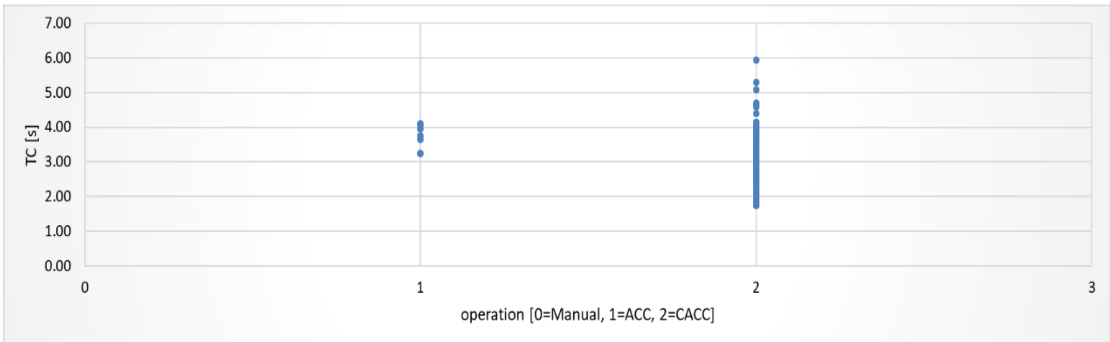


Figure 17: Time to Control with operation (80% MPR, repetition 1)

In order to answer the question if any of the two operation modes reveal higher or lower Time to Control values, a hypothesis test for the two means is performed. For a 5% significance the following are valid (Table 11):

	Variable 1	*Variable 2*
Mean	3.760	3.189
Variance	0.124	0.295
Observations	8	305
Hypothesized Mean Difference	0	
df	8	
t-Stat	4.441	
P(T<=t) one-tail	0.001	
t Critical one-tail	1.860	
P(T<=t) two-tail	0.002	
t Critical two-tail	2.306	

Table 11: Two-Sample test for operation mode significance (80% MPR)

As we can see, the t-statistic value is t-Stat=4.441 which is greater than the t critical values. In addition, the P(T<=t) is smaller than the 0.05 value. As a result, the two means are significantly different. Thus, we can say that it is statistically significant that vehicles equipped with ACC have higher mean Time to Control values. However, the observations for these two samples are substantially different and as a result we cannot safely conclude on the above-mentioned statement.

From Figure 18, we cannot really conclude on which type of class ID is more likely to trigger a conflict. However, a small trend is observed around the time gaps of 1.1 and 0.9 seconds (compared to the 0.7 and 0.6 seconds).

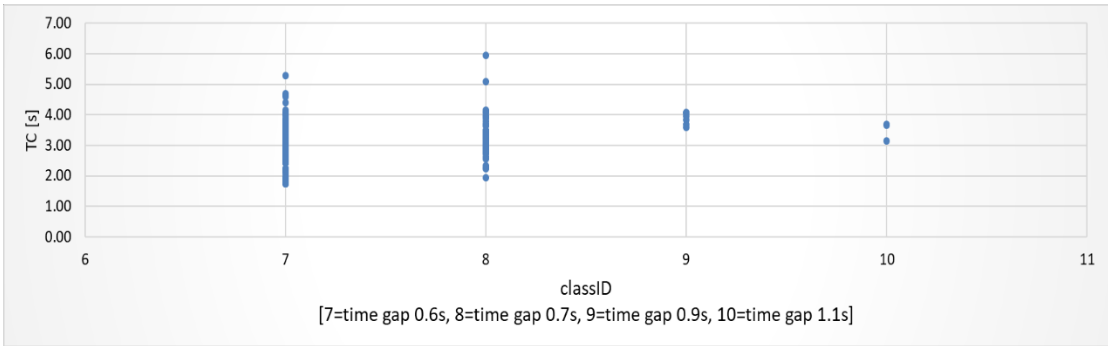


Figure 18: Time to Control with class ID (80% MPR, repetition 1)

In order to conclude on any potential significant difference in the Mean values over the 4 different class ID values, an analysis of the variances was made which reveals the following (Table 12):

SUMMARY

Groups	*Count*	*Sum*	*Average*	*Variance*
class ID 7	251	793.88	3.16	0.26
Class ID 8	53	175.26	3.31	0.44
Class ID 9	6	23.21	3.87	0.04
Class ID 10	3	10.49	3.50	0.09

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	3.89	3	1.30	4.49	0.0042	2.63
Within Groups	89.30	309	0.29			
Total	93.19	312				

Table 12: Analysis of the variances for class ID significance (80%)

After the analysis we can see that vehicles equipped with CACC system capable of achieving desired gaps of 0.9 seconds, show higher Mean values (Mean=3.87, St. Deviation=0.18) than the rest class IDs. This difference is statistically significant (F=4.49 > 2.63=Fcrit. And P value=0.0042<0.05). However, with this simple analysis we cannot come to a definite conclusion on which of the four class ID is significantly different than the rest. For that reason, we used a Post Hoc Test for unequal sizes (Tukey-Kramer) which is a more conservative test.

pairs		Difference	n (group 1)	n (group 2)	SE	q	q critical
class ID 7	class ID 8	0.144	251	53	0.057	2.505	3.63
class ID 7	class ID 9	0.705	251	6	0.157	4.492	3.63
class ID 7	class ID 10	0.334	251	3	0.221	1.512	3.63
class ID 8	class ID 9	0.562	53	6	0.164	3.429	3.63
class ID 8	class ID 10	0.190	53	3	0.226	0.842	3.63
class ID 9	class ID 10	0.372	6	3	0.269	1.383	3.63

Table 13: Tukey-Kramer significance test for class ID comparison (80%)

The results of the Tukey-Kramer test shown in Table 13, reveal that vehicles capable of achieving desired gaps of 0.9 seconds are found to have significantly different Mean values (Mean=3.87 seconds) compared to vehicles with time gaps of 0.6 seconds (Mean=3.16 seconds). This strange result points to the assumption that vehicles with small desired gaps behave better in terms of time to control (and thus safety), compared to vehicles with larger time gaps which in principle allow for more correction time. However, the sample of vehicles equipped with such desired time gaps capabilities is very limited, so a clear conclusion cannot be drawn.

Similar to the 60% MPR, it seems that the Dif is highly influenced by the difference in the initial speed of the vehicles. The larger the difference in speed, the smaller the Difference between the Safe Time Budget and the Time to Control, and therefore less remaining available time left for the drivers after they performed the safety maneuver (critical situation). For the analysis of the statistical significance a t-test was performed. The linear regression line is also shown (($y = -0.3207x + 4.1268$, $R^2 = 0.1429$) in Figure 19.

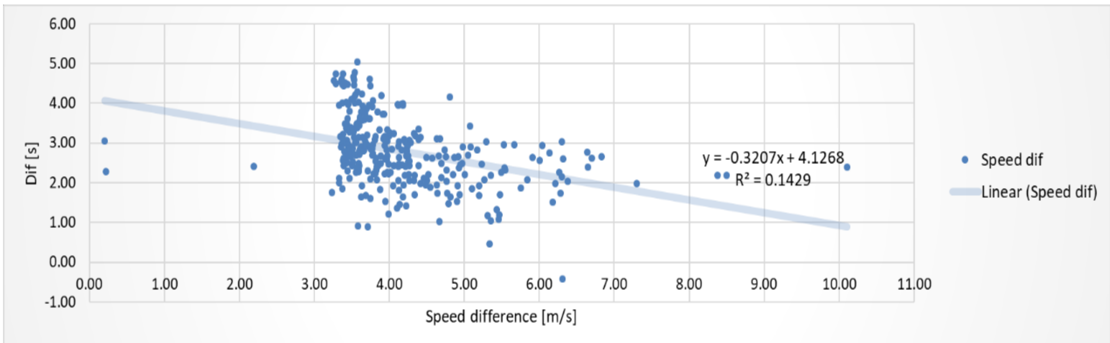


Figure 19: Dif with speed difference (80% MPR, repetition 1)

For the two-sided, 5% significant slope test, the t-statistic is:

$$t = \frac{b_1}{SE_{b_1}} = \frac{-0.321}{0.045} = -7.202 \tag{10}$$

When compared with the critical values as seen below, it seems that the slope of the regression line is statistically significant, revealing that indeed small speed differences are associated with higher Dif values.

$$\pm t_{1-\frac{a}{2},n-2} = \pm t_{0.975,311} = 1.968 \tag{11}$$

Figures 20 and 21 reveal that more critical incidents occur by increasing the market penetration rate. More vehicles violate the threshold of 0.9 seconds making the situation more hazardous. The threshold of the 1.58 seconds for the Dif2 (TOT, TB) is not violated, meaning that no critical incidents were captured with the old approach.

As observed in the 60% market penetration rate analysis, it is evident that using the old key performance indicators (TOT, TB) no critical incidents were captured, while with the new approach 3 critical incidents were captured.

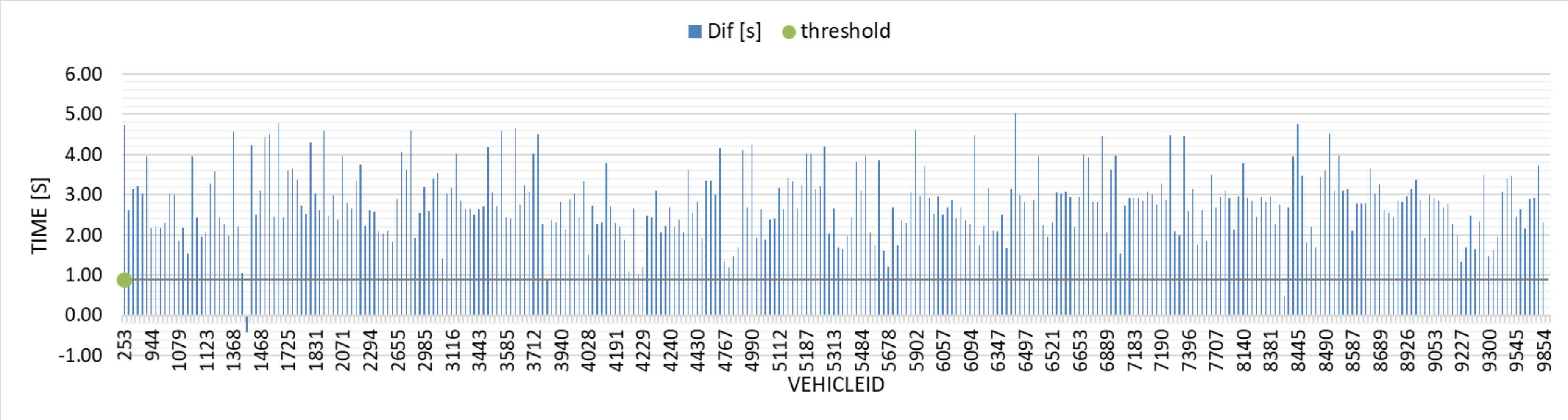


Figure 20: Dif values (80% MPR, repetition 1)

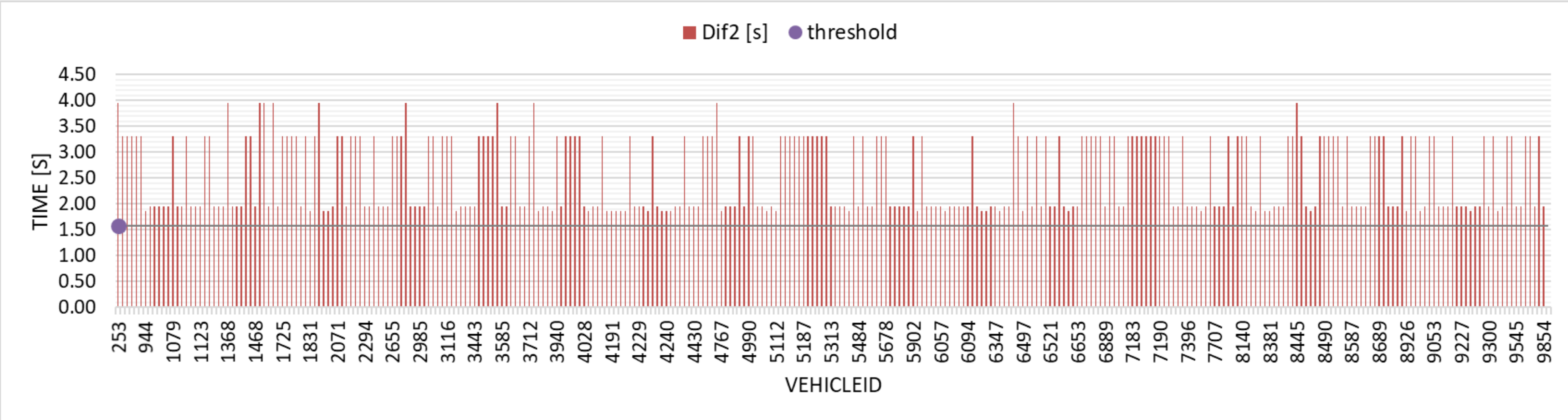


Figure 21: Dif2 values (80% MPR, repetition 1)

5.2.3 Market Penetration Rate 100%

From Figure 22, we can conclude that the Time to Control is highly associated with the initial speed of the rear vehicle in the 100% market penetration rate. Speed can significantly deteriorate the ability of the driver to perform the safety maneuver on time. The linear regression line ($y = 0.0956x + 0.1947$, $R^2 = 0.2787$) is also depicted in the diagram for a better visualization of the increase in the Time to Control.

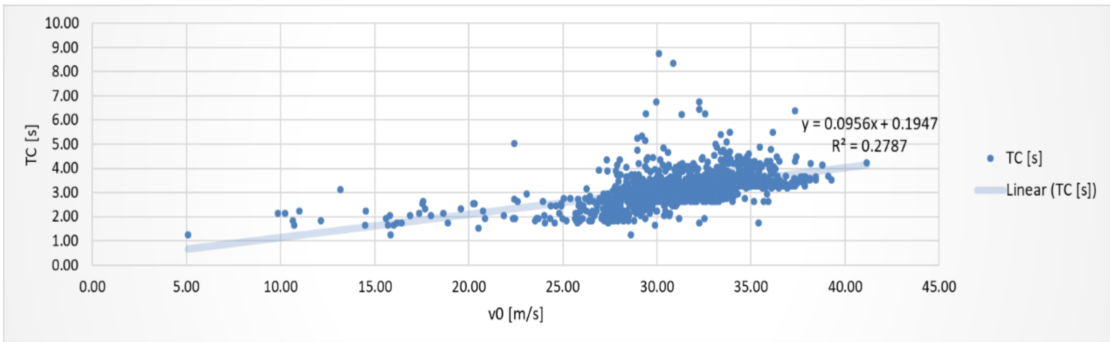


Figure 22: Time to Control with Initial speed (100% MPR, repetition 1)

For the two-sided, 5% significant slope test, the t-statistic is:

$$t = \frac{b_1}{SE_{b_1}} = \frac{0.096}{0.004} = 21.542 \tag{12}$$

When compared with the critical values as seen below, it seems that the slope of the regression line is statistically significant which shows that higher initial speeds are associated with higher Times to Control.

$$\pm t_{1-\frac{a}{2},n-2} = \pm t_{0.975,311} = 1.96 \tag{13}$$

The graph below (Figure 23) shows that all of the automated vehicles are operated with Cooperative Adaptive Cruise Control. In this scenario, there are no vehicles under Adaptive Cruise Control, so the comparison between ACC and CACC mode is not feasible. However, the algorithm created by Xiao et al., (2018) was designed in a way to have an active CACC system enabled as much as possible, so we cannot really gauge the significance of that finding.

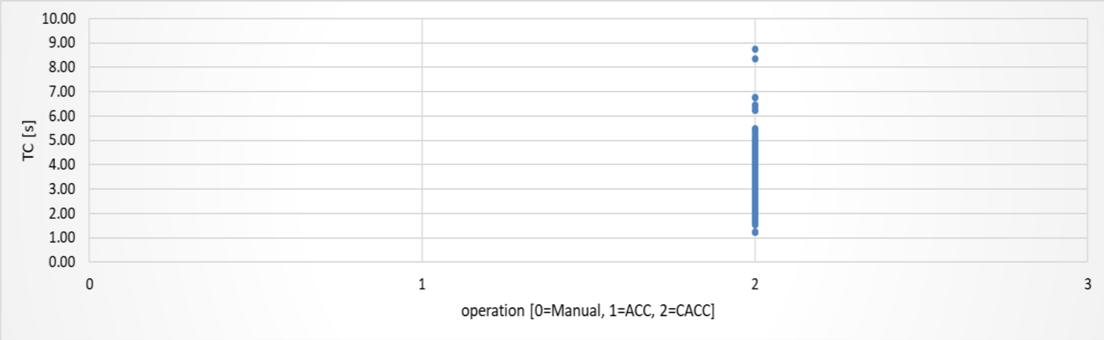


Figure 23: Time to Control with operation (100% MPR, repetition 1)

In the 100% MPR, the majority of the vehicles showed desired gaps of around 0.9 to 1.1 seconds (Figure 24). However, class ID does not seem to strongly affect the likelihood of a conflict.

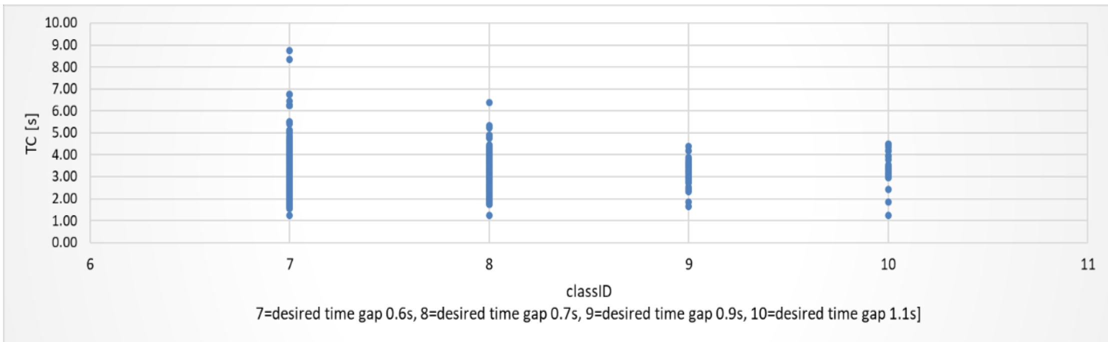


Figure 24: Time to Control with class ID (100% MPR, repetition 1)

As we can see from the analysis of the variances in Table 14, vehicles equipped with CACC system capable of achieving desired gaps of 1.1 seconds, show higher Mean values (Mean=3.35, St. Deviation=0.94) than the rest of the class IDs. The difference is not statistically significant though.

SUMMARY

Groups	*Count*	*Sum*	*Average*	*Variance*
class ID 7	930	2928.28	3.15	0.50
Class ID 8	218	699.93	3.21	0.50
Class ID 9	29	92.62	3.19	0.40
Class ID 10	26	87.17	3.35	0.57

ANOVA

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	1.64	3	0.55	1.09	0.35	2.61
Within Groups	601.44	1199	0.50			
Total	603.08	1202				

Table 14: Analysis of the variances for class ID significance (100%)

The speed difference between the vehicles involved in a conflict is shown in Figure 25 and it seems to significantly affect the Dif KPI. Higher Dif values appear under smaller speed differences. Similar to previous charts, the linear regression line ($y = -0.1467x + 3.248\,, R^2 = 0.0827$) is visible in order to better visualize the decrease in the remaining available time in relation to the speed difference increase.

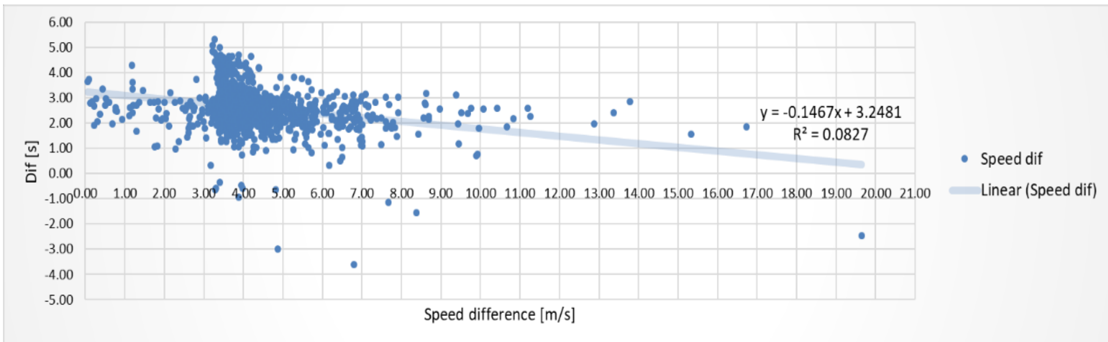


Figure 25: Dif with speed difference (100% MPR, repetition 1)

For the two-sided, 5% significant slope test, the t-statistic is:

$$t = \frac{b_1}{SE_{b_1}} = \frac{-0.147}{0.014} = -10.406 \tag{14}$$

When compared with the critical values as seen below, it seems that the slope of the regression line is statistically significant, which means that small speed differences are associated with higher Dif values.

$$\pm t_{1-\frac{a}{2}, n-2} = \pm t_{0.975,311} = 1.96 \tag{15}$$

The following graphs (Figures 26 and 27) show that the number of critical incidents increases by a factor of around 5 by increasing the MPR from 80% to 100%. This is also the case where the most actual crashes occur, indicating that with higher market penetration rates, there is an increase in both the number of critical incidents as well as the number of accidents in general. Again, there are no critical incidents captured with the TOT and TB KPIs.

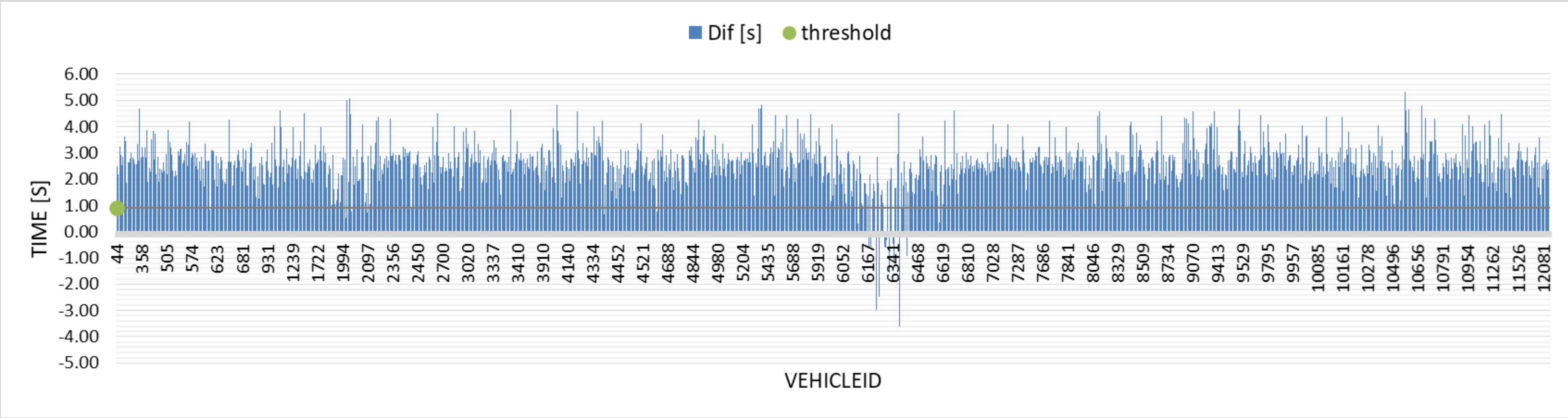


Figure 26: Dif values (100% MPR, repetition 1)

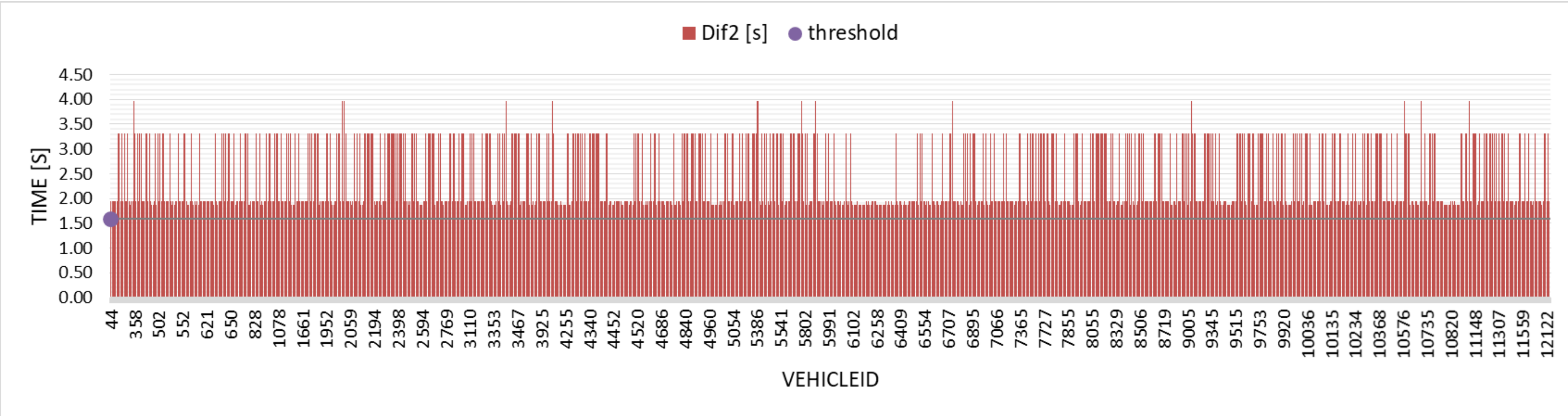


Figure 27: Dif2 values (100% MPR, repetition 1)

5.3 Aggregate Results

The tables shown in this chapter reveal the aggregated results of the basic metrics used in this study, per market penetration rate and per repetition. More specifically, the total number of vehicles and the percentage of manual driving and automated vehicles are shown. In addition, the number of incidents, the number of critical incidents and the number of crashes are presented. From these graphs the analogy in terms of efficiency and safety is shown between the different penetration rates.

MPR	20%				
Repetition	1	2	3	4	5
Total vehicles	7479	7596	7539	7769	7558
Manual	5983	6077	6031	6215	6046
AV	1496	1519	1508	1554	1512
Incidents	5	3	6	5	9
Critical Incidents	0	0	0	0	0
Crashes	0	0	0	0	0

Table 15: Number of vehicles, deactivations and crashes (MPR 20%, all repetitions)

In this scenario (20% MPR), we can see in Table 15 how the total throughput has been formed after the simulation. In this case, only a small number of incidents appeared with none of them revealing significant criticality (in terms of critical incidents). The percentage of the incidents out of the total AV in the network is insignificant (less than 0.5%).

MPR	40%				
Repetition	1	2	3	4	5
Total vehicles	7914	7954	8021	8092	7975
Manual	4748	4772	4813	4855	4785
AV	3166	3182	3208	3237	3190
Incidents	25	21	27	29	20
Critical Incidents	0	0	0	0	0
Crashes	0	0	0	0	0

Table 16: Number of vehicles, deactivations and crashes (MPR 40%, all repetitions)

In the scenario of 40% penetration rate (Table 16), the total throughput has increased by approximately 6%. The number of incidents increased respectively. Similarly with the 20% MPR scenario, no critical incidents occurred. The percentage of the incidents out of the total AV in the network hardly reaches 1%.

MPR	60%				
Repetition	1	2	3	4	5
Total vehicles	8811	8717	8825	8805	8794
Manual	3524	3487	3530	3522	3518
AV	5287	5230	5295	5283	5276
Incidents	145	91	108	103	84
Critical Incidents	8	0	0	2	2
Crashes	3	0	0	1	2

Table 17: Number of vehicles, deactivations and crashes (MPR 60%, all repetitions)

The 60% scenario shown in Table 17, reveals the first critical incidents. The first few crashes also appear in this case which is probably a result of the increase in the traffic throughput in combination with the smaller headways operated in the network. The throughput increased by a factor of 1.1 and the incidents by a factor of 5. The percentage of the incidents out of the total AV in the network reached 3%.

MPR	80%				
Repetition	1	2	3	4	5
Total vehicles	10306	10294	10325	10359	10416
Manual	2061	2059	2065	2072	2083
AV	8245	8235	8260	8287	8333
Incidents	313	361	338	294	374
Critical Incidents	3	1	9	6	8
Crashes	1	1	4	3	3

Table 18: Number of vehicles, deactivations and crashes (MPR 80%, all repetitions)

Similar to the previous cases, the 80% scenario shown in Table 18, revealed a proportional increase in both throughput and incidents. The incident percentage ranges between 4 to 5% and the number of crashes slightly increased.

MPR	100%				
Repetition	1	2	3	4	5
Total vehicles	12672	12468	12808	12617	12743
Manual	0	0	0	0	0
AV	12672	12468	12808	12617	12743
Incidents	1203	1021	1142	1149	1182
Critical Incidents	21	16	43	75	23
Crashes	12	4	29	36	10

Table 19: Number of vehicles, deactivations and crashes (MPR 100%, all repetitions)

In the final scenario (100% MPR, Table 19) we can see how all values increased sharply. The total traffic throughput increased by around 2000 vehicles per repetition. The incidents had a raise of about 1000 conflicts (system deactivations). The number of critical conflicts as well as crashes increased significantly compared to the previous scenarios.

MPR	20%	40%	60%	80%	100%
Total vehicles	7479	7914	8811	10306	12672
Manual	5983	4748	3524	2061	0
AV	1496	3166	5287	8245	12672
Incidents	5	25	145	313	1203
Critical Incidents	0	0	8	3	21
Crashes	0	0	3	1	12

Table 20: Number of vehicles, deactivations and crashes (aggregated, 1st repetition)

From the aggregated results shown in Table 20, we can see how the total throughput rises while increasing the market penetration rate. In the same way, the number of incidents as well as the number of critical incidents increases. This happens mainly due to the fact that automated vehicles are capable of driving closer to each other under smaller time gaps and thus distance headways. The network can actually fit more vehicles, increasing the traffic efficiency. On the other hand, we can see how driving with smaller headways can result in hazardous situations when a deactivation of the automated system occurs. When an authority transition is requested, drivers have to take over and adjust the time gap from 0.6 seconds to 1.4 seconds. This can lead to near misses or even crashes when combined with large speed differences between the vehicles involved in a conflict, especially when the initial speed of the rear vehicle is higher.

5.4 Capture of critical conflicts ability

From the simulation study that has been performed in this thesis, it seems that all the critical incidents that occurred, were captured with the new approach that was introduced. The old approach was not able to capture any critical event. This is the case as the old method is based on the reaction times of the drivers and takes for granted an optimal driver behavior. However, in reality drivers do not behave in such a way, leading to poor safety maneuvers.

Despite that, the old method was capable of achieving smaller Dif_2 (Time Budget – Take Over Time) in some incidents. This happens because, in the new method, the Dif KPI is based on the actual required braking time, which can vary significantly from driver to driver.

In particular, both methods were able to determine conflicts, but only the new one was able to identify the critical ones. However, the proposed new methodology of evaluating critical conflicts on the base of actual braking times is more sensitive and estimates more accurately the remaining available time to react. It is therefore a more conservative approach that leads to a higher number of critical conflicts, making the evaluation of future scenarios more realistic.

5.5 Pattern followed by critical conflicts and crashes

In this section the results after the isolation of the critical incidents are presented. The purpose of this isolation is to identify whether or not the critical conflicts follow a certain pattern, either based on the initial speed of the vehicle for instance, or on other characteristics such as the operation mode, the class ID, the speed difference, etc. All the critical conflicts were isolated, and their combination among the different market penetration rates as well as repetitions led to the following results.

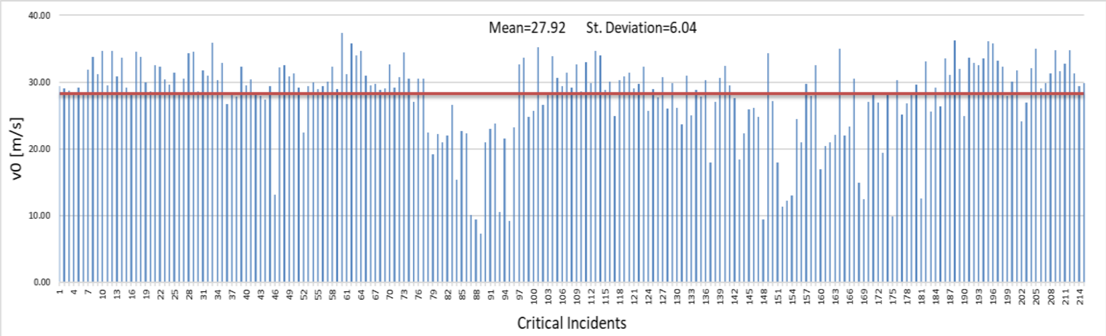


Figure 28: TC in relation to the initial speed (isolated incidents for all MPR and repetitions)

From the first graph (Figure 28), we can see the distribution of the initial speeds of all the (rear) vehicles involved in each conflict. The average speed is 27.92 m/s (100.51 km/h) and the standard deviation is 6.04 m/s (21 km/h) (Mean=27.92, SD=6.04). That means that the critical conflicts could possibly follow a pattern based on which the initial speed of the vehicles involved in a critical incident (or crash) was. In this instance, the vehicles were traveling with a speed of around 100 km/h.

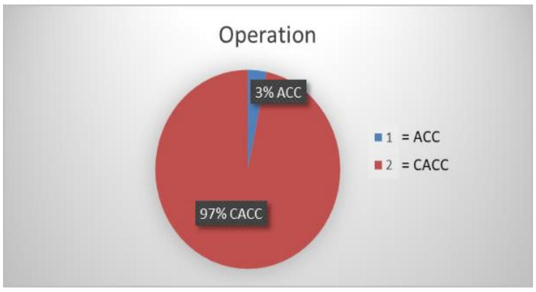


Figure 29: Operation mode of critical incidents

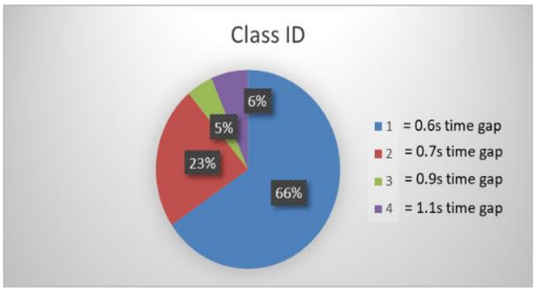


Figure 30: Class ID of critical incidents

The graph on the left (Figure 29) reveals that the majority of the automated vehicles were equipped with Cooperative Adaptive Cruise Control. The vast majority of the conflicts (210/217) were in CACC mode. The reason for that result is the fact that the desired gap under CACC operation mode is smaller than the ACC mode, leaving less time available to the drivers to react during an authority transition. Another reason is that the algorithm was initially designed by Xiao et. al. (2018) in a way to keep the CACC mode active as much as possible.

Therefore, based on that second clue, we cannot draw a conclusion on whether or not there is a pattern followed based on the operation mode.

On the other hand, Figure 30 reveals that the majority of the automated vehicles that were involved in a critical conflict were under CACC mode with desired gap of 0.6 seconds. As expected, the lower the desired time gap, meaning that vehicles drive closer to each other, the less remaining available time is left to the driver after a system deactivation. However, we cannot really draw a conclusion on that, as the majority of the vehicles (6/10) were programmed to drive with such small desired time gap. The desired gap is a setting within the AV program that can highly affect the criticality in case of an emergency where a human driver has to take over and adjust the time gap to a more comfortable one.

Based on the above, it is evident how such a strict setting within the algorithm can become a limitation when it comes to evaluating the most used and influencing operation mode or class ID.

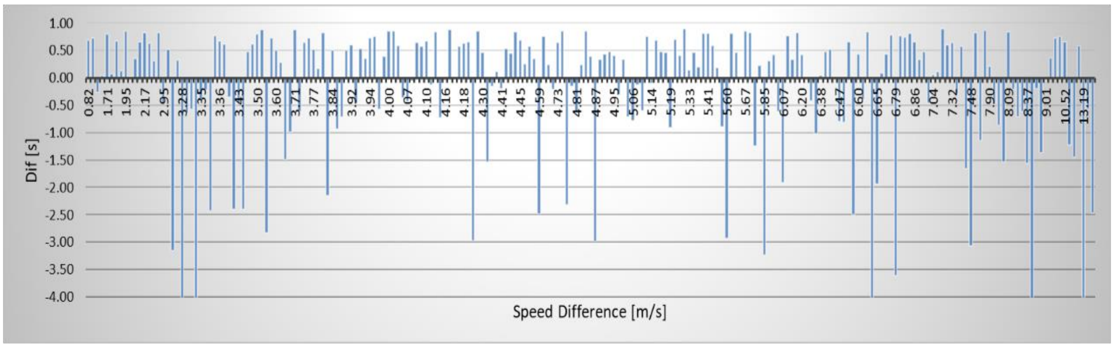


Figure 31: Dif in relation to the speed difference

Finally, after the isolation of the conflicts, we can see how the Dif values (STB - TC) are distributed in Figure 31. Values that are below the threshold of Dif=0, indicate car accidents. This basically means that there is no remaining available time left for the driver to perform additional actions, as the Time to Control exceeds the Safe Time Budget.

The rest points in the graph range between 0 and 0.9 seconds and indicate critical conflicts. In reality, many of these points are also crashes, as the algorithm is designed in a way to jump back into an active automation mode when the driver stopped decelerating with a rate smaller than -2 m/s^2. Therefore, the points that approach the threshold from above, are vehicles which might not have fully performed a safety maneuver. It might be the case that the automation took over control of the vehicle before the completion of the safety maneuver.

The average speed difference is 5.3 m/s (19 km/h) and the standard deviation is 2.3 m/s (8.3 km/h) (Mean=5.3, SD=2.3). However, a clear pattern based on the speed difference of the vehicles involved in a critical conflict cannot be drawn. We can clearly see from the graph that there are low values for Dif KPI for various speed differences, and in the same way, high values of Dif KPI for various speed differences.

6 Discussion and Conclusion

In this chapter, the findings of this research are presented and discussed. In addition, the limitations of this study, together with future recommendations are given. In the first section, an interpretation of the results is given and the most important findings followed by the main contributions of this study are highlighted. Also, the added value compared to other studies performed in the past is claimed. Next, the limitations of this thesis are discussed along with some areas for improvement. Finally, the significance of the research is mentioned, coupled with future directions in AV operations.

6.1 Discussion

Many studies regarding transitions in control have been performed, but to this point very little has been done with regard to finding optimal transition times with respect to safety. On top of that, a universal method of safety assessment of incidents is lacking. The key difference between the current research and previous studies performed in this field is the way of identification and assessment of conflicts' criticality. In this study a full incorporation of action times is considered for the evaluation of critical incidents which is the result of system deactivations when certain thresholds are violated.

The results of this thesis revealed interesting insights regarding the safety characteristics of CACC equipped vehicles. One important finding is that by increasing the penetration rates, safety is compromised during authority transitions. Opposite to other studies performed so far, which claim that safety is increased by the introduction of AV in general, this study revealed deterioration of safety metrics during authority transitions especially in higher Market Penetration Rates. This is the case as the desired time gaps under which active automation systems operate is significantly lower than those that human drivers are comfortable driving with. This difference in the time gaps seems to be critical when it comes to a safety maneuver, since the available time for the driver to react and perform an avoidance action is limited. A solution to that could be the expansion of time gaps to higher values when the operational design domain of the corresponding vehicle has a finite capacity. For example, an automated vehicle that is equipped with a CACC system capable of achieving times gaps of 0.6 seconds, but it is operating under SAE level 2 (limited ODD), should be programmed in such a way that not its entire capability is used and the time gaps allowed are closer to those that human drivers are comfortable driving with. Overall, the results imply the significance of a harmonized automation-driver system, a smooth transition, and the importance for adequate time for drivers to react, as humans' ability to respond in short notice is proved to be limited.

Another interesting finding is the strong relation of the Time to Control with the initial speed of the vehicle. This seems reasonable as the higher the velocity of a car, the more time is required to decelerate to a point that a collision is evaded. However, this time is also dependent on the behavior of the front vehicle. If in a traffic scenario the front vehicle starts accelerating again before coming to a full stop, then there will be no reason for further deceleration of the rear vehicle, avoiding a potential collision in less time. This is the case when shockwave traffic jams appear and disappear, due to various reasons (tolls, on-ramp, etc.). A way to deal with that problem is a dynamic design of TOR strategies with respect to warning times, where the stimulus is triggered depending on the vehicle's speed.

In addition, a rather unexpected finding was the fact that different class IDs and therefore different desired time gaps did not seem to significantly differentiate from each other. It was expected that vehicles capable of achieving smaller time gaps would result in higher numbers of critical incidents. A possible explanation of that, is that the algorithm used in this study was designed in a way that vehicles drive with an active CACC mode under class ID 7 (desired time gap=0.6sec) as much as possible. Thus, no random distribution between different class IDs and operation modes existed, making the sample for the rest of the classes insignificant.

The objective of this research was to give insight into the safety implications of authority transitions in AV operations, by taking into consideration the available time between a collision warning and the potential collision. By emphasizing on that factor, two safety KPIs, namely Time to Control and Safe Time Budget, were created based on the fundamental Time to Collision, and in combination with the alteration from reaction times to braking times, an effort was made to shed light on the safety effects of each individual vehicle under the variation of several factors. The purpose of the alteration from reaction times to braking times was to consider poor driver behavior, who does not always perform optimally especially on critical occasions. The majority of the studies that have been performed so far emphasize on drivers' reaction times, and the overall assessment of safety is based on that - which is incomplete and thus unrealistic. Only by using the actual braking times can we fully incorporate human behavior in this evaluation, which often seems to be decisive in traffic accidents. The model introduced in this dissertation deals with that by considering the missing stochasticity. The new approach is thus more sensitive and estimates more accurately the remaining available time for a driver to react and execute his action.

In conclusion, two main scientific contributions can be claimed. First, this study shed light into the utilization of existing simulation studies performed under slightly different scope, in this case efficiency evaluation. More specifically, by using the simulation results of Xiao et al., (2018), an additional analysis on safety parameters has been performed. The added value is beyond doubt as this study managed to produce significant results and outcomes (actual number of crashes), and as a result, it conveys to the scientific community the post processing of simulation datasets of these types of systems. Additionally, the research performed for the purposes of this thesis, incorporated the actual driver behavior into the safety implications of an authority transition. This innovative approach, revealed the gap between a theoretical and practical transition towards automation in the car industry. This is done, by pointing out the limitation of simulation models to realistically represent human behavior which is undeniably related with safety during authority transitions.

6.2 Implications

Improving safety in AV operations not only has to do with good prediction models and good quality assessment tools, but also with enhancing the AV market itself. These findings may show direction for improvement for vehicle manufacturers to redesign automated driving systems in such a way to improve overall safety, not only under normal conditions, but also under emergency situations. Car manufacturers should emphasize on extending the operational design domain (ODD) of automated systems so that they are capable of addressing more traffic conditions (safety-critical situations, low-speed operations) to limit the amount of system deactivation which causes the deterioration of safety. In this way the improved functionalities of automated systems can enhance the level of resilience of traffic safety. Only by extending the operational design domain of automated vehicles, can society embrace the full benefits of car automation.

In the same direction, road operators could play an important role in the smooth introduction of automated vehicles. This can be done by exploring strategies for isolation of vehicles equipped with automation systems (especially CACC due to lower time gaps), such as dedicated lanes for traffic separation and hazardous situations limitation. Another solution to limit system deactivations could be the usage of I2V (infrastructure to vehicle) communication so that a smoother traffic flow can be achieved. For example, vehicles passing by an infrastructure unit which is capable of communicating traffic conditions downstream, can warn as well as instruct the automated system to lower vehicle's speed accordingly so that it reaches the potential congestion point by the time the congestion is dissolved.

Finally, sufficient education and training of drivers in the capabilities and the limitations of different levels of automation can play an important role to ensure safe operations. In particular, prior experience could potentially achieve smoother transitions, which not only will result in safer situations, but it will also limit the loss in traffic efficiency that comes with system deactivations.

6.3 Limitations

The model applied in this study comes with some limitations. Firstly, the data that were used as input for this study were derived from a simulation study that was initially designed to assess traffic efficiency and not traffic safety. This means that several key performance indicators had to be either calculated outside of the model, deteriorating the consistency of the simulation realism, or assumed based on similar studies. For instance, the estimation of the Take Over Time and the Time Budget was exclusively based on literature.

Next, the reaction times which were extracted from the previous simulation model were equal to zero. This means that by the time a collision warning was triggered, the driver was assumed to immediately start braking at the same timestep. This is not realistic, as the total time that the driver kept braking until the -2 m/s^2 threshold was not the actual braking time but the entire Time to Control. An adjustment had to be made based on the Take Over Time derived from Shladover et. al., (2013). The same applies to the Time Budget metrics. These limitations led to different assumptions for the calculation of various metrics, which could question their validity.

Another limitation was the fact that we lack information on what would have happened if the automation would not automatically reactivate again after the -2 m/s^2 threshold. It might be the case that the braking action performed till that threshold did not suffice to avoid a collision and the automation took over control of the vehicle before the completion of the safety maneuver. This means that if this setting for reactivation was not implemented, the actual number of critical incidents and crashes might have been significantly higher.

In addition, for the calculation of the two thresholds for the corresponding two Dif values (STB-TB & TB-TOT), but also for the TOT and TB itself, the mean values where used. In reality, collision risk is not determined by these mean values, but by the outliers from their distributions instead, as these extreme values better represent poor driver behavior.

Moreover, the research performed for the purposes of this dissertation, is used for the investigation of Take Over times, and not Take Over quality. Papadimitriou et al., (2020) revealed that Take Over Quality (TQ) was found to be better in terms of lateral control and number of steering corrections, in non-emergency transitions, whereas other indicators (Take Over Time) could not reveal different values for emergency and non-emergency situations.

Thus, we cannot draw a full conclusion on the performance of the authority transitions. It might be the case that a response is fast but hazardous at the same time especially if it were to be combined with a high mental workload.

Finally, one important limitation is the fact that almost all the studies used as literature for the realization of this study, were conducted in simulation software or driving simulations. Therefore, there was a risk of limited fidelity as well as lack of behavior validity. Real-world experiments can potentially deal with that issue but current technology and regulations make that option unfeasible.

6.4 Conclusion

The purpose of this study was to evaluate the safety implications of automated vehicles (SAE level 2) equipped with Cooperative Adaptive Cruise Control, during authority transitions. The data used as input for this research were derived from a simulation experiment performed in MOTUS by Xiao et. al. (2018), with the purpose of impacts investigation of CACC vehicles on traffic flow characteristics.

For the realization of this study, the creation of two innovative key performance indicators was deemed necessary. These KPIs were the Time to Control (TC) and the Safe Time Budget (STB) and their purpose of creation was the capturing of the braking times during an authority transition. Their difference (STB-TC) was used to conclude on the criticality of a conflict with the criterion of the 0.9 seconds threshold (section 3.3). The usage of these three metrics sheds light on the importance of the incorporation of driver behavior into AV authority transitions, especially since traffic safety is increasingly dependable on the combined performance of the human driver and the automation.

The results of the simulation showed that by increasing the percentage of automated vehicles in the network, the total number of collision warnings (incidents) increases. However, only in the 80% and 100% MPRs the number of critical incidents increased (125% and 600% increase respectively). In the lower penetration rates (20%, 40%, and 60%) the critical conflicts were limited. This is explained by the nature of CACC-equipped vehicles which are programmed to drive very close to each other, resulting in more vehicles in the network, and also due to the fact that by the time a collision warning is stimulated, drivers have to take over control of a situation with very small time gaps.

In addition, the number of crashes increased by a factor of 2 from the 60% to the 80% MPR, and by a factor of 7 from the 80% to 100% MPR. This sharp rise in car accidents is explained by the fact that in high penetration rates no human drivers control their vehicles, resulting in very small time (and distance) gaps between them. Thus, in the event of a Take Over request, the time for driver intervention is limited.

Finally, we can see how different random seeds (5 repetitions) within vehicle operations, such as vehicle class, desired speed, and arriving interval among two vehicles at the generators, affect the results with respect to the number of (critical) incidents and crashes.

Also, by isolating the critical incidents we were able to conclude on the following patterns:

- Potential pattern on Time to Control in relation to the initial speed of the rear vehicle:

  Higher initial speeds led to higher Times to Control

- Potential pattern on Time to Control in relation to the operation mode of the AV:

  Vehicles equipped with CACC are more likely to involve in a critical conflict than those with ACC (or manual driving)

- Significant pattern on Time to Control in relation to the predefined time gap (class ID):

  Vehicles with high capabilities in desired time gaps (short time gaps) reveal considerably higher chances of critical conflicts

- Insignificant pattern on the remaining available time (Dif=STB-TC) in relation to the speed difference of the vehicles involved in a conflict:

  Large speed differences between vehicles are no more likely to result in critical incidents and/or crashes compared to small speed differences

6.5 Future research

Safety assessment has space for further investigation. Future research can focus on data selected during real-world pilots so that a practical representation of reality is achieved. This is crucial, especially when braking times are required to prove the findings of such research. However, this is not yet possible, especially in high penetration rates, due to limited technology and safety regulations. In order to validate this study, a real-world pilot could be developed at some point in a controlled environment under smaller scale.

Also, the deactivation of the automation system can be tested under different conditions than collision warnings, such as operational design domain exit or system failure. This can improve the overall picture that is currently attained and can gradually give insight into the higher levels of automation.

Moreover, additional research can be performed in more complicated scenarios with interactive bottlenecks (on-ramps, tolls, car accidents) to evaluate the effects on mitigating congestion and shockwave traffic jams, and therefore the impact of more system deactivations.

In addition, this study points in the direction of the importance of actual behavior analysis. Therefore, next to the design and the forecast of safety assessment tools, an effort could be made into drivers' preparation in real life, by training sessions and raising awareness regarding authority transitions.

Finally, efforts should be focused by road operators and traffic engineers into achieving sufficient time for the drivers to take over. Such a concept could be done by improving in-vehicle sensors (larger look-ahead time) and by incorporating V2V and I2V communication to AV operations.

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Appendix – Scientific paper

A method to assess safety implications during authority transitions in automated driving

Omiros Athanasiadis, Bart van Arem, Eleonora Papadimitriou, Gerdien Klunder, Lin Xiao, Simeon Calvert

**Faculty of Civil Engineering and Geosciences,
Delft University of Technology**

Abstract

The question of how well in terms of safety can a driver take over control of an automated vehicle in response to an emergency situation is of crucial importance. Most of the studies performed so far focus on the drivers' reaction times and the mechanisms behind the transition. In this study, an effort is made to incorporate the braking times that are required in order to finalize a safety maneuver, with the aim to assess the safety implications of the entire transition in control. For this purpose, a new methodology was developed and a simulation model was used in order to simulate platoons of CACC equipped vehicles. Two new KPIs were defined: the Time to Control and the Safe Time Budget. The results suggest that higher number of critical events and crashes are associated with higher market penetration rates. This reveals that despite the fact that AV can in general increase traffic efficiency and safety, when it comes to emergency situations where safety is inextricably linked to the combination of AV and driver performance, overall safety may be compromised under certain conditions. In addition, the results revealed a strong connection of the above-mentioned action times with the initial speed of the vehicles involved in a conflict.
The findings of this research, point to new directions particularly in concern to the extension of the operational design domain of automated vehicles in order to minimize system deactivations, and also with regard to the need for better prediction models and safety assessment tools.

Keywords:

Authority transitions, Cooperative Adaptive Cruise Control, Safety, Driver behavior, Simulation, AV

1. Introduction

One of the main challenges for scientists and car manufactures is to make sure, that the operators of automated vehicles are capable of perceiving not only the capabilities but also the limitations of the automated systems (Flemisch et al., 2017). That said, it is clear that until the automated systems become capable of performing all kinds of driving tasks in all kinds of road conditions, human drivers will bear the responsibility to take back control when the system is no longer able to perform because it reaches its operational limits (Varotto et al., 2015). In that sense, Damböck et al. (2012b) state that the more the level of automation increases, the more the role of the driver is about to change. In addition, Merat et al. (2012) draw the conclusion that traffic safety is increasingly dependable on the combination of the performance of the human driver and the automation. As a result, it seems that driver's behavior is crucial, as it determines to a great extent the safety performance during the transitions of control (Peterman & Kiss, 2009).

A transition in control from an automated system to a human driver is necessary under the occasions that the system is not capable of addressing the situation by itself. By the time the automation system identifies a situation that lies outside its operational design domain, it initially sends a warning to the human driver, who is responsible for taking over the control of the vehicle. The driver has to take over within a certain time budget to ensure safe operations. Such a time sequence can be seen in Figure 1, as described by Zhang et al. (2019). The time from the moment of the warning, till the moment of driver's first intervention, is called Take Over Time. The last moment at which the driver can take action is called system limit (last moment of driver's first intervention). The time between a warning and the system limit is called Time Budget. Any effort of taking over after that point would likely result in a collision. (Zhang et al., 2019)

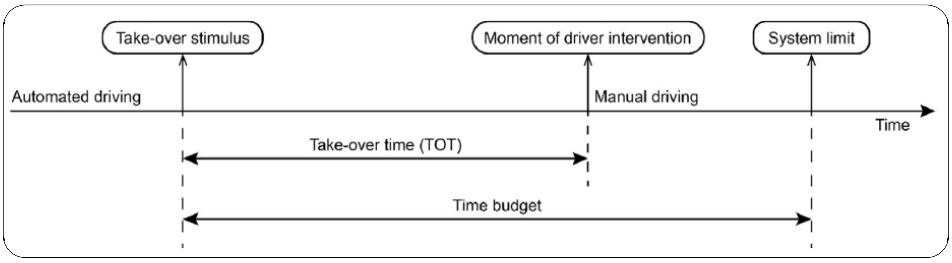

Figure 1: Authority transition sequence (Zhang et al., 2019)

Based on the above, one can make the assumption that if the Take Over Time is smaller than the Time Budget, then the situation is considered to be safe. However, this is not entirely true as both times refer to perception and reaction times. For instance, if from a simulation study both TOT and TB are measured and they reveal the aforementioned desired inequality (TOT < TB), that does not necessarily mean that a critical situation will be evaded. It might be the case that after the driver took over, the deceleration force that he applied, or the maneuver he tried to perform did not suffice to avoid a collision. Although a simulation does not allow in general for such "poor" driver behavior, in reality drivers quite often do not behave in an optimal way (misconception of the situation, bad cognitive process of the available information or simply poor execution etc.). Both Take Over Time and Time Budget metrics, are not designed for capturing that "poor" driver behavior which is critical in terms of safety as the driver is responsible for acting in a potentially hazardous scenario.

Towards that direction, it seems that reliable Key Performance Indicators which can adequately interpret the safety attributes of such a transition in control of AV, are lacking. Therefore, in this study the functionality of such innovative KPIs is explored.

2. Methodology

To fulfill the purpose of this project, post processing of an existing simulation study designed by Xiao et al. (2018) was necessary. Every authority transition initiated by the system is isolated and the incident occurred is explored in order to assess its safety implications. The behavior of the vehicles involved in a conflict is analyzed by means of critical KPIs, and the safety impacts are evaluated.

As mentioned in the previous chapter, drivers, especially in higher levels of automation, may appear to respond "poorly" when asked to take back control, resulting in safety deterioration. Thus, it is of high importance to take that error margin into account when planning towards safe operations of automated vehicles. What could possibly guarantee safe operations and deal with that limitation is the usage of action times (perception/reaction + braking) instead of just reaction times when planning or programming the automated system. The exploration of the action times instead of reaction times can not only predict but they can also conclude on the safety implications of an authority transition. An alteration of the time sequence given by Zhang et al. (2019) is given in Figure 2.

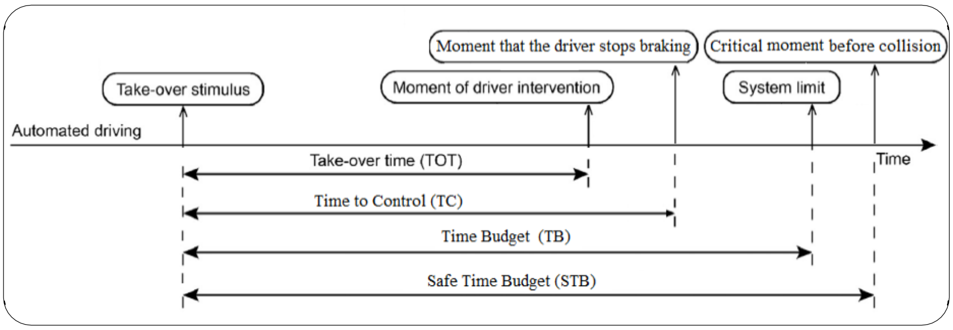

Figure 2: Authority transition sequence (execution stages included)

In the original concept created by Zhang, two additional times are added in the time sequence:

- the Time to Control (TC), and
- the Safe Time Budget (STB)

With the combination of the Time to Control and the Safe Time Budget, we can safely assume that a positive difference (Dif) of these two metrics entails a collision-free situation and can conclude not only on the critical incident possibility, but on the severity of the incident as well.

2.1 Time to Control

Compared to the Take-Over Time which only captures the first moment of driver's intervention and thus cannot guarantee collision avoidance, the Time to Control indicates the moment at which no more deceleration force is required to avoid a potential collision. After this point the driver can either maintain a constant speed, accelerate, or switch control back to the system again. Only when these actions are fully performed we can safely assume that an authority transition took place in a safe manner. The Time to Control for each vehicle is estimated from the simulation model.

2.2 Safe Time Budget

Compared to the Time Budget, the Safe Time Budget spots the moment before the collision under the driving dynamics that the collision is evaded. Thus, it is the total available time for the driver to actually take control of the vehicle. The Safe Time Budget can be estimated as follows:

The moment before the potential collision, the following kinematic equation is valid:

$$x_2 - x_1 - l > 0 \quad (1)$$

x_1: position of rear vehicle (front edge) (m)
x_2: position of preceding vehicle (front edge) (m)
l: vehicle length (m)

The STB is the result of the above equation, divided by the speed difference of the two vehicles. It is basically a safe Time to Collision (sTTC), which captures the last safe moment right before a collision, in such a way that a collision is evaded.

$$STB = (x_2 - x_1 - l)/(v_1 - v_2) \quad (2)$$

v_1: speed of rear vehicle (m/s)
v_2: speed of preceding vehicle (m/s)

2.3 Time to Control with Safe Time Budget difference (Dif)

In this study, another innovative Key Performance Indicator is created. This metric derives from the difference of the Time to Control and the Safe Time Budget.

$$Dif = Safe\ Time\ Budget - Time\ to\ Control \quad (3)$$

When the difference is smaller than 0.9 seconds, it means that the system limit has been exceeded, and a collision is likely to occur. The criticality of these incidents (0.9 seconds value) is estimated based on the research performed by Eriksson & Stanton, (2017).

In a similar way, a threshold for the difference of the Take Over Time and Time Budget (Dif2) had to be determined. The purpose of this threshold is to determine which incidents are critical based on the old approach. The threshold for the Dif2 is found to be 1.58 seconds based on a critical Time To Collision equal to 2.6 sec and an average value for the braking times of 1.58 sec as calculated from the simulation. In this way, a comparison of the new method compared to previous approaches is possible.

3. Results

In order to investigate the implications of CACC systems, Xiao et al., (2018) simulated a merging bottleneck where traffic jams occurred on highways. Six different market penetration rates for CACC operations were tested, starting from 0% to 100% with a 20% increment, each run for 5 times with different random seeds (vehicle class, desired speed, etc.). In this study, an algorithm is created in MATLAB so that several safety indicators can be derived from the efficiency metrics which resulted from the reference study.

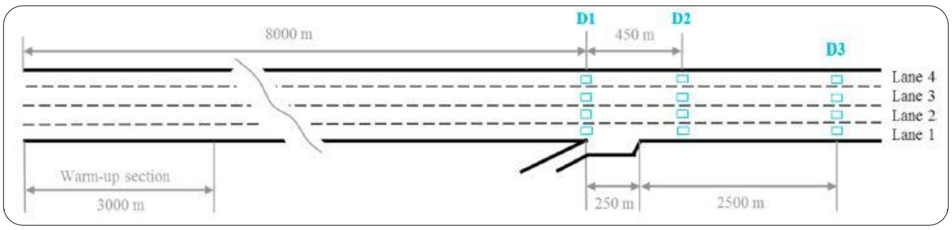

Figure 3: Merging network (Xiao et al., 2018)

One important assumption in the reference study (Xiao et al., 2018), was that the drivers intended to drive with an active system as much as possible. Another assumption was that the automation system cannot be reactivated when the deceleration rate overpass the margin of (-) 2 m/s^2. For that reason, the Time to Control is measured based on that margin. Also, the reaction time of the driver is considered to be equal to zero (0) seconds. For that reason, and for the calculation of the Time to Control, four different Take Over Times have been used based on the research performed by Eriksson and Stanton (2017). The values for the TOTs are 1.14, 2.05, 2.69, and 3.04 seconds and the corresponding Time Budgets are 3 sec, 4 sec, 6 sec and 7 sec. The Time Budget times were selected based on the Safe Time Budget ranges calculated from the simulation model, and the Take Over Times were selected based on the Time Budgets.

The results are trying to address in a quantitative way the following topics:

i. What are the implications with respect to safety?
ii. What is the ability of the proposed method to capture incidents, compared to previous methodologies used so far?
iii. Do the critical incidents reveal any pattern?

MPR	*20%*	*40%*	*60%*	*80%*	*100%*
Total vehicles	*7479*	*7914*	*8811*	*10306*	*12672*
Manual	*5983*	*4748*	*3524*	*2061*	*0*
AV	*1496*	*3166*	*5287*	*8245*	*12672*
Incidents	*5*	*25*	*145*	*313*	*1203*
Critical Incidents	*0*	*0*	*8*	*3*	*21*
Crashes	*0*	*0*	*3*	*1*	*12*

Table 1: Number of vehicles, deactivations and crashes (aggregated, 1st repetition)

From the aggregated results shown in Table 1, we can observe how the total throughput rises while increasing the market penetration rate. In the same way, the number of incidents as well as the number of critical incidents increases. On the other hand, we can see how driving with smaller headways can result in hazardous situations when a deactivation of the automated system occurs. This can lead to near misses or even crashes when combined with large speed differences between the vehicles involved in a conflict, especially when the initial speed of the rear vehicle is higher.

From the next graphs (Figure 4&5) the Dif and Dif2 values (STB - TC, TB - TOT) are depicted. The two horizontal lines (green/purple) represent the threshold of each indicator. If the values of Dif and Dif2 surpass their threshold, then the corresponding incident is considered to be critical (paragraph 2.3).

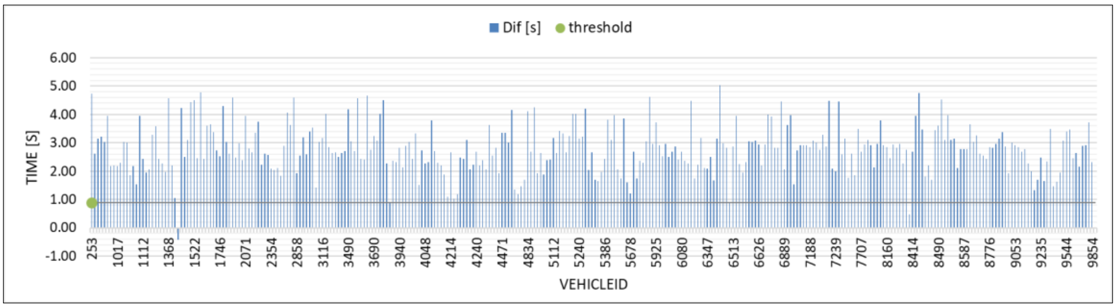

Figure 4: Dif values (80% MPR, repetition 1)

From Figure 4, the one crash which occurred in the 80% MPR (Table 1) can be seen as the time for that incident is negative.

From the simulation study that has been performed in this thesis, it seems that all the critical incidents that occurred, were captured with the new approach that was introduced (violation of the 0.9 sec threshold). The old approach was not able to capture any critical event (Figure 5). This is the case as the old method is based on the reaction times of the drivers and takes for granted an optimal driver behavior.

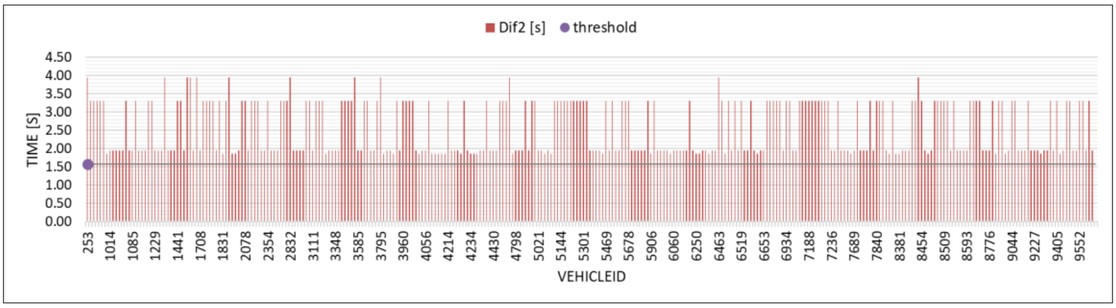

Figure 5: Dif2 values (80% MPR, repetition 1)

In particular, both methods were able to determine conflicts, but only the new one was able to identify the critical ones. Therefore, we could say that the proposed new methodology of evaluating critical conflicts on the base of action times is more sensitive and estimates more accurately the remaining available time to react. It is therefore a more conservative approach that leads to a higher number of critical conflicts, making the evaluation of future scenarios more realistic.

In addition, the 80% MPR graph (Figure 6) of the Time to Control in relation to the initial speed of the vehicle reveals that higher initial speeds result in longer Times to Control the vehicle. The linear regression line $y = 0.0951x + 0.17\,, R^2 = 0.2465$ is visible to better visualize the increase in the Time to Control. The R-squared value is approximately 0.25. This value is considerably low to draw a safe conclusion, however, such low values are common when trying to predict human behavior.

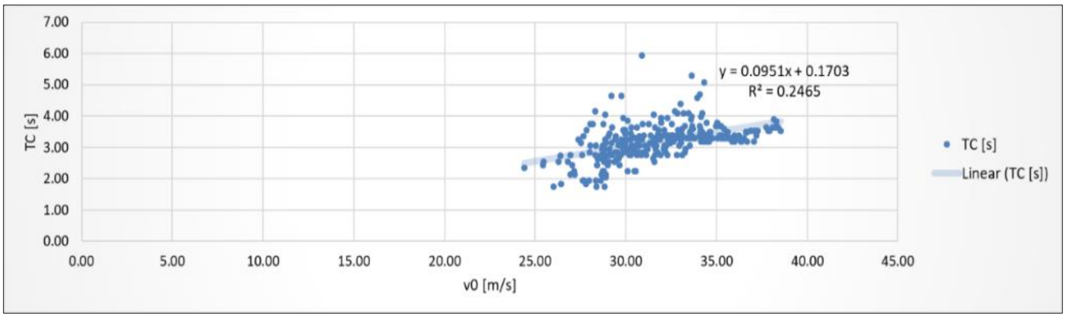

Figure 6: Time to Control with Initial speed (80% MPR, repetition 1)

In conclusion, Figure 7 reveals that the majority of the automated vehicles were equipped with Cooperative Adaptive Cruise Control. The vast majority of the conflicts (210/217) were in CACC mode. The reason for that result is the fact that the desired gap under CACC operation mode is smaller than the ACC mode, leaving less time available to the drivers to react during an authority transition. It is also possible since the algorithm for the automation operations was designed in such a way to keep the CACC mode active as much as possible.

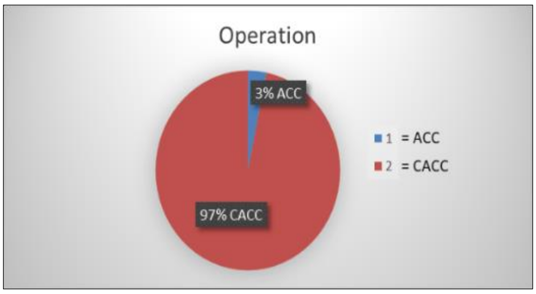

Figure 7: Operation mode of critical incidents

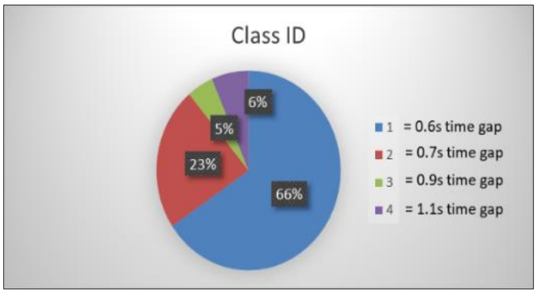

Figure 8: Class ID of critical incidents

On the other hand, Figure 8 reveals that the majority of the automated vehicles that were involved in a critical conflict were under CACC mode with desired gap of 0.6 seconds. As expected, the lower the desired time gap, meaning that vehicles drive closer to each other, the less remaining available time is left to the driver after a system deactivation.

4. Conclusions and Discussion

The results of this thesis revealed interesting insights regarding the safety implications of automated vehicles. One important finding is that by increasing the penetration rates, safety is deteriorated during authority transitions. Another interesting finding is the strong relation of the Time to Control with the initial speed of the vehicle. A way to deal with that problem is a dynamic design of TOR strategies with respect to warning times, where the stimulus is triggered depending on the vehicle's speed. Overall, the results imply the significance of a harmonized automation-driver system, a smooth transition, and the importance for adequate time for drivers to react, as humans' ability to respond in short notice is proved to be limited.

More specifically the results of the simulation showed that by increasing the percentage of automated vehicles in the network, the total number of collision warnings increases. This is explained by the nature of CACC-equipped vehicles which are programmed to drive very close to each other, and also due to the fact that by the time a collision warning is stimulated, drivers have to take over control of a situation with very small time gaps. In addition, the number of crashes increased by a factor of 2 from the 60% to the 80% MPR, and by a factor of 7 from the 80% to 100% MPR. This sharp rise in car accidents is explained by the fact that in high penetration rates no human drivers control their vehicles, resulting in very small time (and distance) gaps between them. Finally, by isolating the critical incidents we were able to conclude that higher initial speeds led to higher Times to Control.

Two main scientific contributions can be claimed. First, this study shed light into the utilization of existing simulation studies performed under slightly different scope, in this case efficiency evaluation. The added value is beyond doubt as this study managed to produce significant results and outcomes, and as a result, it conveys to the scientific community the post processing of simulation datasets of these types of systems. Additionally, the research performed for the purposes of this thesis, incorporated the actual driver behavior into the safety implications of an authority transition. This innovative approach, revealed the gap between a theoretical and practical transition towards automation in the car industry. This is done, by pointing out the limitation of simulation models to realistically represent human behavior which is undeniably related with safety during authority transitions.

The model applied in this study comes with some limitations. Firstly, the data that were used as input for this study were derived from a simulation study that was initially designed to assess traffic efficiency and not traffic safety. This means that several key performance indicators had to be either calculated outside of the model or assumed based on similar studies. In addition, the research performed for the purposes of this dissertation, is used for the investigation of Take Over times, and not Take Over quality (Papadimitriou et al., 2020). Thus, we cannot draw a full conclusion on the performance of the authority transitions.

Future research can focus on data selected during real-world pilots so that a practical representation of reality is achieved. In order to validate this study, a real-world pilot could be developed in a controlled environment under smaller scale. Finally, additional research can be performed in more complicated scenarios with interactive bottlenecks (on-ramps, tolls, car accidents) to evaluate the effects on mitigating congestion and shockwave traffic jams, and therefore the impact of more system deactivations.

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