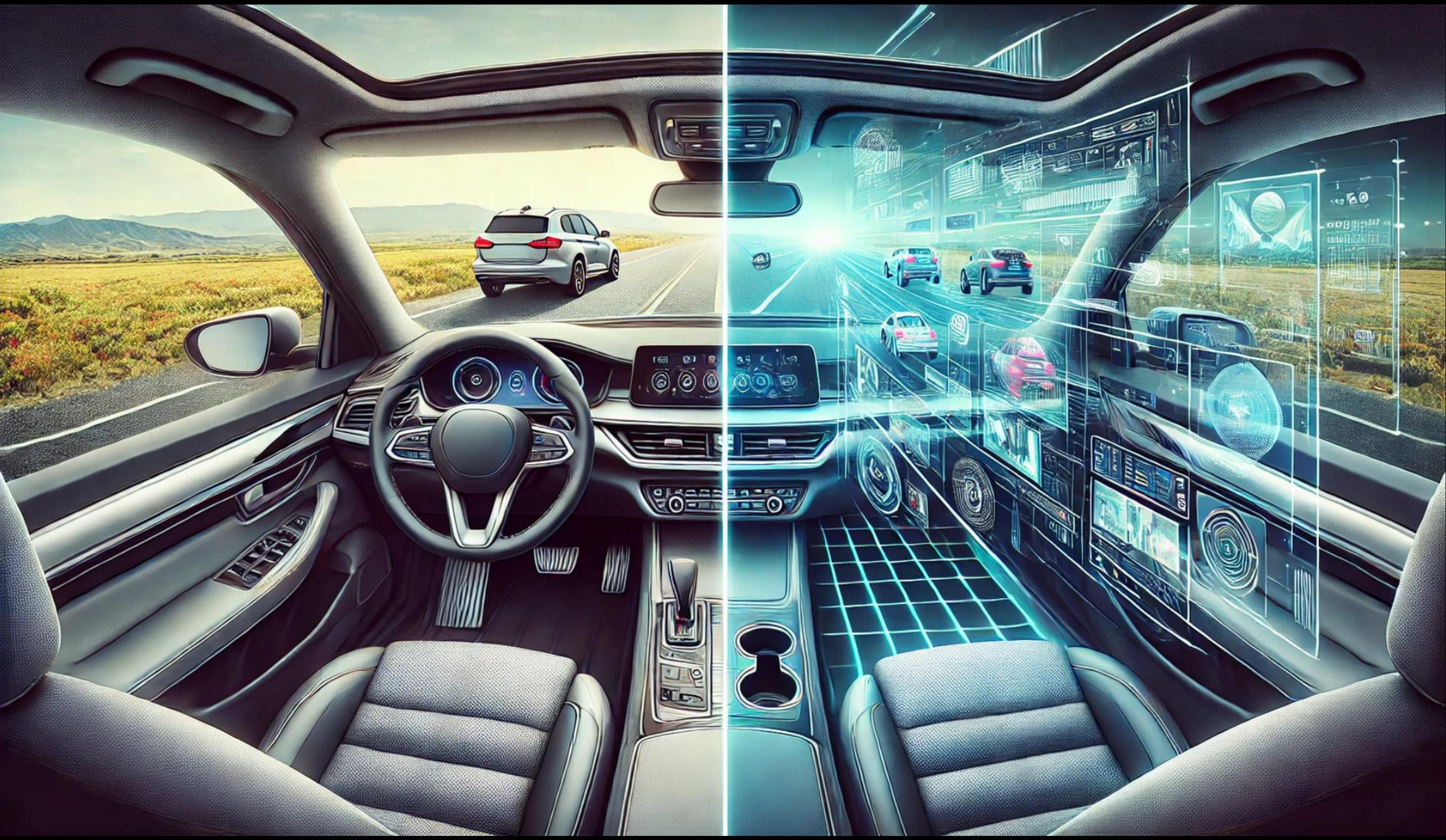
# Transitioning to autonomous driving: Mixed vehicle autonomy levels on freeways



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**MSc Engineering & Policy Analysis**
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Delft University of Technology

# Transitioning to autonomous driving: Mixed vehicle autonomy levels on freeways

by

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# Preface

Throughout my academic journey, I have always sought opportunities to express my creativity. My first introduction to Python during the introductory workshops captured my interest and set me on a path of exploring various programming languages and tools. When I began my master's program in Engineering and Policy Analysis, I was eager to broaden my skill set and explore the domains of data analysis, simulation, and modelling. These aspects of the program challenged me and presented puzzles that fuelled my curiosity. As I searched for a graduation project, I knew I wanted to combine my interests in simulation and data analysis.

Entering into the field of civil engineering to analyse vehicle automation was a new and exciting experience for me. The practical relevance of cars in everyday life, coupled with the future challenges of vehicle automation, inspired me to explore this domain further. This journey, from tackling unfamiliar territory to completing this thesis, has been a challenge, providing me with new perspectives and insights into both the field and myself.

I would like to express my gratitude to my thesis committee for their guidance and support throughout this process. I want to thank Prof.Dr.Ir. Alexander Verbraeck for his assistance during my thesis. His infectious enthusiasm for the project and constant encouragement kept me motivated and focused. I would also like to thank Dr. Iulia Lefter for her insightful feedback and expertise in human-technology interaction. Additionally, I would like to thank Dr.Ir. Wouter Schakel for his support and expertise in working with the OpenTrafficSim software and its driving models.

Finally, I extend my sincere thanks to my friends and family, whose support and friendship provided balance and joy during this demanding period. Their support and the good times we shared helped keep me positive and energized.

Looking back on this intensive journey, I'm really thankful for the challenges and inspiration this project brought. I will carry forward the lessons and experiences from this project as I embrace the next chapter of my life.

Jesse Poland
*Delft, December 2024*

# Executive summary

The increasing presence of vehicle automation is transforming freeways into environments of mixed traffic, where vehicles of varying autonomy levels interact. Before all vehicles become fully autonomous, a transition will be made that causes a high mix of those autonomy levels. Therefore, this thesis researches the impact of different levels of vehicle automation on traffic performance and safety on a multi-lane freeway with an on-ramp. Microscopic simulation is utilised to explore how varying levels of vehicle automation, while taking human driving factors into account, affect traffic flow, speed, density and dangerous car-following interactions.

Currently, the majority of vehicles are defined as level 0 vehicles. This does not mean that these vehicles have no automated features at all but the Advanced Driver-Assistance Systems (ADAS) only provide temporary support such as an emergency brake. This is different for level 1 vehicles where the car-following driving tasks are automated and for level 2 vehicles both the car-following and lane-changing tasks are automated to support the driver. Level 3 vehicles are conditionally autonomous where all driving tasks are automated. The study aims to fill the knowledge gap in understanding the impact of these mixed traffic conditions on overall traffic dynamics.

To simulate the varying levels of automation, the study utilizes OpenTrafficSim (OTS), a microscopic traffic simulation software that incorporates a mental model to realistically represent human driving behaviour. This allows the simulation to account for human factors such as reaction time, perception, cognitive workload, and distractions, which are crucial in differentiating human drivers from automated vehicles. Four automation levels (0, 1, 2, and 3) defined by the Society of Automotive Engineers are modelled for specific driving characteristics within the freeway environment. Model parameters are adjusted for each level based on literature findings and practical considerations.

Simulation results indicate that the introduction of level 1 and level 2 vehicles, characterised by larger headway values, can negatively impact traffic performance but also result in less dangerous car-following behaviour. The increased headway leads to disruptions in traffic flow and an earlier onset of congestion. However, as the penetration rate of level 3 vehicles increases, traffic conditions significantly improve, with higher mean speeds, reduced travel times, and increased traffic flow observed. These findings highlight the potential benefits of higher levels of automation in enhancing traffic performance and safety.

The study also examines the impact of driver distraction on traffic performance and safety. By simulating both in-vehicle and roadside distractions, the research demonstrates that higher cognitive workloads can lead to more disruptive driving behaviour. As automation levels increase, the negative effects of distraction are mitigated.

Overall, this research provides valuable insights into the complexities of mixed traffic with varying automation levels. It demonstrates that while the transition phase may present challenges, higher levels of vehicle automation can significantly improve both traffic performance and safety on multi-lane freeways. Special emphasis is given to accurately simulating human driver behaviour and suggestions are made for future research, including the need for a dual-perception framework for more accurate modelling of level 1 vehicles and further investigation into the impact of different distraction types.

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# 1 Introduction

## 1.1 Background

Vehicle automation can help the European Union (EU) to achieve climate goals. Climate change represents a grand challenge, driving society to search for innovative approaches in various sectors to mitigate global warming. This also includes the transportation sector which needs to lower its greenhouse gas emissions (European Environment Agency, 2023). Research indicates that Autonomous Vehicles (AVs) could offer enhanced fuel or energy efficiency, potentially leading to a substantial reduction of emissions in the transport sector (Vahidi and Sciarretta, 2018). This efficiency is mostly improved when Connected Autonomous Vehicles (CAVs), sometimes called Cooperative Autonomous Vehicles, communicate to optimise their driving path, optimise driving speed, and plan road interactions (Turri et al., 2017). Such coordinated activities require a fleet of fully automated vehicles, all equipped with the corresponding features. However, the current operating vehicle fleet is not equipped with these automation features. Even the newest available consumer vehicles today are not fully autonomous but are provided with new Advanced driver-assistance systems (ADASs). ADAS only automate specific tasks to support the driver but is not responsible for decision-making while driving (Lu et al., 2005). The extent of ADAS varies for different brands and models, meaning that the level of automation varies within the current vehicle fleet. These automation features to support the driver are currently designed to ensure more safety, especially at less engaging driving tasks such as keeping distance on a freeway or maintaining the current lane. Because these ADASs are not autonomous, their use cases are limited and thus mostly used while driving on main roads.

New and more sophisticated automation features are integrated into ADAS. The automotive industry is undergoing technical advances regarding artificial intelligence (AI), big data, and digitalisation enhancing vehicle automation. The European Parliament acknowledges how this automation leads to progression in vehicle safety. Therefore, they are updating motor vehicle type approval requirements for 2026 by adding more ADAS features (Regulation 2019/2144).

The drive to more efficient and more safe vehicles will increase automation within traffic. Given the varying levels of vehicle automation and the economic reality that not all road users can afford the latest vehicle models, the road will be subject to a highly mixed fleet where Human Driven Vehicles (HDVs), vehicles equipped with different ADAS configurations, AVs, and CAVs coexist. Traffic with a heterogeneous mix of vehicle automation levels will be referred to as mixed traffic.

To define the differences between the mentioned automated vehicles (HDV and AV), automation levels of the Society of Automotive Engineers (SAE) can be used. Figure 1 shows the different definitions for six vehicle automation levels (from 0 to 5). HDVs with limited ADAS features such as visual or auditory warnings and emergence braking are considered level 0. When HDVs have more advanced ADAS features to support up to one driving task, it is considered level 1. These more advanced ADAS features consist of driver support for vehicle handling in longitudinal or lateral directions. Longitudinal control is called car-following and support in lateral control is lane-keeping. HDVs become level 2 when the vehicle's ADAS is capable of supporting the driver in both car-following and lane-keeping. Some level 2 vehicles are even capable of supporting the driver in lane-change actions. From level 3 onwards the vehicle is not considered as a HDV anymore. In level 3 the vehicle does not support but controls car-following, lane-keeping and lane-changing decisions. However, the decision-making is still limited, so the AV can only operate under specific conditions. Therefore, the driver in a level 3 AV is only monitoring the vehicle and should take over control when necessary. From level 4 onwards, the AV does not require any monitoring anymore and in level 5 the AV can operate under all conditions.

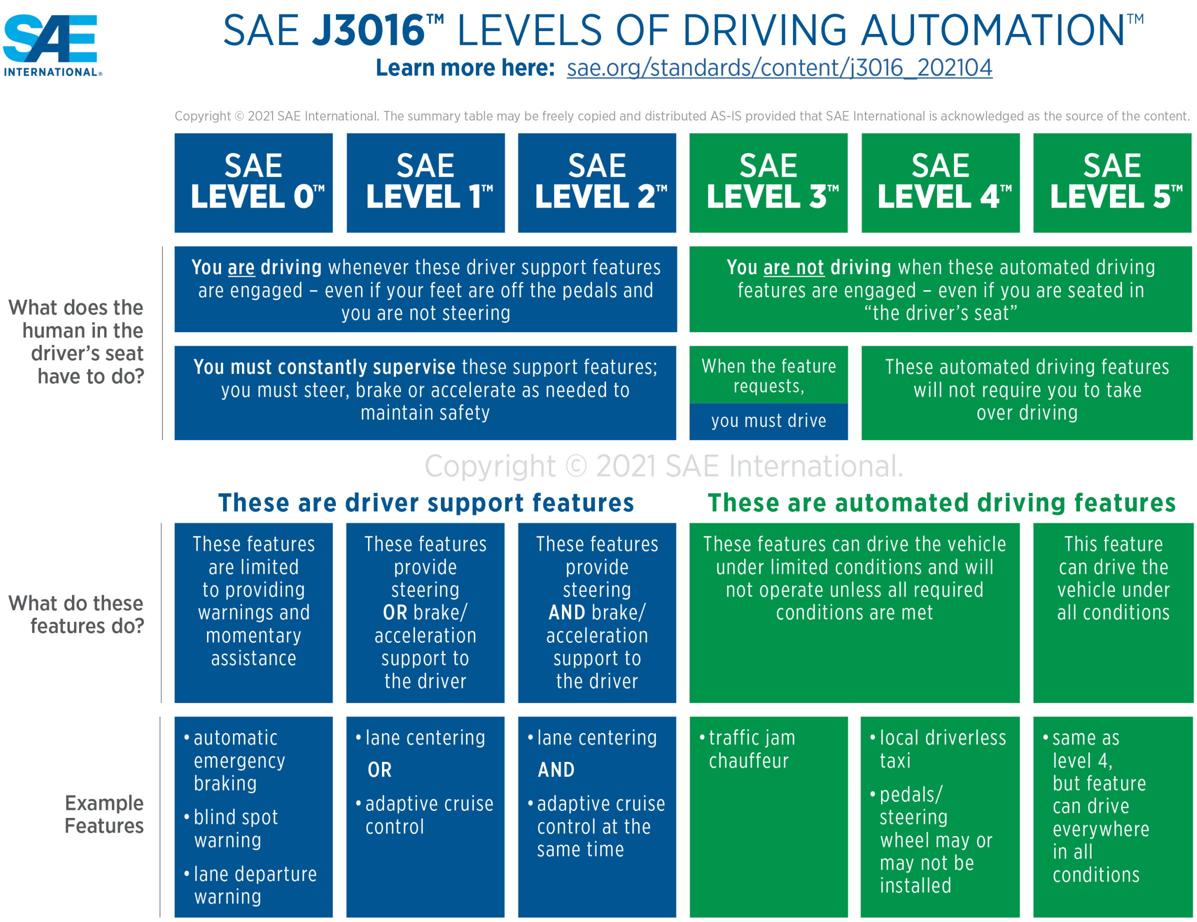


Figure 1: Vehicle autonomy level descriptions by SAE. Retrieved from SAE, 2021.

However, vehicles can also be equipped with communication features to retrieve information from surroundings and thus increase the situational awareness of human drivers or autonomous vehicles. HDVs equipped with features to communicate Vehicle-to-Vehicle (V2V) or Vehicle-to-Infrastructure (V2I) will be called connected vehicles (Talebpour and Mahmassani, 2016). AVs equipped with these communication features become CAVs. Unfortunately, the SAE automation levels do not account for vehicle communication configurations, thus these levels are not affected.

New driving behaviour and vehicle interactions will emerge from mixed traffic. As discussed, vehicle automation levels and communication configurations come in a wide variety, as do the corresponding driving styles. HDVs will remain subject to human errors, higher-level automation HDVs will show different decision-making because of human-interface interactions, and AVs are fully dependent on their control functions. Autonomous control also changes the social interactions that are familiar to road users. Additionally, vehicles will be developed by different manufacturers in a competitive automotive market. This will amplify the differences in the vehicles' driving behaviour.

These new vehicle behaviours and interactions could have consequences for the transport system. Currently, the road network is prone to congestion. On freeways, HDVs drive in strings on their lane following the vehicle ahead. Unfortunately, these HDVs have varying speeds due to human errors and/or ignorance towards the speed limit. These variations cause disruptions in their string and thus the stable flow of traffic on the freeway is disrupted. Furthermore, multiple lanes, road connections and other infrastructure designs allow HDVs to change lanes, change acceleration and merge causing more disruptions. These disruptions cause a shock wave through the string of vehicles. Each vehicle will react slightly differently to this string disruption thereby amplifying the shock wave. When vehicles decelerate to maintain an acceptable headway and finally come to a standstill, congestion occurs. Adding more different driving styles into the string will cause more variations and could thus exacerbate congestion in the road network. However, by adding more automation to traffic, fewer human errors will be the cause for disruptions. Also, for AVs, the preferred headway can be constant. That could mean that mixed traffic will have fewer disruptions. Therefore, this research seeks to understand the effects of the transition between (mostly) human driving and fully automated vehicles by analysing the traffic performance of mixed traffic.

## 1.2 Research questions

To investigate the effects of new behaviour in mixed traffic, micro-simulation will be used to simulate traffic scenarios. Simulation output will be used to analyse these effects and draw conclusions about future traffic performance and safety.

Research questions are developed to outline the research and support the development of a valid mixed traffic simulation. Therefore the main research question is:

*" How do different levels of vehicle automation accounting for human driving behaviour impact traffic performance and safety on a multi-lane freeway? "*

Three separate sub-questions are formulated:

1. How can driving behaviours and automation-specific features across different automation levels be modelled for a multi-lane freeway environment?
2. How do car-following and lane-changing interactions change across different levels of automation?
3. How do vehicle automation levels in mixed traffic affect traffic Key Performance Indicators (KPIs)?

The multi-lane freeway, as discussed in the main research question, will feature an on-ramp to allow vehicles to merge into the main lanes. The inclusion of an on-ramp is essential as it introduces an additional flow of vehicles that must be managed by the post-merge freeway lanes. Ru et al. (2024) show that the vehicle flow from the on-ramp disrupts freeway traffic and significantly impacts overall traffic flow. Further details about the freeway layout are described in Chapter 3.

## 1.3 Report outline

The following chapters will provide more information about the topic and conducted research. At first, a literature review is performed in Chapter 2 to present the currently available literature about mixed traffic simulation regarding traffic performance. A knowledge gap in the literature is identified and the research approach together with the corresponding methodology is presented in Chapter 3. Chapter 4 will then present the designed vehicle models to represent the different automation levels. Chapter 5 will discuss the results from the freeway traffic simulation and present the impact on driving behaviour and traffic performance and safety. At last, the conclusions are presented and discussed in Chapter 6 with successive implications and recommendations.

# 2 Literature review

A literature review is conducted to understand the established research fields involved with mixed traffic and its implications. Firstly, a search strategy is outlined to collect relevant studies focusing on mixed traffic and its effects on traffic behaviour and performance. Secondly, the traffic performance of mixed traffic is discussed. Thirdly, safety aspects and take-over vehicle control situations are reviewed. Thirdly, social influences on road interactions are discussed. Lastly, the literature review findings will identify a knowledge gap and be the foundation for the research questions.

## 2.1 Search strategy

The Scopus search engine is used to search within a comprehensive database of peer-reviewed studies. To ensure a broad search strategy the search terms are divided into three parts.

1. This research is mainly about vehicle automation within traffic and its effects on driving behaviour. Therefore, papers are firstly selected by the search terms: "traffic", "automation", and "behaviour".
2. Then these papers have to include one of the following search terms: "mixed traffic", "autonomous", "self-driving", or "Advanced driver-assistance system". This is done to account for the different types and names of vehicle automation.
3. The resulting papers are then selected once more to include papers about simulation, policy implications, uncertainties within vehicle automation or overall effects. Therefore they have to match one of the following search terms: "uncertainty", "simulation", "policy", or "effects".

The search strategy results in this specific search query: *( TITLE-ABS-KEY ( traffic AND automation AND behaviour ) AND TITLE-ABS-KEY ( "mixed traffic" OR autonomous OR self-driving OR "Advanced driver-assistance system" ) AND TITLE-ABS-KEY ( uncertainty OR simulation OR policy OR effects ) )*

This search resulted in 296 papers. However, not all papers were suitable for this research. First of all, papers had to be available in English and need at least 10 citations within the Scopus database to be considered relevant papers for their research field. Secondly, papers about the design or optimisation of new vehicle or fleet controllers, machine learning approaches for AV controllers, new methods to gather vehicle or traffic data, analyses on transport mode demand, and fuel consumption analyses are left out of the resulting papers because these are outside this research's scope. This means that 48 papers are suitable for the literature review.

## 2.2 Traffic performance of mixed traffic

Already in 1999, researchers expected changes in traffic because of vehicle automation. At that time higher automation-level vehicles were not available yet. However, the first

ADAS-equipped vehicles did enter the road. Therefore, Arnab and Petros performed a microscopic simulation of level 1 HDVs and level 0 HDVs in mixed traffic to analyse the so-called slinky effect, another name for the phenomenon of a wave due to string disruptions (Arnab and Petros, 1999). They found that level 1 HDVs had smooth accelerations and thus did not contribute to the slinky effect.

Changes in driving behaviour are also expected in research of Talebpour and Mahmassani (2016). Talebpour and Mahmassani think that human drivers can sustain a more stable driving style since humans will base their decision-making on multiple vehicles in front. In their research, they implement AVs and CVs to allow human drivers to receive more traffic information and thus improve their perception which could lead to lower human reaction times. Despite the already low AV reaction time, AVs can only make decisions based on their direct surroundings, and it is this sensor limitation that Talebpour and Mahmassani think the driving behaviour would be different. However, this is not what they find in their one-lane microscopic simulation. Results show that an increasing penetration rate of CVs and AVs will increase the stability of traffic flow, where AVs seem crucial to lower string shock waves. Also, traffic throughput is increased up to 50% because of AVs and CVs, where AVs show more influence than CVs.

Results showing that AVs can cause a more stable traffic flow are in line with the overall consensus that HDVs are subject to human errors and thus will disrupt their lane. Cummins et al. (2021) analyse stabilisation by AVs on a multi-lane freeway. Previous studies simulated one-lane roads and observed high stabilisation because of AVs. Cummins et al. find that the stabilisation effect is lower than previously thought because lane changing causes more disruptions within traffic. Despite the lower effects, they still find stability improvements because of AVs. Stability improvements make simulation data more in line with traffic theory. Yao et al. (2019) find that simulation data does not correctly comply with the theoretical curve of the fundamental diagram, but traffic flow stabilisation allows simulations to approach the theoretical curve.

Other research focuses on the effects of CAVs. Liu and Fan (2020) simulate CAVs among HDVs on a four-lane freeway. They expect that freeway capacity will be increased by lower reaction times of CAVs. The results show that a penetration rate of 10-20% lowers the freeway capacity, but sees significant increases from 20% onwards. Also, Liu and Fan find that next to CAV penetration rate, the speed limit is an important factor in increasing freeway capacity.

Similar effects are found for simulations including HDVs, AVs, and CAVs. Olia et al. (2017) perform a micro-simulation to simulate HDVs, AVs and CAVs in mixed traffic. They also find that lane capacity increases when the penetration rate of AVs and CAVs increases. CAVs have a bigger effect than AVs since the V2V communication allows them to drive with even smaller headways. However, these effects are minimal at low penetration rates. Therefore, Olia et al. recommend including AV clustering or dedicated lanes to allow (C)AVs to drive together to benefit from the smaller headways. Additionally, Makridis et al. (2020) show that driving behaviour homogenisation is the most influential factor in stable traffic flows, explaining why traffic performance improvements are seen at higher penetration rates.

Next to micro-simulations, other methods can be used to analyse mixed traffic. Zheng et al. (2020) create a stochastic model to simulate AVs and HDVs. Their model produces similar results, meaning that they find a significant increase in traffic flow stability for

5-50% AV penetration rates.

Also Jiang et al. (2021) and Vranken et al. (2021) choose for another simulation method. They create a cellular automata model to simulate mixed traffic. Jiang et al. accounts for HDVs, AVs vehicles and CAVs on a one-lane road. Their results show similar traffic performance effects because of increasing CAV penetration rates as observed in previous literature, but they also include congestion reduction. According to Jiang et al., a rate of 80% of CAVs can reduce congestion by 63%.

Effects on traffic performance can also be analysed analytically and by numerical simulation. Chen et al. (2020) use these methods to get insights into vehicle interactions regarding accelerations and car-following. They find that heterogeneous traffic is more subject to flow disruptions than homogeneous traffic because of differences in vehicle acceleration. This is even amplified by the different car-following characteristics of different vehicle types.

As seen in the previous studies, researchers create multiple vehicle models by using different perceptions and different car-following and lane-change models to account for varying characteristics of different vehicle automation levels. However, HDVs are still solely based on the car-following and lane-change models. Calvert and van Arem (2020) state that therefore most traffic simulations simulate AVs more accurately than HDVs. AVs are more suitable to be modelled by preset logic, while this logic lacks human heterogeneity for accurate HDV models. To incorporate human aspects in driving models, Calvert and van Arem include the human cognitive ability to influence driving behaviour. Their framework involves driving tasks with specific workloads that saturate the driver's cognitive capacity. The amount of cognitive capacity left will influence the driver's reaction time and the extent of the driver's situational awareness. Pariota et al. (2016) try to analyse human factors by analysing real-life car-following data. Driving style is not accounted for, but they find that vehicle headway increases as the speed increases. Also, drivers tend to leave more space ahead when following heavy vehicles, such as trucks, than following other passenger cars.

## 2.3 Safety in mixed traffic

Automation within traffic is associated with increased safety. However, wrong decision-making by ADAS or autonomous vehicles can lead to dangerous road situations. Especially, when level 1, 2 and 3 vehicles are not sufficiently monitored by the human driver. Therefore, Lengyel et al. (2020) research the behaviour of car-following and lane-changing systems. They define two critical situations where infrastructure influences the decision-making of automated vehicles (could be both ADAS-equipped or autonomous). Situation one depicts an automated vehicle approaching a road section with a lower speed limit. The lower speed limit causes the automated vehicle to decelerate immediately, while the following HDV would not decelerate yet, resulting in a situation of possible collision. In the second situation, an automated vehicle follows an HDV. This HDV will change lanes, but during this change, the HDV occupies both lanes. Human drivers following this HDV would just steer out of the way of the lane-changing HDV, but automated vehicles will detect an incoming vehicle in your lane and thus start decelerating because of brake assistance causing other following cars to get into a dangerous collision situation. In both scenarios, higher driving speed was the most important factor resulting in collisions. Better reaction times of fully automated vehicles only had limited safety improvements. Lengyel et al. therefore state that automated features designed on current infrastructure are not sufficient and recommend that infrastructure is adapted to accommodate automated vehicles.

Other research does find safety gains because of automation. Morando and Truong (2017) and Morando et al. (2018) simulate HDVs and AVs (defined as SAE level 4) on a roundabout and an intersection. They find that potential collisions decrease as AV penetration rates are high (more than 25% or more than 50%). However, an increase in potential collisions is seen at lower penetration rates. The increase in collisions at lower penetration rates is not seen for the simulation of a broader selection of automated vehicle levels. Miqdady et al. (2023) analyse automation levels 1 to 4 on a freeway for increasing penetration rates and find that conflicts are reduced at both low and high penetration rates. Arvin et al. (2020) account for safety by two safety indicators, the number of longitudinal conflicts and driving volatility. They also perform a microscopic simulation to analyse car-following safety of (cooperative) Adaptive Cruise Control (ACC). Arvin et al. show that a penetration rate of 40% or more of level 2 and 3 vehicles made large improvements in driving volatility. Arvin et al. (2020) sees the same results, but adds that CAVs will lead to a larger improvement in safety because of the broader perception.

In addition to simulation, real-life test incident reports can be analysed. Biever et al. (2020) assess AV testing incidents in California. From the 115 assessed reports, no reports state that the AV caused an accident. Incidents involved AVs impacted from the rear while AVs performed braking, turning or gap acceptance manoeuvres and the side during lane-keeping. Therefore, Biever et al. think that the difference between HDV and AV driving styles could cause incidents.

Automation does not only affect safety during operation, but the custom of driving with automation features could change how people drive in traffic. Therefore, Louw et al. (2021) conduct an urban simulator experiment to analyse how drivers change their behaviour after becoming familiar with AV features. While driving AVs or HDVs with ACC features, the driver is not responsible for keeping the headway. The automated car-following function will determine the headway for the driver, which is often lower than the headway maintained in HDVs. Louw et al. find in their experiment that drivers will maintain lower headways in HDVs because they get used to the smaller headways from AVs.

Automation seems to have a significant impact on road safety. But how do other road users perceive this safety with AVs in mixed traffic? Liu et al. (2019) provided respondents with information on road traffic injuries and deaths and gave them a risk situation of HDVs or AVs. The respondents had to assign whether and how much they would accept the risk within the situation. The questionnaire results show that an acceptable risk of driving an AV has to be at least four times safer than for an HDV.

## 2.4 Take-over vehicle control situations

Human drivers are still monitoring AV decisions because current consumer vehicles do not exceed level 3 automation. However, when the driving conditions become too complex for the AV, the human driver has to regain control. This shift in vehicle control from the automated features to the human driver is called a take-over manoeuvre, which should not be confused with overtaking, where one vehicle passes another. Gold et al. (2016) use a driving simulator to emulate take-over situations. In the simulator, participants drive an AV and are involved in non-driving tasks by answering questions. During the simulation, the AV gets into a situation of operational limits, specified in the vehicle's operational design domain, and thus the driver has to take over control to perform an evasive action. While the non-driving task did not significantly impact take-over performance, the number of surrounding vehicles in traffic (traffic density) did decrease take-over performance (Gold et al., 2016). The results show that placing hands on the steering wheel is mostly rule or skill-based, but performing the evasive manoeuvre took more time because of the complexity of higher traffic densities. Calvi et al. (2020) perform a similar simulator experiment, but the participants have to watch a movie whilst driving in an AV. This requires higher cognitive demand and takes all road attention away from the driver. The results show that this higher cognitive load results in more dangerous take-over manoeuvres compared to HDVs.

Next to traffic situations and the human driver aspects, the take-over performance could be affected by the automation level of the vehicle (McDonald et al., 2019). McDonald et al. find conflicting studies on take-over performance in AVs, but the contradictory findings could be the cause of varying automation levels in these studies and different vehicle parameters. Still, it seems that high-level AVs with short headways result in less safe take-over situations.

## 2.5 Social effects of automation

Changes in driving behaviour because of automation do affect both traffic safety and performance. This means that road users will also encounter different behaviour on the road. Cascetta et al. (2022) researches the ability of road users to identify the differences between automated features and HDV driving behaviour. Cascetta et al. find that for level 2 HDVs, car-following behaviour is perceived as very human-like, while road users did observe less strict lane-keeping. This does not mean that other road users are not affected by automated car-following. Soni et al. (2022) perform a real-life field test to analyse HDV driving behaviour while driving among AVs. They take three behavioural aspects into account: gap acceptance, car-following, and overtaking. They observe that HDVs keep a smaller headway towards AVs than other HDVs for gap acceptance, car-following, and after overtaking an AV. Also, Soni et al. show that knowledge about AV technology affects the perceived risks of human drivers and results in higher trust during interactions with AVs. When AVs do impact HDV's driving behaviour, marking AVs is a method to inform road users about the surrounding vehicles. However, Fuest et al. (2020) show that drivers do not perceive an ahead vehicle differently whether it is marked as an AV or not.

Despite road users not always being able to differentiate between human drivers and automated features, research does show that HDV behaviour changes due to AV presence. Gouy et al. (2014) tested how short AV headways impact surrounding HDV behaviour. The driving simulator experiment results show that HDVs lower their mean and minimum headway because of driving next to AV platoons. Also, HDVs spend more time under the headway safety threshold of one second, meaning that more critical situations can occur because of the presence of AVs in mixed traffic. Ma and Zhang (2024) use a web-based simulator to analyse how driving style (defensive, moderate, or aggressive) influences HDV-AV interactions in comparison to HDV-HDV interactions. They find that moderate and aggressive drivers are less comfortable in HDV-AV interactions and adopt a more aggressive driving style. The more aggressive the driving style, the more likely that drivers will take advantage of the AV's more defensive driving style. This is also seen in a real-life analysis. Knoop et al. (2019) analyse the performance of level 2 HDVs in a real-life test. Their test shows that current SAE level 2 vehicles are not capable of creating platoons larger than three or four vehicles because of car-following instabilities. They observed that the headway of ACCs is larger than humans desire, resulting in other vehicles merging into the platoons. However, a larger penetration rate of level 2 vehicles would result in less aggressive driving vehicles and thus fewer HDV-AV interactions.

Schwarting et al. (2019) research driver's selfishness in non-cooperative game theory. Human drivers are able to observe other drivers and estimate the other driver's actions based on their driving style. Schwarting et al. states that this is more difficult for AVs in HDV-AV interactions. Therefore, AVs have to receive a selfish score from the other vehicle to adjust their decisions accordingly. In this research, they found that incorporating such a score can reduce prediction errors in human trajectories by 25%.

AVs will also interact with pedestrians in urban areas. Simulator research is conducted to analyse how pedestrians will behave towards AVs. Rad et al. find that the pedestrian's behaviour at crossings depends mostly on their age and knowledge of AV technology. In this situation, AVs signal their lights when they will stop for the pedestrian. Pedestrians with an age below 40 cross the street twice as much as older pedestrians (Rad et al., 2020). Jayaraman et al. (2018) also see a link between knowledge of AV technology and crosswalk behaviour. However, in their research, the driving style of the AV varies in experiments. The results show that aggressive driving AVs prevent more pedestrians from crossing the street at non-signalised crosswalks. This behaviour is not seen at signalised crosswalks.

## 2.6 Knowledge gap

The literature review shows that the introduction of automation into traffic has and will result in increased traffic performance and safety. A variety of vehicle configurations in mixed traffic have been analysed numerically, in driving simulators, but mostly in microscopic simulation. However, in some cases, the differences between HDV and AVs become blurry because conditional car-following functionality, such as ACC, is considered fully autonomous in freeway situations. At lower penetration rates there is no improvement of traffic performance or even a reduction in traffic performance is found. However, Miqdady et al. find that simulation of SAE level 1 to 4 vehicles shows a reduction in traffic conflicts for both low and high penetration rates. This could mean that the smaller increments of automation in the vehicle configurations could reduce the differences in driving behaviour and thus lower traffic disruptions.

Also, the use of ACC is not always autonomous. The conditional car-following feature as well as any lateral movements need human monitoring until level 3 automation. Literature shows that these take-over situations are not always safe and McDonald et al. find that short headways cause less safe take-over situations. Especially short headways are one of the important aspects of improving road capacity and thus traffic performance.

In most mixed traffic studies, human factors are not taken into account. Calvert and van Arem therefore state that AVs are simulated more accurately than HDV, which will impact simulation results. The importance of human factors is emphasised by findings that driving style influences social road interactions. If AVs show a defensive driving style, HDVs will try to gain from them. While on the other hand, an aggressive AV is perceived as more dangerous.

These aspects indicate that existing studies lack detailed modelling to capture nuanced differences between automation levels and, particularly regarding conditional automation features and human factors in mixed traffic environments. This limitation contributes to inconsistent and sometimes conflicting outcomes for traffic performance and safety. Therefore, a more refined modelling approach is required to account for human driving behaviour, vehicle interactions, and incremental levels of automation.

## 2.7 Research scope

These findings emphasise why the research question is relevant and that indeed the driving behaviour should be analysed within mixed traffic. Therefore, this research will use microscopic simulation to simulate vehicles with automation increments in mixed traffic to gain insights into traffic performance and safety for different penetration rates. These vehicle configurations will account for conditional ADAS and autonomous features and take human factors into account. Also, to allow for sufficient road interactions, the simulation will be based on a multi-lane road.

As the knowledge gap states that the differences in driving behaviour are most important for mixed traffic performance, this research will focus on the implementation of human factors into driving models and not research all different car-following and lane-changing models existing for traffic simulation. Also, take-over control situations, where autonomous features shift back control to the human driver, are important for traffic safety but first require the implementation of human factors. When both human and autonomous simulation are defined accurately, a framework could be constructed for how such a take-over control manoeuvre would be built into the vehicle model. This will be discussed in the recommendations in Chapter 6.5, however, it will not be part of this scope.

To quantify traffic performance and traffic safety, metrics used by the reviewed literature are selected to form the traffic KPIs. Traffic performance will be assessed by accounting for traffic flow, speed, density and travel time. Traffic safety is assessed by accounting for car-following conflicts. Miqdady et al. (2023) shows that these conflicts can be identified by calculating the time-to-collision for vehicles.

# 3 Methodology

This chapter provides a comprehensive overview of the methodologies used in this research, aimed at analysing the impact of varying levels of vehicle automation, considering human factors, on traffic performance and safety on a multi-lane freeway with an on-ramp. Building upon insights from the literature review, this chapter will present the approach taken to address the discussed knowledge gap. This includes a focus on human factors, as current traffic simulations offer only limited representations of human driving behaviour. Additionally, small increments in vehicle automation will be used to analyse the effect of current and near-future available ADAS features and AVs. Differences and similarities between automation levels will be discussed explicitly.

To address these research gaps, this chapter outlines the methodologies designed to answer each research question in a structured and targeted manner. Chapter 3.1 will present how human factors and automated driving features are incorporated into the vehicle models and discuss different microscopic simulation software packages. Chapter 3.2 discusses the vehicle interactions on multi-lane freeways with an on-ramp and presents the experiment setup to analyse those interactions. The effects of automation levels of vehicles on traffic KPIs are then discussed in 3.3, where the experiment setup is discussed.

## 3.1 Sub-question 1

To answer the research question *"How can driving behaviours and automation-specific features across different automation levels be modelled for a multi-lane freeway environment?"*, the different automation levels that apply to the freeway scenario need to be identified. While the SAE provides a framework for vehicle automation levels, the corresponding driving behaviour is not specified. Therefore, best practices in simulation as well as distinct vehicle characteristics are explored. These findings determine how the vehicle models used in the traffic simulation will be configured.

### 3.1.1 Simulation of autonomous vehicles

AV driving behaviour remains relatively unknown since AV features are subject to continuous development and can have different designs, which results in varying model parameters. Additionally, since higher automation-level AVs have not entered the market or have done so only in limited numbers, there is insufficient traffic data to determine model parameters or validate simulation outcomes accurately.

Vehicle driving behaviour in traffic simulations is determined by underlying car-following and lane-changing models. Sadid and Antoniou (2023) state that it would be important to calibrate such driving models with real-world data, however, the currently available field data is limited. Therefore, they research what factors within car-following models are important to simulate AVs. Sadid and Antoniou take the following factors into account to simulate AVs:

- **Headway:** AVs will maintain different headway distances than human drivers. For example, advanced AVs, such as CAVs, can maintain a smaller headway compared to human drivers due to precise control of the vehicle and understanding of its environment.

- **Reaction time:** AVs have a negligible reaction time compared to human drivers.
- **Perfect driving:** The controller has precise control of the vehicle's driving behaviour.
- **Driving style:** AVs can exhibit different driving styles from cautious to more aggressive driving styles.

These factors can be incorporated into already existing car-following models. Adjusting existing behavioural model parameters is one of the most frequently used methods to incorporate AV behaviour in vehicle models (Sadid and Antoniou, 2023 and Olstam et al., 2020). As Olstam et al. note, this approach has the advantage of allowing simulation of unverified AV behaviour by adjusting parameters relative to human driving behaviour. Thus, details of AV decision-making processes are not necessary to achieve AV-like driving behaviour in simulations. Therefore, this research uses findings on driving behaviour in mixed traffic to design vehicle models. For AVs, this will include the four listed factors from Sadid and Antoniou (2023). Chapter 3.1.4 will present how these factors are applied to reflect the different automation levels.

### 3.1.2 Simulation of human drivers

Car-following and lane-changing models are designed to recreate real-life traffic dynamics and decision-making. The earliest car-following model is the Gazis-Herman-Rothery (GHR) model, which determines the vehicle's acceleration based on its relative speed to its leader and the headway distance (Ahmed et al., 2021). Since car-following and lane-changing models are algorithmic, they are inherently closer to the nature of AVs than HDVs. Therefore, AVs are simulated more accurately than HDVs (Calvert and van Arem, 2020). Furthermore, models created from an engineering perspective make bold assumptions that are not suitable for human driving behaviour. For example, Saifuzzaman and Zheng (2014) state that such car-following models focus on physical driver signals rather than psychological reactions, model driver actions based on optimised traffic performance, model driver perception with inputs they cannot fully perceive. Consequently, mathematical and logic-based models provide an overly simplistic representation of human driver decision-making.

To make car-following models more human-like, it is important to consider several key aspects. Saifuzzaman and Zheng (2014) present a list of human factors that are crucial for human driving behaviour. An explanatory overview of these factors is presented here.

- **Personal characteristics and driving style:** Human drivers show different driving behaviours based on socioeconomic characteristics and driving experience.
- **Driving needs:** Driving behaviour is influenced by the purpose of the trip.
- **Reaction time:** Reaction time affects driving behaviour and human drivers have different reaction times in different situations.

- **Estimation errors:** Humans rely on estimations to perceive the traffic situation, this process can be prone to errors.
- **Perception thresholds:** Because humans rely on estimations, small changes in stimuli will not be noticeable by the driver.
- **Imperfect driving:** Human drivers can make unintended vehicle control errors that do not reflect their intentions.
- **Temporal anticipation:** Human drivers can estimate future traffic situations.
- **Spatial anticipation:** Human drivers take the direct follower vehicle and more vehicles ahead into consideration.
- **Distraction:** Attentiveness of drivers affects driving performance.
- **Desired speed, spacing and time headway:** Human drivers exhibit driving behaviour that corresponds to their preferred levels for speed, following distance, and time headway.

Models such as the Wiedemann model try to incorporate human aspects. The Wiedemann model is a psychophysical model that incorporates human factors by adjusting driver attentiveness for the relative speed and the headway distance (Ahmed et al., 2021). Also, the Wiedemann model incorporates different driving capabilities by using normal distributions for its parameters.

Saifuzzaman and Zheng also show that existing car-following models (including the Wiedemann model) try to incorporate human factors by accounting for:

- Driver perception cannot perceive very small input changes.
- Include attentive zones based on headway distance.
- Drivers estimate time-to-collision based on visual angles rather than longitudinal distances.
- Include risk-taking behaviour.
- Include human driver errors and distractions.

These efforts show that it is possible to include key aspects from the human factors list in vehicle models to account for human driving behaviour. So, to allow this research to simulate human drivers more realistic, personal characteristics, reaction time, distraction, desired speed, and desired headway are taken into account.

Simulation of mixed traffic should account for behaviour in HDV-AV traffic interactions. Raju and Farah (2020) say that current micro-simulations do not adjust driving behaviour based on vehicle types in the traffic situation. However, they see this as an important limitation towards realistic simulation of vehicle automation types in mixed traffic.

The literature study shows conflicting findings for human driving behaviour among AVs. Soni et al. (2022) and Gouy et al. (2014) show that HDV headway decreases while driving in mixed traffic among AVs with short headways. Fuest et al. (2020) show that human drivers do not recognize AVs easily and when an AV is marked as one, no changes are seen in car-following behaviour. Fuest et al. do think that humans will change this behaviour over time as they get more familiar with driving in mixed traffic.

This research does include human driving behaviour adaptations due to the presence of level 3 vehicles. Another research from de Zwart et al. (2023) shows that HDVs indeed adopt AV behaviour when penetration rates increase. Human drivers show adaptations for smaller headways and smaller speed variations in cruising scenarios. The AVs used in this research are AVs with very small time headway settings that do not reflect nowadays ACC systems, but rather represent level 3 vehicles or CAVs. Because it is understandable that vehicles with significantly different behaviour will cause human drivers to adapt, this research will account for adaptation in vehicle interactions regarding time headway. It is assumed that the smaller variety in speed will be achieved automatically by increasing the penetration rate of level 3 vehicles since human drivers will need to follow these vehicles.

Additionally, aggressive HDVs will try to gain an advantage over defensive AVs. As seen in the literature study, the driving style of HDVs highly influences HDV-AV interactions. This is logical since the road is a social space where HDVs try to communicate by their driving actions. Personality influences people's interactions and so does it on the road. AVs observe their surroundings but do not understand the intentions of other road users (Brown and Laurier, 2017). Therefore, AVs do not participate in road interactions in the same way HDVs do. Also, AV manoeuvres are perceived differently by human drivers. More aggressive drivers perceive these actions as more aggressive and unsafe, while defensive human drivers are more likely to perceive positive interactions (X. Li et al., 2023). This perception of aggressive human drivers towards AVs leads to HDVs taking advantage of traffic situations (Ma and Zhang, 2024).

### 3.1.3 Automation features

The previous paragraphs were aimed at the simulation of HDVs and AVs. However, the different levels of automation are not covered. Therefore, the automation features in automation levels are discussed here, based on the clearly described levels from the SAE.

Since this research simulates mixed traffic on a freeway, the only automation levels to distinguish are level 0, 1, 2 and 3 vehicles. The differences between level 3, 4 and 5 vehicles lie more in their operational design domain, which describes in what specific situations the automation features are in control of the vehicle. Now the freeway is considered a suitable situation for a level 3 vehicle, so this means that a vehicle will become autonomous from level 3 onwards. This is not completely true when take-over control requests are taken into account which could technically still occur for level 3 vehicles. However, these take-over control situations are not simulated in this research. Furthermore, level 4 and 5 vehicles are considered more advanced than level 3 vehicles, which could have implications for specific model parameters, however, the differences in autonomy are just too small to create significant differences between the higher level automation vehicles in this freeway scenario. That is why no distinction is made between automation level 3, 4 and 5 vehicles.

While the level definitions from SAE are great for showing the boundaries of the automation levels, specific automation features are chosen to provide a practical basis for the automation levels in this research. Dutch research from the Rijkswaterstaat institute shows that many ADAS features are already used (MuConsult in opdracht van RWS, 2023). Applicable features, divided into categories of temporary, longitudinal and lateral assistance, for a freeway scenario are:

- **Temporary assistance**
  - Emergency braking system
  - Forward collision warning
  - Lane departure warning
  - Blind spot warning
- **Longitudinal assistance**
  - Cruise Control (CC)
  - ACC
- **Lateral assistance**
  - Lane keep assist

Additionally, newer vehicles enter the market with more ADAS features. Huang et al. (2018) research supports features of level 2 vehicles, which contain active lane change assistance to perform a lane change manoeuvre. The active lane change assist will perform a safe lane change manoeuvre when the driver requests one. However, a level 3 vehicle is capable of planning lane changes by itself and thus becomes fully autonomous within its operational design domain (Oh et al., 2021).

### 3.1.4 Automation level configurations

The previous paragraphs have discussed key elements in simulating human- and autonomous driving behaviour. Also, the different automation features for automation levels are discussed. Now, these findings are used to explain how the vehicle model for each automation level will be built. A summary of all vehicle model concepts is shown in Table 1.

Level 0 automation states that a vehicle only provides temporary support by ADAS features such as forward collision warning, emergency braking, and blind-spot warning. The driving tasks for car-following and lane-changing are performed by the human driver and are affected by the current task load. This task load also influences the driver's perception and reaction time. Reaction time is defined by maximum and minimum values and driving traits such as driving style and speed adherence are set by distributions. Also, minimum and maximum headway settings are set by values found in the literature. This allows the level 0 vehicle to include personal characteristics, reaction time, distractions, desired speed, and desired headway into account for human factors.

For a level 1 vehicle, additional ADAS is present to support the car-following task. This feature will be equivalent to nowadays (A)CC systems. This automated car-following affects the response time, headway and acceleration of the vehicle. While take-over control manoeuvres are not simulated, the driver is still responsible for lane-changing behaviour and can adjust ACC settings. Therefore, a distribution is added to the vehicle's speed. Because the driver is supported for car-following tasks, the driving task is lower. Also, the car-following task will now become defensive which means that social pressure is not taken into account anymore. This configuration allows the level 1 vehicle to perform automated car-following but still account for human factors for lane-changing decisions.

A level 2 vehicle is supported for both car-following and lane-changing tasks. Support in lane-changing allows the human driver to request a lane change and the active lane change assist system will perform the manoeuvre. Therefore, the driving task load decreases more and the driving style becomes defensive. At level 2 the driver is still responsible, so a distribution is added to its speed to account for human comfort settings. At this level, only the driving speed is subject to human personality traits. Other human aspects such as distraction are excluded. Also, the desired headway and reaction time are set to values that represent the (A)CC car-following system.

At level 3, both car-following and lane-changing are controlled by the automated features and thus the driving load disappears for the human driver. Additionally, because the freeway scenario falls within the operational design domain of level 3 vehicles, no human control is expected. This means that the variability in speed adherence will be lower. No other distributions are used to set parameter values for a level 3 vehicle. This makes level 3 even more AV-like because it will use parameters to represent AV behaviour for headway, reaction time, and driving settings. No human factors are included anymore.

Table 1: Concepts of vehicle model configurations.

| Characteristics | Level-0 | Level-1 | Level-2 | Level-3 |
|---|---|---|---|---|
| CF | Human | Automated | Automated | Automated |
| LC | Human | Human | Automated | Automated |
| Response time | Human response time | Automated response time | Automated response time | Automated response time |
| Headway | Based on literature | Based on literature | Based on literature | Improvement on level 2 vehicles |
| Driving style | Distribution of values | CF: Defensive<br>LC: distribution of values | Defensive | Defensive |
| Driving task | High | Mediocre | Low | None |

To account for changes in human driving behaviour due to surrounding traffic, interactions between vehicle types are included. Table 2 shows how driving behaviour changes for the following vehicles when they interact with other automation levels. Since HDVs show smaller headways when they drive among AVs, the headway becomes smaller for level 0 vehicles when they drive in between level 3 vehicles. This is only applied for level 3 vehicles since level 3 is the only automation level with a lower minimum headway than level 0 vehicles, see Chapter 4.6. Furthermore, human drivers are in charge of lane-changing for level 0 and level 1 automation, so they will be less cooperative towards level 3 vehicles where the level 0 and level 1 drivers can observe that the level 3 vehicle is not controlled by the human driver.

Table 2: Matrix for changes in driving behaviour due to vehicle type interactions.

| | Leading vehicle | | | |
|---|---|---|---|---|
| **Following vehicle** | **Level-0** | **Level-1** | **Level-2** | **Level-3** |
| **Level-0** | No change | No change | No change | Shorter headway, less cooperative |
| **Level-1** | No change | No change | No change | Less cooperative |
| **Level-2** | No change | No change | No change | No change |
| **Level-3** | No change | No change | No change | No change |

The described configurations have direct implications for the vehicle models used in the simulation. The precise description of the designed vehicle models is further discussed and researched in Chapter 4.

## 3.2 Sub-question 2

The vehicle automation level configurations from Chapter 3.1 will be used to create vehicle models for traffic simulation to analyse their driving behaviour and answer the second research question: "How do car-following and lane-changing interactions change across different levels of automation?"

### 3.2.1 Freeway layout

The simulation will explore a multi-lane road network with a (merging) on-ramp. The main research question specifies the situation of a multi-lane freeway which allows vehicles to perform lateral movements. These lateral movements will show emerging vehicle interactions and prevent the simulation of a single string of vehicles. To increase the number of interactions and make the situation more complex, an on-ramp is added, resulting in the road network displayed in Figure 2. This on-ramp adds a new flow of vehicles to the freeway flow, causing a higher traffic flow for downstream lanes. The on-ramp forces vehicles to perform lateral movements, causing turbulence in the merging influence area. This should disturb car-following planning and increase the task load for human drivers. It is this combination of the effects on traffic demand, car-following, lane-changing, and human factors that make this situation suitable for analysing mixed traffic interactions. The total length of the freeway is 2,000 meters. This allows the traffic stream to widely show free-flow behaviour before and after the on-ramp and analyse merging behaviour in the merging influence area, or turbulence area. The lengths of the on-ramp and influence area are determined by Rijkswaterstaat (2022).

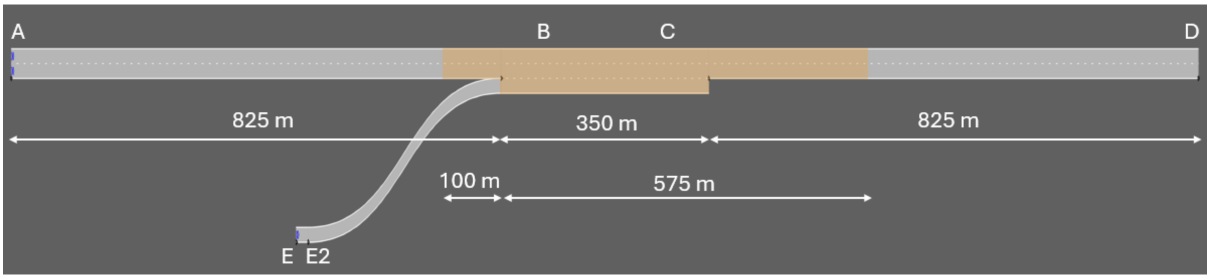


Figure 2: Road network layout for a two-lane freeway with a merging ramp. Including lengths of pre-ramp link AB, merging ramp link BC, and post-ramp link CD. The merging ramp influence area is depicted as an orange area. Developed by the author.

The multi-lane freeway is chosen over an intersection road network. An intersection situation could introduce more complexity and thus more complex behaviours affected by the automation level. However, the current ADAS equipped in the Dutch vehicle fleet is aimed at short-term warnings, car-following support and lane-keeping support (MuConsult in opdracht van RWS, 2023). These ADAS features cannot be used or are less used in intersection scenarios. So, for research aiming to understand the differences and effects of all automation levels on traffic, the intersection scenario is less suitable.

#### 3.2.2 Scenarios

A selection of scenarios is required to test the mixed-traffic simulation for the main research question. To investigate the different behaviours of the vehicle models, each vehicle model is simulated for a 100% penetration rate. While these scenarios can clearly show the differences between automation levels, a mixed traffic scenario is included of 25% per automation level to ensure that their driving behaviour is sampled for the same traffic conditions. Additionally, a scenario is simulated for 50% level 0 and 50% level 3 vehicles to analyse how human adaptations from Table 2 impact the driving behaviour of both the human drivers and the level 3 vehicles. Therefore, the following scenarios are listed in Table 3:

Table 3: Scenarios with varying vehicle automation penetration rates for the analysis of driving behaviour.

| **Scenario** | **Vehicle Models** | | | |
|---|---|---|---|---|
| | Level 0 | Level 1 | Level 2 | Level 3 |
| 100-0-0-0 | 100% | | | |
| 0-100-0-0 | | 100% | | |
| 0-0-100-0 | | | 100% | |
| 0-0-0-100 | | | | 100% |
| 25-25-25-25 | 25% | 25% | 25% | 25% |
| 50-0-0-50 | 50% | | | 50% |

However, the designed freeway can be subject to very different situations because of traffic demand. Whenever the road is quiet, vehicles will maintain their lane and continue their journey without much interaction with other vehicles. Relevant situations can be identified by searching for the critical road capacity. The literature seems to show that high level AVs, in this research represented by level 3 vehicles, are capable of increasing road capacity because of lower headways and less variation in speed. Congestion occurs at the critical capacity and is disastrous for traffic performance. Also, bottlenecks, such as a merging area, bring more variance in vehicle speeds, which can result in more congestion.

The critical capacity is dependent on two variables: Critical density, and critical speed. This can also be expressed as traffic density and flow as shown in Figure 3. The left side of the curve, called the free flow, is the situation where traffic performs well. The fundamental diagram seems to show a gradual decrease in flow when congestion starts. However, in real life, an immediate decrease of 5-25% in flow (road capacity) occurs at the second congestion appears (van Lint, 2019). This is caused by the increase in the driver's preferred follow-distance and causes the driver to lower its speed. It would be ideal when automation features could shift the critical capacity up and thus extend the free flow part of the curve to improve traffic performance for higher demands. Therefore, it is interesting to simulate the scenarios for a traffic demand where the critical capacity is reached. The base scenario of 100% level 0 vehicles will be explored in Appendix III: Exploratory analysis to determine suitable traffic demand values for the main freeway lanes and the on-ramp.

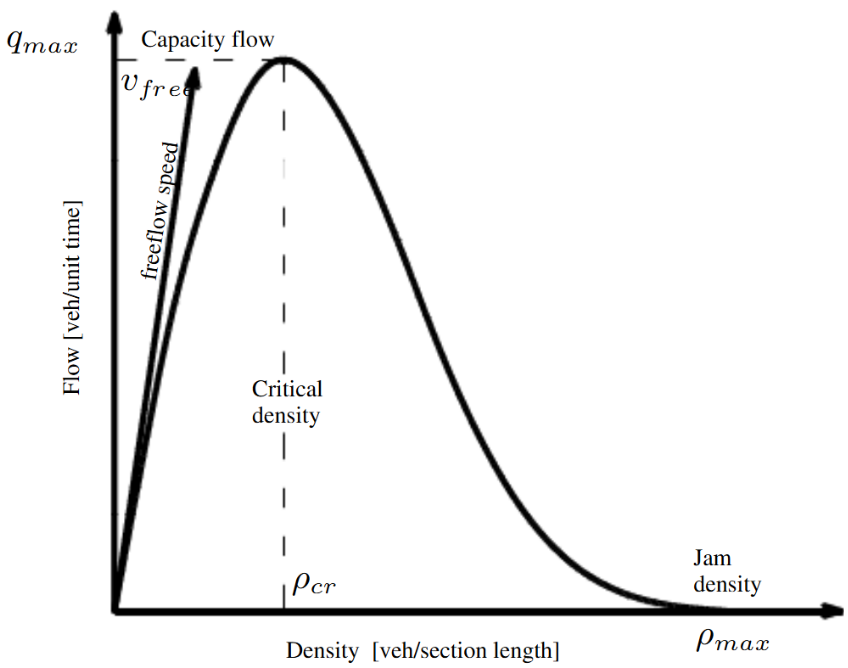


Figure 3: Fundamental diagram for traffic density and flow. Retrieved from Majid et al., 2014.

### 3.2.3 Vehicle interactions

To be able to analyse changes in vehicle interactions for different automation levels, the specific interactions need to be identified. The automation levels have different driving behaviour for both the car-following and lane-changing models. Therefore, the following driving behaviour will be analysed:

- Vehicle car-following acceleration [$m/s^2$];
- Vehicle following headway [$s$];
- Vehicle headway during lane changes [$s$];
- Number of lane changes;
- Number of switches in leader vehicles;

These variables will be analysed for the main lanes of the freeway and the on-ramp. Vehicle grouping is the phenomenon where vehicles will start driving in a convoy and leave no space between the vehicles that could be taken by others. This is an extra variable that can help to explain merging behaviour.

## 3.3 Sub-question 3

The same simulation setup from Chapter 3.2 is used to answer: *"How do vehicle automation levels in mixed traffic affect traffic KPIs"*. The analysis is also based on different automation levels. However, other penetration rates are used and other variables are analysed to get insights into traffic performance and safety.

### 3.3.1 Scenarios

Vehicle driving behaviour is analysed for scenarios of 100% penetration rates per automation level (scenarios 100-0-0-0, 0-100-0-0, 0-0-100-0, and 0-0-0-100), a scenario with equal penetration rates across automation levels (scenario 25-25-25-25). As we have stated in the introduction as well as in the literature review, the vehicles with higher automation levels are introduced to the road gradually resulting in mixed-traffic situations. The transition of the vehicle fleet from human drivers to AVs is very uncertain (Olstam et al., 2020)). Therefore, seven other scenarios are designed to account for intermediate penetration rates. While penetration rates are hard to predict, Tillema et al. (2020) have broad qualitative forecasts based on different technology development and acceptance scenarios. However, rigid penetration rate values are required for mixed traffic simulations, like Miqdady et al. (2023) has done. Therefore, this research assumes that when higher automation level vehicles are introduced to the vehicle fleet, lower automation vehicles will gradually fade out based on the diffusion of innovation. This is also what the European Road Transport Research Advisory Council expects to happen in their development path for automated driving (European Road Transport Research Advisory Council, 2017). This results in the following list of penetration rates in Table 4.

Table 4: Scenarios with varying vehicle automation penetration rates for the analysis of traffic performance and safety.

| **Scenario** | **Vehicle Models** | | | |
|---|---|---|---|---|
| | Level 0 | Level 1 | Level 2 | Level 3 |
| 100-0-0-0 | 100% | | | |
| 80-20-0-0 | 80% | 20% | | |
| 60-20-20-0 | 60% | 20% | 20% | |
| 40-20-20-20 | 40% | 20% | 20% | 20% |
| 25-25-25-25 | 25% | 25% | 25% | 25% |
| 0-33-33-33 | | 33% | 33% | 33% |
| 0-0-50-50 | | | 50% | 50% |
| 0-0-20-80 | | | 20% | 80% |
| 0-0-0-100 | | | | 100% |

To analyse what impact the higher automation features have on traffic each scenario is compared incrementally. So, scenario 80-20-0-0 will be compared to scenario 100-0-0-0 with a lower penetration rate for automation. This stepwise approach allows for observing the gradual effects of higher automation penetration. The scenario of only level 0 vehicles (scenario 100-0-0-0) is considered the baseline scenario since no higher automation features are present.

Additionally, the effect of human factors is tested by introducing driver distractions. The literature review has shown that situational awareness changes when the driver's attention is divided. Since this research seeks to simulate human drivers and is also aimed at traffic safety, traffic implications for distracted drivers are taken into account in two ways:

1. In-vehicle distraction;
2. Static roadside distraction.

Bamney et al. (2022) find that distractions involving cognitive, visual and manual engagement lead to the highest risk in near-crash situations. These types of distractions correspond to in-vehicle distractions, which simulate distractions such as incoming calls, navigation prompts, and other secondary tasks. The high required engagement will therefore result in a high workload affecting the driver's mental model. The in-vehicle distractions can occur randomly throughout a car ride, so the simulation will randomly select GTUs that will experience a higher workload due to secondary tasks as depicted in Figure 4.

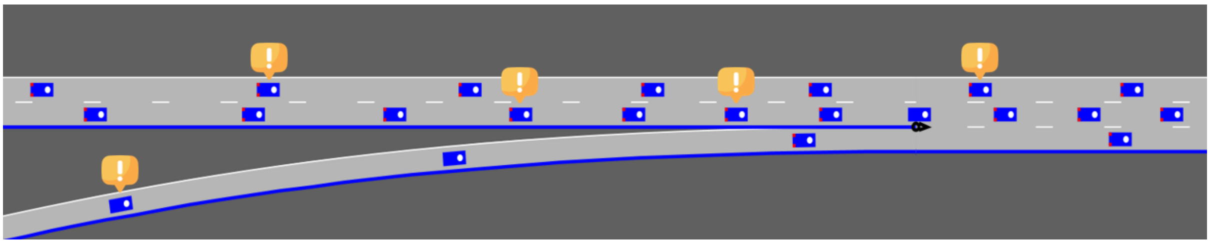

Figure 4: Scenario of randomly applied in-car distractions for drivers. Developed by the author.

Secondary tasks are a major subject in driver workload research and occur all the time in real-world car rides. Because this is so common for human drivers, in-vehicle distractions are considered part of the vehicle model and thus are always present in the listed scenarios.

A static roadside distraction, such as a crash on the other side of the road, is not always present. Roadside distractions may require less engagement because the driver is not manually involved. However, it will affect many drivers at the same time and place. The so-called "rubbernecking" phenomenon is observed when drivers are visually distracted by events or objects alongside the road and lower their speed (Reina, 2021). Furthermore, Divekar et al. (2012) state that external distractions increase due to video billboards and message signs. Therefore, including scenarios with static roadside distractions will be helpful to get safety insights.

To simulate a static roadside distraction, GTUs that perceive this distraction will experience an extra workload. This workload will imitate the diverted attention to the object alongside the road. Figure 5 presents the setup of the fixed environmental distraction and which GTUs are affected. The distraction point is set to the start of the merging area. Because of this placement, distracted drivers will experience a higher workload in an already demanding situation. Therefore, it is expected that this higher workload will show clear effects on driving behaviour.

Unfortunately, no research has been found on the specific distances before and after a distraction point where human drivers become distracted. Still, it is known that distraction effects are not only during the distraction, but driver anticipation skills remain weakened after a distraction (Borowsky et al., 2016). Additionally, a visual distraction such as a crash can also be seen from the vehicle's rear-view mirror. Therefore, it is assumed that drivers will be visually distracted within their perception range. This range is set by the look-forward and look-back distances of the driver.

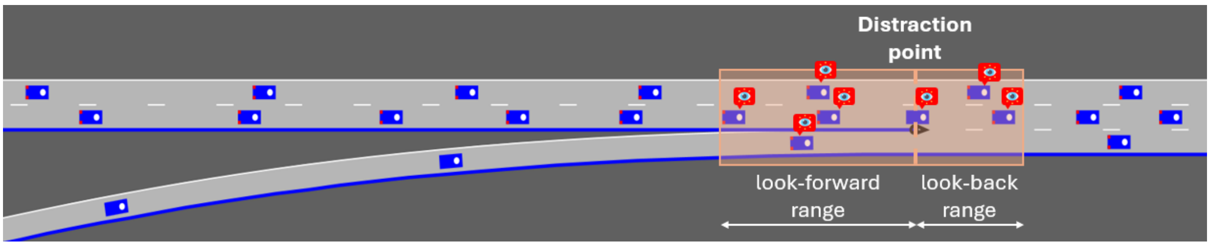


Figure 5: Scenario of an external distraction affecting nearby drivers. The distraction balloons show the distraction level (blue: low, yellow: medium, red: high). Developed by author.

The addition of a roadside distraction has introduced a new variant for the penetration rate scenarios. Because all scenarios are simulated both with and without a static roadside distraction, the resulting number of simulation runs is set to 18 runs. These will provide the data used for analysing the impact of increasing automation levels on traffic performance and safety.

### 3.3.2 Key performance indicators

To determine the effects of vehicle automation levels on traffic, KPIs are designed. The main research question already shows that this paper focuses on traffic performance and safety. Variables are identified to measure the KPIs. The following variables are used:

**Traffic performance:**

- Vehicle speed $[m/s]$;
- Vehicle travel time $[s]$.
- Traffic flow $[vehicles/s]$;
- Traffic density $[vehicles/s]$;

**Traffic safety:**

- Number of critical time-to-collision measurements.

In this case, a time-to-collision ($TTC$) is considered critical whenever it is lower than the vehicle's response time. However, since automated features have no reaction time in this research, a value of 0.5 $s$ is considered the threshold. Literature shows that many different values can be chosen for this threshold (Miqdady et al., 2023). However, when the emergency brake and low reaction times are taken into account and the lowest headway parameters are set just above $0.5\,s$, this seems the most suitable threshold. The time-to-collision is calculated while taking the speed difference between the vehicle and its leader into account. It does not exist when the leader vehicle drives faster because a collision can only occur when the preceding vehicle approaches the leader vehicle. Thus, time-to-collision is determined as follows:

$$TTC = \frac{headway\ distance}{vehicle\ speed - leader\ vehicle\ speed} \tag{1}$$

The shown variables are not only used internally to measure KPIs but will also be presented in the analysis of simulation output. For this analysis, the variables will be expressed in different units since the internal units do not match commonly used units in real-world driving applications. For example, people are more likely to understand the magnitude of speed when it is expressed in $[km/h]$ rather than in $[m/s]$. Therefore, analytical graphs shown in Chapter 5 will display other units for these variables.

# 4 Vehicle models in OTS

As discussed in Chapter 3.1, SAE defines six levels of vehicle automation, from which four levels can be differentiated in freeway situations, and each level comes with its own characteristics. These characteristics are incorporated in driver behaviour models to bring the different levels of automation to the traffic simulation. This chapter will research which simulation packages are capable of modelling these different vehicle models in Chapter 4.1. How car-following and lane-changing behaviour models should be configured in Chapter 4.2 and 4.3. Furthermore, the mental model is discussed to see how driving task workloads affect human drivers in Chapter 4.4 and how distractions play a role in Chapter 4.5. Finally, Chapter 4.6 uses the insights gained from OpenTrafficSim (OTS) behaviour models to determine what parameter values are selected to represent the level 0, 1, 2, and 3 vehicles.

## 4.1 Software package for traffic simulation

The research reviewed in the literature review has been conducted with different software packages to run traffic flow simulations. The simulation package Vissim seems to be the most used software package for traffic simulations. Vissim is a commercial simulation software package but other researchers use open-source simulation packages such as SUMO, Aimsun or OTS.

All four packages are capable of microscopic traffic simulations. It is possible to build a road network and specify demand data, whether this is build in an integrated editor, in code or by the means of importing files. Also, various road users such as pedestrians or specific vehicle types can be defined in the simulation packages. For this research, the applicable differences between those packages lie in the availability of driving models.

Table 5 is constructed to provide a clear overview of the available models in Vissim (Zeidler et al., 2019 and Saifuzzaman and Zheng, 2014), SUMO (Barceló et al., 2010), Aimsun (Barceló et al., 2010 and Saifuzzaman and Zheng, 2014), and OTS (Schakel et al., 2010, Schakel et al., 2012 and van Lint and Calvert, 2018). Be aware that the driving behaviour is dependent on core driving models such as car-following and lane-changing models. However, OTS is unique among these packages in its inclusion of a mental model that simulates human cognitive processes. This model affects how perception is integrated into both car-following and lane-changing behaviours, enabling a more realistic representation of human driving behaviour.

Table 5: Overview of simulation package driving models.

| Simulation package | Driving behaviour models | Model features |
|---|---|---|
| Vissim | Car-following: Wiedemann 74 / 99 models | - Perception thresholds |
| | Lane-changing: Sparmann model | - Speed incentive |
| SUMO | Car-following: Krauss model | - Imperfect driving |
| | Lane-chaning: SUMO lane-changing model | - Route incentive |
| Aimsun | Car-following: Gipps model | - Desired speed<br>- Desired acceleration<br>- Reaction time |
| | Lane-changing: Gipps model | - Speed incentive<br>- Route incentive |
| OpenTrafficSim | Car-following: IDM+ | - Desired headway<br>- Desired speed<br>- Social pressure |
| | Lane-chaning: LMRS | - Speed incentive<br>- Route incentive<br>- Hindering incentive |
| | Mental model: Fuller | - Driver capability<br>- Dynamic reaction time<br>- Dynamic workload<br>- Car-following adaptations |

It is possible to extend the existing models in these packages and adjust various parameters or processes to achieve human driver or AV behaviour. However, this research is not aimed at the design of new frameworks, so a simulation package is chosen because of its out-of-the-box functionalities.

When considering human factors, OTS is the most suitable simulation package due to its mental model, which allows the simulation to differentiate vehicle models based on their autonomy. While autonomous vehicles are controlled by algorithms, human drivers rely on cognitive processes, which is incorporated by the mental model. This model manages the perception of the driver and adjusts its reaction time and car-following behaviour accordingly (van Lint and Calvert, 2018). Additionally, the car-following model simulates social pressure, enabling the simulation of tailgating, and the lane-changing model contains a social incentive. These social aspects further differentiate human drivers from automated driving controllers.

In comparison, Vissim accounts for human perception only through perception thresholds, lacking other cognitive factors that affect driving behaviour. Aimsun provides basic parameters like desired speed and acceleration factors, and SUMO introduces human factors solely by adding variability to the desired speed. Thus, OTS is preferred over

Vissim and SUMO and Aimsun do not include any human perception features, so neither are suitable for this research.

These considerations are fully aimed at the capability of simulating human drivers. However, this research also includes automated driving features to simulate level 1, 2 and 3 vehicles. As discussed earlier in this chapter, automated driving features will be modelled by adjusting existing driving models. Thus, when the parameters for the car-following and lane-changing models in OTS are adjusted for automation levels and the mental model does not affect their behaviour, also the level 1, 2 and 3 vehicles can be simulated in OTS.

## 4.2 Car-following model

In OTS, the car-following behaviour is based on the IDM+ model. The IDM+ model is designed by Schakel et al. (2010) to show realistic shock-wave patterns and to accommodate higher capacity levels than the original IDM model. The IDM+ model determines whether the vehicle is in a free traffic stream or following another vehicle. Based on this state, the model determines the appropriate acceleration according to input variables such as comfortable deceleration, maximum acceleration, acceleration flattening, and speed adherence. The logic from the IDM+ model is explained by Schakel et al. and is available in the OTS code. However, a block diagram in Figure 6 is created to provide a practical overview of the vehicle's decision-making regarding the car-following acceleration.

To account for interactions between level 0 and level 3 vehicles, headway settings are adjusted when a level 0 vehicle is positioned between level 3 vehicles. Therefore, the following and leading vehicles around a human driver are tracked. If both surrounding vehicles have level 3 automation, the human driver adjusts its minimum time headway parameter ($T_{min}$) to approach the time headway of a level 3 vehicle. This adjustment is made proportionally, based on the human driver's social speed sensitivity parameter ($socio$).

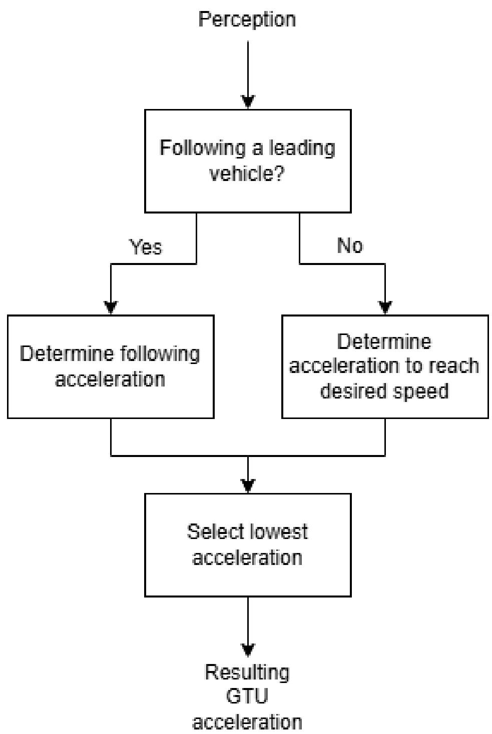


Figure 6: Block diagram of GTU acceleration selection by IDM+ model in OTS. Developed by the author.

## 4.3 Lane-changing model

Lane changes are managed by the LMRS model. The LMRS model is designed to accompany existing car-following models and shows realistic lane-changing decision-making (Schakel et al., 2012). To incorporate realistic lane change behaviour, LMRS does not only take lane change incentives into account but also accounts for the desire to change lanes. The model divides the desire to change lanes into four stages: no lane change, change lanes when free, match acceleration with the other lane to change lanes (synchronisation), and provide space for other vehicles to change lanes (cooperation). By accounting for different desires to change lanes, realistic lane-changing interactions appear within the simulation. In addition to the presented LMRS model by Schakel et al., a block diagram is created in Figure 7 to show the lane-changing process for the vehicle. This block diagram for the LMRS model is derived from both Schakel et al. and the OTS LMRS code.

The block diagram of the LMRS model shows that the lane change desire is based on the combination of the driver's perception and the intended route. These are required to determine which incentives are applicable and how much they contribute to the lane change desire. The following lane change incentives are included:

- **Route incentive:** Contribute to lane change desire based on the required lane changes to follow the intended driving route.
- **Speed incentive:** Contribute to lane change desire by considering gains in speed.

- **Lane-keeping incentive:** Contribute to lane change desire by compliance to freeway rules to keep right or left.
- **Socio-speed incentive:** Contribute to lane change desire based on hindering other traffic.

The route, speed and lane-keeping incentives will also apply for automated lane-changing since an AV controller will be designed to drive its route as best as possible and adhere to local laws. However, since AVs are not communicating, they have no understanding of the traffic conditions past their direct environment. Therefore, the socio-speed incentive will not be applicable as it is for human drivers who have a more complete perception to understand traffic conditions. The difference will be made by providing a social lane-changing sensitivity parameter for human drivers, while this sensitivity parameter will be zero for AVs.

Additionally, in interactions with level 0 and level 3 vehicles, aggressive human drivers will try to gain an advantage over the level 3 vehicles. Therefore, it is assumed that level 0 vehicles will have varying behaviour in lane-changing cooperation. To simulate this adaptation, the $D_{coop}$ threshold to start lane change cooperation is increased by the social lane-changing parameter ($socio_{lane}$). The social parameter is only added to the default $D_{coop}$ threshold when the cooperation is for a level 3 vehicle.

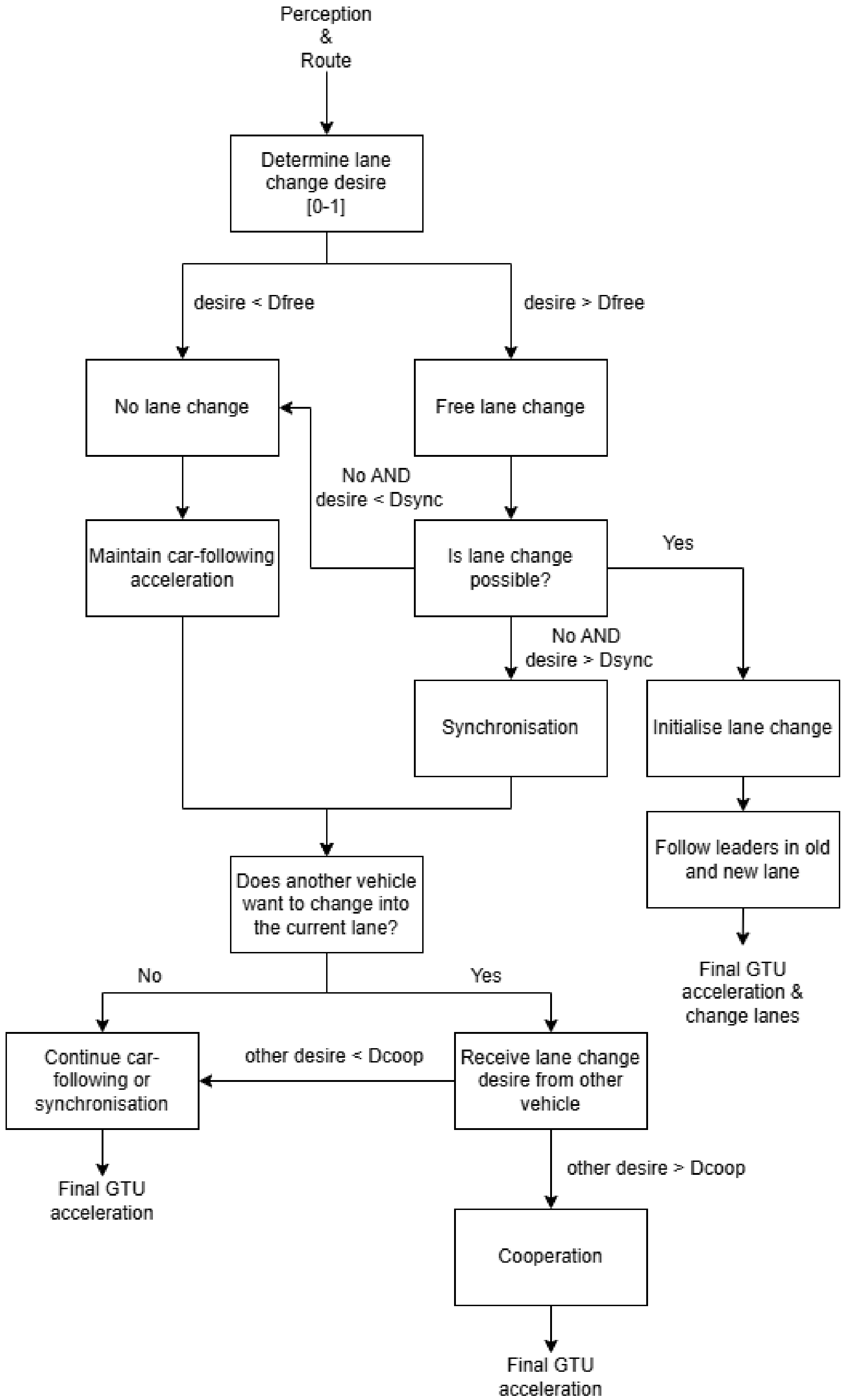


Figure 7: Block diagram of lane change decision-making by the LMRS model in OTS. Developed by the author.

## 4.4 Mental model

As can be seen in the block diagrams of both the IDM+ and LRMS models, perception is required to determine valid accelerations for the GTU and check whether lane changes are possible. This perception consists of multiple layers of perception to control what the GTU is capable of perceiving. To get an understanding of its environment the GTU uses DirectEgoPerception to keep track of its own dimensions, speed and acceleration, DirectInfrastructurePerception to perceive lanes and speed limits, DirectNeighborsPerception to account for surrounding vehicles, AnticipationTrafficPerception to anticipate the speed of surrounding vehicles, and DirectIntersectionPerception to perceive intersection conflicts. This information is stored to provide an understanding of the GTU's environment for the behavioural models.

In real life, it is the human driver who must perceive all this information while executing driving tasks. This creates a high mental workload, which can at times exceed the driver's capacity to process and respond effectively. Therefore, the Fuller model is applied to manage the balance between task demand and task capacity. This is a task-capability interface described by Fuller (2000), where the risk of driving contains two aspects: The difficulty of the driving tasks and the driver's competence in handling them. Whenever the difficulty exceeds the capability threshold of the driver, the driver is not in control and becomes a risk for other road users who have to compensate by adjusting their behaviour to avoid collisions.

Fuller tracks the task demand of driving and determines how much the task capacity is saturated. Whenever the task capacity is critically saturated, the workload of the driving tasks becomes uncomfortable for the driver, so the driver will adjust its headway and speed to lower the workload of the driving tasks. Additionally, task saturation influences the situational awareness of the human driver and thus increases its reaction time, meaning that the GTU will receive a less up-to-date perception. How much the reaction time is increased is dependent on the current task saturation $TS$ and the critical task saturation $TS_{critical}$. These relations are described by van Lint and Calvert (2018) and show how this is implemented in OTS. Again, a block diagram of the Fuller model is presented in Figure 8 to clarify its process, which is derived from the Fuller and task manager code available in OTS.

An implementation of driver distraction is added to the task-capability interface to account for increased workloads whenever drivers get distracted. This is an addition to the original Fuller design, highlighted red in Figure 8, and adopts van Lint and Calvert (2018) their framework of increased task saturations because of driver distractions. Chapter 4.5 explains how this distraction is handled within the Fuller model.

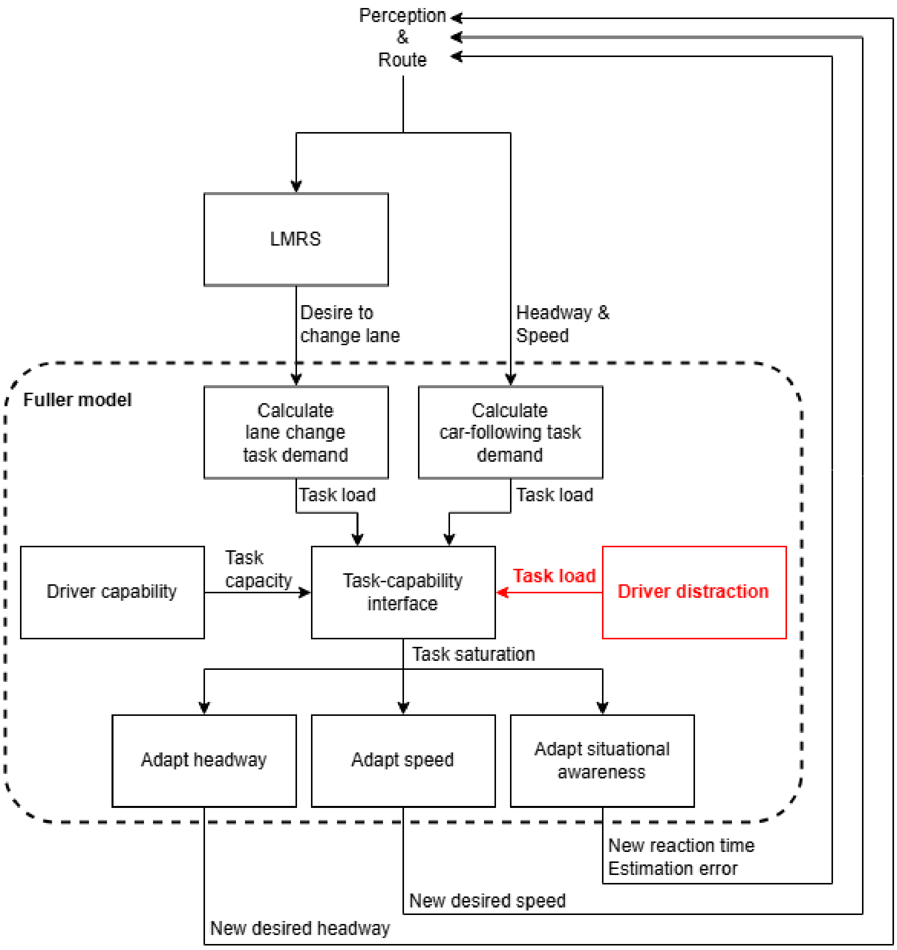


Figure 8: Block diagram of Fuller model in OTS. Developed by the author.

The task load of driving tasks is not present, or only limited, for automated driving tasks. This means that an automation level 1 vehicle will have no task load for car-following, and no task load is present for car-following and lane-changing from level 2 onwards. This is because the capability of automated features is assumed to be high enough to never lose control. An AV has sensors that will always perceive its surroundings in the same way, and no psychological processes will alter the AV's decision-making.

On the other hand, level 0 and level 1 vehicles not only deal with their driving tasks but also engage with the in-car ADAS. Research seems to show that ADAS could cause both an increase or decrease in workload depending on the situation. Ruscio et al. (2017) and Birrell and Young (2011) show through simulator tests that ADAS will help to improve the driver's performance. This is confirmed in a real-life scenario where police officers showed better driving performance while using ADAS in normal circumstances. However, ADAS did not provide the same gains in more complex situations. Also Ruscio et al. finds that outside predictable situations ADAS can increase cognitive workload, especially for incorrect warnings. In these cases, they see that the additional stimuli do increase the cognitive workload of the driver. Because ADAS has in general a positive effect on the driver's performance, no additional task loads are introduced for the presence of ADAS in the vehicle models. Additional task loads will only deteriorate the situational awareness of drivers, which does not match the general use of ADAS.

Despite the benefits of ADAS, Strayer (2015) shows that voice-based in-car prompts are related to high cognitive loads.

## 4.5 Distraction

As described in the methodology, the freeway scenario with vehicle automation levels also runs for distraction scenarios. Unlike automated driving tasks, human drivers experience a cognitive workload while driving. While the utilisation of the Fuller model is already discussed, only the workload of car-following and lane-changing is accounted for. These are not the only activities that influence the human driver's cognitive workload. Often human drivers are distracted by in-vehicle or external factors. Examples of these distraction factors can vary from navigation prompts and mobile phone usage to a crashed car on the side of the road. Both in-vehicle and external distractions affect the driver's situational awareness (Bamney et al., 2022 and Divekar et al., 2012). Therefore, both of these distractions are included in this research.

Varying numbers are found on secondary task engagement. Sagberg et al. (2019) utilise both on-road observations and roadside interviews to estimate the prevalence of secondary tasks. Their research indicates that self-reported engagement in secondary tasks in the interviews is higher than the observed engagement on the motorway. However, they think that participants were likely overestimating the duration of secondary tasks. For example, participants reported driving time for passenger interaction, while their actual interaction time would be lower. Also, the interview included mental states that could not be observed in the on-road observations. Combining the findings of observations and interviews, they find that 24% of driving time involves secondary task engagement. the most secondary task was talking on the phone, both handheld and hands-free, followed by eating and drinking, and passenger interaction. When Metz et al. (2014) analysed naturalistic driving data of in-vehicle recordings, similar results were found. The combination of video recordings and vehicle data shows that drivers without passengers spend around 25% on secondary tasks. Most of the time was spent talking on the phone, followed by vehicle console inputs and handling the mobile phone. However, because of video recordings, Metz et al. can analyse passenger interactions more precisely. With passengers, drivers spent 40% of their driving time in secondary tasks, of which 35% of driving time is spent on passenger interactions and 5% on other secondary tasks. The presence of a passenger decreases the variability of secondary tasks and could even be beneficial for the driver's attentiveness because passengers can take over certain secondary tasks.

Because passengers seem to have different effects on driver attentiveness, this research does not include passenger support or distraction. So, secondary task data without passengers is considered. From this, it is assumed that 25% of the vehicles in the simulation are distracted. While most secondary tasks take less than 10 seconds, handling a phone has a significantly longer duration (Metz et al., 2014). In this simulation, it is interesting to see how varying in-vehicle distractions influence driving behaviour. Thus, the duration of secondary tasks is set to 10 seconds to account for both short and longer distractions. To prevent that more than 25% of the vehicles will be distracted for a simulation time step, the activation formula for the distraction will account for the fraction of distracted vehicles, the task duration, and the time step. By dividing the fraction of distracted vehicles by the task duration, and dividing the task duration by the time step, a suitable threshold is created to ensure that only 25% of the vehicles will be distracted at once, even when vehicles evaluate at each time step for the potential to become distracted, after which they remain distracted for the duration of the task. This results in the following activation formula for in-vehicle distractions:

$$distraction_{state} = \left[ Random(0,1) \leq \left( \frac{distraction_{fraction}}{task_{duration}/dt} \right) \right] \tag{2}$$

Where $distraction_{state}$ is the boolean indicating whether a driver is distracted by in-vehicle distractions, $distraction_{fraction}$ is the fraction that represents the percentage of distracted drivers, $task_{duration}$ the duration of the distraction, and $dt$ the time step that the GTU uses in the simulation.

The workload of secondary tasks can be measured with various methods. Tarabay and Abou-Zeid (2018) use physiological indices such as heart rate and skin conductance level because these are objective measurements linked to mental workload. While the study shows increased measurements for drivers involved in secondary tasks and that drivers will mitigate higher cognitive loads by adapting their driving behaviour, no workload value can be determined from these measurements. Also, analysing brain activity does not identify a specific quantification for secondary task workload (Xu et al., 2017).

Since estimating the cognitive workload itself is difficult, the impact on driver performance is assessed. Research shows that driver performance is highly affected by higher workloads. For example, Collet et al. (2009) show that reaction times can increase by 20% due to secondary tasks. For external distractions, researchers analyse human gaze directions to indicate driver attentiveness to the road. Divekar et al. (2012) find that both novice and experienced drivers take long glances towards external distractions at the expense of the ability to identify road hazards. This shows that the situational awareness of drivers decreases when they are distracted by external stimuli. Results from Divekar et al. show that drivers recognise moving hazards poorly while being distracted by a roadside object. Therefore, a driver is considered distracted by roadside distractions as long as the distraction is in their perception range.

A driver distraction occurs when a portion of the driver's attention is diverted to non-primary driving tasks. Since research shows that driving performance deteriorates while the driver is distracted, the reduced mental capacity limits the driver to perform primary driving tasks. In OTS, situational awareness deteriorates whenever the workload is larger than the critical task saturation of the driver. Therefore, whenever a human driver is distracted by either an in-vehicle (secondary driving task) distraction or a static roadside distraction, the distraction will add a task demand to the Fuller model to exceed the critical task saturation. The formula in Equation 3 is used to determine the distraction task demand. To always exceed the critical task saturation, the formula ensures that the distraction task demand is 1.1 times the remaining non-critical task capacity (critical task saturation minus current task saturation). The chosen value of 1.1 is an assumption and only ensures that the threshold of the critical task saturation is exceeded. Adjusting this value by increasing or decreasing the value will affect the deterioration of situational awareness because of the higher or lower total driving workload. However, since no quantitative studies are available for distraction levels in traffic, the amount of situational awareness deterioration is still unknown and thus can only be assumed. Additionally, a distraction cannot lower the driver's driving workload when the current car-following and lane-changing task saturation already exceeds the critical task saturation. So, the distraction task demand will always have a minimum value of 0.

$$distraction\,task\,demand = Max\big[0,\ (TS_{critical} - TS) * 1.1\big] \tag{3}$$

Where $TS_{critical}$ is the critical task saturation and $TS$ is the current task saturation.

## 4.6 Vehicle model parameters

Here, the parameters are presented that are used to configure the driving models. However, code modifications were required to enable different vehicle interactions between automation levels and control model parameters. Therefore, Appendix I: Modified OTS classes explains which classes are modified. The OTS vehicle models can now be configured using multiple parameters. Appendix II: Vehicle model parameters discusses these parameters and substantiates why certain values are chosen. An overview of all parameter values is presented in Table 6.

Some values are based on a range of values, such as the speed adherence factor. This means that a triangular distribution is used to vary the value given to each vehicle in the simulation. The bounded triangular distributions are preferred over normal distributions because some model parameters must be between specific ranges to prevent simulation errors. The triangular distribution will be defined as follows:
$TriangularDist(lower\,value,\ mean,\ highest\,value)$.

Table 6: Parameter values for GTU behavioural models.

| Parameter | Symbol | Level 0 | Level 1 | Level 2 | Level 3 | Units |
|---|---|---|---|---|---|---|
| Minimum reaction time | $RT_{min}$ | 0.17 | 0.0 | 0.0 | 0.0 | s |
| Maximum reaction time | $RT_{max}$ | 2.0 | 0.0 | 0.0 | 0.0 | s |
| Look-ahead | $lookahead$ | 295.0 | 140.0 | 250.0 | 300.0 | $m$ |
| Look-back | $lookback$ | 200.0 | 200.0 | 200.0 | 200.0 | $m$ |
| **IDM+ specific parameters** | | | | | | |
| Minimal headway time | $T_{min}$ | 0.58 | 0.8 | 0.8 | 0.522 | $s$ |
| Maximum headway time | $T_{max}$ | 1.84 | 1.5 | 1.5 | 1.104 | $s$ |
| Maximum desired car-following acceleration | $a$ | 1.25 | 1.17 | 1.17 | 1.12 | $m/s^2$ |
| Maximum comfortable car-following deceleration | $b$ | 2.09 | 1.95 | 1.95 | 1.87 | $m/s^2$ |
| Maximum critical deceleration | $b_{crit}$ | 3.5 | 3.5 | 3.5 | 3.5 | $m/s^2$ |
| Maximum adjustment deceleration | $b_0$ | 0.5 | 0.5 | 0.5 | 0.5 | $m/s^2$ |
| Speed adherence factor | $f_{speed}$ | (0.8 - 1.2) | (0.9 - 1.1) | (0.9 - 1.1) | (0.95 - 1.05) | - |
| Socio-car-following sensitivity | $socio_{cf}$ | (0.0 - 1.0) | 0.0 | 0.0 | 0.0 | - |
| **LMRS specific parameters** | | | | | | |
| Socio-speed sensitivity | $socio$ | (0.0 - 1.0) | (0.0 - 1.0) | 0.0 | 0.0 | - |
| Anticipation speed for full desire | $v_{gain}$ | 69.6 | 69.6 | 69.6 | 69.6 | $km/h$ |
| **Fuller specific parameters** | | | | | | |
| Task capacity | $TC$ | (0.9 - 1.1) | N/A | N/A | N/A | - |
| Critical task saturation | $TS_{critical}$ | 0.8 | N/A | N/A | N/A | - |

# 5 Simulation results

The created OTS simulation runs for the road setup and scenarios discussed in Chapter 3. Before discussing the simulation results, some preliminary analyses are discussed in Chapter 5.1 to explain traffic demand parameters and the chosen simulation warm-up and sampling time. These settings are used to run the traffic simulation. Vehicle behaviour from the automation levels is discussed in Chapter 5.2. Then, Chapter 5.3 will discuss the results regarding traffic performance and safety, and Chapter 5.4 will look at the effects of roadside distractions.

## 5.1 Simulation setup

The base scenario, scenario 0 which contains 100% level-0 vehicles, is analysed first to determine the traffic demand for the main road and the on-ramp. This scenario is chosen because the successive scenarios of increased automation will be compared to the human-only scenario to observe what effects the automation levels have on traffic. Analysis of the main road and on-ramp traffic demand in Appendix III: Exploratory analysis shows that the following simulation settings are used to simulate traffic states near the critical traffic density:

- Main road demand: 2800 - 4000 veh/h;
- On-ramp demand: 200 - 450 veh/h.

Furthermore, a warm-up time is specified to ensure that data will only be collected when the simulation is in a quasi-stable state. When the simulation starts, the first generated GTUs will have no leader vehicles, which means that the start of the simulation does not represent the near-critical traffic density scenario. The simulation will not reach a truly stable state due to the chaotic nature of traffic dynamics and frequent disruptions from the on-ramp. Also, vehicles generated on the on-ramp need some time to reach the merge area. Gurupackiam et al. (2011) use the stabilisation of simulation output variables such as road capacity, flow, and travel time to determine when the simulation has reached its stable state. This method is also applied in Appendix III: Exploratory analysis. The analysis shows that a warm-up time of 500 seconds is required.

After the warm-up time, data is sampled for 1200 seconds. The exploratory analysis shows that most vehicles travel through the freeway network in less than 100 seconds. However, congestion highly affects this travel time and these dynamics should be included to analyse whether higher automation levels have different capabilities to prevent this heavy congestion. To include vehicles with longer travel times, the sample time is based on three times a travel time of 400 seconds.

## 5.2 Vehicle behaviour

Vehicle behaviour is analysed by assessing overall driving indicators from Chapter 3.2. Appendix V: Simulation of pure scenarios shows that separate simulations with 100%

penetration rates per automation level show very different traffic conditions. Level 1 and level 2 vehicles are prone to congestion. The traffic conditions for these scenarios become congested very fast and vehicles show low mean speed measurements for a large amount of the simulation. Level 0 and level 3 vehicles are more capable of dealing with disruptions from the on-ramp and are able to maintain higher speeds throughout the simulations. However, because of these differences, these "pure" scenarios cannot be used to compare driving behaviour.

As a result, a scenario is simulated for 25% of each automation level (scenario 8). This will ensure that the measured data is sampled within the same traffic conditions for all automation levels. The observations are discussed in this chapter. First, the driving behaviour is observed as discussed in Chapter 3.2. Also, the effects of the introduced human adaptation toward level 3 vehicles are discussed.

### 5.2.1 Overall driving behaviour

Figure 9 shows how speed levels differ between levels within the same traffic conditions in scenario 25-25-25-25. As the figure shows, the automation levels seem to have a similar speed distribution. However, level 1 and level 2 vehicles have the highest frequency for low-speed measurements between 0 and 5 $km/h$.

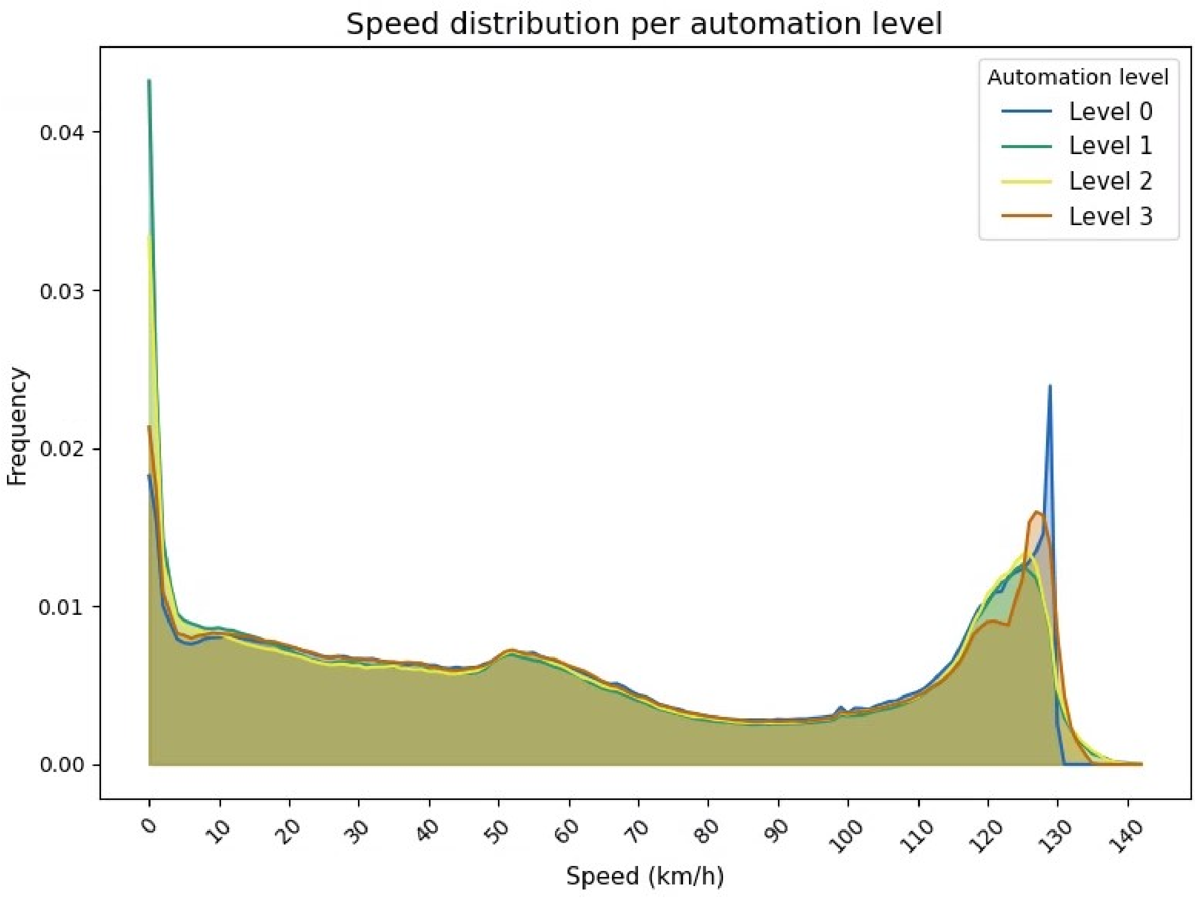


Figure 9: Speed distribution for automation levels in scenario 25-25-25-25.

Very small differences in acceleration are seen between the levels. Figure 10 depicts a boxplot for acceleration without outliers measured in the simulation runs from scenario 25-25-25-25. The simulation shows many outliers regarding acceleration since low speeds cause high decelerations when the vehicle comes to a stop. However, the simulation also contains vehicles at higher speeds with very high decelerations. These are enabled to simulate the use of the emergency braking system that is present in all automation levels. However, these outliers do not reflect the acceleration behaviour of the vehicle level. Therefore, the outliers are excluded. The boxplots show that variation indeed becomes smaller when car-following is automated. However, this difference is small and no significant decrease in variability is seen from level 2 to level 3 vehicles.

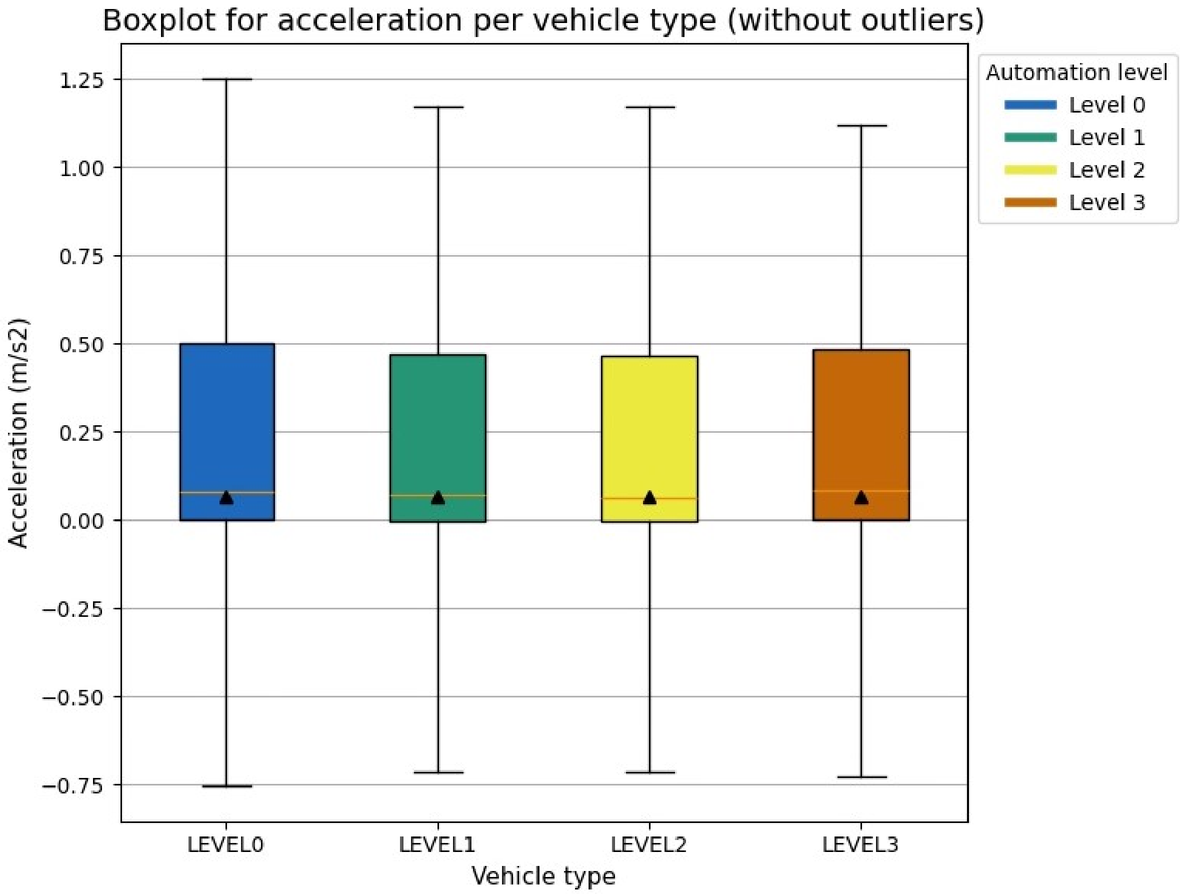


Figure 10: Acceleration boxplot for automation levels in scenario 25-25-25-25.

Vehicle headway data is also analysed for scenario 25-25-25-25. To observe the differences in time headway during car-following, only headway values under four seconds are included. This is done to prevent high headways, where the vehicle is not performing any car-following, to interfere with the actual car-following behaviour. As Figure 11 shows, human drivers in level 0 vehicles maintain the lowest time headway. Level 1 and level 2 vehicles show a significantly higher time headway which corresponds to their ADAS functionality.

Level 3 vehicles do show a lower time headway which corresponds to the assumption that level 3 vehicles are capable of maintaining shorter headways because of technological advancements over level 2 vehicles. However, the maximum time headway parameter for level 3 vehicles was also lower than for level 0 vehicles. Still, more larger headway times are observed for level 3 vehicles than level 0 vehicles. This could be explained by the smaller acceleration range. Figure 10 did show that differences were small but these differences can be enough to limit level 3 vehicles from following leader vehicles more closely.

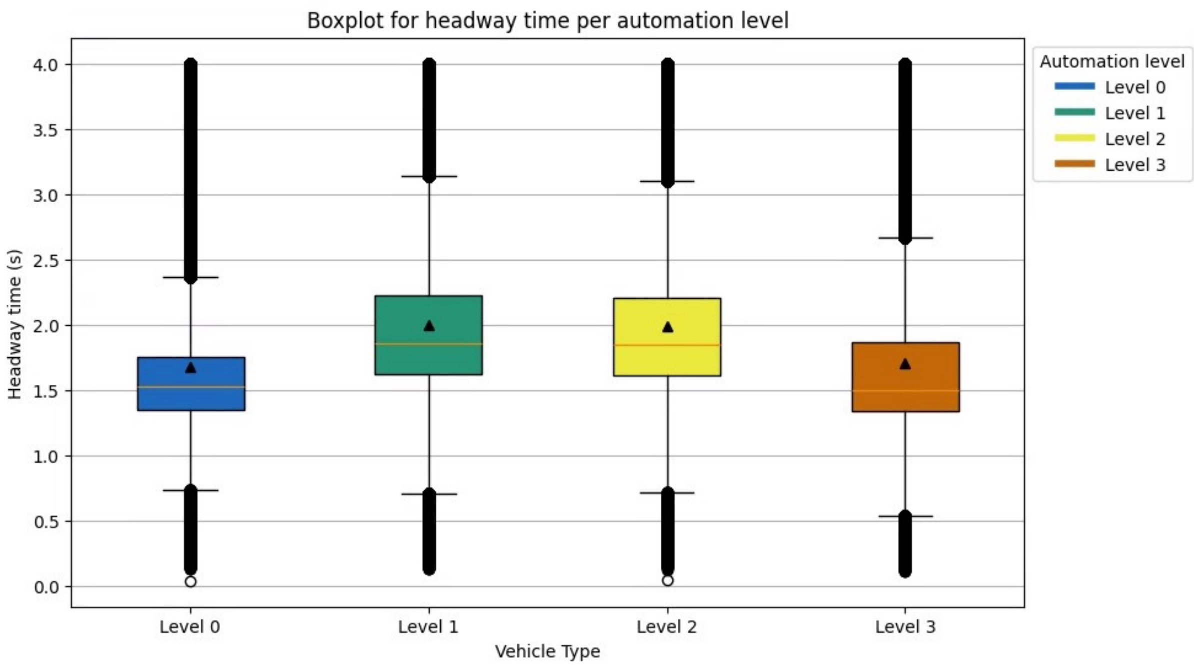


Figure 11: Headway boxplot for automation levels in scenario 25-25-25-25.

The larger headway observed for level 1 and level 2 vehicles does not mean that other vehicles gain from these gaps and merge more easily. Figure 12 shows that level 1 vehicles are subject to many switches in their leader vehicle, while the other levels have approximately the same number of leader switches per hour. So, the magnitude of time headway does not necessarily lead to more vehicles taking advantage of this gap.

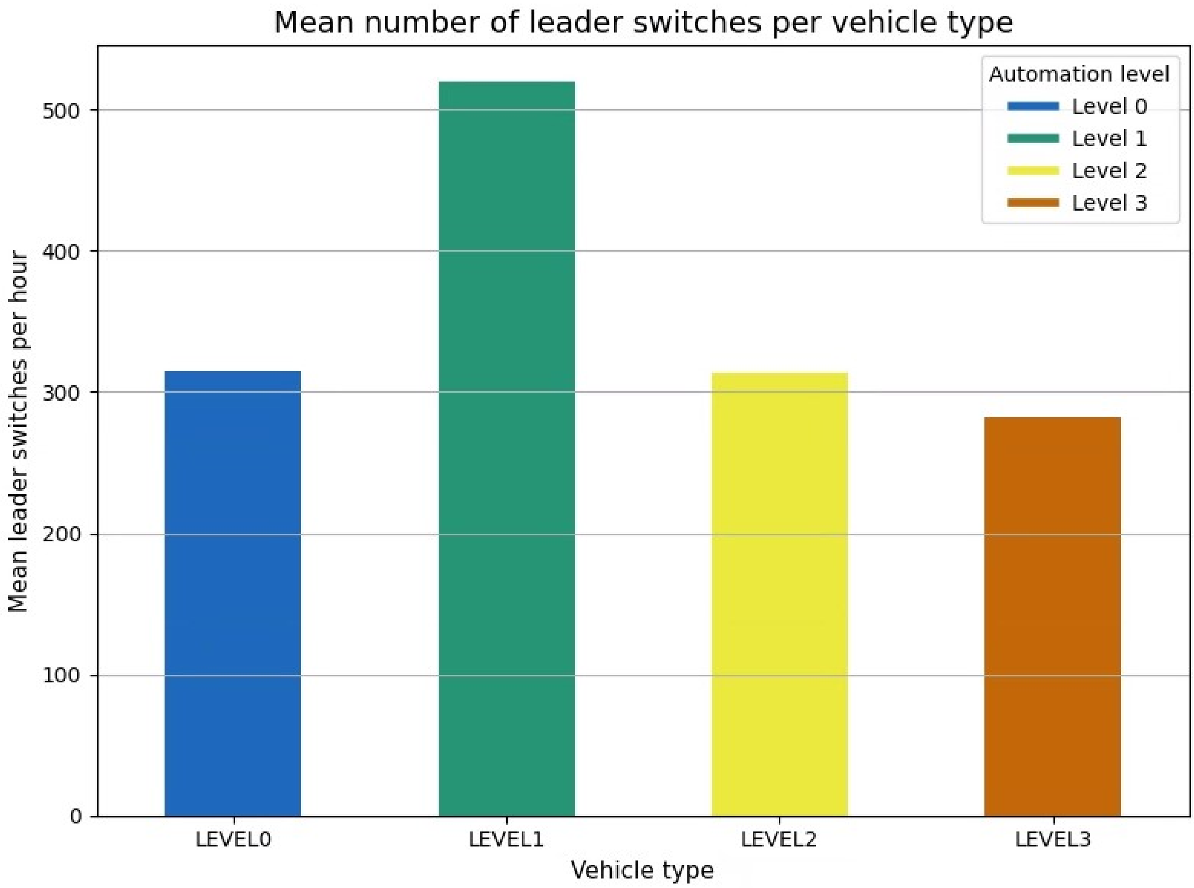


Figure 12: Switches in leader vehicles for automation levels in scenario 25-25-25-25.

The large number of leader vehicle switches for level 1 vehicles can be explained by its lane-changing behaviour. A switch in the leader vehicle is also detected when the vehicle itself performs a lane change. Figure 13 shows that level 1 vehicles have many lane changes before the on-ramp and the most lane changes at the merging area. These are the road sections with the most lane changes and thus explain why level 1 vehicles have much more leader switches than level 2 vehicles while they have similar headway distances.

Furthermore, simulation of scenario 25-25-25-25 identifies different lane change behaviour for the automation levels. Because lane-changing is automated for level 2 and level 3 vehicles and not for level 0 and level 1, it is expected that these vehicle levels show similar lane-changing behaviour. However, large differences are seen for level 0 and level 1 at sections AB and BC. These differences are hard to explain since level 0 and level 1 vehicles share the same lane-changing incentives and level 1 and level 2 vehicles have the same car-following settings. Also, level 1, level 2, and level 3 vehicles have the same reaction time.

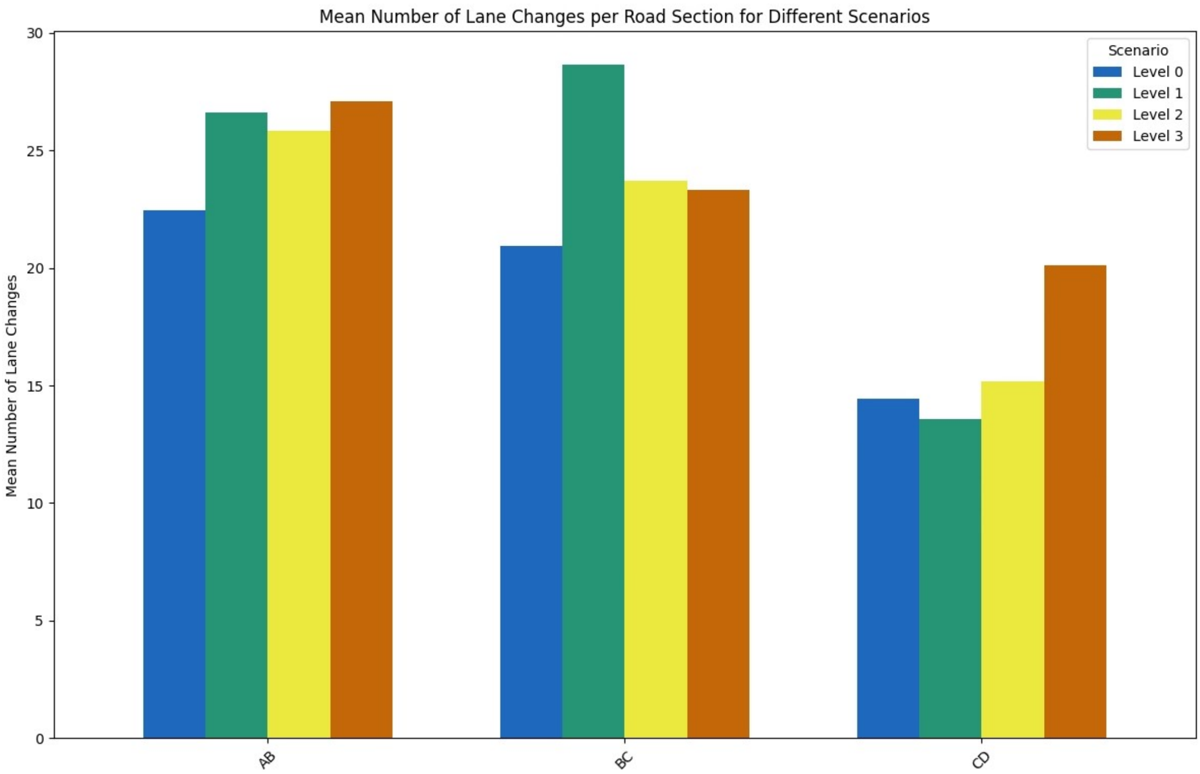


Figure 13: Lane changes per freeway section in scenario 25-25-25-25.

When analysing the headway during these lane changes, Figure 14 shows that car-following behaviour during a lane change is significantly different between vehicles. It shows that vehicles will accelerate during their lane-changing manoeuvre because the headway distance increases but the time headway decreases. Especially, level 3 vehicles stand out because the time headway increases a lot during the lane change manoeuvre.

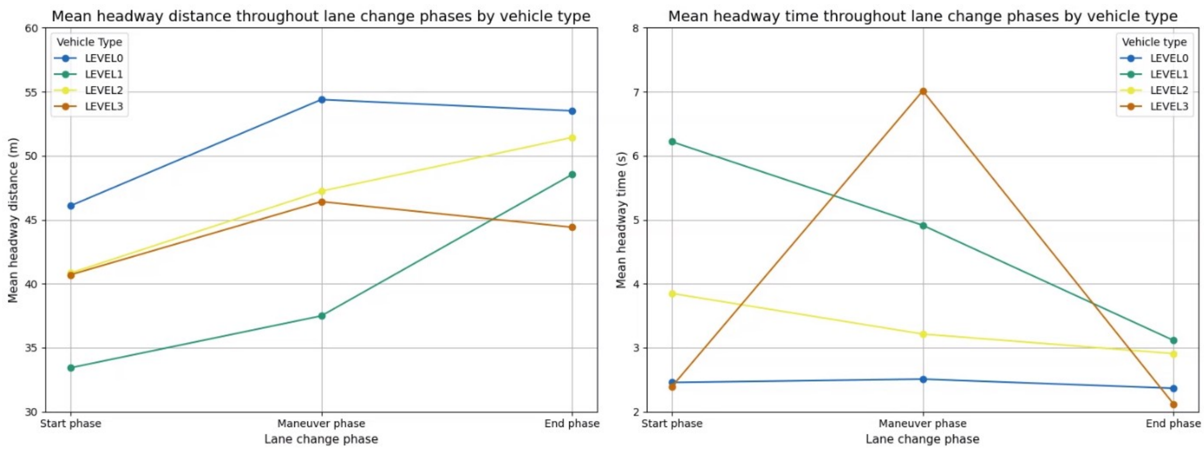


Figure 14: Headway during the lane change process in scenario 25-25-25-25.

Level 0 vehicles have a stable time headway during their lane changes. The larger range in comfortable car-following acceleration allows the vehicle to follow leader vehicles more strictly even during lane changes. Level 1 vehicles seem to speed up the most during their lane change. It is noticeable that level 1 vehicles have the lowest mean headway distance during lane changes, which can indicate that level 1 vehicles perform more lane changes because the vehicle can significantly increase its speed in the other lane. However, this behaviour is not seen for level 0, which shows that level 3 vehicles end up in significantly different interactions. Level 2 vehicles show lane change behaviour that is similar to level 0 vehicles but has a less stable time headway. Level 3 vehicles show a very different time headway progress during a lane change. The mean time headway during the lane change is much higher but at the end of the lane change the time headway is approximately back to the time headway of the start of the manoeuvre. This shows that the smaller car-following acceleration range limits the ability to keep a certain time headway during the lane change manoeuvre.

### 5.2.2 Human adaptations

Modifications to perception, explained in Appendix I: Modified OTS classes, enable level 0 vehicles to adjust driving behaviour for road interactions with level 3 vehicles. To analyse this, a scenario is simulated for 50% level 0 and 50% level 3 vehicles.

The data is split into groups of level 0 vehicles that are located between level 3 vehicles and the rest of level 0 vehicles. Analysis on their headway in Figure 15, shows that the temporary decrease in minimum car-following time headway does not result in an actual decrease in the effective time headway.

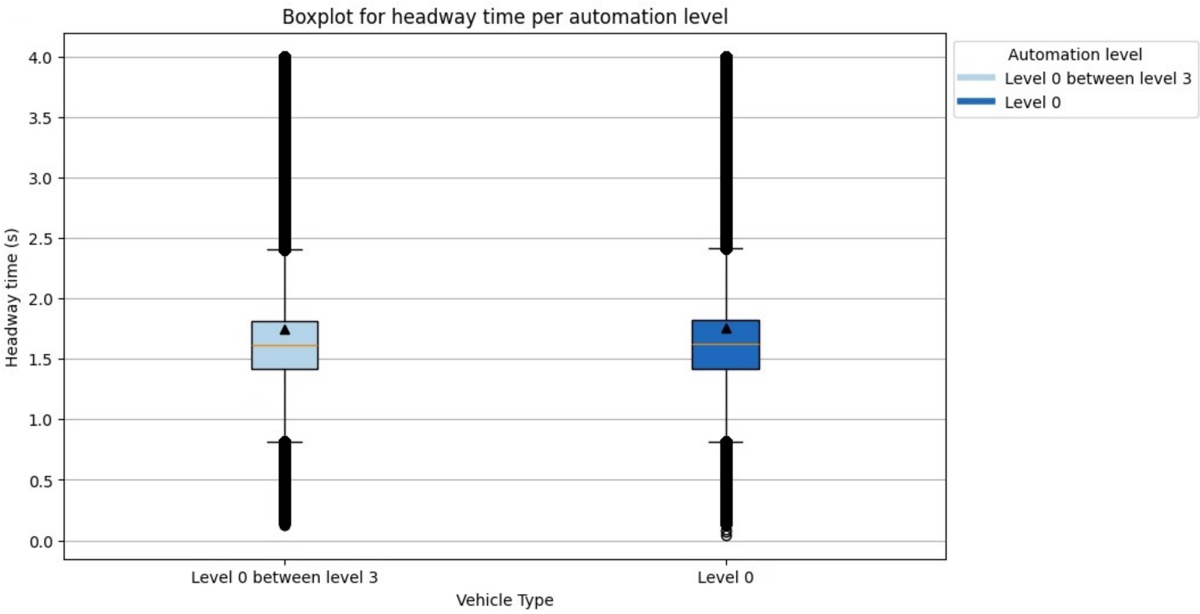


Figure 15: Headway distribution of level 0 vehicles with and without adaptations toward level 3 vehicles in scenario 50-0-0-50.

Analysis of lane-changing data shows no differences in the number of lane changes. Figure 16 shows that in the scenario of 50% level 0 and 50% level 3 vehicles, level 3 vehicles perform more lane changes than in a scenario of 100% level 3 vehicles. Therefore, the human adaptations of performing less cooperation towards level 3 vehicles do not necessarily prevent level 3 vehicles from changing lanes.

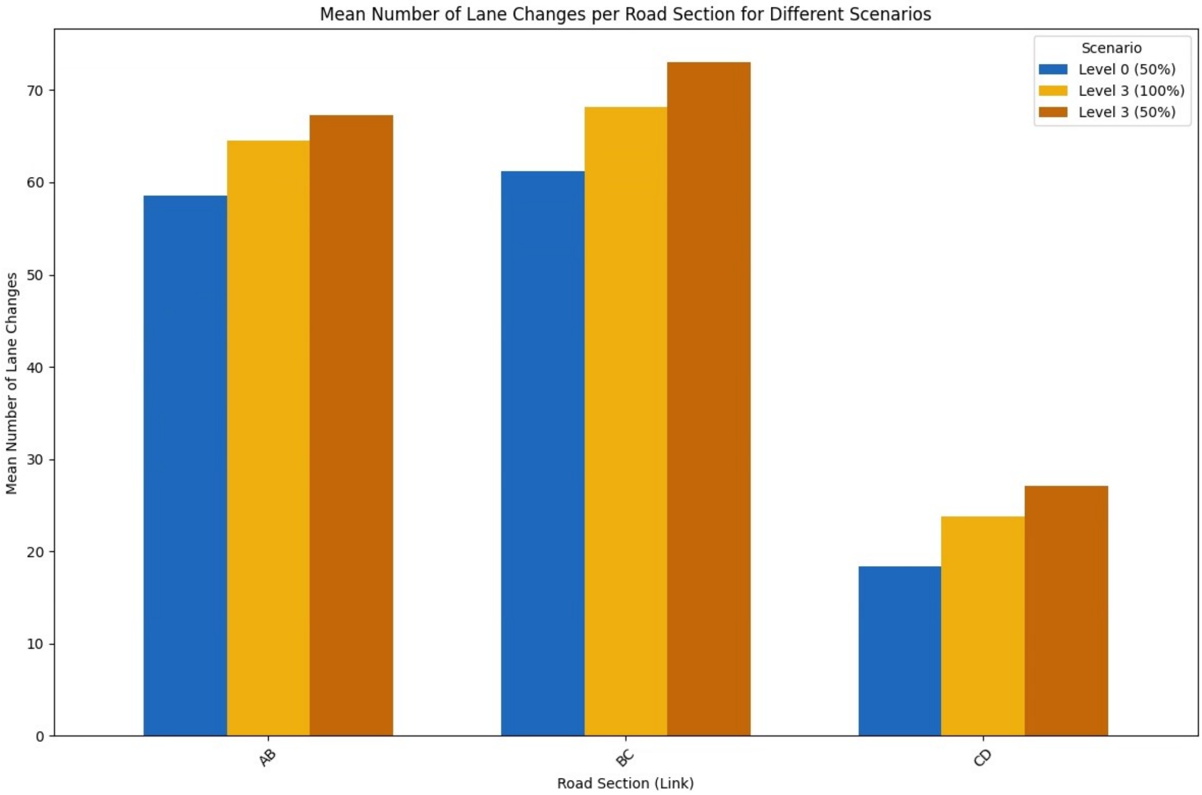


Figure 16: Comparison of lane changes for human adaptations towards level 3 vehicles in scenario 50-0-0-50 compared to scenario 0-0-0-100.

Figure 17 does show that the behaviour during lane changes is different between scenario 50-0-0-50 and scenario 0-0-0-100. Level 3 vehicles experience a lower headway while interacting with level 0 vehicles. Also, level 3 vehicles have to increase the headway time during the lane change, while this is not required when level 3 vehicles change lanes among themselves.

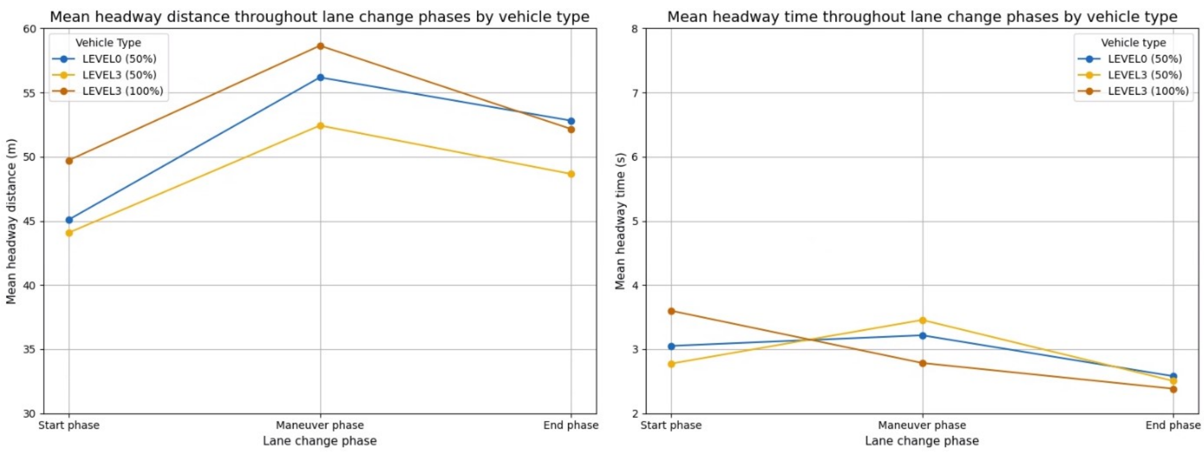


Figure 17: Comparison of headway during lane changes for human adaptations towards level 3 vehicles in scenario 50-0-0-50 compared to scenario 0-0-0-100.

These findings show that the introduced headway adaptation does not result in a lower headway for level 0 vehicles. However, because of human adaptations that increase the cooperation threshold for lane-changing, level 3 vehicles have to perform lane-change manoeuvres with a lower headway and have to increase the time headway during their manoeuvre. Indicating that the lack of cooperation from level 0 vehicles does provide less space for lane changes.

### 5.2.3 Summary of driving behaviour

The different parameter values for time headway and acceleration ranges indeed lead to different driving behaviour. Level 0 vehicles can maintain a small time headway during both car-following and lane-changing, however, this does come with a higher variation in measured accelerations. Level 1 vehicles keep a larger headway and have a slightly lower variation in acceleration. Level 1 vehicles stand out because of the many lane changes in mixed traffic. The changes in headway distance and time during the lane change indicate that level 1 vehicles have much speed to gain when changing lanes. Level 2 vehicles keep the same time headway as level 1 vehicles but do not change lanes as much. Level 3 vehicles show a lower variation in acceleration and their time headway is similar to that of level 0 vehicles. However, the smaller range in acceleration causes the level 3 vehicle to also keep a higher time headway. This also causes a higher mean time headway during lane change manoeuvres. This higher mean time headway is not present in lane change interactions with level 0 vehicles. The human adaptations towards level 3 vehicles cause a lower time headway for level 3 vehicles during lane changes. Also, the mixed traffic scenario with 50% level 0 and 50% level 3 vehicles, had higher mean speed. So, the difficulty of maintaining a short time headway is more difficult at lower speed levels seen in the scenario of 25% penetration rates for all automation levels. Another human adaptation, the temporary lower time headway while the level 0 vehicle is in between level 3 vehicles, is not effective in the simulation. No differences in measured time headway are seen for these level 0 vehicles.

## 5.3 Traffic performance and safety

A thorough analysis is performed in Appendix VI: Analysis of traffic performance and safety to identify the impact of vehicle automation levels on traffic performance and safety. This chapter will present and support the main findings by including speed level, fundamental diagram, and critical time-to-collision comparisons between scenarios.

### 5.3.1 Mean speed levels on the freeway

Figure 18 shows the transition in speed levels on the freeway throughout the simulation of different scenarios. The speed heatmap shows that vehicles decelerate before and in the on-ramp section (BC) and then accelerate again to reach speed levels of more than 100 $km/h$ in the post-on-ramp section (CD). The figure clearly shows that the introduction of level 1 vehicles for scenario 80-20-0-0 shifts the acceleration in the on-ramp section downstream. This indicates that the higher time headway settings for level 1 vehicles and the increased number of lane changes do make merging more difficult. So, vehicles have to maintain a lower speed level for longer.

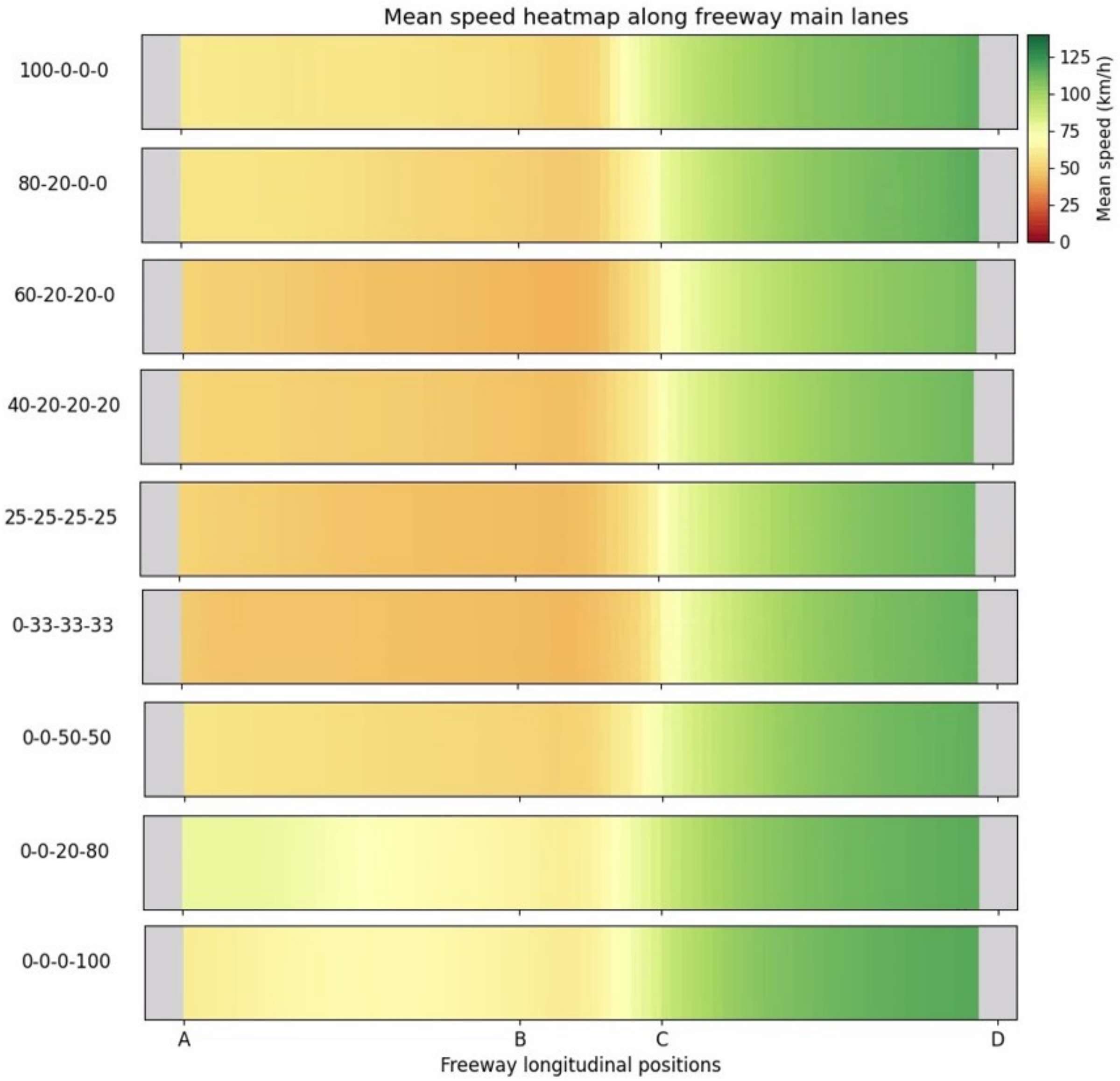


Figure 18: Comparison of speed levels along the freeway for all penetration rate scenarios.

The introduction of level 2 vehicles further increases automation on the freeway. Speed levels see a significant drop in scenario 60-20-20-0 compared to scenario 80-20-0-0. The fraction of human drivers that maintain a smaller headway relative to level 1 and 2 vehicles reduces to 60% which means that merging becomes even more difficult. The position of acceleration on the freeway does not change.

The speed heatmap does not identify significant changes from scenario 60-20-20-0 to scenario 0-33-33-33. The acceleration position remains the same. Only slightly higher speed levels are seen for scenarios 40-20-20-20 and 25-25-25-25 which can be explained by the sum of level 0 and level 3 vehicles. Level 0 and level 3 vehicles are both capable of maintaining smaller headways. So when their penetration rate together is high, the speed at which vehicles merge increases. This is also observed when scenario 0-0-20-80 is compared to scenario 0-0-50-50, where the increase in level 3 vehicles significantly increases speed levels.

Whenever 80% of the vehicles are level 3, the mean speed on the freeway increases significantly. Speed levels remain above 75 $km/h$ before the merge area (AB) while previous scenarios could not achieve this. Also, the acceleration position on the on-ramp section (BC) shifts upstream showing that vehicles are capable of merging earlier and start accelerating. The high speed levels in the pre-on-ramp section (AB) do drop a little when the scenario has 100% level 3 vehicles. However, this does not change the position of acceleration.

### 5.3.2 Fundamental diagrams of the freeway

Appendix VI: Analysis of traffic performance and safety shows that vehicle automation affects the disruption in traffic flow at the on-ramp section (BC). Differences are also observed for the other freeway sections, however, these are caused by the disruption in the on-ramp section. Therefore, the fundamental diagrams of only the freeway section BC are presented in this chapter. Figure 19 shows how the introduction of automation levels impacts the maximum traffic flow measured on the freeway for scenarios 100-0-0-0, 80-20-0-0, 60-20-20-0, 40-20-20-20, and 25-25-25-25.

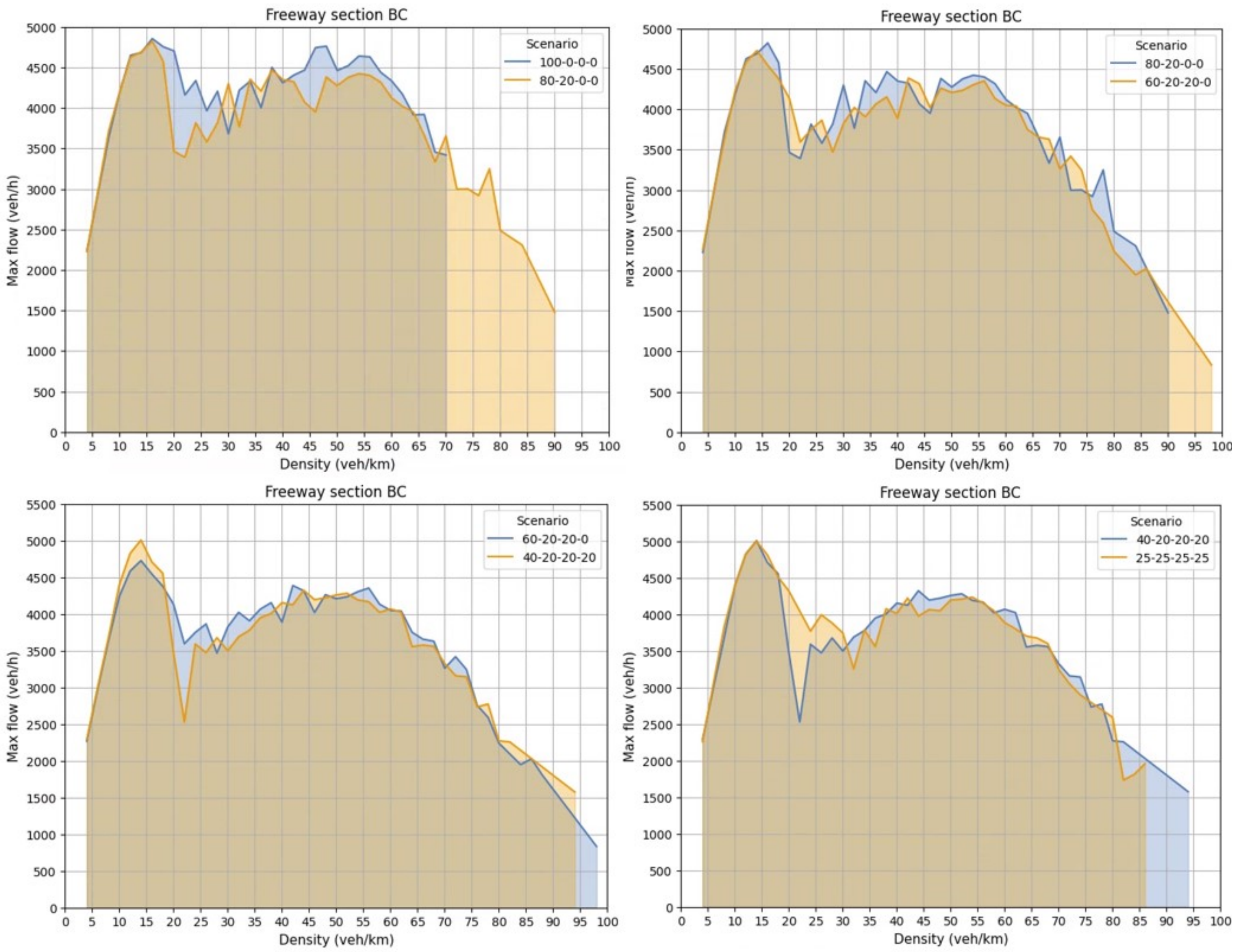


Figure 19: Comparison of fundamental diagrams for freeway section BC for scenarios 100-0-0-0, 80-20-0-0, 60-20-20-0, 40-20-20-20, and 25-25-25-25.

The introduction of 20% level 1 vehicles lowers the maximum traffic flow from 4856 to 4823$veh/h$. Also, the drop in traffic flow after reaching the maximum value increases. For scenario 100-0-0-0 a drop in flow is observed of 24.2%, while scenario 80-20-0-0 has a drop in flow of 29.7%. Additionally, Figure 19 shows that not only the drop in flow is larger, but it also occurs at a lower density level. This results in a loss in traffic performance and matches the previous speed heatmap observations.

It is noticeable that the maximum traffic flow decreases for scenario 60-20-20-0 compared to scenario 80-20-0-0. The maximum flow decreases from 4823 to 4728 $veh/h$. However, significant changes are observed for scenario 40-20-20-20 where the introduction of level 3 vehicles increases the maximum traffic flow from 4728 to 5008 $veh/h$. Unfortunately, this scenario of highly mixed traffic also shows a drop in traffic flow of 49.5%. Scenario 25-25-25-25 shows that an equal penetration rate for vehicle levels damps the traffic flow drop. The drop in traffic flow is for scenario 25-25-25-25 34.9% and occurs more gradually than in scenario 40-20-20-20.

Figure 20 shows that from scenario 0-33-33-33 onwards, the increase of level 3 vehicles results in an increase in maximum flow values. However, the drop in traffic flow remains significant. Scenario 0-33-33-33 has a maximum flow of 5002 $veh/h$ and the drop in traffic flow due to merging vehicles is 42.7%. Scenario 0-0-50-50 improves the traffic performance with a maximum flow of 5187 $veh/h$ and a drop in flow of 44.3%. This trend continues for scenario 0-0-20-80 where the maximum traffic flow is 5363 $veh/h$ and the drop in flow is 43.1%.

Scenario 0-0-0-100 does increase the maximum traffic flow to 5487 $veh/h$ and a drop in flow is observed of 39.7%. However, Figure 20 shows that the drop in traffic flow does occur earlier for scenario 0-0-0-100 than for scenario 0-0-20-80. Therefore, a penetration rate of 100% level 3 vehicles is not necessarily better but does allow for a higher maximum traffic flow.

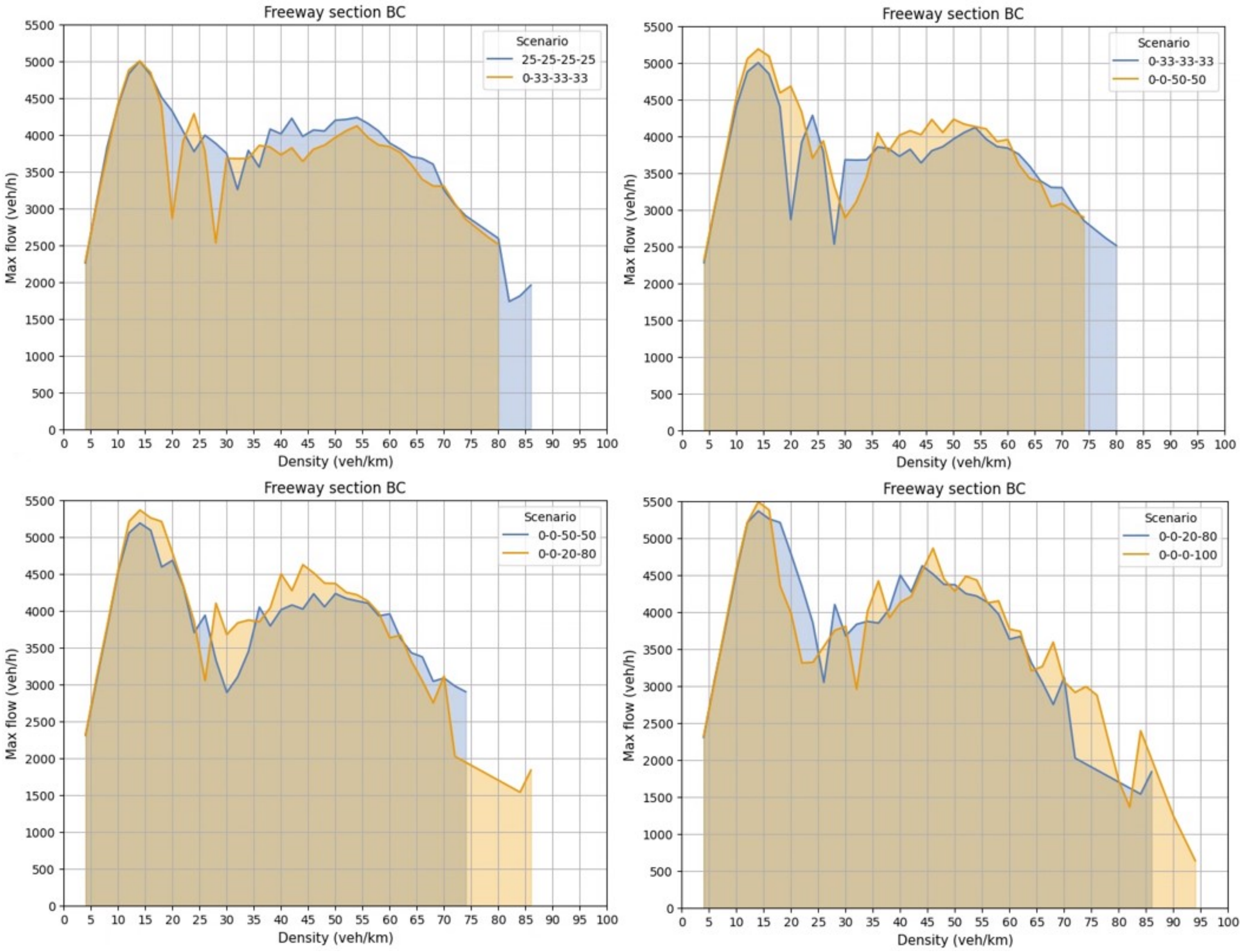


Figure 20: Comparison of fundamental diagrams for freeway section BC for scenarios 25-25-25-25, 0-33-33-33, 0-0-50-50, 0-0-20-80, and 0-0-0-100.

### 5.3.3 Safety on the freeway

To analyse traffic safety, the critical time-to-collision headways are observed. A dangerous vehicle headway is determined each time step within the simulation. Whenever the headway becomes dangerous as described in Chapter 3.3, the headway is counted as a critical time-to-collision. Appendix VI: Analysis of traffic performance and safety shows that the number of critical time-to-collisions decreases when automation levels on the freeway increase. Table 7 presents the number of critical time-to-collision measurements for each scenario. As the table shows, human drivers tend to cause dangerous headway distances. The number of critical time-to-collision headways is just a fraction of all measured headway values, however, it does show that automated car-following decreases the number of dangerous headway distances.

Table 7: Number of critical time-to-collision measurements per scenario.

| **Scenario** | **Critical time-to-collision count** | | | |
|---|---|---|---|---|
| | Level 0 | Level 1 | Level 2 | Level 3 |
| 100-0-0-0 | 502 | | | |
| 80-20-0-0 | 152 | 0 | | |
| 60-20-20-0 | 39 | 0 | 0 | |
| 40-20-20-20 | 15 | 0 | 0 | 0 |
| 25-25-25-25 | 11 | 0 | 2 | 0 |
| 0-33-33-33 | | 0 | 0 | 0 |
| 0-0-50-50 | | | 0 | 0 |
| 0-0-20-80 | | | 0 | 0 |
| 0-0-0-100 | | | | 0 |

## 5.4 Traffic performance and safety with roadside distraction

Previous results have shown that automation levels affect traffic performance in both a positive and negative way. Low penetration rates of level 1 and level 2 vehicles cause more disruptions while merging, while the introduction of level 3 vehicles increases the maximum traffic flow. Additionally, levels 1, 2, and 3 vehicles are less prone to dangerous headway distances. Now, this is also tested in scenarios with a roadside distraction. The roadside distraction causes all nearby drivers to become distracted and thus the assumption is made that this will have a significant impact on traffic performance and safety. Figure 21 shows that the roadside distraction causes a large increase in mean task saturation. At the on-ramp section (BC) the mean task saturation decreases to 0.51 in scenario 100-0-0-0, however, with a roadside distraction this increases to 0.84.

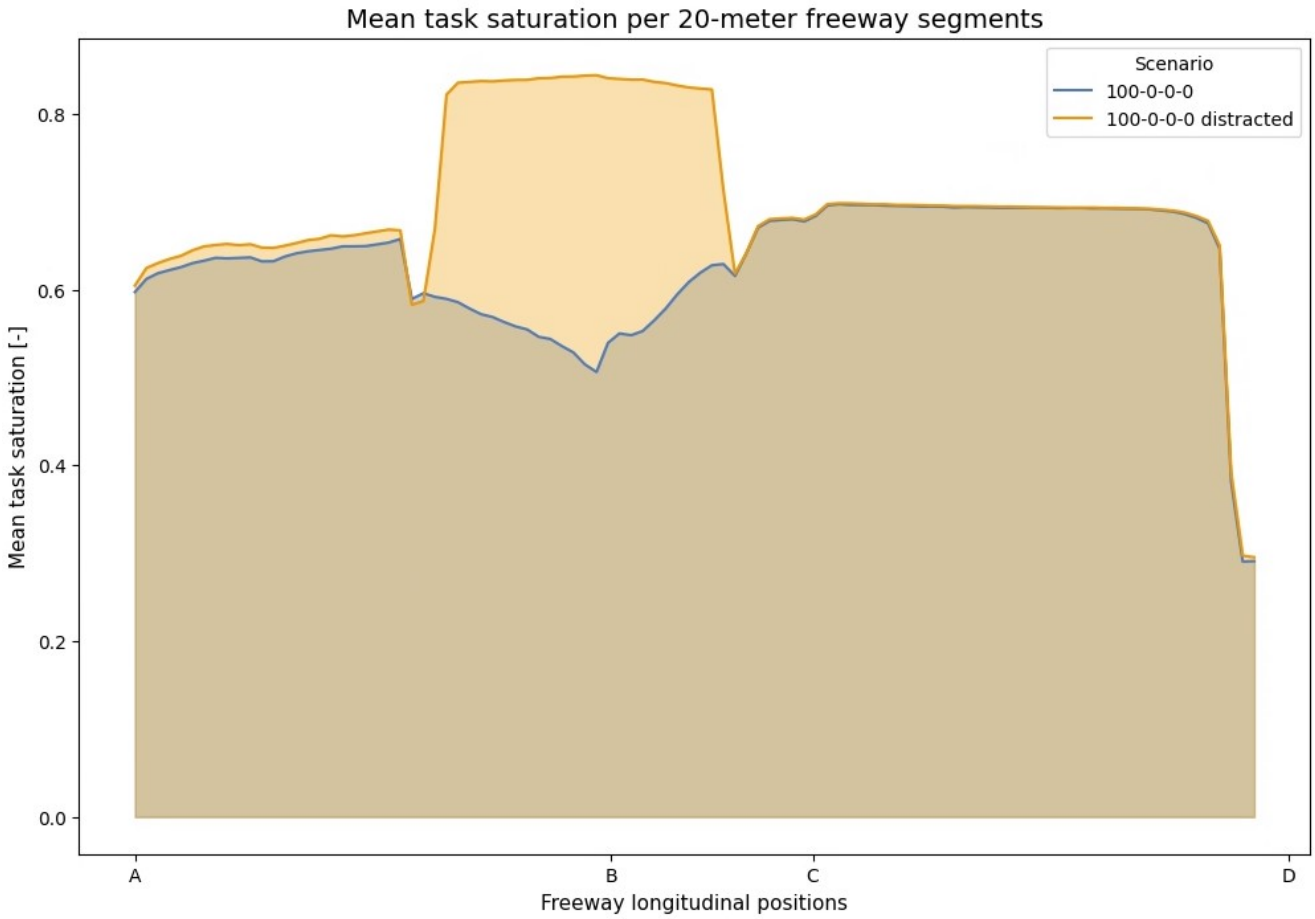


Figure 21: Mean task saturation distribution on the freeway for scenario 100-0-0-0.

The increase in task saturation does not show remarkable differences regarding mean speed levels or travel times. However, Appendix VI: Analysis of traffic performance and safety shows that it does affect fundamental diagrams and the number of critical-time-to-collision measurements. Therefore, both the fundamental diagrams and the critical time-to-collision count per vehicle level are presented in this chapter.

Figure 22 shows that the drop in traffic flow increases for both scenarios and occurs at lower density levels. The roadside distraction in scenario 100-0-0-0 lowers the maximum traffic flow by 0.5% (from 4856 to 4831 $veh/h$) and increases the drop in traffic flow from 24.2% to 37.1%. For scenario 80-20-0-0 the impact of the roadside distraction causes the maximum traffic flow to decrease by 2.3% (from 4823 to 4710 $veh/h$) and the drop in traffic flow increases from 29.7% to 36.2%.

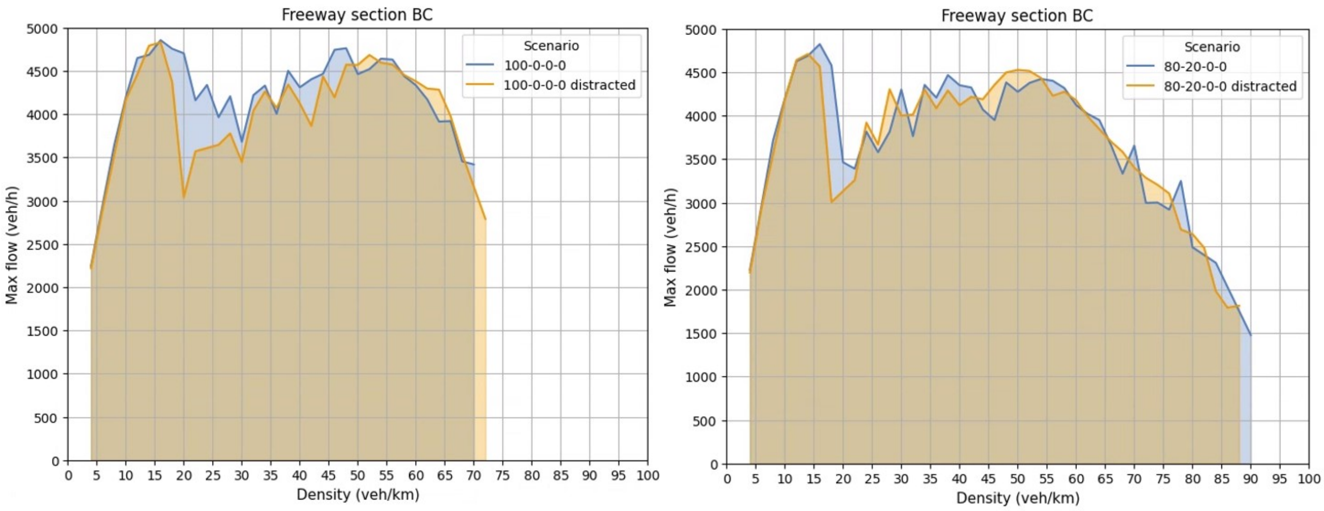


Figure 22: Fundamental diagram of freeway section BC for scenarios 100-0-0-0 and 80-20-0-0 with roadside distraction.

The impact of roadside distraction on traffic safety is presented in Table 8. The table shows the number of critical time-to-collisions counted for each scenario with and without roadside distraction. It clearly shows that less critical time-to-collision headways are seen for human drivers with the roadside distraction. However, this is only true for scenarios 100-0-0-0 and 80-20-0-0. For scenarios with higher penetration rates for level 1, level 2 and level 3 vehicles the number of critical time-to-collisions measured for human drivers increases.

Table 8: Comparison for number of critical time-to-collision measurements between scenarios with and without roadside distraction.

| **Scenario** | **Critical time-to-collision count** | | | |
|---|---|---|---|---|
| | Level 0 | Level 1 | Level 2 | Level 3 |
| 100-0-0-0 | 502 | | | |
| 100-0-0-0 distracted | 442 | | | |
| 80-20-0-0 | 152 | 0 | | |
| 80-20-0-0 distracted | 99 | 0 | | |
| 60-20-20-0 | 39 | 0 | 0 | |
| 60-20-20-0 distracted | 51 | 0 | 0 | |
| 40-20-20-20 | 15 | 0 | 0 | 0 |
| 40-20-20-20 distracted | 34 | 0 | 0 | 0 |
| 25-25-25-25 | 11 | 0 | 2 | 0 |
| 25-25-25-25 distracted | 12 | 0 | 0 | 0 |

This shows that the higher reaction times and human adaptations to cope with this higher reaction time are problematic in mixed traffic scenarios. When 100% or 80% of vehicles are human, the larger headway as a result of human adaptations increases safety. However, when traffic becomes more heterogeneous, and only 60% of vehicles are human, the higher reaction times result in more dangerous car-following behaviour.

# 6 Conclusions and discussion

Autonomous Vehicles (AVs) promise efficiency and traffic performance improvements. However, current available vehicle automation cannot and should not be called AVs. These vehicles only have automated features to support the driver in certain driving tasks, while AVs suggest that the vehicle is driving by itself. The Society of Automotive Engineers (SAE) has defined six levels of vehicle automation. The Advanced driver-assistance systems (ADASs) in currently available vehicles corresponds to an automation level of 1 where car-following or lane-changing tasks are supported, or level 2 where both car-following and lane-changing tasks are supported. Also, level 0 vehicles are equipped with ADAS but these features only support the driver temporarily such as an emergency brake. This mix of automation levels already results in mixed traffic where these different automation levels interact with each other on the freeway.

Additionally, more advanced vehicles are researched and developed to actually take over driving tasks from the human driver. These vehicles can be considered to be AVs, however, they can be divided into level 3, level 4 and level 5 vehicles. The difference between those levels is the complexity of the technology. Level 3 vehicles can drive mostly autonomously on freeway sections until the situation exceeds the operational design domain of the vehicle. Level 4 has a more broad operational design domain and thus is capable of driving autonomously in more situations. Vehicles can drive fully autonomously in automation level 5.

However, the literature study shows that current research lack the detailed modelling of incremental automation levels to include conditional automation features and human factors to simulate mixed traffic more realistic. Therefore the following main research question is formulated:

*" How do different levels of vehicle automation accounting for human driving behaviour impact traffic performance and safety on a multi-lane freeway? "*

To answer the main research question, three sub-research questions are defined. The first sub-question will be discussed in Chapter 6.1, the second sub-research question in Chapter 6.2, and the third sub-research question in Chapter 6.3. Then, an overall conclusion is provided in Chapter 6.4 and the resulting implications and recommendations are discussed in Chapter 6.5.

## 6.1 Sub-question 1

### 6.1.1 SQ1 findings

*"How can driving behaviours and automation-specific features across different automation levels be modelled for a multi-lane freeway environment?"*

This research question aims to investigate the characteristics of SAE automation levels by reviewing current literature and considering practical applications. The automation levels by SAE perfectly describe the boundaries of automation levels. Since take-over control situations are not accounted for, level 3 vehicles can drive autonomously in freeway scenarios. Therefore, only level 0, 1, 2, and 3 vehicles are included in this research.

A key finding is that AVs can be modelled by tuning existing driving models (Olstam et al., 2020). The car-following and lane-changing models that define driving behaviour are algorithms and thus are inherently closer to the decision-making of AV controllers than human drivers. It is the accurate simulation of human drivers that defines the difference between human and automated driving. The car-following and lane-changing models used in previous research prioritise optimised routes and traffic performance but lack the cognitive processes that underlie human decision-making within traffic. Some models can account for driver profiles to incorporate different driving styles for human drivers but this does not change the over-simplified decision-making process of the driver.

To overcome this limitation, this research utilises the perception framework from van Lint and Calvert (2018), which incorporates the task-capability interface model of the driving process designed by Fuller (2000). This framework integrates mental processes in the driving models and thus enables a more realistic simulation of human drivers. OpenTrafficSim (OTS) is a simulation package that contains this mental model out-of-the-box. Also, other human factors such as tailgating, social pressure and taking hindering of follower vehicles into account are available in OTS to integrate even more human factors into the simulation.

Since ADAS is present in all automation levels, the nowadays available ADAS features are used to define vehicle models. This resulted in configurations where level 0 vehicles only have temporary support such as emergency braking. Level 1 vehicles are equipped with Adaptive Cruise Control (ACC) to support the human driver in car-following tasks. Level 2 vehicles are equipped with both ACC and active lane change assist to support the driver in car-following and lane-changing tasks. Level 3 has the same functionalities as level 2 vehicles but will be configured so that the technological advancement is more complex than level 2 vehicles since level 3 vehicles have to fully control the vehicle on their own without human supervision.

Next to the ADAS functions, the driving behaviour of humans is affected by the driving styles of surrounding vehicles. It is found that human drivers tend to gain from defensive AVs and adapt lower headways from AV. Since level 3 vehicles are considered AVs in this research, these adaptations are included in the level 0 vehicle models.

The IDM+ car-following model in OTS can be tuned to reflect the configurations of automation levels. Minimum and maximum reaction time, the perception range, minimum and maximum car-following headways, minimum and maximum acceleration, speed adherence, and a social car-following parameter can be adjusted to define the different driving behaviour across automation levels. Level 0 vehicles are mainly characterised by relative short time headway values, a large acceleration range, high variability in speed adherence, and varying social parameter values for social pressure and tailgating. Additionally, level 0 vehicles will adopt level 3 headways, dependent on their social parameter, whenever they are located between level 3 vehicles to account for human behavioural adaptations. Level 1 and level 2 vehicles have due to their ACC system no reaction time, larger headway values, lower variability in acceleration and speed adherence, and do not account for the car-following social parameter. Level 3 vehicles are assumed to be more advanced and thus better equipped to deal with lower headways but also lower the variability in acceleration and speed adherence.

OTS comes with the LMRS model to determine lane-changing behaviour. The LMRS model adds up different incentives to determine whether a lane change is desired. This includes the socio-speed incentive that considers whether this vehicle is hindering followers. To differentiate between human and automated lane-changing, the socio-speed parameter that influences how much hindering of following traffic is considered has a varying value for human drivers but is zero for level 2 and level 3 vehicles.

Now the perception used for these car-following and lane-changing models is affected by the task-capability interface from the Fuller mental model. The Fuller model takes driving tasks into account and calculates the corresponding task demand. Whenever the task demand exceeds the capacity of the human driver, the cognitive workload becomes too high and thus deteriorates its situational awareness resulting in higher reaction times. To introduce different driver skills, varying values are provided for the task capacity parameter. The inclusion of workload and limited mental capacity allows the modelling of distraction. Distractions can differentiate human drivers even further from AVs since the situational awareness is also influences by the attentiveness of the driver while AVs always have the same perception due to their sensors. 25% of all drivers are engaged in secondary driving tasks which deteriorates their driving performance. Therefore, the level 0 vehicles also contain in-vehicle distractions that can become active during the simulation randomly.

### 6.1.2 SQ1 discussion

The scope of this research does not include the take-over of control situations where human drivers have to gain back control from the automated driving features when prompted to do so. This is excluded because the operational design domain of the different automation levels is not precisely documented and would need its own detailed investigation. Modelling the take-over situations would introduce unique complexities where vehicles have to switch between driving models and the corresponding parameters. Additionally, the take-over control situations can only be simulated when the simulation of automation levels is achieved. Therefore, this research can be used as a basis to extend on for future research on take-over control simulations, which is explained further in Chapter 6.5. However, the literature study shows that the take-over control situations are crucial in assessing driving safety for automation levels (Gold et al., 2016, Calvi et al., 2020 and McDonald et al., 2019). Calvi et al. also finds that the cognitive workload of human drivers increases from secondary tasks while they are driving an AV, showing that the mental model is crucial for the simulation of the different automation levels. This means that the current automation levels do not include important aspects for human and AV interaction within the vehicle. Still, this research does focus on the documented driving behaviour with ADAS features where these kinds of dynamics are already included. So while it is not directly simulated, the effects of human interactions with automated features on driving performance are part of the vehicle models.

The approach of modelling automated driving functions by adjusting existing car-following and lane-changing models is an oversimplification of the true driving behaviour of automation levels. While the approach does allow to simulate automation levels by explicitly defining the differences between them, it does not reflect the actual process of the AV or ADAS controllers that are used in real-life vehicles. Where current efforts in this research are aimed at simulating human drivers as realistically as possible, this approach could also be used for the simulation of automated driving models. Olstam et al. (2020)

therefore describes a nanoscopic approach where the automated model will incorporate vehicle dynamics, sensors, and for example the gearbox to define driving behaviour based on the most detailed level of the vehicle. These detailed aspects of automated driving are not incorporated in the designed vehicle models, which means that the emerging driving behaviour does not reflect their real-life behaviour.

While the simulation of automated features is oversimplified, it is the simulation of human drivers that has limited previous research of simulating mixed traffic more realistic (Calvert and van Arem, 2020). Therefore, this research aims to simulate the differences between human and AV driving behaviour by simulating human drivers more realistic and defining precise boundaries for each automation level. The current vehicle models for level 1, level 2 and level 3 vehicles comply with state-of-the-art simulation because of their negligible reaction time and perfect driving. However, the headway configurations are different. Sadid and Antoniou (2023) state that headway values for AVs should be lower. While this can be true for Connected Autonomous Vehicles (CAVs), non-cooperative automated features that are currently available in ADAS show to have larger headway values than humans would normally maintain. Therefore, this research uses larger headway ranges for level 1 and level 2 vehicles, while it is assumed that level 3 vehicles can achieve lower headway ranges because of near-future technological advancements without any cooperative features. Also, specific driving styles are not included since the IDM+ car-following model already dynamically set time headway values based on the traffic situation. Also, level 1, level 2, and level 3 vehicles have no true understanding of the traffic situation and thereby will always be cautious during their driving manoeuvres.

The modelling aspects for human drivers are based on the list of human factors from Saifuzzaman and Zheng (2014). Simulation package OTS has most of the human factors incorporated in its car-following, lane-changing, and mental models. However, distraction, perception thresholds, and imperfect driving are not included. While these are limitations, driving needs, and imperfect driving factors have less impact on the vehicle models than the human aspects that are included. Desired parameters, anticipation, estimation errors and personal characteristics touch the fundamental elements of human-driving decision-making. Furthermore, the perception thresholds are not directly implemented but a whole mental model is used to model human decision-making. Fortunately, the mental model can easily be expanded on. So, distraction was added to the mental model to incorporate this factor and test how varying cognitive workloads impact traffic. The distraction and workload of car-following and lane-changing tasks dynamically set the reaction time and thus dynamically affect the determined acceleration and headway. Therefore, it is chosen to vary the task capability parameter for human drivers and not use distributions for the acceleration, headway and reaction time parameters. This research aimed to incorporate different driving behaviours by utilising the mental model to its full extent which also makes configuring the vehicle models easier. Distributions were used to set the varying task capability parameter, and also the speed adherence factor and social parameters receive values from a distribution. These parameters are not set dynamically and thus require varying values to account for different driver characteristics.

Unfortunately, simulation of high reaction times for human drivers leads to many collisions. So many collisions that it does not provide a realistic picture of traffic dynamics. The cause of the collisions was the highly delayed perceptions of human drivers that could not account for its leader vehicle. This is not realistic since drivers will be cautious in dangerous situations and thus most of the time respond to the actions of leader vehicles. To prevent these collisions a small reaction time range is chosen and the minimum reaction time is set to $0.17\,s$, which is found to be the lowest reaction time for human drivers. This allows the mental model to vary human reaction times but limits the occurrences of high reaction times that become problematic.

While the accessible mental model makes it possible to extend on, this also introduces more modelling choices into the research. Calvert et al. (2020) show that the Fuller model in OTS is a framework which can be extended immensely. This means that the current HDV models can be extended to incorporate more internal and psychological processes to match human driving behaviour. The model could incorporate more driving tasks, include more complex task demand processes, and make the driver capability dynamic for different situations (Calvert et al., 2020). Despite these possibilities, the current HDV models use the existing OTS Fuller model as it is, limiting realistic human driving behaviour.

Most of the default values used in OTS are calibrated. Parameters used in the LMRS model are calibrated on a Dutch freeway while being incorporated with the IDM+ model (Schakel et al., 2012). However, the addition of the mental model changes driver perceptions and triggers adaptations for reaction time, desired speed, and desired headway, changing driving dynamics for the IDM+ and LMRS models. Therefore, the new composition of driving models should be calibrated to verify the model parameters. This is not performed in this research and thus the exact values chosen for these vehicle models not be considered as realistic. The current parameter values mainly represent differences between automation levels. Literature is used to find parameter values that reflect human driving behaviour for level 0 vehicles, ACC functionality for level 1 and level 2 vehicles, and adjusted parameter values for level 3 vehicles to reflect technical advancements.

The technical advancements for level 3 vehicles result in assumed parameters for the vehicle model. However, these parameters are not verified and no further sensitivity analysis is performed. Sensitivity for level 0 vehicles already showed that larger headway values will lead to unrealistic large mean time headway values and other parameters such as acceleration and deceleration has small effects. Even when a thorough sensitivity analysis was performed for level 3 parameters, these results could not be compared since other studies are mostly aimed at CAVs. Therefore, parameter values are chosen that are similar to human drivers and also bring improvements from level 1 and level 2 vehicles.

Unfortunately, the perception class in OTS is nested within the core of the vehicle model. While this allows the incorporation of the Fuller model, it limits the adjustments that can be made for vehicle perceptions. Vehicles with an automation level of 1 should have automated car-following which indicates that the headway is larger, the acceleration range is smaller, and the reaction time is 0 seconds. However, the lane-changing model, which is controlled by the human driver for level 1 vehicles, uses the same perception and thus makes lane-changing decisions instantly. This is of course not realistic and forms a significant limitation for the level 1 vehicle model. However, car-following reaction time is considered more important since car-following reaction time directly affects traffic safety because it can lead to crashes. Also, the car-following behaviour of ACC is researched a lot, so parameter values could be set by literature. Lane-changing behaviour is less documented and no research on differences between human drivers and ADAS features or AV controllers could be found.

Because level 1 vehicles have a reaction time of 0 seconds and lane-changing behaviour differences between human drivers and automated features are unknown, the differences between the level 1 and level 2 vehicles are small. Currently, the only difference is the social incentive for lane changes. The social parameter for this incentive varies to represent different human characteristics for level 0 and level 1 vehicles but is 0 for level 2 and level 3 vehicles. This limits the differences in vehicle models that this research is aiming for, so future work should investigate the lane-changing behaviour of automation levels.

### 6.1.3 SQ1 conclusion

This study demonstrates that the fundamental and practical differences across automation levels can be modelled by the use of simplified automated driving models and more complex human driver models that increase the realism of human decision-making. By integrating cognitive processes and social factors, the human vehicle models developed in this research provide a nuanced representation of human decision-making, which is often under-represented in existing mixed traffic simulations. Although certain features, such as take-over control situations and detailed AV dynamics, are beyond the scope of this study, the approach effectively differentiates between automation levels in freeway environments. Future work can build on this foundation by incorporating more detailed AV controller behaviours, recalibrating model parameters, and investigating lane-changing behaviour, further advancing the accuracy and applicability of mixed traffic simulation for traffic performance and safety analyses.

## 6.2 Sub-question 2

### 6.2.1 SQ2 findings

*"How do car-following and lane-changing interactions change across different levels of automation?"*

To answer this question, microscopic simulation in OTS is performed. The designed vehicle models are put in a freeway scenario with specific penetration rates per automation level. Since the research question focuses on car-following and lane-changing interactions, a scenario has to be created where vehicles are forced to act on changes in traffic conditions and thus interact with other vehicles. To do this, an on-ramp is added to the freeway that disrupts the traffic flow of the main freeway lanes and forces vehicles to deal with an additional flow of vehicles merging into the main lanes.

Different scenarios are defined by varying penetration rates for automation levels. However, the pure scenarios where only one automation level is present for a penetration rate of 100%, result in such different traffic conditions that those scenarios could not be compared to analyse driving behaviour. So, also a scenario is simulated where all automation levels are present equally (scenario 25-25-25-25). Vehicle interactions are then analysed by assessing their car-following headway, number of switches in leader vehicles, lane change frequency and headway during lane change manoeuvres.

Additionally, because human drivers show driving adaptations towards AVs, the behaviour of these vehicle model adaptations are analysed for a scenario where 50% of vehicles is level 0 and 50% is level 3. This scenario simulates enough level 0 vehicles that are surrounded by level 3 vehicles to analyse but also includes many level 0 vehicles that are not surrounded by level 3 vehicles and thus will not show any adaptations, which are the basis of this comparison.

The "pure" 100% scenarios show that the vehicle models have different driving behaviour across the automation levels. Level 0 and level 3 vehicles are able to maintain a higher mean speed on the freeway than level 1 and level 2 vehicles could. However, these differences in speed lead to different traffic conditions where level 1 and level 2 vehicles are subject to more congestion. Therefore, these scenarios can not be used to compare driving behaviour.

For the equal penetration rate scenario, the mean speed on the freeway is similar for the different automation levels. This simulation shows that level 0 vehicles have the largest variability in acceleration where accelerations are measured (without outliers) between $-0.75$ and $1.25\,m/s^2$. Level 0 vehicles also had the lowest mean time headway where time headway values are measured (without outliers) between 0.75 and $2.4\,s$. Also, low time headway values are seen during the lane change manoeuvre where the level 0 vehicle is able to maintain a stable time headway.

Level 1 vehicles show a slightly lower variation in acceleration but also a larger time headway for car-following and lane-changing interactions. The car-following headway is significantly higher with a mean that is $0.3\,s$ higher than for level 0 vehicles. What stands out for level 1 vehicles is the large increase in switches in leader vehicles. The switches in leader vehicles help to identify whether other vehicles can gain from the larger headway of level 1 and level 2 vehicles. However, the increase in leader switches is caused by lane changes from the vehicle itself in busy lane-changing areas of the freeway. So, no advantage from other vehicles over level 1 vehicles was observed. The headway details during lane-changing do identify that level 1 vehicles gain much speed during their lane changes. This would indicate that level 1 vehicles tend to be in slower traffic and is able to find ways to gain speed by switching lanes. This behaviour is not seen for other automation levels. Level 2 vehicles show similar behaviour as level 1 vehicles for car-following acceleration and headway. However, level 2 vehicles do not change lanes as much and show a more stable mean headway during lane change manoeuvres.

Level 3 vehicles show to be able to maintain a low headway. However, the smaller acceleration range of level 3 vehicles limit the vehicle to keep these close headways. Therefore, also higher headways are measured, which means that level 3 vehicles do not necessarily maintain a lower headway than human drivers. Furthermore, a significant increase in headway during lane changing is observed. Also, this observation can be explained due to the smaller acceleration range. While other vehicles gain speed during the lane change manoeuvre, the level 3 vehicles cannot follow the leader in the new lane closely. Simulation of level 3 vehicles with 50% level 0 vehicles confirms that the acceleration limit is problematic since this lane-changing behaviour is not observed at a higher mean speed where accelerations are lower.

Analysis of human adaptations shows that the current design of headway adaptations is not effective. While level 0 vehicles will adjust their desired headway downwards to headway values of level 3 vehicles dependent on their car-following social parameter, this does not result in lower headway values for level 0 vehicles. Results do show that cooperation adaptations do make lane changing more difficult for level 3 vehicles. Human drivers provide less space for lane-changing level 3 vehicles, thus level 3 vehicles have to slow down themselves to increase the headway to a comfortable level. However, this does not have a high effect on the mean number of lane changes since level 3 vehicles change lanes almost as much in interactions with level 1 vehicles as without level 0 vehicles.

### 6.2.2 SQ2 discussion

Scenarios of 100% penetration rates for each automation level are designed to expose the distinct driving behaviour across automation levels. However, the differences in driving behaviour resulted in such different traffic conditions that no comparisons on specific driving factors such as acceleration and headway could be made. The scenario of equal penetration rates ensures that the measurements are performed in the same traffic conditions for all automation levels. However, because this scenario already has a highly mixed composition of different vehicle levels, the found behaviour could possibly only apply in this very specific scenario. When the high frequency of level 1 lane-changing is observed, this could possibly be caused by the behaviour of other automation levels that cannot be identified in the current analysis. Therefore, future work could analyse at which traffic demand values different penetration rate scenarios show free-flow, saturated, and congested traffic. This will help in designing a more detailed decisive analysis setup for driving behaviour.

The high frequency of lane changes for level 1 vehicles cannot directly be explained by the vehicle model parameters. Level 1 vehicles have the same car-following settings as level 2 vehicles and the same lane-changing settings as level 0 vehicles. Both of these automation levels do not show as much lane changes in the pre-on-ramp and merging section of the freeway. It could be that the human factor of the socio-speed incentive in combination with the larger headway settings from the ACC results in more lane changes. However, since lane-changing behaviour is not studied well in combination with vehicle automation in existing literature, it cannot be verified in this study. Investigation and calibration of the lane-changing model is required to get a deeper understanding of the lane-changing model.

The decreasing variability of acceleration follows the parameter values used for the vehicle models. However, these are not as significant as the findings from Schakel et al. (Schakel et al., 2017). This indicates that the vehicle parameters should be calibrated for the current composition of driving models to reflect human and ACC acceleration behaviour. The same can be said about the human adaptations. The current implementation of headway adaptation shows to be not effective and thus is not simulated in the current simulation setup. As Raju and Farah (2020) have stated, the exclusion of human and AV behavioural adaptations limit the realism of mixed traffic interactions. While this limits realism, level 0 vehicles still maintain a low time headway, so the behaviour in this simulation still represents human driving behaviour, just the detailed interaction between level 0 and level 3 vehicles is affected.

The overall trend of changes in headway values across automation levels does reflect the parameters set for the vehicle models. Level 1 and level 2 vehicles show a significant increase in headway values compared to level 0 vehicles. However, the mean headway values in this analysis are higher than for other found research. Schakel et al. (2017)

shows that the mean value for human time headway is 0.98 $s$ which increases to 1.2 $s$ for ACC equipped vehicles. This is lower than the found 1.7 $s$ and 2.0 $s$ for the level 0 and level 1 and 2 vehicles in this research respectively. Still, the trend among level 0, level 1, level 2 and level 3 vehicles show that ACC equipped vehicles have larger headways and level 3 vehicles will show more human like headways because of its technological advancements.

However, the limited acceleration range of level 3 vehicles may not result in the most realistic lane-changing behaviour. The findings show that level 3 vehicles are not able to follow leader vehicles closely for the highly mixed traffic scenario. This could occur whenever level 3 vehicles are designed to limit their acceleration variability. Still, it is more likely that future level 3 vehicle controllers will be designed to perform well in traffic. The large headway gaps that currently occur therefore seem to be unrealistic. Fortunately, the overall headway values are similar to level 0 vehicles which was the intention of the level 3 vehicle model.

### 6.2.3 SQ2 conclusion

Car-following and lane-changing interactions vary significantly across automation levels, reflecting their differences in driving behaviour. Automated car-following vehicles equipped with ACC show less variability in acceleration and maintain larger time headways than human drivers. The larger headway values show that level 1 and level 2 vehicles have a more cautious driving style but this does lead to lower speed levels at the freeway.

For level 3 vehicles, headway values are closer to human drivers and can even maintain lower headways. This reflects the more advanced automation technology aimed to show more human-like driving behaviour compared to the level 1 and level 2 vehicles. However, the lower acceleration variability that is associated with level 3 vehicles limits the vehicle in maintaining low headway distances. Therefore, the variability in time headway of level 3 vehicles is higher than human drivers and results in large gaps during lane changes. This might not align with near future level 3 vehicles in real-world applications.

The high lane-changing frequency observed in level 1 vehicles, likely influenced by ACC settings combined with socio-speed incentives, highlights a potential need for further model calibration, as this behaviour diverges from typical lane-changing patterns at other levels of automation. Additionally, behavioural adaptations from human drivers towards level 3 vehicles is not completely effective. Human drivers do show less cooperation but do not lower their headway values while surrounded by level 3 vehicles. Nonetheless, human drivers do maintain low time headway values compared to other automation levels so the differences in car-following behaviour are clear.

These findings underscore that, while each automation level shows distinct car-following and lane-changing characteristics, current simulation models may still oversimplify some interactions. Future research should focus on refining lane-changing behaviours and calibrating acceleration parameters to improve the realism of automated driving models, especially in mixed traffic settings.

## 6.3 Sub-question 3

### 6.3.1 SQ3 findings

*"How do vehicle automation levels in mixed traffic affect traffic KPIs?"*

An important aspect of mixed traffic is the composition automation levels. However, the expected composition of future traffic is uncertain because the introduction of higher automation levels is dependent on technological advancements and the willingness of road users to adopt certain vehicle automations. Therefore, an incremental approach for penetration rates is adopted. Nine scenarios are defined to reflect the transition of only human drivers to only AVs.

To further investigate how the integrated mental model of human drivers affects traffic, two types of distractions are simulated. In-vehicle distraction, also called secondary driving tasks, and static roadside distractions. These will expose human drivers to driving task demands that exceed their capability. This is included to further improve the realism of the human driver. However, the in-vehicle distractions are inherently part of level 0 vehicles and thus are embedded in the vehicle model. It is the roadside distraction that introduces new scenarios for the analyses of the impact of automation levels on traffic. The roadside distraction will be simulated for all scenarios where human drivers are present.

Effects on traffic can only be analysed when traffic Key Performance Indicators (KPIs) are identified. To analyse traffic performance, speed, flow, density and travel time are observed. These variables will help to identify what traffic conditions are simulated and identify how the penetration rate of automation levels affects it. To also account for safety, time-to-collision is observed. Whenever a vehicle's time-to-collision becomes critical, this situation of the vehicle is considered unsafe.

Simulation of these scenarios for the specific penetration rates shows that traffic performance is affected significantly by the different driving styles of automation levels. The base scenario of 100% level 0 vehicles shows that vehicles have to slow down before the merging section to safely interact with the vehicles from the on-ramp and vehicles that switch lanes on the main lanes. When vehicles approach the end of the merging area, vehicles can speed up again and continue their travel. Travel times are mostly under 200 $s$. However, vehicles that have to merge from the on-ramp to the main lanes can take up to 700 $seconds$. This shows that the freeway becomes congested and hinders vehicles on the on-ramp. The fundamental diagrams also show that the pre-on-ramp section of the freeway has free-flow conditions until 4500 $veh/h$ and then has a small drop in traffic flow due to disruptions from the downstream on-ramp. However, the real disruptions take place at the merging area where the freeway cannot handle more than 4800 $veh/h$. The resulting outflow on the post-on-ramp section does not exceed a flow of 4300 $veh/h$.

Whenever automated driving functionalities are introduced to the freeway, vehicles slow down more when they approach the merging section and travel times increase. The corresponding fundamental diagrams show that the disruptions on the merging section become larger and more congestion occurs. The introduction of level 1 vehicles does not benefit the traffic performance at all. It does not only lead to larger drops in traffic flow but they also occur at lower density values. However, further increases in level 1 and level

2 vehicles lead to similar traffic conditions until a penetration rate of 25% per automation level (scenario 25-25-25-25). This scenario shows that the highly mixed traffic damps the drop in traffic flow. Travel times are still rising but the disruptions in traffic become smaller. The subsequent scenario has 33% of level 1, 2 and 3 vehicles. This means that the share of vehicles with low headway values decreases when compared to the scenario with 25% per vehicle level and thus the maximum flows decrease. However, from here on the traffic conditions improve and also travel times reduce when the share of level 3 vehicles increases from 50% to 100%. this leads to higher mean speed levels on the freeway and the maximum traffic flows easily exceed the base scenario with 5500 $veh/h$. Nonetheless, when level 3 vehicles reach a penetration rate of 100% the drop in traffic flow does occur slightly earlier but the drop decreases from 43.1% to 39.7%.

Regarding critical time-to-collision counts, the number of critical time-to-collisions reduces significantly throughout the introduction of automation levels. Human drivers start with a critical time-to-collision count of 500 during the full simulation time of all runs. However, this is already reduced to 40 when just 60% of vehicles is a level 0 vehicle. The occurrences of critical time-to-collisions disappear when no human drivers are present anymore. This does not mean that higher automation levels do not show any critical time-to-collisions at all. Also level 2 vehicles have shown 2 critical time-to-collisions.

The higher cognitive workload for human drivers by simulating a roadside distraction next to the merging section of the freeway exceeds the critical task saturation and thus deteriorates the driver's perception. However, this does not lead to changes in mean speed levels. Also, the travel time remains similar for most vehicles. The higher workload does strongly affect the drop in traffic flow on the merging section and this effect smooths out as fewer human drivers are present. From 60% level 0 vehicles and less, the traffic conditions in the fundamental diagrams show similar patterns as the scenarios without the roadside distraction.

The effect of higher cognitive workloads on critical time-to-collisions does not follow a specific trend. At first, scenarios with a roadside distraction show less critical time-to-collision numbers. However, when the penetration rate reaches 60% for level 0 vehicles the roadside distraction causes more critical time-to-collision numbers until the human drivers are phased out from the penetration rates.

### 6.3.2 SQ3 discussion

The travel times throughout the different scenarios show that vehicles from the on-ramp are subject to much congestion. While congestion is inevitable when traffic disruptions are severe and traffic demand is continuously high, this can limit the number of vehicles that merge into the main lanes. This limits the current research in the observation of how automation levels might solve the congested traffic and how easily vehicles can merge into main lanes. Currently, congestion on the on-ramp further limits vehicles from merging because of speed differences. However, to analyse the improvements that automation levels can cause, high traffic demand is required to see at which point the traffic flow becomes too much. Also, in this research, it is the drop in traffic flow that can provide an indication of how large the disruptions are.

The base scenario of 100% human drivers shows that a maximum traffic outflow of

4300 $veh/h$ is achieved at the post-on-ramp section. This is significantly lower than the standard of 4945 $veh/h$ that is used for Dutch two-lane freeways with an on-ramp (J.W. Goemans, 2015). Increasing the penetration rate of level 0 vehicles does show that the larger headway settings result in lower speed levels and thus deteriorate traffic flow. This does follow the consensus of existing research that states that lower headway values enable higher traffic densities and thus higher traffic performance (Liu and Fan, 2020 and Olia et al., 2017). However, the increments of automation levels expose that the introduction of level 2 vehicles and more level 1 vehicles does not have a worse effect on traffic. More level 1 and level 2 vehicles even seem to damp the drop in traffic flow. This indicates that human drivers are so different from level 1 and level 2 vehicles, that even a small percentage will impact traffic performance. However, further introduction of automation levels makes the traffic composition less diverse and thus more stable. This explains the dampening of the drop in traffic flow and aligns with findings from Makridis et al. (2020) who state that homogenisation of traffic will increase traffic performance.

Level 3 bring traffic performance improvements to the freeway from a penetration rate of 50%. It brings back the lower headway values that were also present for human drivers but also comes with less variety in driving behaviour since human drivers were subject to personal characteristics and deteriorating perception. While this aligns with Liu and Fan (2020) and Olia et al. (2017), they find improvements from 20% and 30% respectively. This can be explained by the configuration of the level 3 vehicle in this research. Liu and Fan and Olia et al. find these improvements for CAVs. These have a significant technology advantage because of communication features. These are not present in level 3 automation vehicles and thus have less impact on the traffic performance.

The findings regarding safety show that dangerous headways, defined by critical time-to-collisions, strongly reduce whenever the share of level 0 vehicles decreases. This is an expected outcome since human drivers with deteriorating perceptions will encounter more dangerous situations. This is also in line with findings from Miqdady et al. (2023). However, Miqdady et al. does observe critical time-to-collisions for higher automation levels. In this research critical time-to-collisions are quite rare when the numbers are compared to the number of vehicles simulated throughout all the different simulations. Additionally, human reaction times are simulated between 0.17 $s$ and 0.6 $s$ which are low in comparison to existing studies. Together with a low critical time-to-collision threshold, the rare occurrences for human drivers and the negligible occurrences for higher automation levels do not present a realistic number of dangerous situations. However, it does provide insights in automation level safety since even for very low thresholds, human drivers do encounter these dangerous situations.

The simulation of human distraction is currently based on the assumption that a distraction always exceeds the critical task saturation of drivers. This approach is chosen because studies on driving tasks try to observe these higher workloads through eye movements, body characteristics or deteriorating driving performance. However, studies do not quantify the impact of distractions on human mental capacity. However, studies show that driving performance does deteriorate (Collet et al., 2009). This is achieved by always exceeding the driver's critical task saturation. Therefore, no distinction is made between in-vehicle distractions and roadside distractions. This might not be representable for driver distractions in real-life since in-vehicle and roadside distractions provoke a different kind of engagement from the driver. Where roadside distractions cause a visual and mental distraction, in-vehicle distraction often requires manual attention from the driver.

This shows that further research on driver distraction can increase the complexity of distractions in the mental model.

The effect of the roadside shows expected results where the decrease in human drivers results in a decrease in distraction effects. However, since human drivers have behavioural adaptations to deal with high cognitive workloads, such as lowering speed and increasing the desired headway, it is expected that the speed levels will drop. This is not seen and thus indicates that human drivers already slow down a lot when approaching the merging section of the freeway and thus focus more on maintaining a higher headway. This does explain the large drop in traffic flow that occurs for a 100% penetration rate of human drivers. On the other hand, the decrease in critical time-to-collision numbers is unexpected since higher reaction times can get dangerous. However, it does show that human drivers indeed maintain larger headways when distracted. Unfortunately, this is not always the case. For penetration rates of 60% and lower, human drivers experience more dangerous car-following situations when distracted. This can be caused by the increasingly different perceptions when level 1 and level 2 vehicles are introduced, while in scenarios with mostly human drivers, every driver is subject to deteriorating perceptions which homogenises reaction times for distracted human drivers.

### 6.3.3 SQ3 conclusion

The study for this research question demonstrates that vehicle automation levels in mixed traffic significantly affect traffic KPIs. The traffic performance is observed by including traffic flow, density, speed and travel time and safety aspects are taken into account by observing critical time-to-collision numbers. Lower levels of automation, such as level 1 and level 2 vehicles, contribute to lower speed levels, reduced flow rates and larger drops in traffic flow due to large headway settings. Resulting in less smooth driving behaviour at the merging section and thus larger disruptions in traffic. However, when the share of level 1 and level 2 vehicles increase these disruptions become smaller because of more homogenous traffic.

It is the high penetration rate of level 3 vehicles that significantly improves traffic performance. From a penetration rate of 50%, traffic flow increases and higher speed levels are maintained. Improving traffic performance when compared to all other scenarios. This improvement in performance aligns with findings in the literature, suggesting that higher automation leads to smoother, more homogeneous traffic flows, ultimately enhancing traffic efficiency.

In terms of safety, as measured critical time-to-collision numbers, higher automation levels substantially reduce dangerous car-following interactions. Critical time-to-collision incidents are rare for the current vehicle model configurations but it shows that level 1, level 2 and level 3 vehicles improve traffic safety.

However, several limitations impact the interpretation of these findings. For example, the modelled human distraction assumes that all distractions exceed the critical task saturation, a simplified approach that may not capture the realistic effects of different distraction types on driver behaviour. Real-life distractions differ in engagement, and future studies should model these nuances to improve the realism of human driver responses.

In summary, vehicle automation levels in mixed traffic impact traffic KPIs by enhancing both performance and safety as automation levels increase, particularly when level 3 vehicles constitute the majority of traffic. However, small penetration rates of level 1 and level 2 vehicles will impact traffic performance negatively. Future research should focus on refining the reaction time settings and differentiating distraction types.

## 6.4 Overall conclusion

To answer the main research question of how automation levels that account for human simulation factors and driving behaviour impact traffic performance and safety for a multi-lane freeway situation, the previous discussions on vehicle models, driving behaviour and traffic implications are summarised.

The findings demonstrate that automation levels can be modelled in OTS by using simplified driving models for AVs and more complex HDV driving models that account for human perception by modelling the mental workload of driving tasks and social factors. Level 0 vehicles are therefore modelled more detailed than in existing mixed traffic studies and effects of distraction can be studied because the mental model influences how the car-following and lane-changing models behave. Level 1 and level 2 vehicles are modelled more conservative, which means that the vehicle will maintain larger headways and smaller variability in acceleration. This represents the current available ACC systems. Level 3 vehicles are assumed to be more technological advanced and thus are capable of maintaining lower headway values and show low variability in acceleration. However, these vehicle models are subject to limitations. The current configurations do not take take-over control situations into account while literature shows that this introduce high safety risks for automation levels (Gold et al., 2016 and Calvi et al., 2020). Also, the current implementation of perception in OTS prevents the simulation of both human and automated decision-making in one vehicle model. Still, the current models show to be effective in differentiating the different driving characteristics of the automation levels. To make the simulation more realistic, calibration on model parameters is recommended.

Car-following and lane-changing behaviours differ significantly across automation levels. Level 1 and level 2 vehicles generally maintain larger headways and show reduced acceleration variability compared to human drivers. Level 3 vehicles show closer headway values but are constraint by the smaller acceleration range impacting the maintained headway and especially causes large gaps during lane change manoeuvres. This leads to potential unrealistic driving behaviour for level 3 vehicles. Additionally, human drivers only demonstrate limited behavioural adaptation toward level 3 vehicles, which requires additional research to improve modelling of behavioural adaptations due to surrounding AVs.

Traffic performance KPIs, including flow, density, speed, and travel time, show significant improvements as automation levels increase, especially when level 3 vehicles represent at least 50% of traffic. Other studies show that traffic performance gains are achievable for lower penetration rates of AVs. However, the currently designed vehicle model for level 3 is less advanced than most AVs in current literature, and the restricted acceleration range does limit the level 3 vehicle to maintain lower headways. Higher levels of automation reduce drops in traffic flow and increase mean speed levels, which is consistent with the overall consensus that homogenous traffic results in better traffic performance. Safety metrics, defined by critical time-to-collision numbers, also improve when automation levels increase. Higher automation levels such as level 1, level 2 and level 3 vehicles are shown to be less prone to dangerous car-following interactions. However, simplified assumptions regarding reaction times and critical time-to-collision thresholds lead to the need for future research to take traffic safety into account in more detail. This also holds for the simulated distractions that show that distractions do impact traffic performance and safety. However, more research into distractions is needed to include more nuance between different types of distractions and their effect on the human driver.

## 6.5 Recommendations

The findings on traffic performance show that the introduction of level 1 vehicles deteriorates traffic performance on a freeway with an on-ramp. Further increases of vehicle automation by means of level 1 and level 2 vehicles will damp these negative effects. However, it does only really improve when level 3 vehicles enter the vehicle fleet. This implicates that the current situation on Dutch freeways, where many vehicles are equipped with ACC systems and newer level 2 vehicles are entering the market, was already subject to deteriorating traffic performance. Meaning that the introduction of level 3 vehicles will bring significant traffic performance improvements regarding speed levels at merging sections and traffic flows. Let alone, what further improvements CAVs could bring. Therefore, these findings support the goals of the European Parliament that incorporate ADAS features in the motor vehicle type approval requirements (Regulation 2019/2144, n.d.). It is even recommended that these requirements are frequently updated to incorporate the latest, and of course thoroughly tested, automation features to ensure vehicle innovation finds its way to the freeway.

One of the biggest limitations left for the designed vehicle models is the precise simulation of level 1 vehicles. As discussed earlier, OTS uses one perception for each vehicle model which is intertwined with fundamental behaviour models underneath the car-following and lane-changing models. This means that both car-following and lane-changing decisons are performed for a reaction time of 0.0 $s$, while only car-following is automated. To enable the simulation of different reaction times, the vehicle model must be able to base its decision-making on at least two different perceptions. This could be achieved by providing two perceptions for each vehicle model (dual-perception factory) and specify in the driving models which perception to use. This would not only enable the simulation of two different reaction times, one for automated car-following and the other for human lane-changing, but would also create a foundation for switching between vehicle control for take-over control situations. However, this could introduce more complex decision-making because vehicles have to combine all considerations into one car-following acceleration and lane-changing decisions. Therefore, future work is recommended on modelling level 1 vehicles and/or take-over control situations for automation levels.

Additionally, it is recommended to calibrate the new driving models combination of the IDM+ model, LMRS model, and the mental Fuller model. This would clarify what values have to be used for specific parameters. Reducing the uncertainty around model parameters and providing a starting point for the design of vehicle models. Also, the behavioural adaptations due to HDV-AV interactions should be researched more deeply since the current headway adaptation proves to be ineffective in the current level 0 model.

A significant limitation in the simulation of driver distractions is the unknown quantification of driver distraction. Currently, driver distraction is defined as exceeding the critical task saturation. However, in this research, the distraction is always the same. No distinction is made between high-engagement and low-engagement secondary tasks. This results in a high percentage of human drivers that are effectively distracted. However, not all distractions have to result in a deterioration of driving performance. Therefore, further research is required to determine how different levels of distraction can be incorporated and what framework is suitable to quantify these distraction levels for simulation purposes.

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# Appendices

## Appendix I: Modified OTS classes

Some classes from the OTS Java code have been modified to allow the simulation of automation levels and enable adaptations regarding interactions between automation levels. The traffic simulation project is available on GitHub: https://github.com/J-Poland/GraduationOTS. However, some modifications will be explained here to clarify how the different levels and interactions are implemented.

### Car-following modifications

Tailgating in OTS is managed in the Tailgating class. However, a CustomTailgating class is introduced to only apply tailgating on level 0 vehicles. This is necessary to prevent automated car-following from levels 1, 2 and 3 vehicles to adapt to followers.

The automation levels have different configurations for their car-following and lane-changing behaviour. Where level 0 vehicles have a human driver that controls both car-following and lane-changing actions, level 1 vehicles have automated car-following. This also means that social factors for car-following interactions should be ignored or at least adjusted for automated features. To allow level 0 vehicles to have different social parameters regarding car-following and lane-changing, an additional social parameter is implemented. The socio-speed sensitivity parameter ($socio$) was already used in OTS, now the socio-car-following sensitivity parameter ($socio_{cf}$) is introduced. The new parameter is used in the SocioDesiredSpeed class to make the desired speed dependent on social pressure.

Also, it lets human drivers adapt to their surroundings in mixed traffic. The AdaptationHeadway class is replaced by a CustomAdaptationHeadway class. The class is responsible for determining the minimum time headway dependent on the task saturation of the driver but now also considers the follower and leader vehicle. Whenever a level 0 vehicle is positioned between two level 3 vehicles, the level 0 vehicle will adapt to the minimal time headway of level 3 vehicles based on the driver's car-following social parameter. The applied minimum time headway is thus calculated as follows:

$$T_{min} = T_{min\,level0} * (1 - socio_{cf}) + T_{min\,level3} * socio_{cf} \tag{4}$$

### Lane-changing modifications

The Cooperation class in OTS enables vehicles to decide whether they will create space for merging vehicles. The threshold for cooperation ($D_{coop}$) is calibrated by Schakel et al. (2012). However, this is a social decision and thus for human drivers depends on their social parameter and surrounding vehicle levels. To make cooperation dependent on the socio-car-following sensitivity parameter ($socio_{cf}$) for interactions between level 0 and level 3 vehicles, the CustomCooperation class is created where the cooperation threshold ($D_{coop}$) is determined as follows:

$$D_{coop} = D_{coop\,min} + (D_{coop\,max} - D_{coop\,min}) * (1 - social_{cf}) \tag{5}$$

Where $D_{coop\,min}$ and $D_{coop\,max}$ are set based on ±10% of the default $D_{coop}$.

### Mental model modifications

In previous paragraphs, it is stated that distractions are distractions because they affect the driving behaviour of human drivers. In OTS this only happens when the task saturation exceeds the critical task capacity. In order to let distractions exceed the critical task capacity, the remaining (un-saturated) task capacity is calculated. Whenever drivers become distracted by either in-vehicle distractions or roadside distractions, an extra workload is applied to exceed the critical task saturation, see Equation 3. This is handled in the TaskManagerAr class.

The AdaptationSituationalAwareness class adjusts the driver's reaction time based on situational awareness. However, to control the minimum and maximum values for reaction times for human drivers, a CustomAdaptationSituationalAwareness class is created. The new formula to calculate the reaction time ($RT$) is:

$$RT = RT_{min} + (RT_{max} - RT_{min}) * (SA_{max} - SA) \tag{6}$$

Where $RT_{min}$ is the minimum reaction time, $RT_{max}$ is the maximum reaction time, $SA_{max}$ is the maximum situational awareness, and $SA$ is the current situational awareness.

Unfortunately, the reaction time values are only applicable for level 0 vehicles. Human drivers are still in control of lane-changing in level 1 vehicles. However, the single perception in OTS does not allow different reaction times within one vehicle.

The new CustomAdaptationHeadway class also includes a statement to check whether the vehicle is a level 0 vehicle. This is checked because only human drivers can adapt their headway because of high task workloads. The same holds for speed adaptations. A CustomAdaptationSpeed class is implemented only to apply speed adaptations for level 0 vehicles.

# Appendix II: Vehicle model parameters

This appendix will explain exactly what parameters are used for vehicle models to represent their automation level. The available research is discussed and the chosen parameter values are presented.

### Reaction times

Driver reaction times are crucial in traffic. Human drivers base their desired headway on comfortable following distances. When the time headway becomes lower than their reaction time, human drivers tend to decelerate to increase the time headway. This is also incorporated into behaviour adaptations in OTS. Whenever the situational awareness of the driver decreases, the reaction time increases and the desired speed and headway are adjusted to mitigate the mental workload.

The increase in reaction time to match the driver's situational awareness is determined by:

$$RT = RT_{max} * (SA_{max} - SA) \tag{7}$$

The reaction time ($RT$) is determined by scaling the maximum reaction time ($RT_{max}$) according to the difference between maximum situational awareness ($SA_{max}$) and the current situational awareness level ($SA$). As situational awareness decreases, reaction time increases proportionally, reflecting slower responses under reduced awareness.

The default maximum reaction time is set to $RT_{max} = 2.0\,s$. By default, this means that the reaction time is between 0.0 and 2.0 seconds. While a reaction time of 0.0 seconds does not correspond with real-life reaction times, it does reflect the quick responsiveness of emergency braking systems that are available in all vehicle automation levels.

Automated car-following behaviour has a low reaction time because the processing time of sensor data by computers is quicker than human reaction times. Still, Makridis et al. (2019) claims that available ACC controllers have high reaction times. This is observed in car-following data because the response time depends on comfort settings and does not reflect the reaction time of data processing. When a vehicle encounters a dangerous situation, the system ignores comfort settings, enabling a faster, more immediate response. Additionally, the reaction time only increases whenever the driver's situational awareness deteriorates because of the mental workload. This does not occur for automated driving tasks. Therefore, the maximum reaction time of automated car-following is assumed to be $RT_{max} = 0.0\ s$ to simulate their fast data processing and prevent performance deterioration by situational awareness. The comfort settings will still affect the vehicle's acceleration and headway parameters.

For human drivers, determining reaction time is more complicated. Humans could have to undergo decision-making without the latest information, which is highly dependent on their attentiveness. Research from Mehmood and Easa (2009) for braking scenarios and Fu et al. (2019) for car-following scenarios show that human reaction times go up to 2.0 seconds. Therefore, level 0 vehicles will use the default maximum reaction time of $RT_{max} = 2.0\,s$. Their attentiveness is then taken into account by increasing their reaction time up to this maximum reaction time based on their situational awareness as shown in Equation 7.

#### Acceleration

For human drivers in OTS, the default values for acceleration variables are:

- Maximum desired car-following acceleration $a = 1.25\, m/s^2$.
  This acceleration value is found for passenger cars during calibration of the LMRS model in combination with the IDM+ model (Schakel et al., 2012).
- Maximum comfortable car-following deceleration $b = 2.09\, m/s^2$.
  This deceleration value is found for passenger cars during calibration of the LMRS model in combination with the IDM+ model (Schakel et al., 2012).
- Maximum critical deceleration $b_{crit} = 3.50\, m/s^2$.
- Maximum adjustment deceleration $b_0 = 0.50\, m/s^2$.

The default values are calibrated for human traffic on a Dutch highway, so these values are used for level 0 vehicles. However, for higher automation level vehicles these values will be different.

Observed data from vehicles equipped with ACC show that car-following support lowers the variability of acceleration while driving. Schakel et al. (2017) find that enabling ACC will result in a 13.1% and 31.5% decrease in the mean standard deviation of acceleration while in free and saturated traffic respectively. However, in congestion, they observed only a decrease of 4.5% which is not statistically significant. This shows that the ACC will have a more smooth driving style than human drivers in faster driving situations. Additionally, T. Li et al. (2021) observe that the ACC's acceleration magnitude is decreased due to comfort settings. Therefore, for ACC both the maximum desired car-following acceleration and maximum comfortable car-following deceleration are lowered.

Since the experiments in this research are simulated near critical road capacity, traffic will mostly be saturated. Therefore, the 13.1% reduction in acceleration variability should be realised. To achieve this, the maximum desired car-following acceleration is set to $a = 1.17 m/s^2$ and the maximum comfortable car-following deceleration is set to $b = 1.95 m/s^2$. These are determined by calculating the reduction factor based on the standard deviation:

$$reduction\, factor = \sqrt{1 - variance\, reduction} \tag{8}$$

$$ACC\, acceleration\, value = reduction\, factor * human\, acceleration\, value \tag{9}$$

When congested, the ACC is still able to perform the same decelerations as humans because the maximum critical deceleration is not changed. Also, the maximum adjustment deceleration is not adjusted since the maximum adjustment deceleration will only be effective in a free traffic flow which will not be simulated much.

For level 3 AVs it is assumed that similar acceleration ranges will be applicable. However, since the level 3 AV will be more optimised, it is assumed that the variability for acceleration values will be lower. As the ACC had a reduction of 13.1% in variability, it is assumed that a level 3 AV will achieve a 20% reduction in variability.

This leads to the following selection of acceleration parameters:

- Level 0: $a = 1.25\, m/s^2$, $b = 2.09\, m/s^2$, $b_{crit} = 3.50\, m/s^2$, and $b_0 = 0.50\, m/s^2$;
- Level 1: $a = 1.17\, m/s^2$, $b = 1.95\, m/s^2$, $b_{crit} = 3.50\, m/s^2$, and $b_0 = 0.50\, m/s^2$;
- Level 2: $a = 1.17\, m/s^2$, $b = 1.95\, m/s^2$, $b_{crit} = 3.50\, m/s^2$, and $b_0 = 0.50\, m/s^2$;
- Level 3: $a = 1.12\, m/s^2$, $b = 1.87\, m/s^2$, $b_{crit} = 3.50\, m/s^2$, and $b_0 = 0.50\, m/s^2$.

**Relaxation**

The LMRS model also includes relaxation. In addition to lane change, synchronisation, and cooperation actions, the LMRS model also smooths out changes in acceleration. It gradually increases the vehicle's headway toward the maximum, preventing abrupt or frequent large changes in acceleration. The headway time will be between the minimum and maximum headway time. The relaxation ratio $\frac{timestep}{\tau}$ influences how fast the headway adjusts. Since the time step is already set, the relaxation time parameter ($\tau$) controls the adjustment speed. Since the acceleration parameters are already adjusted to account for the low variability in ACC acceleration, the relaxation time parameter is kept at the default value ($\tau = 25s$). This value is calibrated for the LMRS model on data collected from a Dutch freeway (Schakel et al., 2012).

**Maximum and minimum headway**

The default maximum and minimum time headway settings in OTS are as follows:

- Maximum time headway $T_{max} = 1.2\, s$.
  This maximum time headway value is found for passenger cars during calibration of the LMRS model in combination with the IDM+ model (Schakel et al., 2012).
- Minimum time headway $T_{min} = 0.56\, s$.
  This minimum time headway value is found for passenger cars during calibration of the LMRS model in combination with the IDM+ model (Schakel et al., 2012).

While AVs have low reaction times, level 1 and level 2 vehicles do not seem to lower the vehicle's headway. The literature review showed that automated car-following would improve road capacity because of lower headways. However, research on the use of ACC, which corresponds to the car-following features of level 1 and level 2 vehicles, shows that larger headways are observed (Kummetha et al., 2018). Without ACC the headways were 20.5% smaller. This is also seen by Schakel et al. (2017) during their driving study. They observe a mean human time headway of 0.98 seconds (with a standard deviation of 0.4 seconds) and with ACC a mean time headway of 1.2 seconds (with a standard deviation of 0.3 seconds) in saturated traffic.

For level 3 automation vehicles it is often assumed that they can maintain very small headways. However, the literature review shows that this assumption is only tested in scenarios for CAVs. Without communication between vehicles the level 3 AV needs to be more careful in its decision-making to ensure a safe driving style. However, this research does assume that the technology within the level 3 AV is sophisticated enough to handle complex traffic situations better than current ACC systems. The low reaction time of the AV would then allow the vehicle to maintain slightly lower headways than human drivers could. Also, the variability in time headway values will be smaller. Therefore, it is assumed for level 3 AVs that the minimum time headway is 10% lower than for human drivers and the maximum time headway is 20% lower than for human drivers.

The simulation does simulate tailgating in traffic. Vehicles can feel the social pressure of their following vehicle and increase their desired speed. This will lead to smaller headways and thus the default maximum time headway value of 1.2 seconds is multiplied by $1\frac{1}{3}$ to maintain its effective time headway of 1.2 seconds while experiencing tailgating. This is also performed for the level 0 maximum time headway.

When including time headway ranges for one standard deviation from Schakel et al., accounting for tailgating effects for level 0 vehicles, and assuming level 3 automation values, the following values are set:

- Level 0: $T_{min} = 0.58\,s$ and $T_{max} = 1.84\,s$;
- Level 1: $T_{min} = 0.8\,s$ and $T_{max} = 1.5\,s$;
- Level 2: $T_{min} = 0.8\,s$ and $T_{max} = 1.5\,s$;
- Level 3: $T_{min} = 0.522\,s$ and $T_{max} = 1.104\,s$.

Now, the human time headway settings in level 0 vehicles are not drawn from a distribution which means that all human drivers have the same minimum and maximum time headway parameters. While variability in time headway is seen in data, the variability is mostly caused by traffic conditions. Qin et al. (2023) find that drivers do not have a static driver profile. The driver could exhibit an aggressive driving style in one moment and behave more calmly in another. They state that the traffic condition is leading to the behaviour of the driver. Since the desired time headway is already dynamically determined in OTS by taking traffic conditions into account, no further distributions are used for the time headway parameters.

### Speed limit adherence factor

Automated vehicles will comply with freeway speed limits more strictly than human drivers do. Vollrath et al. (2011) and Kummetha et al. (2018) research the effect of CC and ACC on driving behaviour. This research shows that human drivers have a speed variability of 5-20%, while utilisation of (A)CC lowers this variability. With (A)CC, the mean speed is decreased by 5-10% and less time is spent above the speed limit by at least 20%. These studies are used to set the speed adherence factor for the vehicle models. The speed adherence factor for level 3 vehicles will be even lower since the driving tasks are completely controlled by its AV features, so the human passenger will not necessarily set the vehicle's speed. A level 3 AV can still exceed the speed limit slightly whenever lane-changing is required but the variability in speed will be lower.

For human drivers, speed adherence depends on personal characteristics. To incorporate these characteristics, a triangular distribution is used to set the speed adherence factor for each vehicle. Additionally, levels 1, 2, and 3 will use an adherence factor drawn from a triangular distribution, as human drivers influence the precise driving speed in level 1 and level 2 vehicles, and different algorithms are applied in automated features across specific car brands.

Thus, the following speed adherence factor values are chosen:

- Level 0: $f_{speed} = TriangularDistribution(0.8, 1.0, 1.2)$;
- Level 1: $f_{speed} = TriangularDistribution(0.9, 1.0, 1.1)$;
- Level 2: $f_{speed} = TriangularDistribution(0.9, 1.0, 1.1)$;
- Level 3: $f_{speed} = TriangularDistribution(0.95, 1.0, 1.05)$.

### Social parameters

Vehicles experience social pressure from their follower that can cause tailgating and an increased desired speed. A social pressure ($\rho$) for the following vehicle is set dynamically based on the speed difference compared to the leader vehicle. The leader vehicle then calculates a desired speed while taking the social pressure of the following vehicle into account:

$$desired\ speed = desired\ speed + \rho * socio_{cf} * v_{gain} \tag{10}$$

As can be seen, next to social pressure ($\rho$), also a social car-following sensitivity ($socio_{cf}$) and anticipation speed for full lane change desire ($v_{gain}$) is required to determine the desired speed based on social pressure.

The social car-following sensitivity parameter determines whether a driver will increase its speed because of the speed of followers. While humans could feel rushed by following vehicles, automated car-following features will maintain their speed. AVs are designed to safely execute car-following and lane-changing manoeuvres and maintain a legal speed. Adjusting their speed to please other, more aggressive, drivers is not a priority. Therefore, the human social car-following sensitivity is set by a triangular distribution and for levels 1, 2 and 3 the sensitivity is set to 0.

The anticipation speed for full lane change desire is normally used to determine the lane change desire whenever drivers can increase their driving speed by going to another lane. However, in this context, the parameter affects the response to tailgating by taking the desire to increase speed into account. The default value is set to $v_{gain} = 69.6\ km/h$ calibrated for a Dutch freeway (Schakel et al., 2012). Because this parameter affects both lane-changing and tailgating, it is kept at the default value. So, the difference in tailgating response between automation levels is solely set by the social speed sensitivity.

Next to the desired speed, a social speed sensitivity parameter *socio* is used to set how thoughtful the driver is about going out of the way of other vehicles or refraining from changing lanes when it can improve the traffic flow. The default value is $socio = 1.0$, but commonly a distribution from 0 to 1 is used to account for less and more sensitive drivers. These are driving aspects that cannot be considered by level 2 vehicles. Also, level 3 vehicles will not show social lane-changing behaviour since they will prioritise their own route and safety considerations. However, for level 0 and 1 vehicles, the human driver is still fully engaged in lane-changing tasks, so they can also make social decisions for lane changes. This parameter will have a distribution from 0 to 1 for level 0 and 1 automation.

The resulting settings are:

- Level 0:

$$socio_{cf} = TriangularDistribution(0.0, 0.5, 1.0),$$
$$socio = TriangularDistribution(0.0, 0.5, 1.0) \text{ and}$$
$$v_{gain} = 69.6\, km/h;$$

- Level 1:

$$socio_{cf} = 0.0,$$
$$socio = TriangularDistribution(0.0, 0.5, 1.0) \text{ and}$$
$$v_{gain} = 69.6\, km/h;$$

- Level 2:

$$socio_{cf} = 0.0,$$
$$socio = 0.0 \text{ and}$$
$$v_{gain} = 69.6\, km/h;$$

- Level 3:

$$socio_{cf} = 0.0,$$
$$socio = 0.0 \text{ and}$$
$$v_{gain} = 69.6\, km/h.$$

### Look-ahead and look-back

In OTS the vehicles have look-ahead and look-back parameters to control the perception range of drivers. Default values for human drivers are:

- $lookahead = 295.0\, m$;
- $lookback = 200.0\, m$.

Regarding automatic car-following's range of perception, Jeong et al. (2012) states that long-range radars are used to provide ACC with ranges from 70 to 250 meters, while short-range radars cover the lower ranges. Current vehicles have a variety of ranges for their car-following control. Renault claims that their vehicle front radars have a range of 130 to 140 meters (Renault, n.d.). Available premium Bosch front radars already have up to around 300 meters (Bosch Mobility, n.d.). Additionally, Tesla utilises computer vision for their autopilot with a 360-degree perception up to 250 meters (Tesla, n.d.). Therefore, it is acceptable to assume that current level 1 vehicles have a perception of up to 140 meters. More automated vehicles are better equipped and level 3 vehicles will be the newest vehicles on the road, so an increase in technology and thus an increase in vehicle perception is expected.

The vehicle's perception is not only aimed forward. Also, rear sensors are available for automated vehicles. Current ADAS are often equipped with rear radars that detect objects within 20 meters (Jeong et al., 2012). When taking Tesla's computer vision into account, their backward camera has a range of up to 50 meters. However, the 360-degree coverage ensures that objects can be detected within a range of 100 meters. The higher the automation level, the better the perception coverage. Therefore, it is assumed that level 1 vehicles have a look-back of 20 meters, which increases for each automation level as it does for the look-ahead parameter.

These findings suggest significant differences between perception ranges for different automation levels. Research on human perception does not state a specific range for look-ahead and look-back parameters. The default values ensure that level 0 vehicles have the highest range of perception, and higher automation levels get an increasingly larger perception range. This fits the development of technology and also shows the limitations of AVs as long as they are not connected such as CAVs. Therefore, the default values are kept for level 0 vehicles.

However, the short look-back parameters for level 1 and 2 vehicles are problematic for safe lane changes in OTS. It is not possible to brake-off a lane change. So when a lane change is initialised, the vehicle will complete this lane change no matter how fast followers in the new lane approach. Because a short look-back parameter does not provide the vehicle with information about potential followers, it results in many collisions in the simulation. This does not reflect real-world lane changes since in real life the driver or AV controller can check the surroundings continuously and brake off a lane change when the manoeuvre is not considered safe anymore. Thus, the default look-back value is kept for all vehicle types to ensure realistic lane-changing behaviour.

The resulting look-ahead and look-back values are:

- Level 0: $lookahead = 295.0\,m$ and $lookback = 200.0\,m$;
- Level 1: $lookahead = 140.0\,m$ and $lookback = 200.0\,m$;
- Level 2: $lookahead = 250.0\,m$ and $lookback = 200.0\,m$;
- Level 3: $lookahead = 300.0\,m$ and $lookback = 200.0\,m$.

### Task capacity of the human driver

The task saturation determines whether a human driver experiences limited situational awareness. Equation 11 from van Lint and Calvert (2018) shows that the task saturation $TS$ is directly dependent on the task capacity $TC$. This means that drivers can handle different levels of mental workload before it affects their driving behaviour.

$$TS = \frac{total\ task\ demand}{TC} \tag{11}$$

The paper from van Lint and Calvert do not show a method to determine a driver's task capacity. To account for different experience levels among human drivers, the task capacity is varied by ±10% from its default value of 1.0. This adjustment does not affect higher automation level vehicles, as no take-over control situations are simulated and the perception of level 1 vehicles is based on a maximum reaction time of 0. Therefore the following values are used:

- Level 0: $TC = TriangularDistribution(0.9, 1.0, 1.1)$;
- Level 1: N/A;
- Level 2: N/A;
- Level 3: N/A.

## Parameters overview

The last paragraphs have explained which values are chosen for which parameters. To provide an overview of these assumed parameters, Table 9 is shown here. The assumed values are substantiated, however, Appendix IV: Sensitivity analysis checks these values and presents an overview of the final selected parameters.

Table 9: Assumed parameter values for GTU behavioural models.

| **Parameter** | **Symbol** | **Level** 0 | **Level 1** | **Level 2** | **Level 3** | **Units** |
|---|---|---|---|---|---|---|
| Minimum reaction time | $RT_{min}$ | 0.17 | 0.0 | 0.0 | 0.0 | s |
| Maximum reaction time | $RT_{max}$ | 2.0 | 0.0 | 0.0 | 0.0 | s |
| Look-ahead | $lookahead$ | 295.0 | 140.0 | 250.0 | 300.0 | $m$ |
| Look-back | $lookback$ | 200.0 | 200.0 | 200.0 | 200.0 | $m$ |
| | | | **IDM+ specific parameters** | | | |
| Minimal headway time | $T_{min}$ | 0.58 | 0.8 | 0.8 | 0.522 | $s$ |
| Maximum headway time | $T_{max}$ | 1.84 | 1.5 | 1.5 | 1.104 | $s$ |
| Maximum desired car-following acceleration | $a$ | 1.25 | 1.17 | 1.17 | 1.12 | $m/s^2$ |
| Maximum comfortable car-following deceleration | $b$ | 2.09 | 1.95 | 1.95 | 1.87 | $m/s^2$ |
| Maximum critical deceleration | $b_{crit}$ | 3.5 | 3.5 | 3.5 | 3.5 | $m/s^2$ |
| Maximum adjustment deceleration | $b_0$ | 0.5 | 0.5 | 0.5 | 0.5 | $m/s^2$ |
| Speed adherence factor | $f_{speed}$ | (0.8 - 1.2) | (0.9 - 1.1) | (0.9 - 1.1) | (0.95 - 1.05) | - |
| Socio-car-following sensitivity | $socio_{cf}$ | (0.0 - 1.0) | 0.0 | 0.0 | 0.0 | - |
| | | | **LMRS specific parameters** | | | |
| Socio-speed sensitivity | $socio$ | (0.0 - 1.0) | (0.0 - 1.0) | 0.0 | 0.0 | - |
| Anticipation speed for full desire | $v_{gain}$ | 69.6 | 69.6 | 69.6 | 69.6 | $km/h$ |
| | | | **Fuller specific parameters** | | | |
| Task capacity | $TC$ | (0.9 - 1.1) | N/A | N/A | N/A | - |
| Critical task saturation | $TS_{critical}$ | 0.8 | N/A | N/A | N/A | - |

## Appendix III: Exploratory analysis

This appendix contains the exploratory analysis to determine basic simulation settings such as the warm-up time, traffic demand, and the sampling time based on travel times observed in the traffic simulation. For each section, the method is discussed and graphs from the exploratory notebooks are selected to explain why certain simulation settings are chosen. The complete analyses are available on GitHub.

The simulation runs for exploratory analysis have vehicle configurations from the assumed parameter values in Table 9 from Appendix II: Vehicle model parameters. The base scenario of 100% human drivers is chosen to find the near-road capacity scenarios for human drivers which can be compared to the introduction of automation levels. To analyse a broad range of traffic conditions, the following input parameters were used:

- **Seeds:** [0, 1, 2, 3];
- **Warm-up time:** 0 seconds;
- **Sample time:** 1800 seconds;
- **Main demand:** 1000 - 5000 veh/h;
- **Ramp demand:** 200 - 1000 veh/h;
- **Level 0 fraction:** 1.0;
- **Level 1 fraction:** 0.0;
- **Level 2 fraction:** 0.0;
- **Level 3 fraction:** 0.0;
- **In vehicle distraction:** True;
- **Roadside distraction:** False;

### Warm-up time

Traffic simulations require a warm-up time to fill the road network with vehicles. The first vehicles to enter the road have no other vehicles in their surroundings, resulting in unrealistic behaviour and measurements for traffic conditions and dynamics. The warm-up time will ensure that sampled data is based on traffic conditions and dynamics that correspond to the provided traffic demand settings.

The progress of vehicle count is shown in Figure 23. The graph clearly shows the initial phase where the simulation is filling the road network. However, some simulation runs show a quicker stabilisation than others. This can be explained by the broad demand settings that are used to explore the traffic simulation. Additionally, while stabilisation behaviour is observed, the vehicle count does not actually get stable. The freeway with an on-ramp scenario will be subject to disruptions based on the demand for on-ramp traffic. This is clearly visible in the graph where low runs with vehicle count show less variation than higher vehicle count runs. Despite these differences, no significant changes are observed after 500 seconds in the simulation.

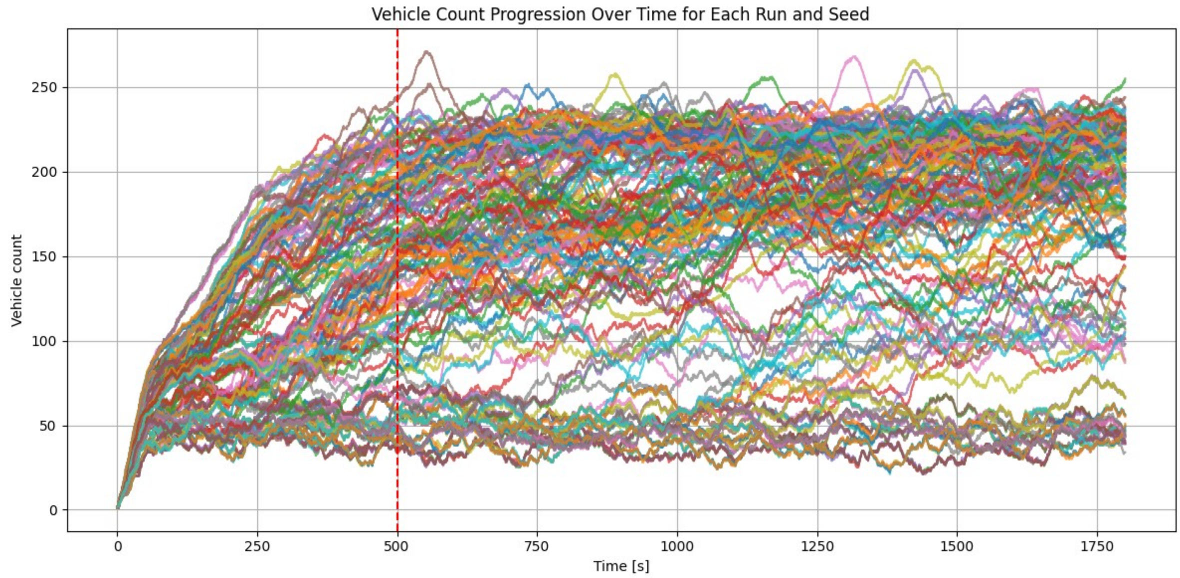


Figure 23: Progress of simulation vehicle count.

The warm-up time is often determined by analysing the stabilisation of traffic characteristics such as traffic flow, density, and speed. Therefore, the progress of these characteristics is analysed for the post-on-ramp lanes (section CD) in Figure 24 and for the on-ramp in Figure 25.

The speed, density, and flow progress observations throughout the simulation for section BC look similar to the progress of the vehicle count. The runs show different variabilities for speed, density and flow measures but need a maximum of 500 seconds to reach a quasi-stable state.

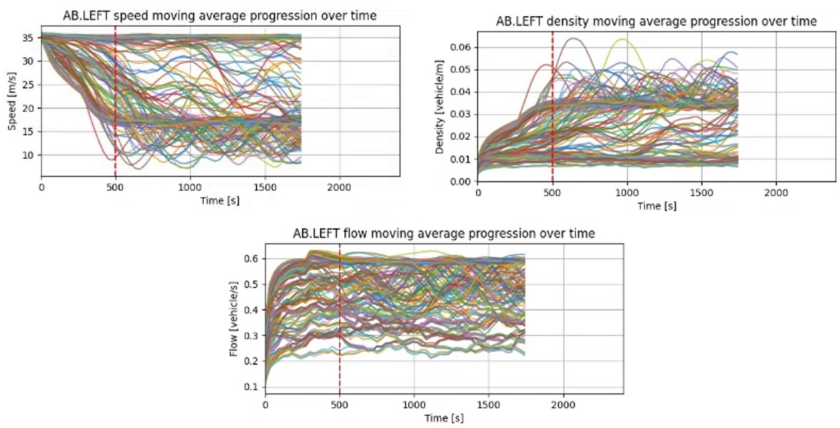


Figure 24: Progress of fundamental diagram variables for the main lanes.

On the on-ramp, no distinct point in time can be identified where all simulation runs seem to reach a quasi-stable state. The speed, density and flow characteristics indicate that the on-ramp becomes congested at different points in time. This also means that the observations will be dependent on the combination of main lanes and on-ramp traffic demand.

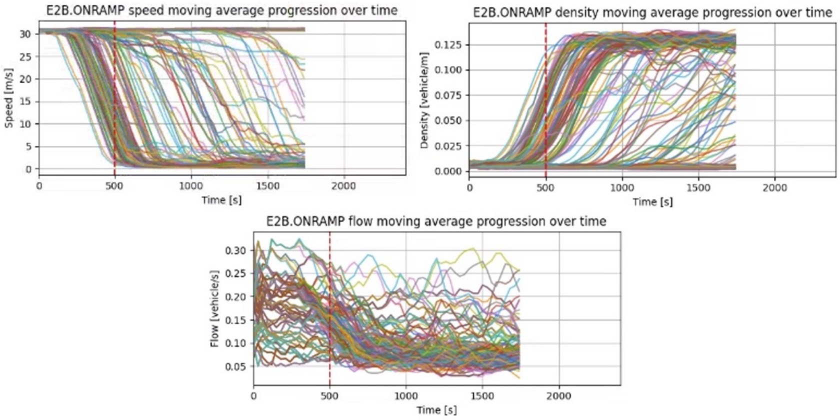


Figure 25: Progress of fundamental diagram variables for the on-ramp.

However, the development of traffic on the on-ramp is of interest to show how well vehicles can merge into the main lanes. This means that the warm-up time should not be determined based on the on-ramp.

Based on these observations, the warm-up time of the simulation is set at 500 seconds. This duration allows the simulation to fill the road network for both low and high-traffic demand settings and allows the vehicle outflow of merging lanes to reach a quasi-stable state.

**Traffic demand**

Ranges of freeway traffic demand for the main lanes and the on-ramp have to be determined. This analysis will seek to identify traffic demand ranges that simulate near-critical road capacity conditions as much as possible. This near-critical road capacity scenario can be identified by using the fundamental diagram that depicts the relation between traffic flow and traffic density. Each section of the freeway has different traffic conditions. Therefore, Figure 26 shows the fundamental diagram for the pre-on-ramp section (AB), merging section (BC), post-on-ramp section (CD), and the on-ramp lane (E2B) throughout the simulation. The variables speed, density and flow are measured every 30 seconds to show short-time traffic developments but not too detailed that the variability becomes too high.

The pre-on-ramp section clearly shows the distinct traffic conditions. A linear increase in flow can be observed for low-density values. This is the free-flow condition where the road capacity can easily handle traffic demand. However, as demand keeps increasing, vehicles have to share the road length with more vehicles. The limited space will slow down vehicles and thus end the linear increase in flow. Figure 26 shows that for density values between 20 - 35 veh/km traffic gets saturated and transforms into congestion. Additionally, the graph shows that changes in traffic conditions occur throughout the whole simulation. Because data points are coloured based on the simulation time. Whereas free-flow conditions are more common at the start of the simulation and congestion more common at the end of the simulation, changes between those conditions occur throughout the simulation.

The merging section also depicts distinct free-flow and congestion conditions. However, the transition from free-flow to congestion is different. The merging section shows a capacity drop at a density of 25 veh/km. This can be explained by the disruptive nature of the on-ramp. Vehicles can merge into the main lanes as long as there is available space. However, when the demand from the on-ramp is too high or there is limited space on the main lanes, fewer vehicles are able to merge.

Another trend is observed for the post-on-ramp fundamental diagram. This section has to handle vehicle outflow from the merging section. Since the merging section is highly subject to disruptions, the outflow is decreased and thus are the two available lanes of the post-on-ramp section able to handle this traffic flow.

The on-ramp lane also shows a clear free-flow relationship. However, the congestion condition is more difficult to identify. High flow measures are observed, even for density values higher than 35 veh/km. This could be explained by varying combinations of main lane traffic demand and on-ramp traffic demand. Whenever the main lane demand is low, there is enough merging space for a high flow of on-ramp traffic. However, it is not possible to achieve a flow of 2000 veh/h for the current on-ramp demand settings. These values are measured because of the stochastic nature of the vehicle generator in OTS. Fundamental diagram variables such as speed, density and flow are measured every 30 seconds. Whenever many vehicles are generated on the on-ramp right after each other, which can also happen in real-life scenarios, the flow for that measure interval is high. If the main lane traffic flow is low for that interval, all vehicles can enter the merging area and thus do not cause any disruptions.

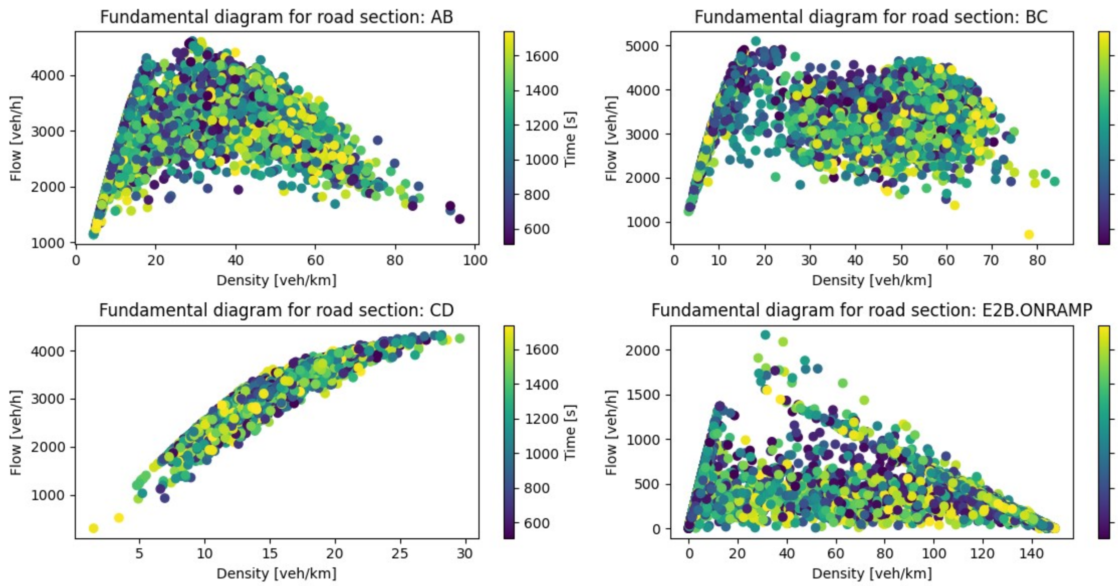


Figure 26: Fundamental diagram for all simulation runs.

The discussed fundamental diagram insights show that many free-flow and congestion conditions are simulated. Therefore, the demand ranges are reduced to focus more closely on the saturated traffic conditions. First, it is important to not only simulate congestion conditions for the on-ramp. High density values for the on-ramp will significantly slow vehicles down which will further complicate merging because of speed differences. Additionally, it is important to lower the amount of free-flow and congestion on the main lanes.

To achieve this, the simulation runs are filtered on minimum and maximum demand values. The following demand settings were found:

- **Main demand:** 2800 - 4000 veh/h;
- **Ramp demand:** 250 - 400 veh/h.

By applying these ranges new fundamental diagrams are created for each road section in Figure 27. The data points that remain in the fundamental diagrams show less congestion on both the on-ramp and the main lanes. Also, the lowest flow data points are excluded.

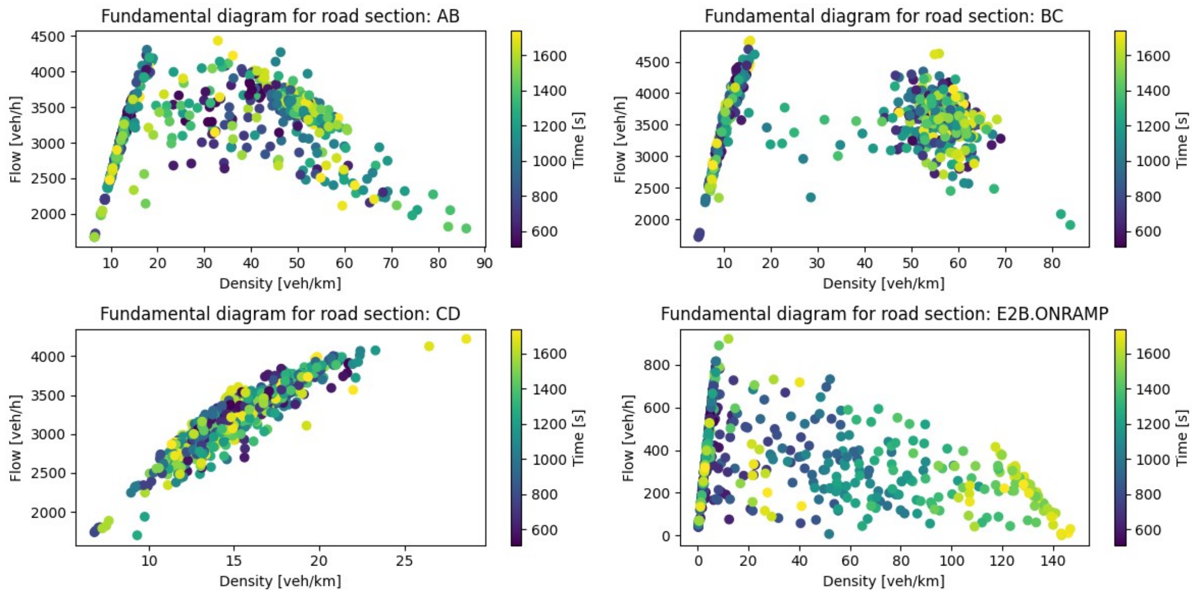


Figure 27: Fundamental diagram for selected simulation runs.

### Sampling time

The simulation duration is dependent on both the warm-up time and sampling time. Now that the demand ranges are chosen and the warm-up time is known. These insights are used to select the appropriate sampling time.

As a rule of thumb, the sampling time for traffic simulations should be at least three times the travel time of vehicles. Figure 28 shows that the majority of vehicles have a travel time of less than 100 seconds. However, vehicles that are generated on the on-ramp show many outliers that can have a travel time of up to approximately 900 seconds. These vehicles have been stuck in congestion on the on-ramp and only can merge into the main lanes when preceding vehicles are able to feed in. The dynamics of congested vehicles on the on-ramp lane are not within the scope of this research. So, not all congested on-ramp vehicles have to be included within the simulation time. However, the ability to absorb disruptions or merge more easily of higher automation levels could be interesting. Therefore, a part of the congested travel times is included in the sampling time to allow analysis of this ability. By taking this into account a sampling time of 1200 seconds is selected. This means that many non-congested vehicles will be sampled, this sample time is significantly higher than three times the travel time, and a large portion of congested vehicles are sampled.

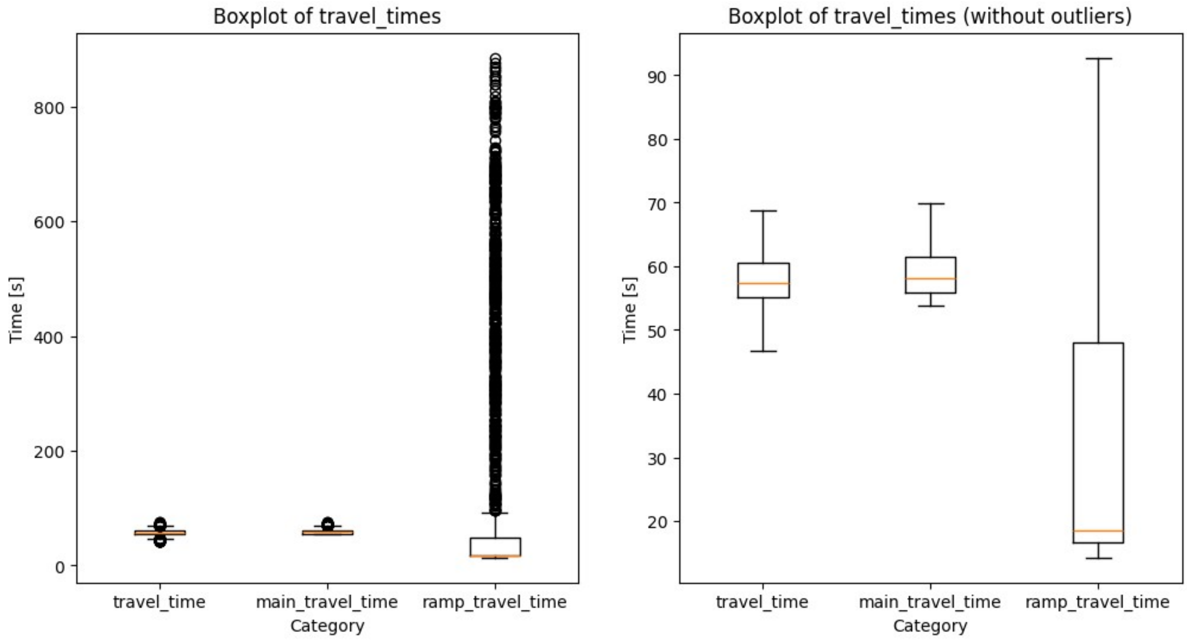


Figure 28: Travel time observed for selected simulation runs.

## Appendix IV: Sensitivity analysis

Parameter values are based on default OTS settings and research for automation levels and mixed traffic. However, some parameters are still uncertain. This uncertainty is caused by conflicting findings in literature or dynamical processes in OTS driving models. Therefore, sensitivity analysis is performed to analyse how the parameter affects the driving behaviour. The assumed values, based on the previous paragraphs, are presented in Table 9. These values are the base values on which the sensitivity analysis is performed. However, insights from the analysis will be used to determine a resulting parameter value. These resulting parameter values will be used in the scenario runs of this research and will be presented in Table 10.

### Human reaction time

Varying human reaction times where found in Mehmood and Easa (2009) and Fu et al. (2019). Additionally, reaction times are determined dynamically in the Fuller model. The workload experienced by the human driver is decisive in determining the effective reaction time. To see how reaction time varies for different maximum reaction time settings, sensitivity analysis is performed for a maximum reaction time of 2.0 seconds, which is approximately the mean reaction time found by Fu et al. and the default value in OTS, to a maximum reaction time of 4 seconds, which includes the 3.32 seconds that was the maximum reaction time in research from Fu et al. To perform the sensitivity analysis, the Latin Hypercube sampler within the EMA Workbench will select a value within this range for each run.

This maximum reaction time is only applicable for human drivers in level 0 vehicles, therefore the base scenario of 100% level 0 vehicles is used. The scenario runs 10 times for 6 seeds. The following simulation settings are used:

- **Seeds:** [0, 1, 2, 3, 4, 5];
- **Warm-up time:** 500 seconds;
- **Sample time:** 1200 seconds;
- **Main demand:** 3400 veh/h;
- **Ramp demand:** 325 veh/h;
- **In vehicle distraction:** True;
- **Roadside distraction:** False;
- **Level 0 maximum reaction time:** 2.0 - 4.0 seconds.

Results are plotted in Figure 29. This plot shows that the mean reaction time does not change significantly whenever the max reaction time increases. Most human drivers do not experience a deteriorating situational awareness and thus have a reaction time of 0.17 seconds. However, the maximum observed reaction times do increase significantly.

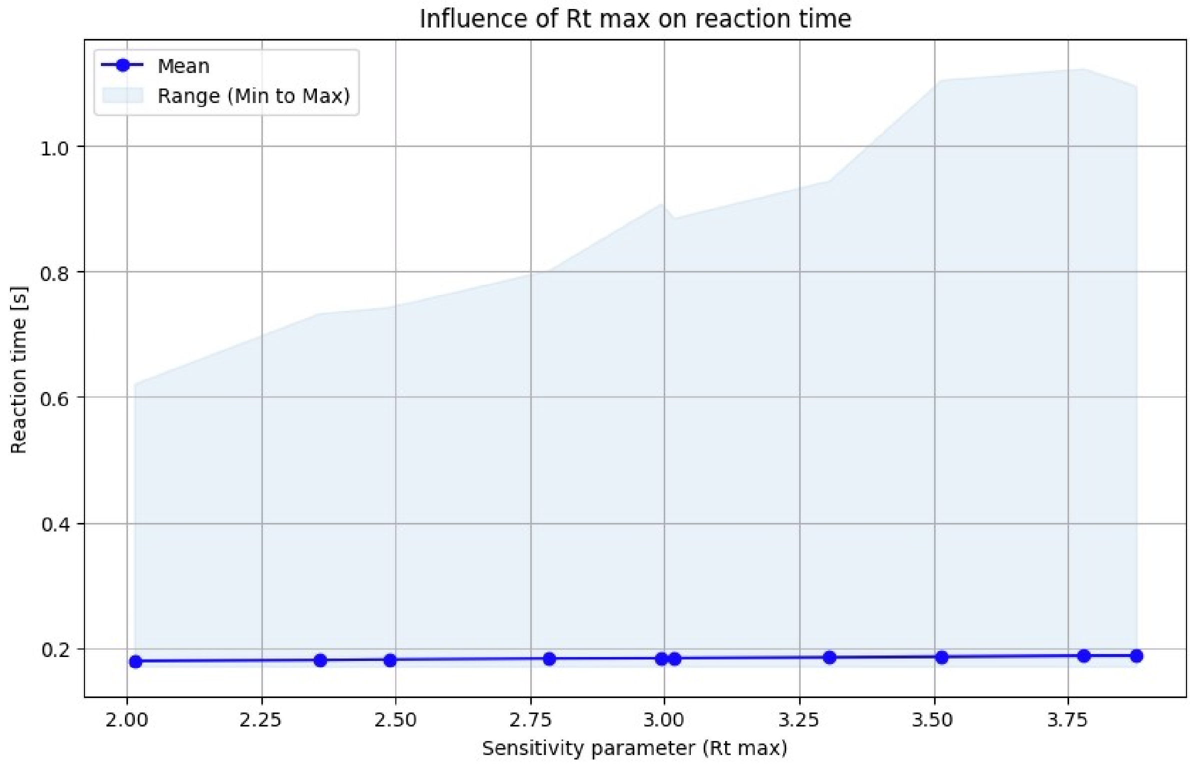


Figure 29: Effect of maximum reaction time on human reaction time.

When the influence of the maximum reaction time is analysed for human drivers that experience deterioration of their situational awareness, the mean reaction time does increase slightly (Figure 30). Therefore, the maximum observed reaction time is chosen to be the determinant for the selection of a maximum reaction time value. Because this simulation requires lower reaction times than real-life human drivers, otherwise an unrealistic number of collisions occur, a maximum reaction time of 2.0 seconds is chosen. This enables the simulation to differentiate between human drivers and automated features for car-following behaviour and does not introduce too large reaction times. A reaction time of 0.6 seconds is just above the time step of the simulation but does not cause many collisions since it does not occur often.

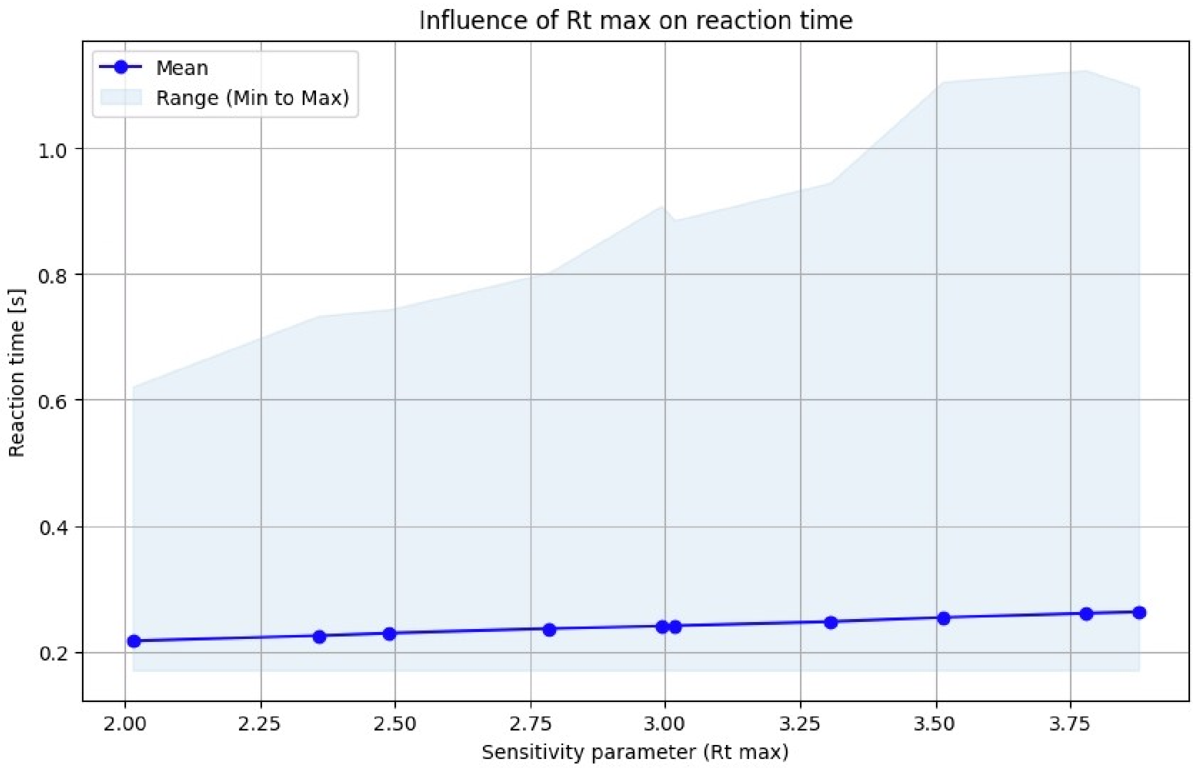


Figure 30: Effect of maximum reaction time on human reaction time for deteriorated situational awareness.

### Maximum headway

The maximum headway is based on research from Schakel et al. (2017). They measure headway time with and without an ACC system. The found mean headway time and the standard deviation are used to set minimum and maximum time headway parameters for level 0, 1, and 2 vehicles. For level 0 vehicles, this would mean that the maximum time headway is $T_{max} = 1.38\ s$. However, because of tailgating the maximum time headway parameter should be increased. In the example code from OTS, the maximum time headway is multiplied by $1\frac{1}{3}$ to maintain an effective time headway of 1.2 seconds. A sensitivity analysis was performed to identify the maximum time headway value required to have an effective time headway of 1.38 seconds for level 0 vehicles. The maximum time headway value will range from 1.2 to 2.0.

Because this analysis is based on human drivers in level 0 vehicles, the base scenario of 100% level 0 vehicles is used. The scenario runs 10 times for 8 seeds. The following simulation settings are used:

- **Seeds:** [0, 1, 2, 3, 4, 5];
- **Warm-up time:** 500 seconds;
- **Sample time:** 1200 seconds;
- **Main demand:** 3400 veh/h;
- **Ramp demand:** 325 veh/h;

- **In vehicle distraction:** True;
- **Roadside distraction:** False;
- **Level 0 maximum time headway:** 1.2 - 2.0 seconds.

The time headway is observed during the sensitivity analysis. Boxplots in Figure 31 show how the time headway of level 0 vehicles changes for varying maximum time headway values. The minimum and maximum time headway range becomes effective whenever the vehicle experiences a headway within this range. Therefore, the effective time headway values are only analysed for the applied ranges.

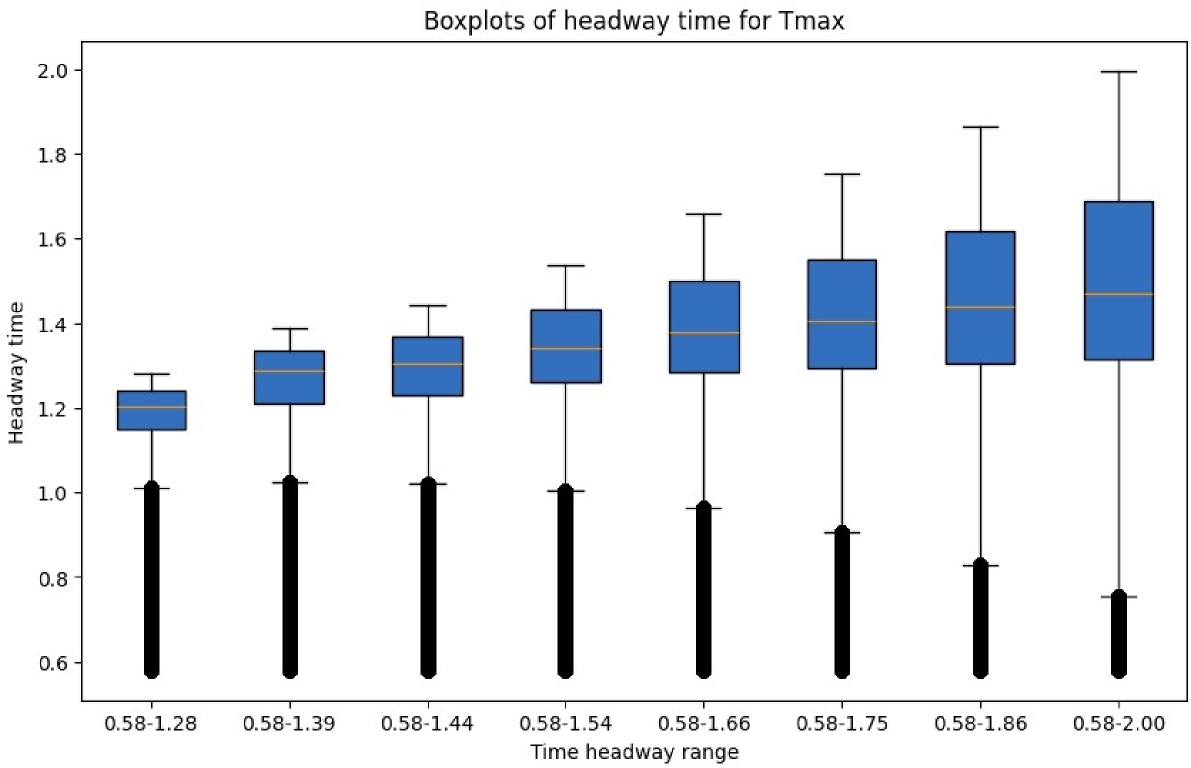


Figure 31: Effect of maximum time headway on the mean time headway.

The figure shows that the mean time headway increases for an increasing maximum time headway. The larger the maximum time headway, the larger the distance to the mean. It was found that the mean time headway of human drivers was 0.98 seconds and with one standard deviation distance 1.38 seconds. As the boxplots show, this is not observed in the simulation data. However, this concludes that lower maximum time headway values better represent human drivers, thus the assumed maximum time headway value is replaced by a maximum value of 1.38 seconds based on findings in the literature.

Also, many outliers are observed. This shows that the vehicle is likely to maintain its headway in the upper area of the time headway range. However, the larger the range, the more small headways become common. This could be explained because a large range also means more variations in the desired headway, which could lead to overshooting.

**Maximum critical deceleration**

The maximum critical deceleration is not covered in the reviewed research on human drivers and automated driving features. The assumed values are the default values in OTS. However, sensitivity analysis is performed to see how the maximum critical deceleration parameter affects traffic. To include a broad range of values, the range is based on ±20% of the default value.

The maximum critical deceleration parameter applies for all vehicle levels, therefore scenario 25-25-25-25 is used to simulate all levels for a penetration rate of 25%. The scenario runs 10 times for 6 seeds. The following simulation settings are used:

- **Seeds:** [0, 1, 2, 3, 4, 5];
- **Warm-up time:** 500 seconds;
- **Sample time:** 1200 seconds;
- **Main demand:** 3400 veh/h;
- **Ramp demand:** 325 veh/h;
- **In vehicle distraction:** True;
- **Roadside distraction:** False;
- **Level 0 maximum critical deceleration:** 2.8 - 4.2 seconds.

The sensitivity analysis shows the same patterns for different automation levels. So the rest of this analysis does not differentiate between them. A plot of vehicle acceleration shows that increasing the maximum critical deceleration causes the mean acceleration to decrease. However, this trend does not continue. This pattern is hard to explain, therefore also the rate of acceleration change is considered.

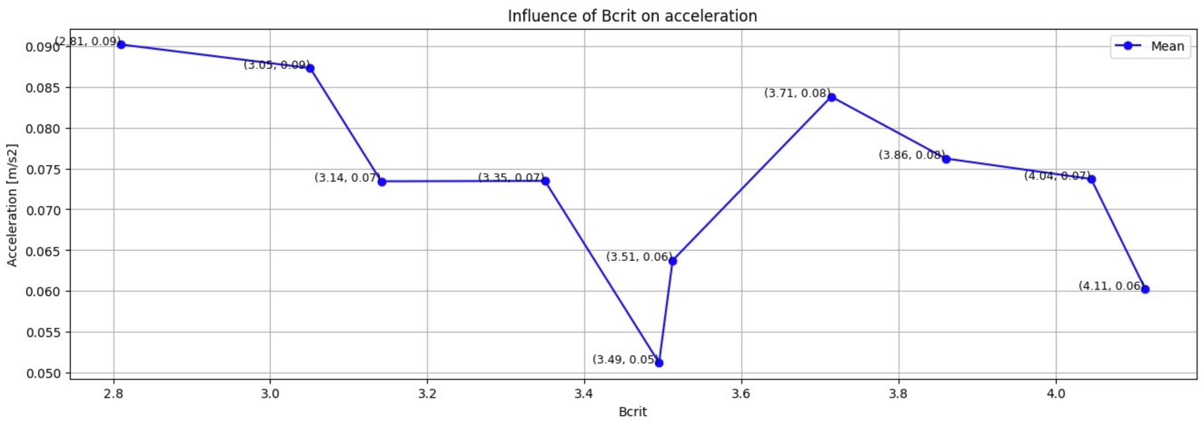


Figure 32: Effect of maximum critical deceleration on acceleration.

The rate of change in acceleration is shown in Figure 33. The overall trend shows that a higher maximum critical deceleration will increase the rate of change of acceleration. This can be explained because higher decelerations may overshoot and force the vehicle to accelerate again. However, the change in the trend may be caused by dynamics between the car-following model and the specific following conditions.

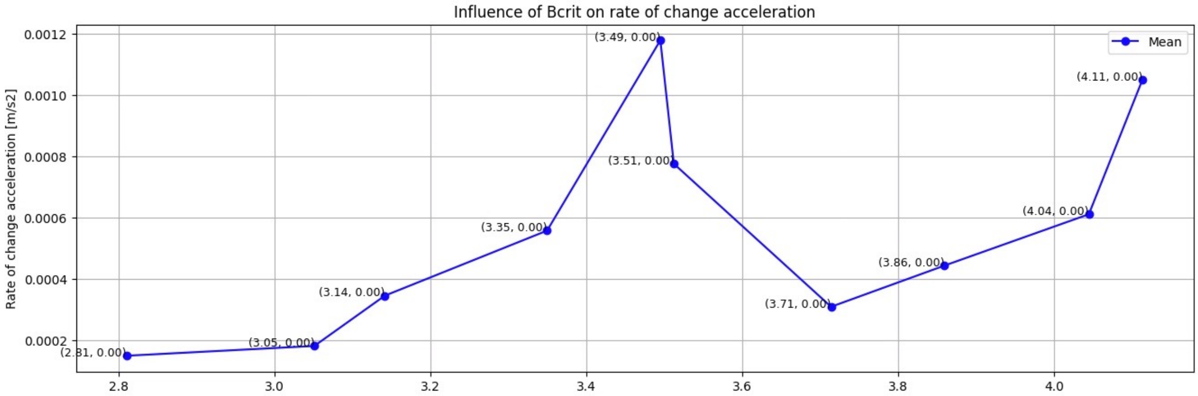


Figure 33: Effect of maximum critical deceleration on change in deceleration.

The default value of 3.5 $m/s^2$ is selected because of the assumption that all automation levels have the same braking capacity. Also, variance in acceleration is achieved by adjusting the maximum desired car-following acceleration and maximum comfortable car-following deceleration, and no convincing reason was identified to alter the default value.

### Maximum adjustment deceleration

Like the maximum critical deceleration parameter, also the maximum adjustment deceleration is only based on the default value in OTS. The adjustment deceleration is responsible for the upper bound for deceleration for adjustments to slow down. Where critical deceleration is used in critical situations, the adjustment deceleration is applicable when the vehicle has to slow down but does not necessarily use the brake. When the adjustment deceleration is too high, it means that people do use their brakes for small changes in speed. Of course, this is not preferred but could also happen in the real world. Therefore, sensitivity analysis will help to get further insights into this parameter. Also, this parameter is applicable for all vehicle levels, so scenario 25-25-25-25 is used for 10 simulation runs for 6 different seeds. A range of ±20% is taken from the default value, resulting in the following simulation settings:

- **Seeds:** [0, 1, 2, 3, 4, 5];
- **Warm-up time:** 500 seconds;
- **Sample time:** 1200 seconds;
- **Main demand:** 3400 veh/h;
- **Ramp demand:** 325 veh/h;
- **In vehicle distraction:** True;
- **Roadside distraction:** False;

- **Maximum critical deceleration:** 0.4 - 0.6 seconds;

The maximum adjustment deceleration is the deceleration applied for small changes in speed. Figure 34 shows that the mean acceleration does decrease when the maximum adjustment deceleration increases. However, like the maximum critical deceleration parameter, this trend does not continue completely, indicating that accelerations are highly dependent on other simulation dynamics.

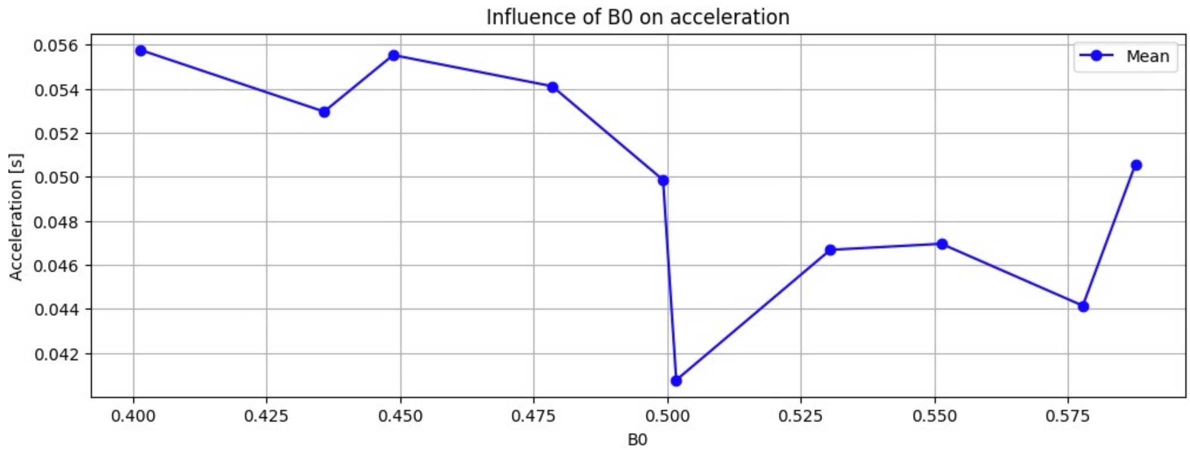


Figure 34: Effect of maximum adjustment deceleration on acceleration.

Because the maximum adjustment deceleration is aimed at adjusting the vehicle's speed, also the influence on the mean speed is observed. Figure 35 shows that the speed is indeed affected by the maximum adjustment deceleration parameter. However, also here no distinct trend is observed.

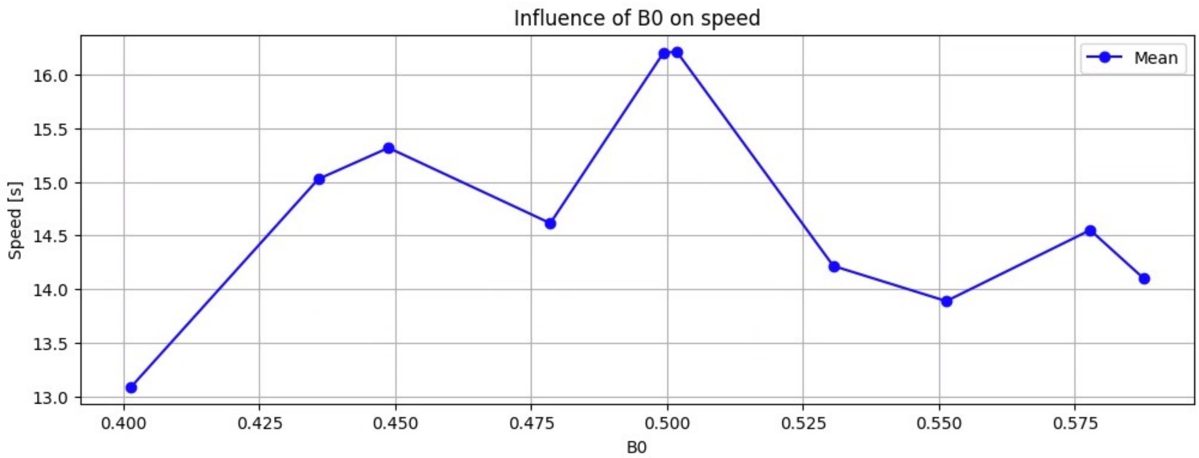


Figure 35: Effect of maximum critical deceleration on change in deceleration.

The default value of 0.5 $m/s^2$ for the maximum adjustment deceleration achieves the highest speed and corresponds to the lowest mean acceleration. This could indicate that the default value in OTS was selected carefully. Therefore, no change is made for this value.

Table 10: Resulting parameter values for GTU behavioural models.

| Parameter | Symbol | Level 0 | Level 1 | Level 2 | Level 3 | Units |
|---|---|---|---|---|---|---|
| Minimum reaction time | $RT_{min}$ | 0.17 | 0.0 | 0.0 | 0.0 | s |
| Maximum reaction time | $RT_{max}$ | 2.0 | 0.0 | 0.0 | 0.0 | s |
| Look-ahead | $lookahead$ | 295.0 | 140.0 | 250.0 | 300.0 | $m$ |
| Look-back | $lookback$ | 200.0 | 200.0 | 200.0 | 200.0 | $m$ |
| **IDM+ specific parameters** | | | | | | |
| Minimal headway time | $T_{min}$ | 0.58 | 0.8 | 0.8 | 0.522 | $s$ |
| Maximum headway time | $T_{max}$ | 1.84 | 1.5 | 1.5 | 1.104 | $s$ |
| Maximum desired car-following acceleration | $a$ | 1.25 | 1.17 | 1.17 | 1.12 | $m/s^2$ |
| Maximum comfortable car-following deceleration | $b$ | 2.09 | 1.95 | 1.95 | 1.87 | $m/s^2$ |
| Maximum critical deceleration | $b_{crit}$ | 3.5 | 3.5 | 3.5 | 3.5 | $m/s^2$ |
| Maximum adjustment deceleration | $b_0$ | 0.5 | 0.5 | 0.5 | 0.5 | $m/s^2$ |
| Speed adherence factor | $f_{speed}$ | (0.8 - 1.2) | (0.9 - 1.1) | (0.9 - 1.1) | (0.95 - 1.05) | - |
| Socio-car-following sensitivity | $socio_{cf}$ | (0.0 - 1.0) | 0.0 | 0.0 | 0.0 | - |
| **LMRS specific parameters** | | | | | | |
| Socio-speed sensitivity | $socio$ | (0.0 - 1.0) | (0.0 - 1.0) | 0.0 | 0.0 | - |
| Anticipation speed for full desire | $v_{gain}$ | 69.6 | 69.6 | 69.6 | 69.6 | $km/h$ |
| **Fuller specific parameters** | | | | | | |
| Task capacity | $TC$ | (0.9 - 1.1) | N/A | N/A | N/A | - |
| Critical task saturation | $TS_{critical}$ | 0.8 | N/A | N/A | N/A | - |

## Appendix V: Simulation of pure scenarios

This appendix contains the data analysis of simulation output aimed at understanding the behaviour of level 0, 1, 2, and 3 vehicles in the 100% penetration rate scenarios per automation level. Each automation level is analysed based on speed, headway and acceleration data.

### Overall driving behaviour

Speed is analysed to get an understanding of the traffic situation wherein the behaviour of the automation levels is observed. Figure 36 shows the frequency of speed levels. It clearly shows that level 3 vehicles are able to maintain a higher speed relative to the other levels. This means that the behaviour of level 3 vehicles is often at high-speed levels which should correspond to larger headway distances than in slower situations. On the other hand, level 1 and level 2 vehicles experience mostly low-speed levels. Level 0 vehicles have a more equal distribution in terms of speed levels.

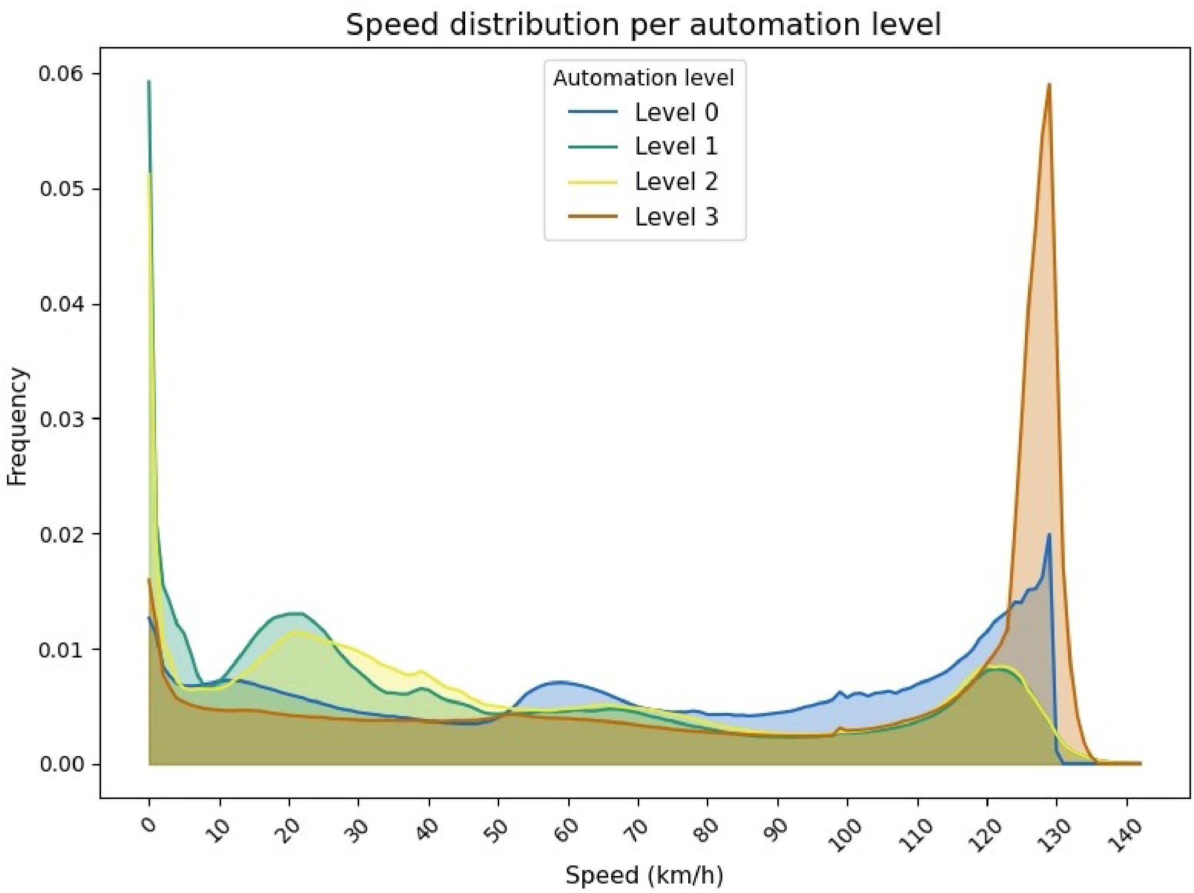


Figure 36: Speed distribution for automation levels in scenarios with penetration rates of 100%.

The automation levels have different settings for their maximum and minimum car-following time headway. The boxplot for headway time in Figure 37 shows that the headway does differ between automation levels. Only headways lower than four seconds are included. This is done to observe how small headways differ between automation levels. Higher headways do not reflect car-following behaviour. Level 0 vehicles show the lowest time headway with a relatively small variability. Level 1 and 2 vehicles have a generally higher time headway which corresponds to their parameters. However, level 2 vehicles do show a lower variability.

Level 3 vehicles do show a similar mean time headway as the level 0 vehicles. However, it is likely that the smaller comfortable acceleration range does prevent the level 3 vehicle of maintaining smaller headways more strictly. Another reason for larger headways is the higher speed levels associated with the simulation runs of 100% level 3 vehicles.

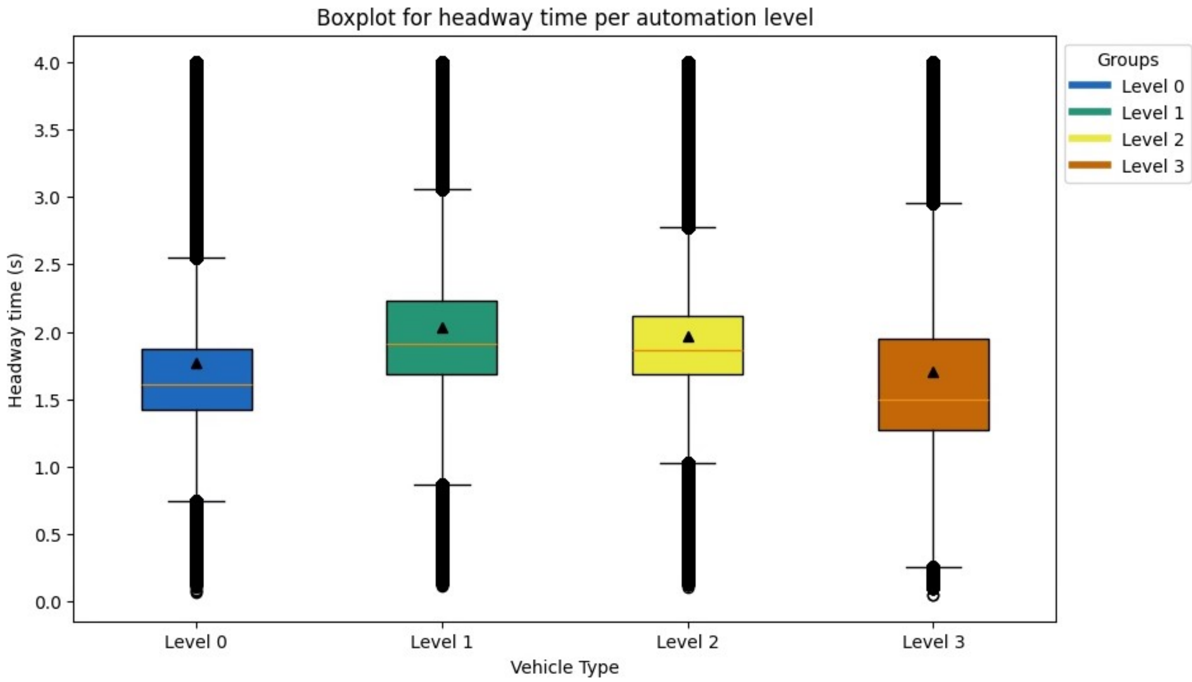


Figure 37: Distribution of time headway for different automation levels in scenarios with penetration rates of 100%.

Figure 38 shows the distribution of vehicle acceleration. The simulation simulates decelerations up to $8\,m/s^2$. These large decelerations happen often because of acceleration at very low speeds. Also, the disruptions of merging vehicles occasionally require followers to brake significantly. Because of the emergency brake of the vehicles these decelerations are achievable. However, because these are observed equally for all levels, the very high decelerations do not reflect characteristic behaviour for the different vehicle levels. Therefore, outliers are not included in this boxplot.

The figure shows that automated car-following does lower the variability in acceleration. However, the smaller maximum and minimum car-following acceleration settings range does not to result in a lower variability for level 3 vehicles. Level 3 vehicles show a slightly larger variability than level 1 and 2 vehicles.

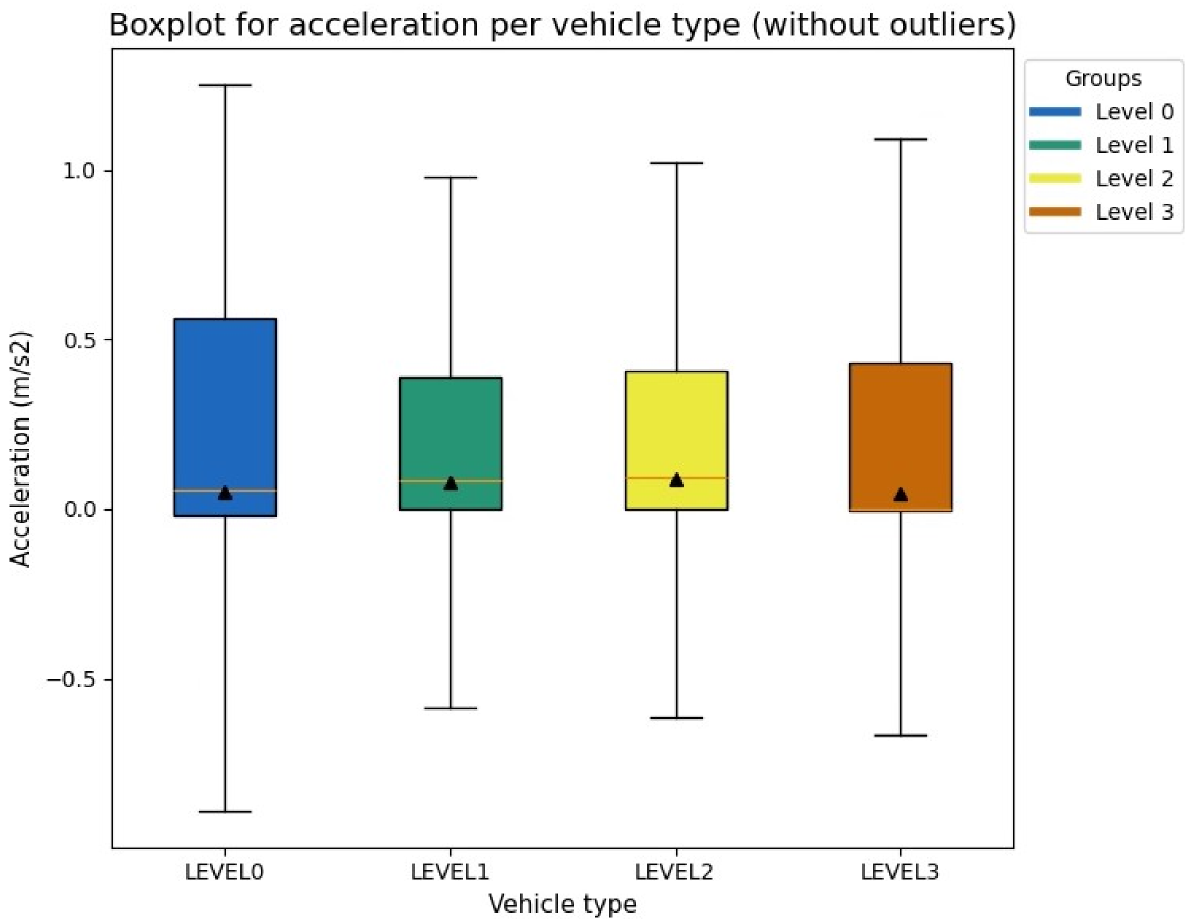


Figure 38: Boxplot for automation level acceleration for scenarios with penetration rates of 100%.

Also, differences are seen in the rate of change of acceleration. Figure 39 shows that level 3 vehicles have a smaller variability for the rate of change of acceleration. This is likely because of the higher speed levels in their simulation runs. However, this could also indicate that the smaller comfortable car-following acceleration parameters limit the vehicle in responding to quick adjustments in the desired acceleration.

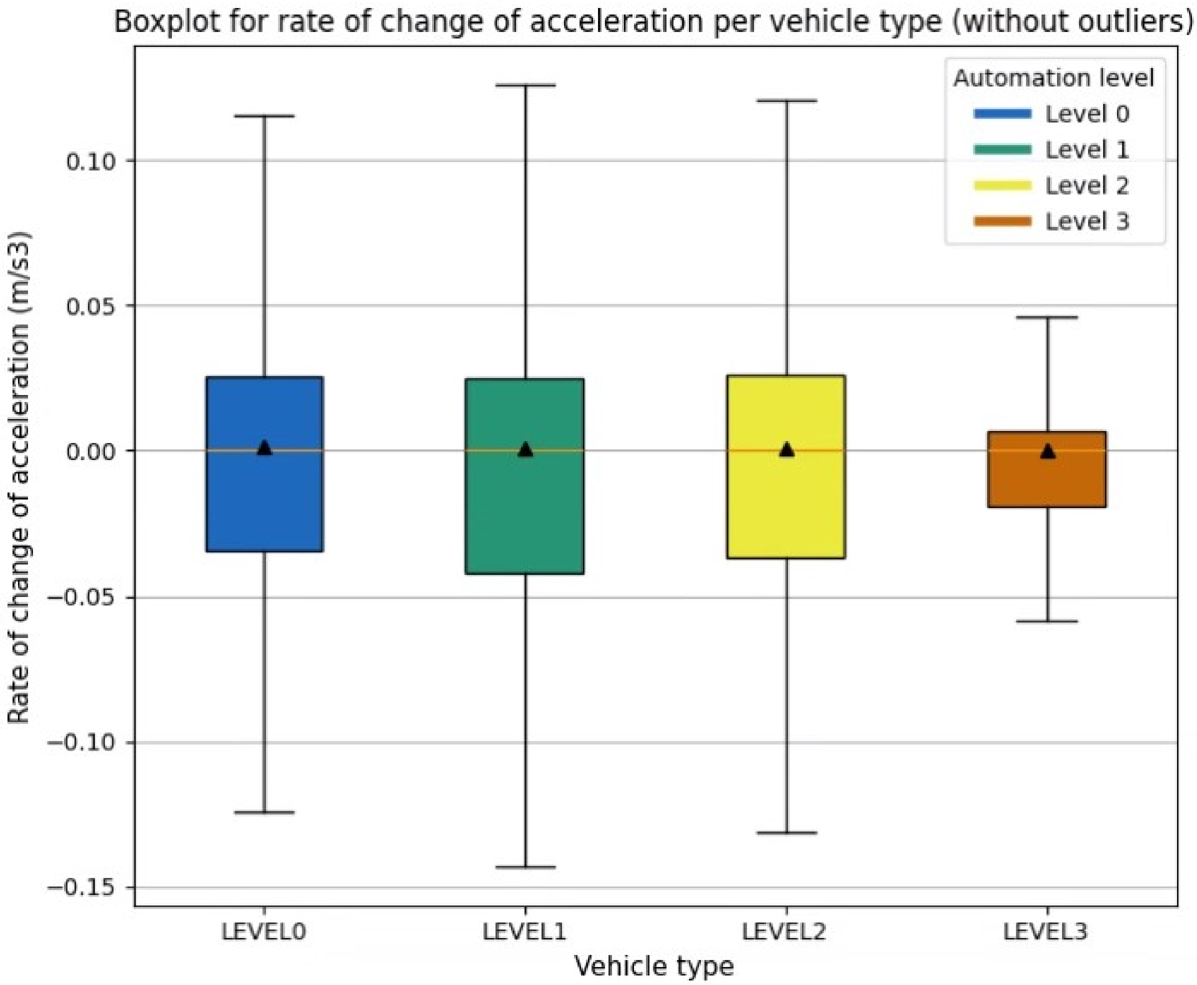


Figure 39: Boxplot for automation level rate of change of acceleration for scenarios with penetration rates of 100%.

This analysis, based on simulations of automation levels for pure scenarios (100% penetration rate for each automation level), does show that the penetration rates result in different traffic conditions. The speed levels differ across the simulations and these effects are seen in the observed driving behaviour. This comparison of driving behaviour across automation levels primarily reflects the influence of traffic conditions on the observed data, rather than capturing the true differences in how automation levels handle traffic situations. Therefore, these simulation runs cannot be used for the driving behaviour analysis. Simulation of mixed traffic where all automation levels are present, such as in scenario 25-25-25-25, is required to compare driving behaviour across automation levels for equal traffic conditions.

# Appendix VI: Analysis of traffic performance and safety

### Traffic performance and safety

The effects of different penetration rates for automation levels in mixed traffic will be analysed in this chapter. Different scenarios from Chapter 3.3 with increasing vehicle automations are explored. The analysis will include comparisons between penetration rates for speed levels, travel times, traffic density, traffic flow and critical time-to-collision headways measured on the freeway.

### Base scenario 100-0-0-0

To start the analysis of traffic performance, the base scenario of 100% human drivers is observed. This means that no car-following or lane-changing automation is present, only temporary ADAS features and all vehicles are subject to deterioration of perception with corresponding reaction times.

Figure 40 shows the mean speed distributed on the main lanes of the freeway. As the distribution shows, vehicles have to slow down a lot to manage the disruption of the additional traffic flow of the on-ramp. The lowest speeds are observed in the middle of the merging section (BC) and vehicles can speed up again from the post-on-ramp section (CD) onwards.

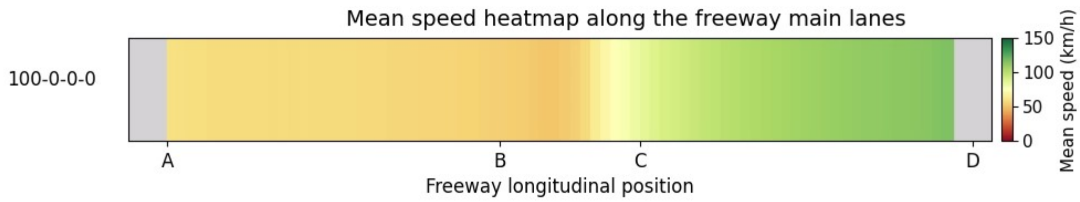


Figure 40: Speed heatmap on freeway main lanes for scenario 100-0-0-0.

The travel times for this scenario from Figure 41 show that many vehicles are subject to congestion and vehicles spend a lot of time on the on-ramp.

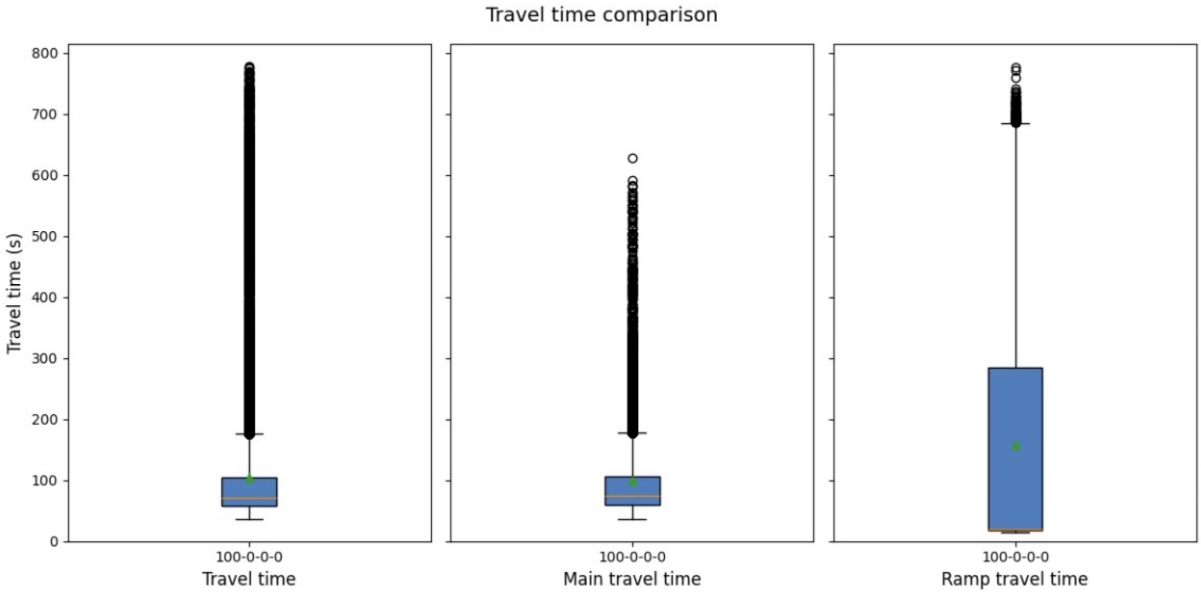


Figure 41: Travel time boxplots for scenario 100-0-0-0.

The fundamental diagrams in Figure 42 show the maximum flow simulated for each density. This plot is designed like this to visualise the road capacity for the freeway and analyse the capacity drop. As the figure shows, the pre-on-ramp section (AB) has a free-flow until 4500 veh/h. At the critical density, a capacity drop is seen whereafter the congested traffic continues to decrease in flow.

A higher capacity drop is observed for the merging section (BC) and also the congested part of the fundamental diagram has a steep decrease in traffic flow. The resulting outflow reaches a maximum flow of 4300 veh/h. When considering the access road or on-ramp towards the merging area (E2B.ONRAMP), it shows that a flow of 900 veh/h could be reached, but is mostly in a state of congestion.

Furthermore, 502 critical time-to-collision headways are measured throughout all simulation runs. While this is only a fraction of the total headway measurements, it indicates that human drivers sometimes maintain a dangerous small headway which could lead to collisions.

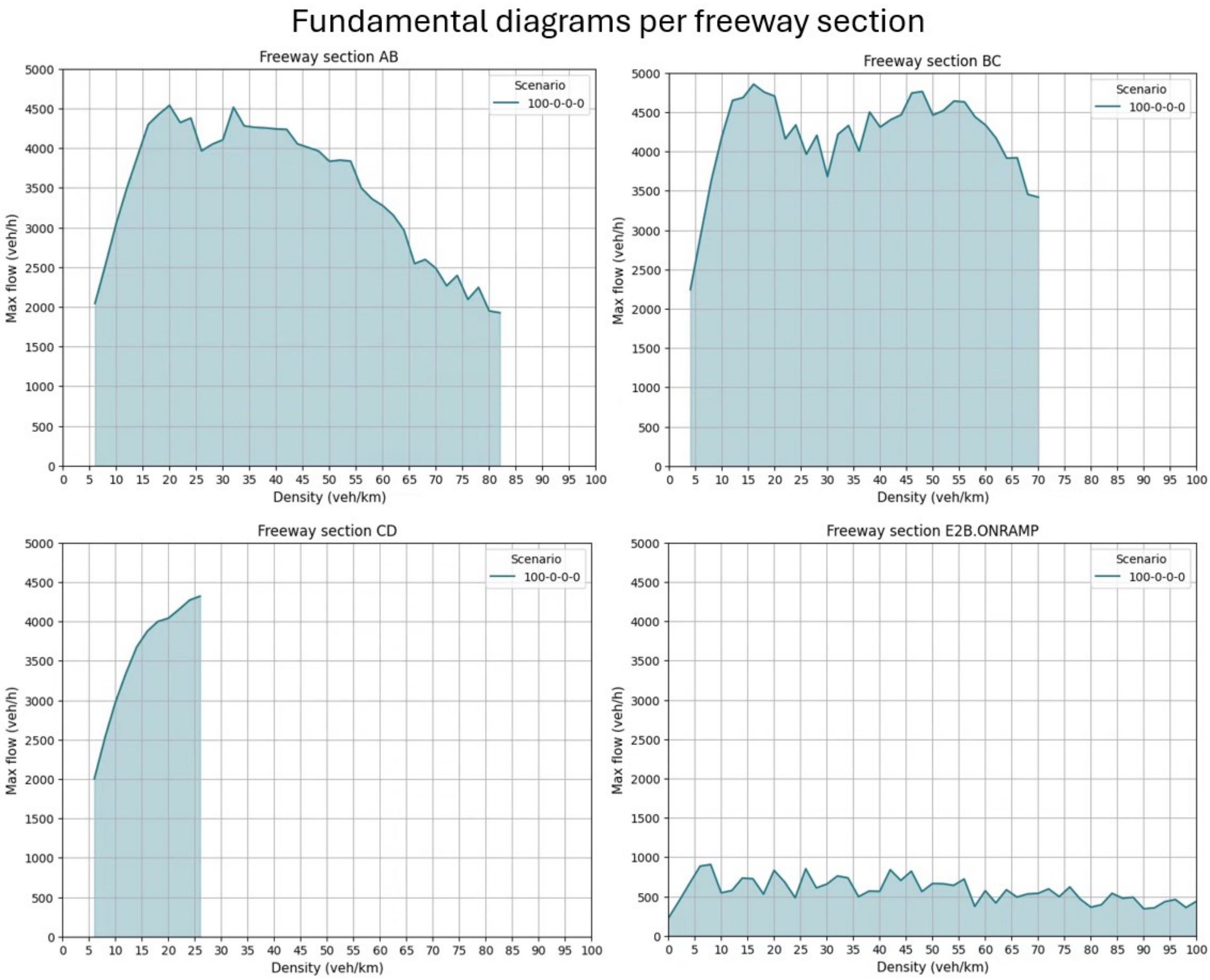


Figure 42: Fundamental diagram for freeway sections for scenario 100-0-0-0.

An expected reduction in speed is observed when vehicles approach the merging section. While many vehicles have a travel time of less than 200 seconds, the freeway is subject to a large amount of congestion and this makes merging more difficult for vehicles on the on-ramp. The fundamental diagrams per freeway section clearly show the conditions for free-flow and congestion. As well as the capacity drop during saturated traffic conditions. This results in a maximum outflow of 4300 veh/h on the post-on-ramp section, which is lower than the 4945 veh/h that is considered a standard traffic flow for this freeway layout (two main lanes and one on-ramp) for traffic of passenger cars (J.W. Goemans, 2015). Also, the critical time-to-collisions show that vehicles can maintain dangerous small headway distances.

**Scenario 80-20-0-0**

Now automation will slowly be introduced to the vehicle fleet. Level 1 vehicles are equipped with ADAS to support car-following and people are slowly utilising these features. Therefore, scenario 80-20-0-0 is compared to scenario 100-0-0-0 to see what effects the introduction of this automation level has. Level 1 behaviour shows that it maintains a longer time headway and has a higher frequency of changing lanes. Therefore, it is expected that the introduction of level 1 vehicles will disrupt the traffic flow. The following penetration rates are analysed here:

- **Previous scenario:** 100% level 0;
- **Current scenario:** 80% level 0, 20% level 1.

The speed heatmap in Figure 43 shows that this new penetration rate with level 1 vehicles shows similar speeds for the pre-on-ramp section (AB). However, vehicles seem to speed up less quickly at the end of the merging area.

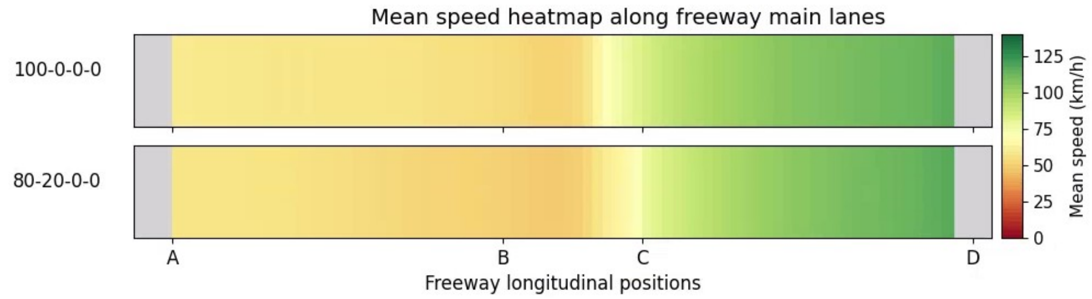


Figure 43: Speed heatmap on freeway main lanes for scenario 80-20-0-0.

Also, Figure 44 shows that the introduction of level 1 vehicles causes longer travel times for vehicles on the main lanes and for vehicles on the on-ramp.

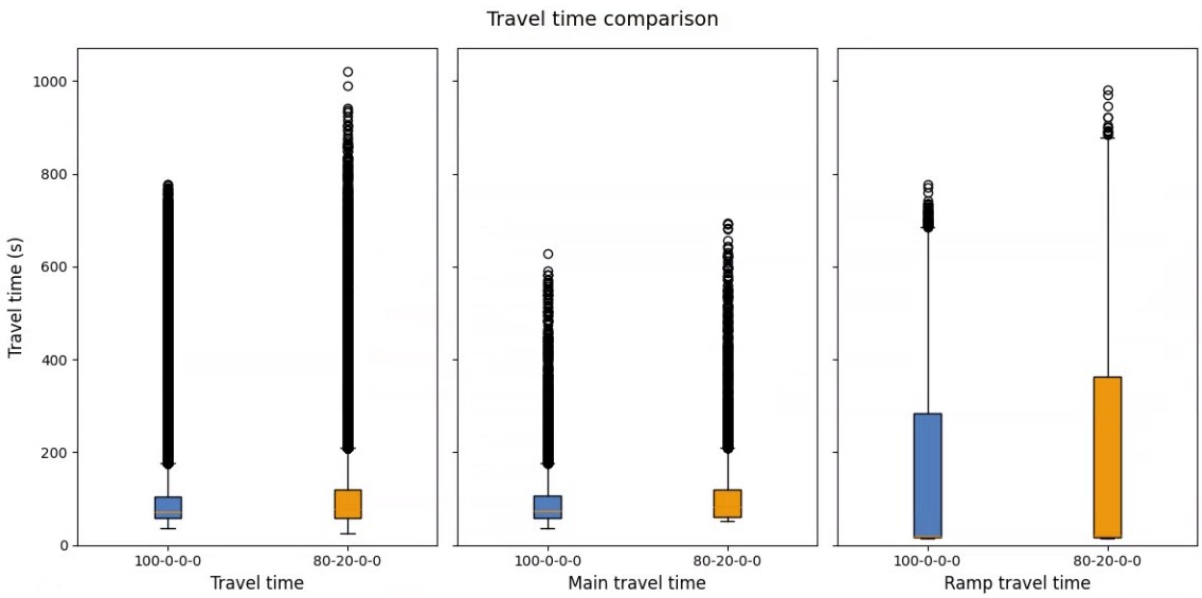


Figure 44: Travel time boxplots for scenario 80-20-0-0.

The lower speeds observed in the merging area and the longer travel times cause traffic to be more disrupted. This is also seen in the fundamental diagrams from Figure 45. With a penetration rate of 20% for level 1 vehicles, similar results are seen for the pre-on-ramp section (AB). However, a larger capacity drop is observed for the merging area (BC). This results in a slightly lower maximum traffic flow for the post-on-ramp section (CD).

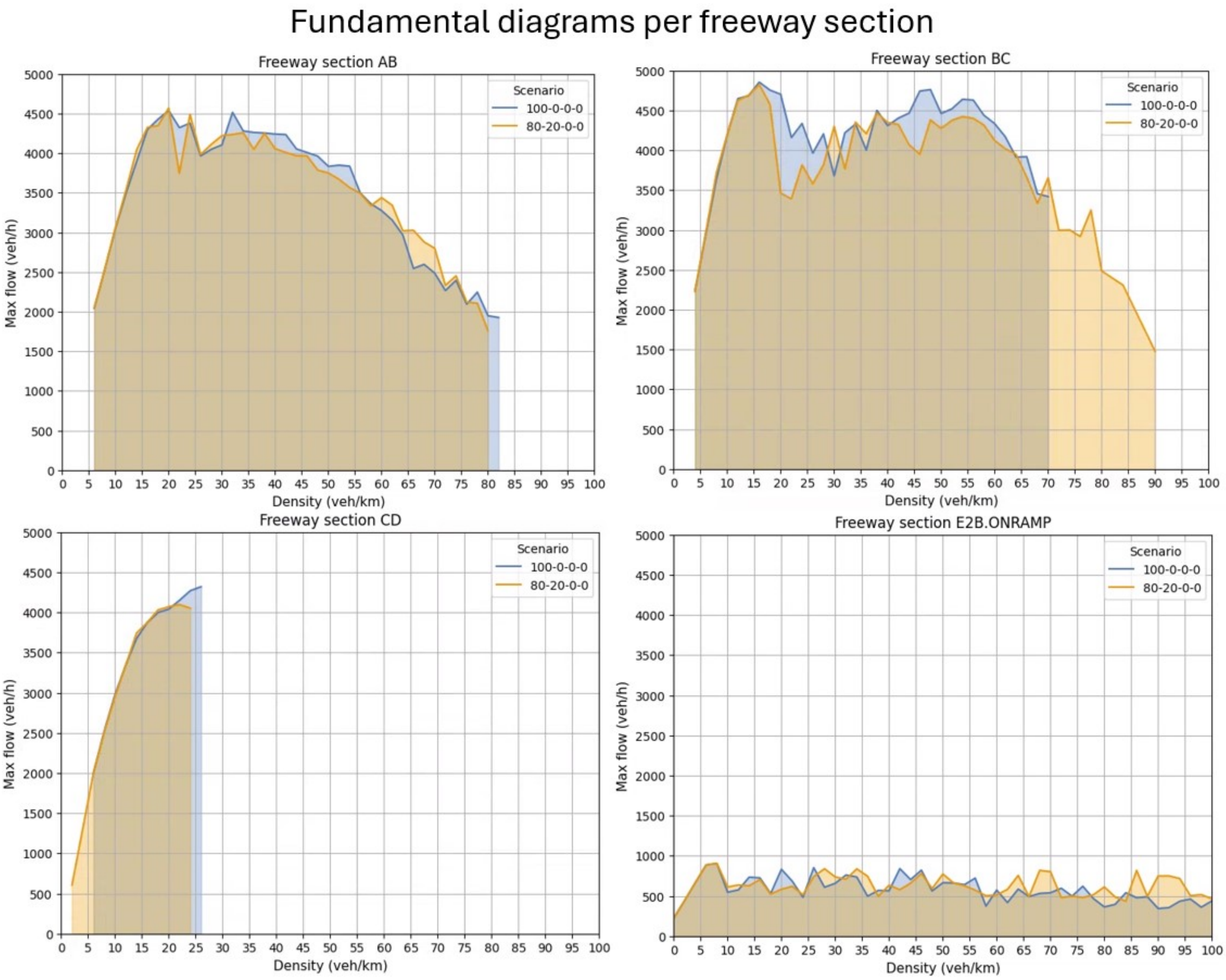


Figure 45: Fundamental diagram for freeway sections for scenario 80-20-0-0.

Figure 46 shows that while only 20% of human drivers are replaced by level 1 vehicles, the number of measured critical time-to-collisions is reduced significantly from 502 to 152. Also, it shows that no critical time-to-collision measurements are available for level 1 vehicles, showing that they keep a safer headway distance.

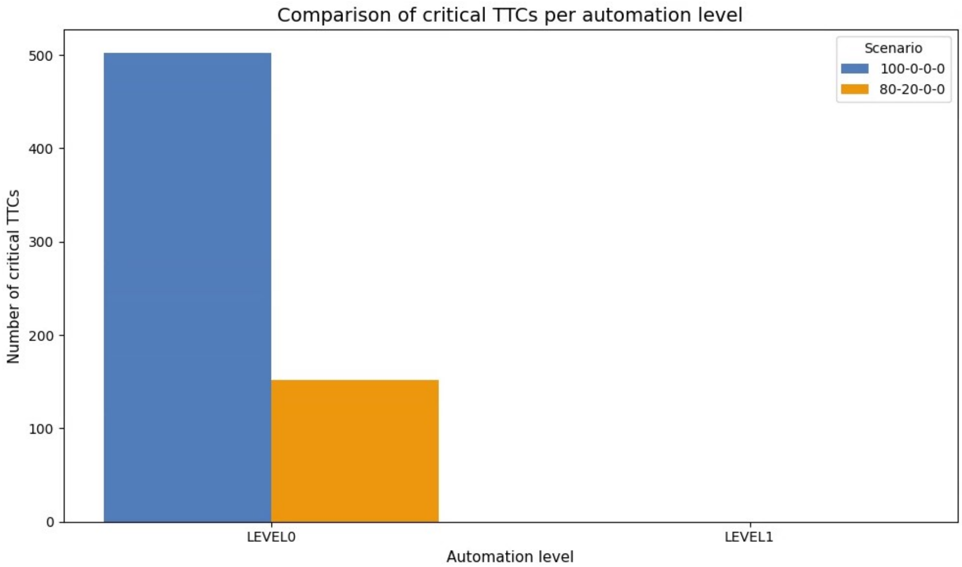


Figure 46: Number of measured critical time-to-collision headways for scenario 80-20-0-0.

The introduction of level 1 vehicles has already affected the traffic performance with a penetration rate of 20%. It mostly affected the traffic flow in the merging area, which complies with the expectancy of more disruptions due to their time headway and lane change frequency, causing a larger disruption. Also, safety has improved since the number of critical time-to-collisions has been reduced.

**Scenario 60-20-20-0**

More ADAS features are entering the market, so vehicles can now support drivers in their car-following and lane-changing tasks. This means that level 0, level 1 and level 2 vehicles are all present in the same scenario. Level 2 vehicles also have a high time headway, so the share of vehicles with a higher time headway increases. The following penetration rates are simulated:

- **Previous scenario:** 80% level 0, 20% level 1;
- **Current scenario:** 60% level 0, 20% level 1, 20% level 2.

The further increase in vehicle automation does not seem to affect the speed of vehicles on the freeway significantly. Figure 47 shows that similar speed distributions on the main lanes are observed. However, the mean speed is decreased a bit for sections AC and BC.

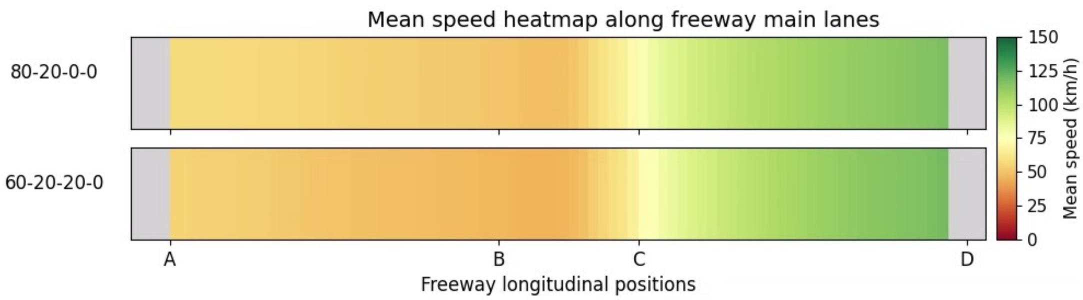


Figure 47: Speed heatmap on freeway main lanes for scenario 60-20-20-0.

Figure 48 shows the boxplot of travel times which indicates that the lower speed causes travel times to increase even further. Long travel times become more common indicating that more congestion is taking place.

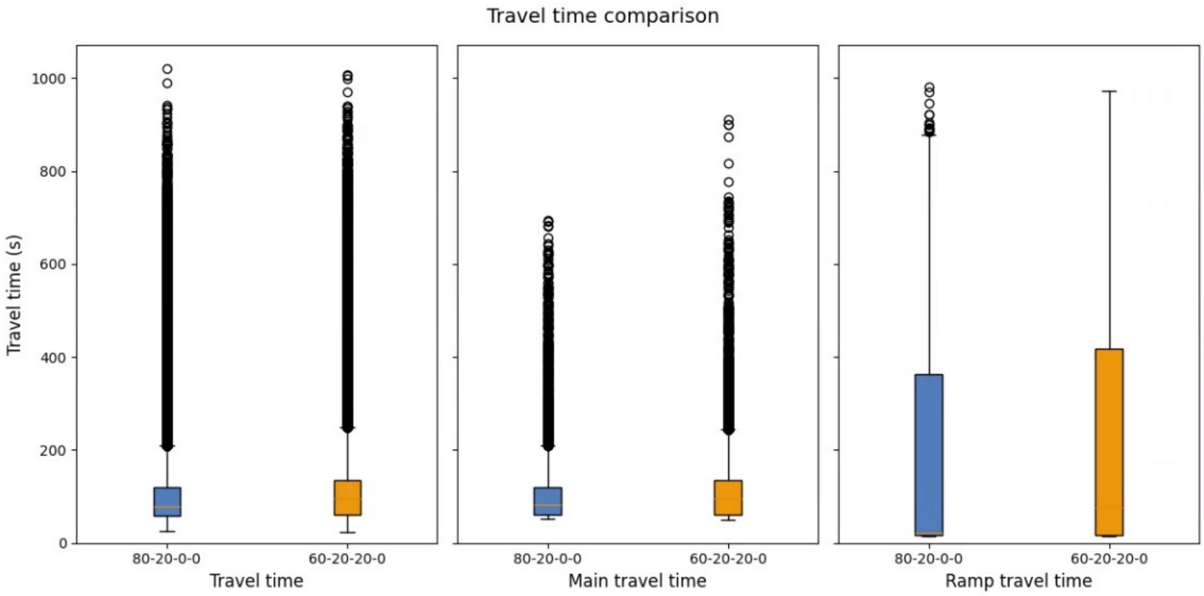


Figure 48: Travel time boxplots for scenario 60-20-20-0.

The fundamental diagrams in Figure 49 reflect the increase in congestion by showing higher densities for even lower traffic flows. The free-flow condition of traffic remains the same for the pre-on-ramp section (AC). However, the capacity drop occurs at a lower density level and the maximum traffic flow just past the capacity drop is lower than previously.

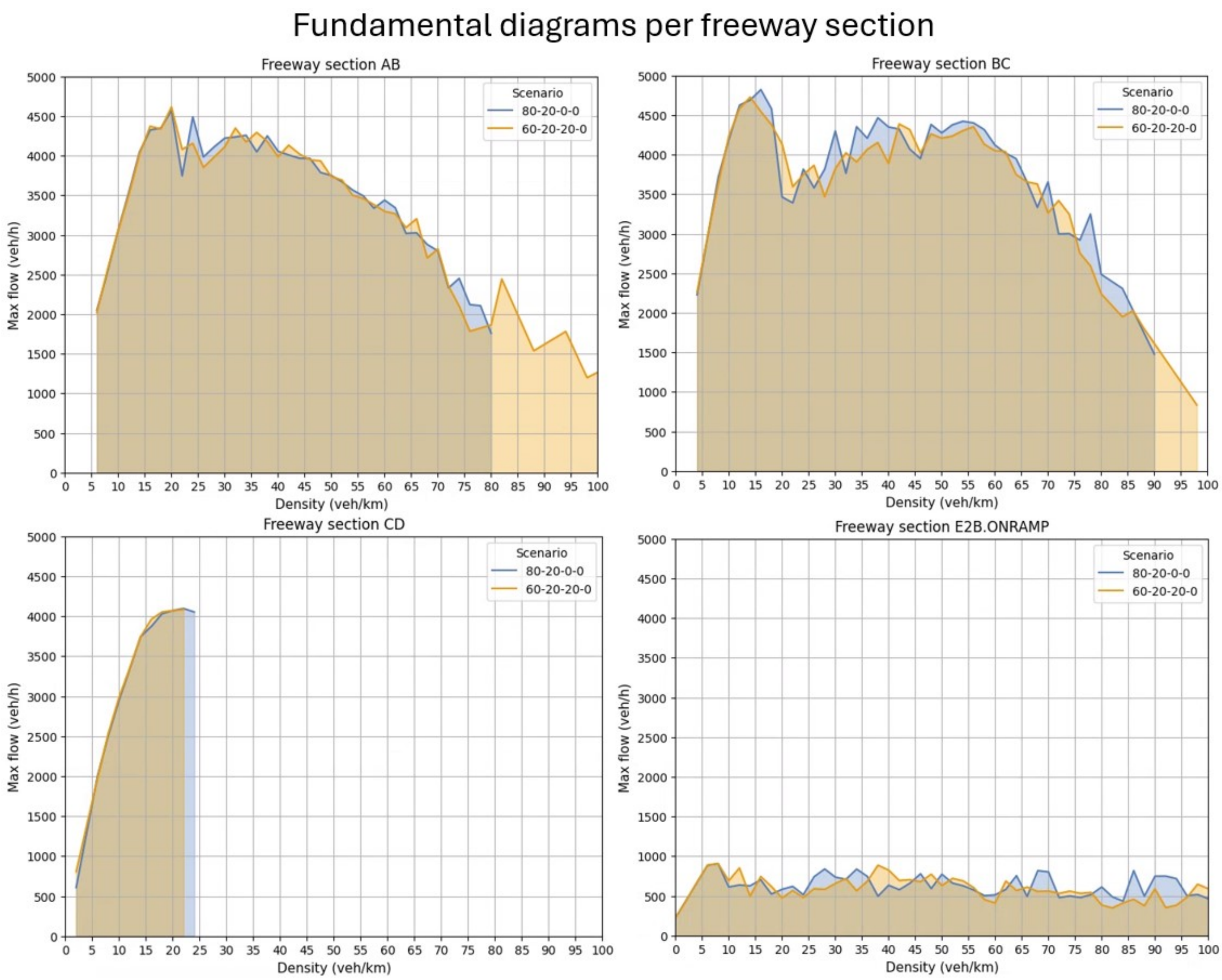


Figure 49: Fundamental diagram for freeway sections for scenario 60-20-20-0.

The trend of reductions in critical time-to-collisions by introducing automation levels continues. Figure 50 shows that the number of critical time-to-collision measurements reduces from more than 152 to just 39.

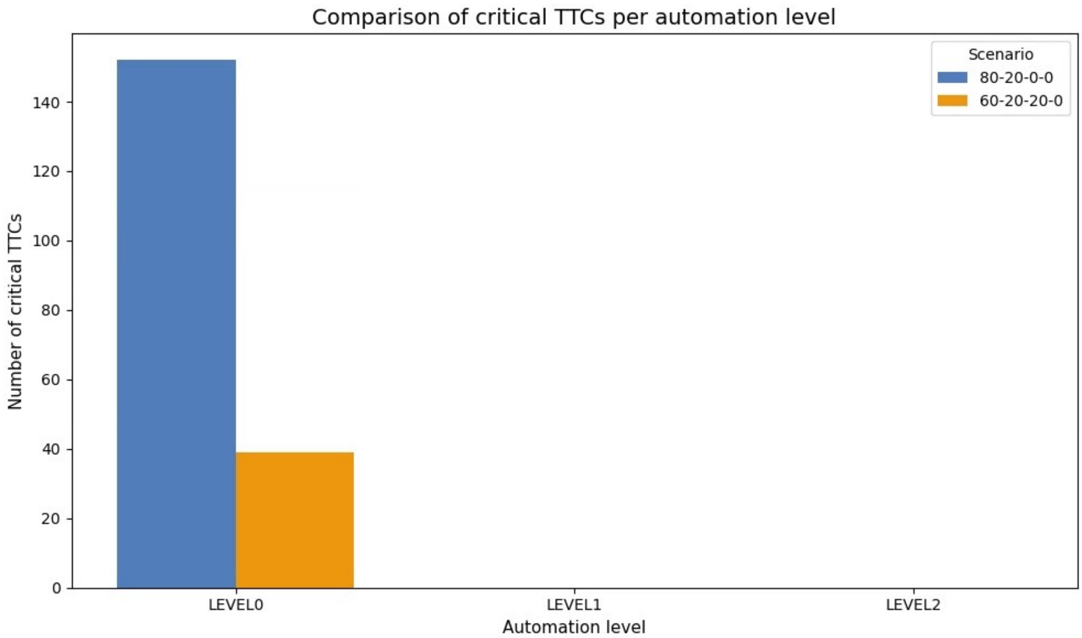


Figure 50: Number of measured critical time-to-collision headways for scenario 60-20-20-0.

The increase of level 1 vehicles and the introduction of level 2 vehicles seem to increase the congestion of the freeway while other aspects of the fundamental diagrams remain similar. The increase in vehicles with a large time headway clearly introduces more disruptions at the merging section. Despite the increase in disruption, the number of critical time-to-collisions is again reduced.

**Scenario 40-20-20-20**

Level 3 vehicles are finally available for customer use and thus make their way into the vehicle fleet. This is a major technological advancement since earlier vehicle automations were only considered level 2 vehicles. These level 3 vehicles have a lower variability in acceleration and can maintain a lower time headway than level 1 and level 2 vehicles. However, this low time headway increases much during lane changes in mixed traffic. So, the effects on traffic performance are still unclear. This results in the following penetration rates:

- **Previous scenario:** 60% level 0, 20% level 1, 20% level 2;
- **Current scenario:** 40% level 0, 20% level 1, 20% level 2, 20% level 3.

Figure 51 shows that the decrease in human drivers and the increase in level 3 vehicles does affect the mean speed positively. The mean speed is slightly higher than before.

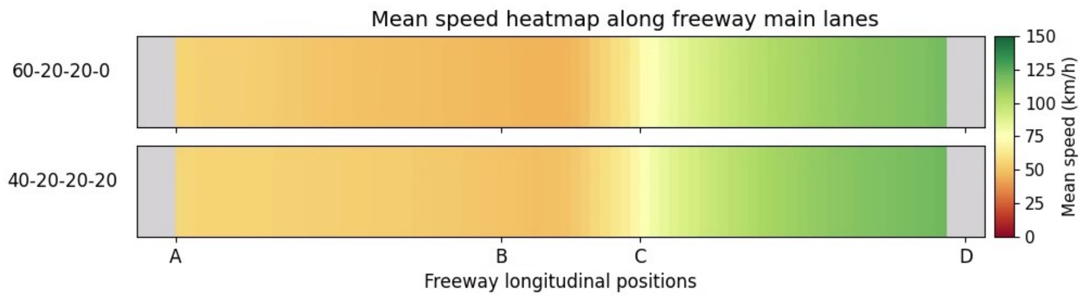


Figure 51: Speed heatmap on freeway main lanes for scenario 40-20-20-20.

Also, the difference in travel time is negligible. Figure 52 shows that the boxplots are almost similar so the new penetration rate has no further implications on travel time.

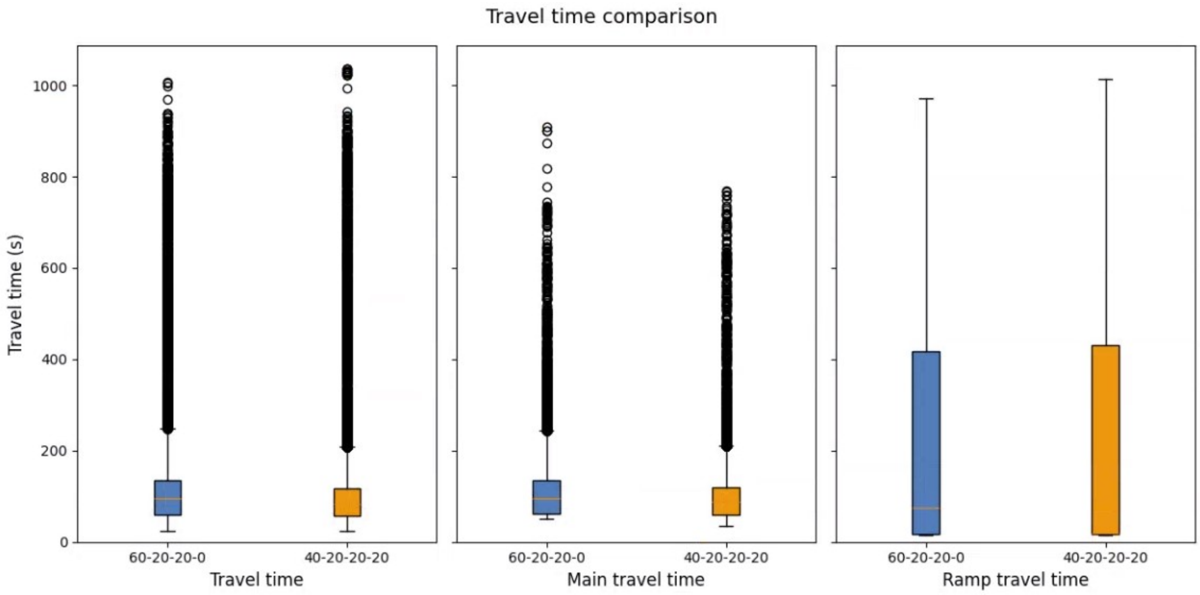


Figure 52: Travel time boxplots for scenario 40-20-20-20.

While the travel time and speed heatmap did not show any differences, Figure 53 shows some differences in the fundamental diagrams. The fundamental diagrams have similar shapes for the different freeway sections. However, a higher maximum flow is observed for this scenario in the merging area (BC) and also the outflow to section CD is higher. Furthermore, Figure 54 shows that the decrease in level 0 vehicles still reduces the number of critical time-to-collision measured in the simulation.

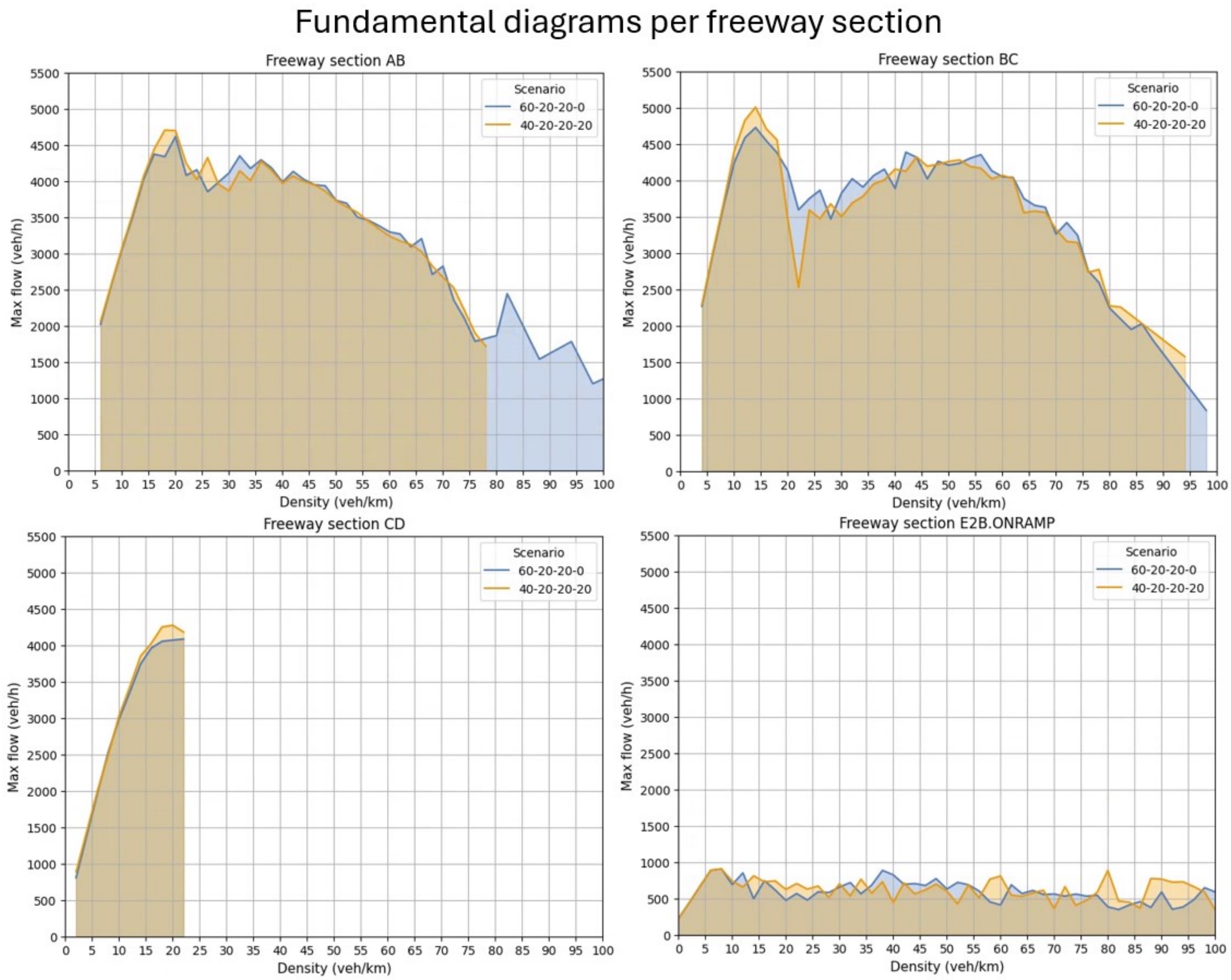


Figure 53: Fundamental diagram for freeway sections for scenario 40-20-20-20.

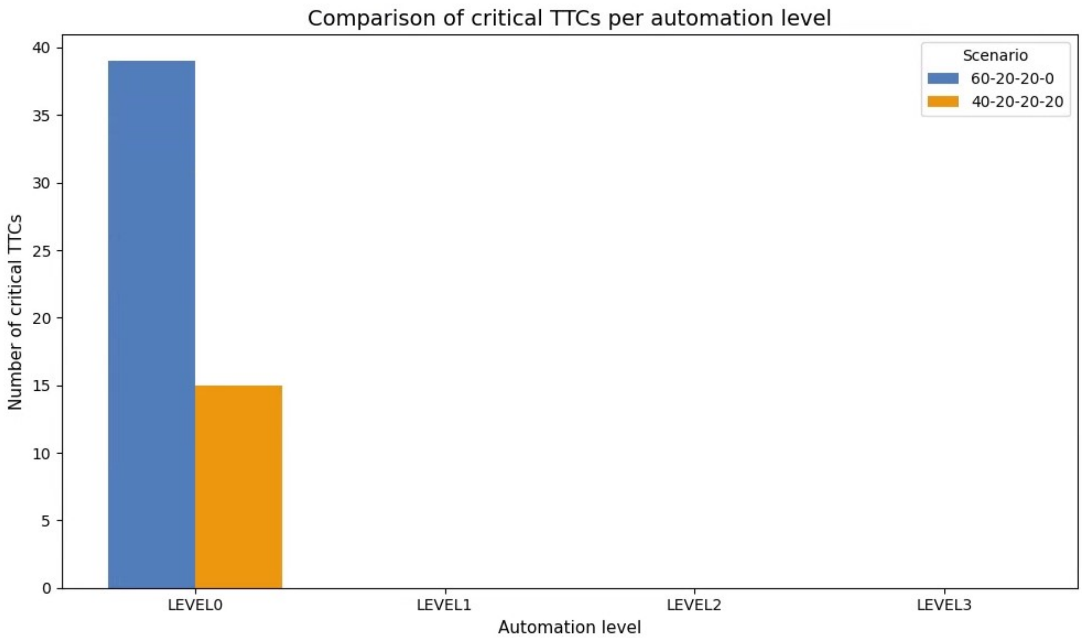


Figure 54: Number of measured critical time-to-collision headways for scenario 40-20-20-20.

Further progress in vehicle automation has introduced level 3 vehicles to the freeway. This does not have much effect on the speed and travel time, however, the traffic flow improved. Despite the decrease in level 0 vehicles and the large headway values for level 3 vehicles during lane changes, the further increase of automation levels has shown to be helpful. This also holds for the safety aspect of traffic where critical time-to-collision counts are reduced.

**Scenario 25-25-25-25**

Penetration rates of the different automation levels have reached equal fractions of the vehicle fleet. This means that the majority of car-following is automated and half of the vehicles have automated lane-changing. The following penetration rates are simulated:

- **Previous scenario:** 40% level 0, 20% level 1, 20% level 2, 20% level 3;
- **Current scenario:** 25% level 0, 25% level 1, 25% level 2, 25% level 3.

Some change in mean speed is observed in Figure 55. A slightly lower mean speed is seen at the start of the merging area. Also, the travel time boxplots in Figure 56 do show another increase in travel time for both the main lanes and vehicles on the on-ramp.

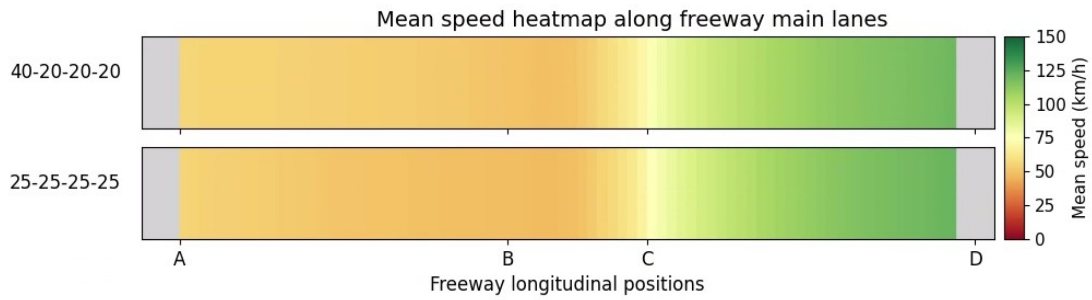


Figure 55: Speed heatmap on freeway main lanes for scenario 25-25-25-25.

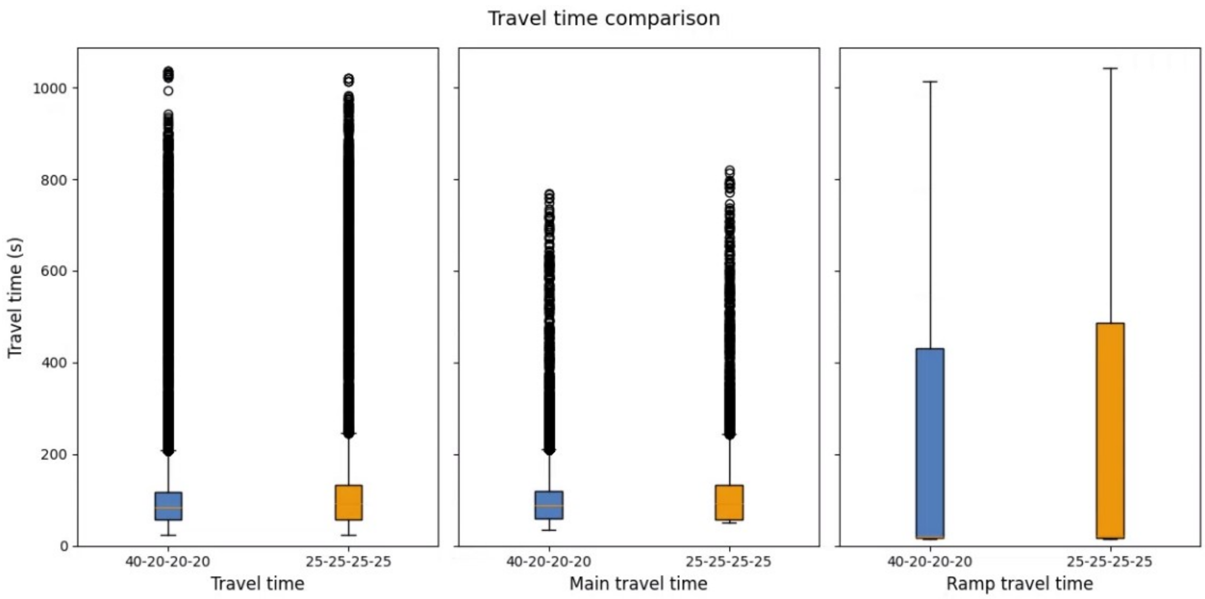


Figure 56: Travel time boxplots for scenario 25-25-25-25.

While the increase in travel time indicates more congestion on the freeway, the fundamental diagrams show that the new composition of the vehicle fleet allows traffic to dampen the capacity drop. No other changes in the free-flow or congestion conditions are observed.

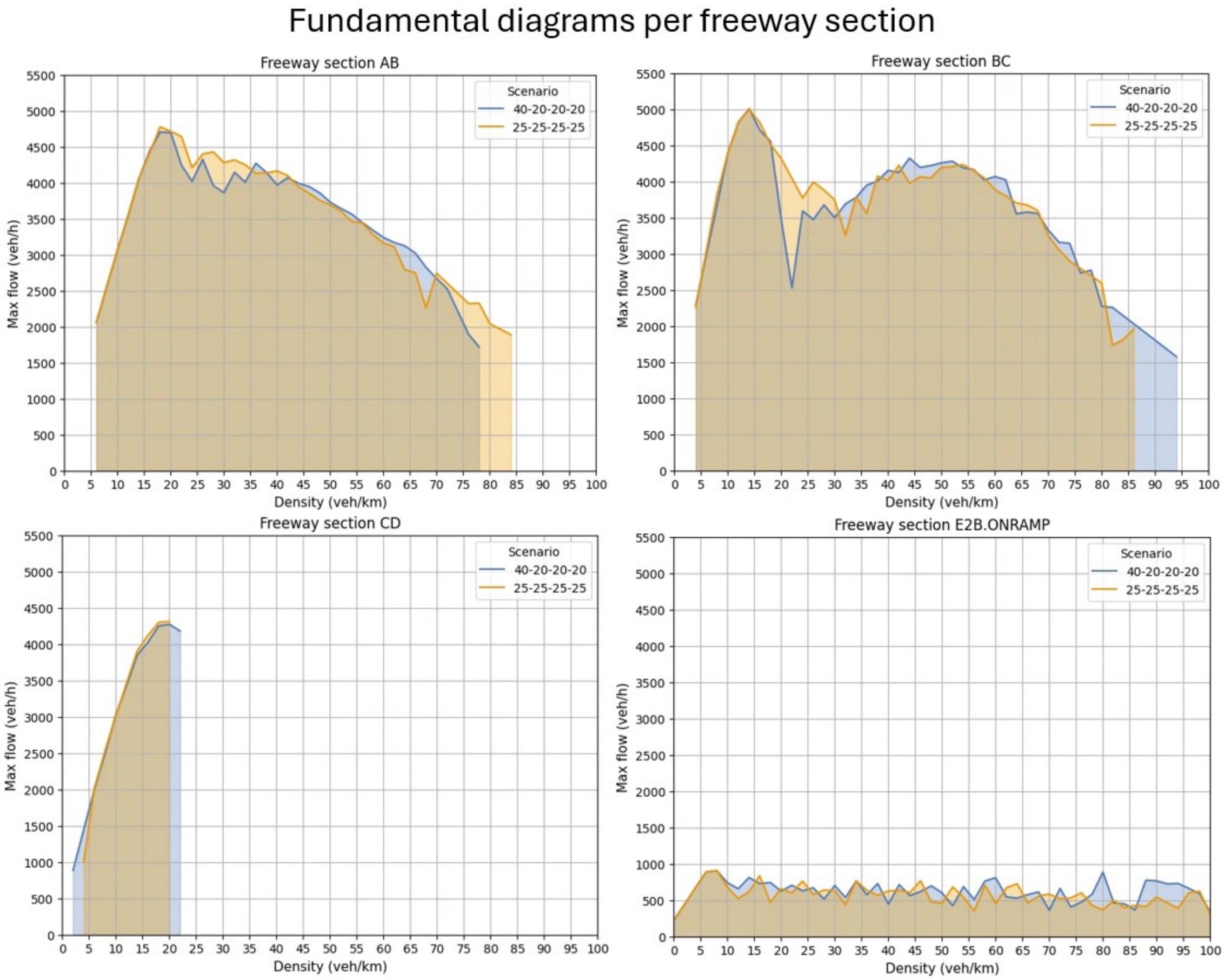


Figure 57: Fundamental diagram for freeway sections for scenario 25-25-25-25.

In previous scenarios the number of critical time-to-collisions in the simulation has been reducing significantly. However Figure 58 shows that this decrease in counted critical time-to-collisions does not continue for this scenario. Human drivers have a 15% lower penetration rate but the total count of critical time-to-collisions is not lowered as much as in previous scenarios. Also, this is the first scenario where level 2 vehicles have maintained a dangerously close headway distance. However, the occurrence of two time-to-collisions is negligible compared to a main lane traffic demand of at least 2800 veh/h.

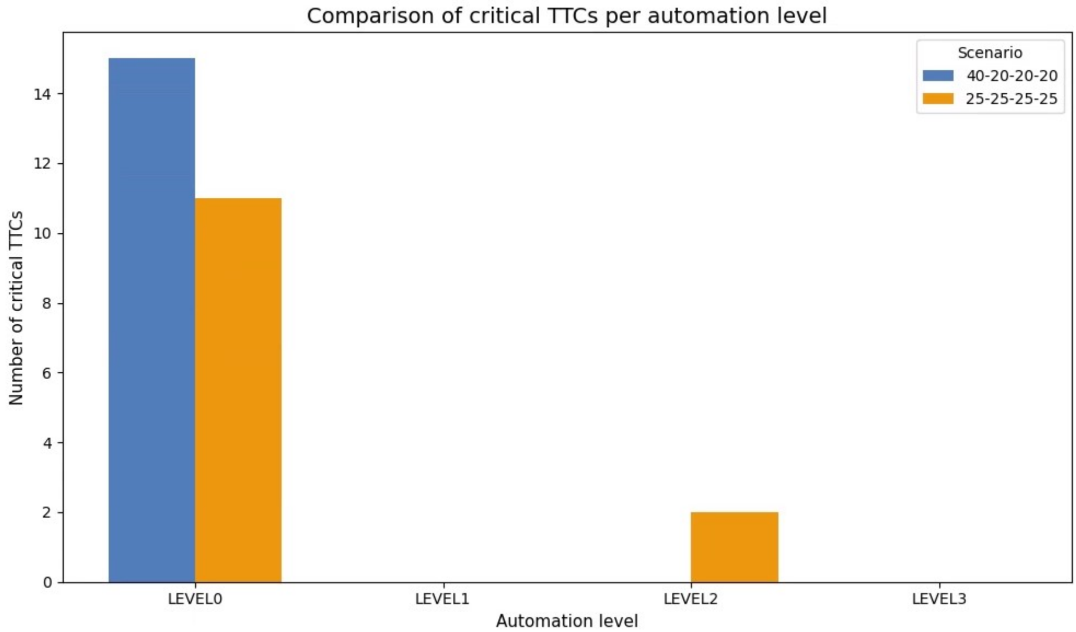


Figure 58: Number of measured critical time-to-collision headways for scenario 25-25-25-25.

The highly mixed composition of the vehicle fleet does increase travel time. However, the capacity drop is dampened showing that the vehicles are better equipped to handle disruptions. Nonetheless, this does still end up in similar congestion conditions as seen in the previous scenario. However, less improvements are seen for the counted critical time-to-collisions. However, the current count can be considered negligible.

### Scenario 0-33-33-33

Level 0 vehicles are phasing out of the vehicle fleet. This means that all vehicles are now equipped with car-following support. Level 1, level 2 and level 3 vehicles are now simulated for penetration rates of:

- **Previous scenario:** 25% level 1, 25% level 2, 25% level 3;
- **Current scenario:** 33% level 1, 33% level 2, 33% level 3.

Figure 59 shows that the mean speed at the merging area (BC) drops slightly again, but also a higher mean speed is measured at the end of the post-on-ramp section (CD).

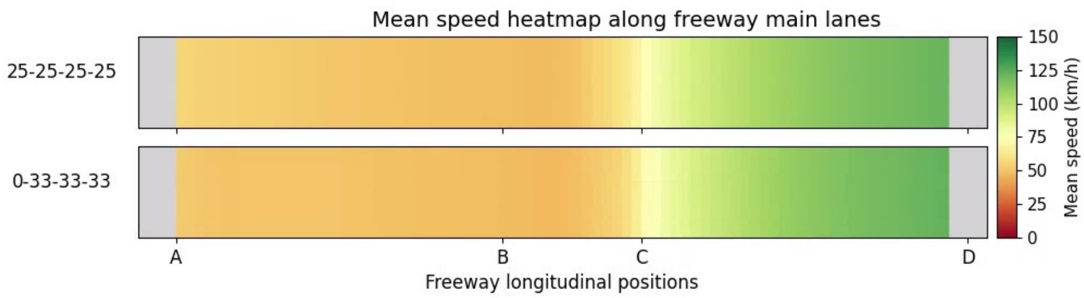


Figure 59: Speed heatmap on freeway main lanes for scenario 0-33-33-33.

Boxplots for travel time in Figure 60 show that most vehicles have similar travel times as in the last scenario. However, outliers for longer travel times are observed and also the time that vehicles spend on the on-ramp is increased.

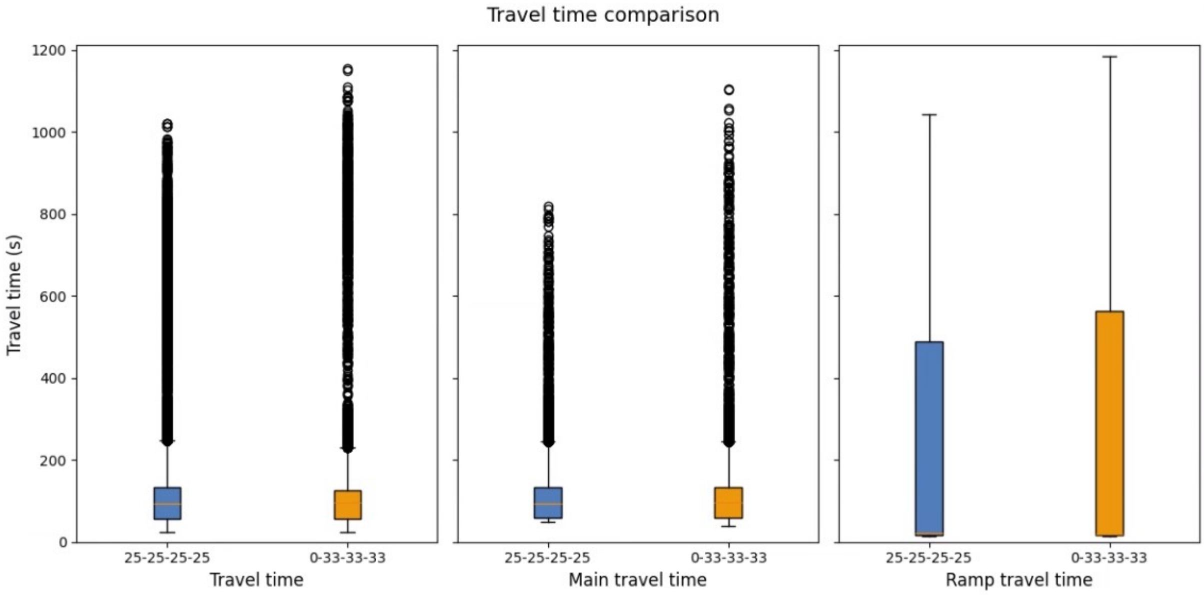


Figure 60: Travel time boxplots for scenario 0-33-33-33.

The lower mean speed and longer travel times are also reflected by the fundamental diagrams in Figure 61. These graphs show that lower maximum traffic flows are measured for the pre-on-ramp (AB) and merging sections (AB). However, the outflow towards the post-on-ramp section (CD) seems to be higher which also reflects the higher mean speed at the end of the section. Regarding traffic safety, no critical time-to-collisions are observed anymore in Figure 62.

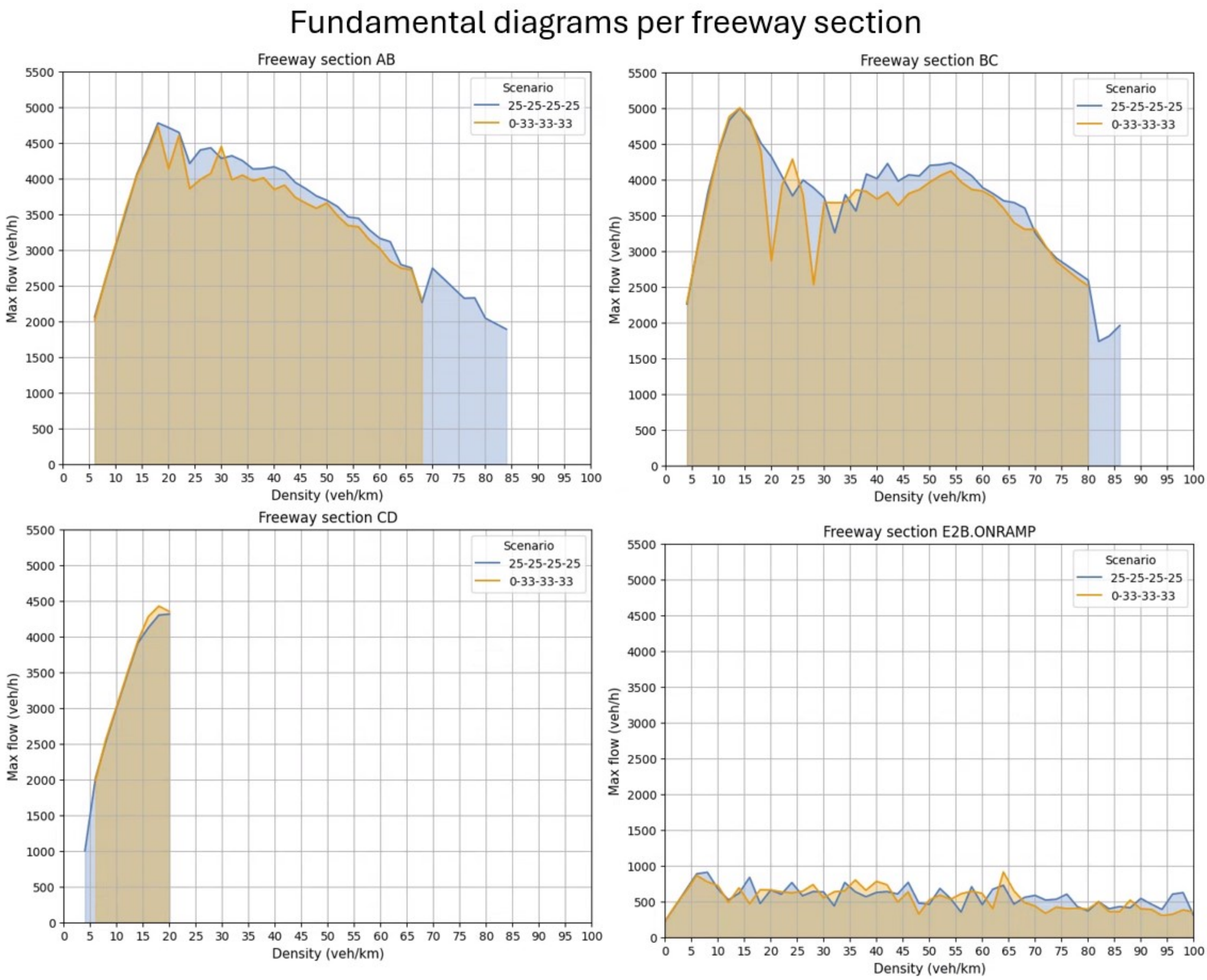


Figure 61: Fundamental diagram for freeway sections for scenario 0-33-33-33.

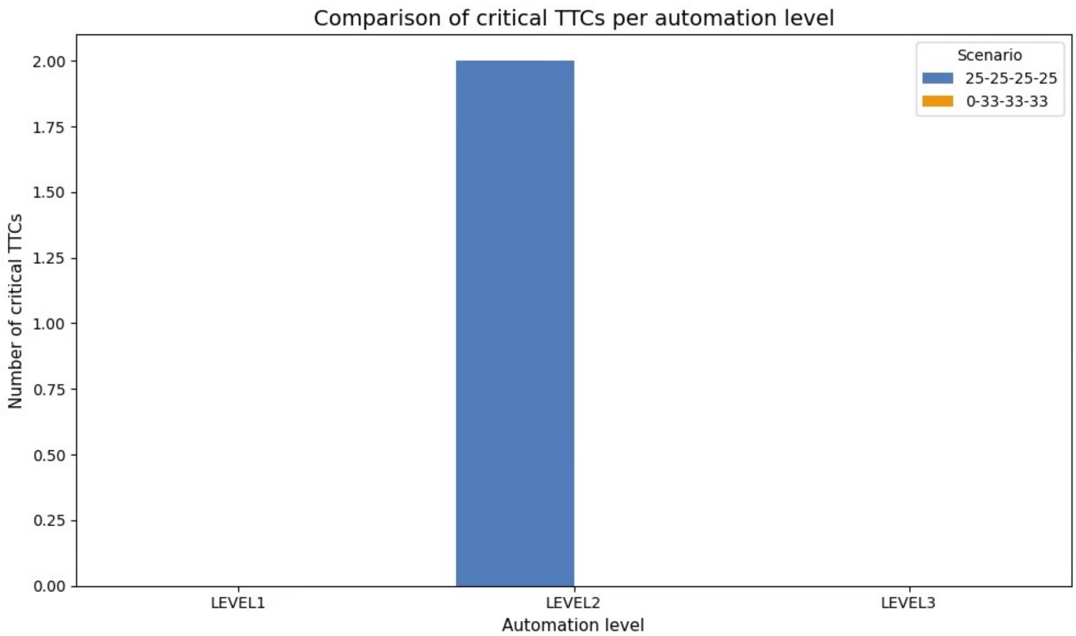


Figure 62: Number of measured critical time-to-collision headways for scenario 0-33-33-33.

The phase-out of level 0 vehicles did increase vehicle automation in the vehicle fleet but did not improve traffic performance. The mean speed at the merging section became lower, travel times are mostly similar and lower maximum traffic flows are observed. The new composition of only automated car-following did remove any critical time-to-collision headway distances from the simulation.

**Scenario 0-0-50-50**

In this scenario, level 2 vehicles become the standard and level 3 vehicles are widely accepted by road users. Level 0 and level 1 vehicles are both retired by now, which means that both car-following and lane-changing tasks are supported or controlled by automated features. The following penetration rates are simulated:

- **Previous scenario:** 33% level 1, 33% level 2, 33% level 3;
- **Current scenario:** 50% level 2, 50% level 3.

The phase-out of level 1 vehicles results in a significant improvement in mean speed. Figure 63 shows that vehicles keep a higher speed at until the merge section and are able to increase their speed more quickly.

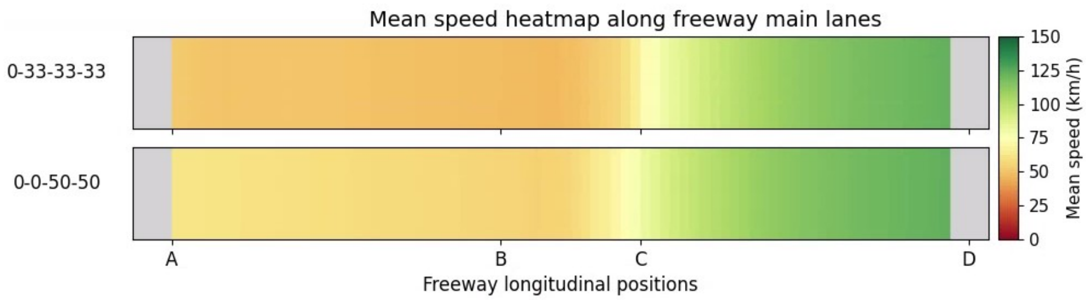


Figure 63: Speed heatmap on freeway main lanes for scenario 0-0-50-50.

Figure 64 shows that the travel time changes from scenario 0-33-33-33 to scenario 0-0-50-50. Travel times for both main lanes and vehicles on the on-ramp are improved, especially the travel time on the on-ramp decreases significantly.

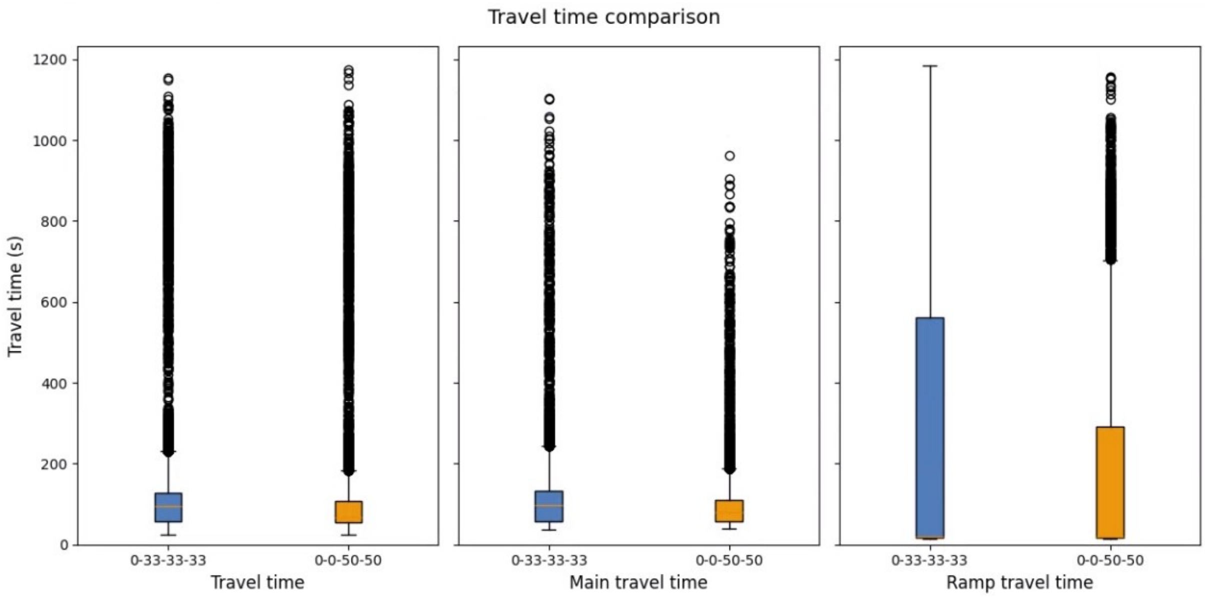


Figure 64: Travel time boxplots for scenario 0-0-50-50.

These improvements are also observed in the fundamental diagrams in Figure 65. Higher maximum vehicle flows are measured for all freeway sections. Also, the capacity drop decreases more gradually but is still subject to a large drop.

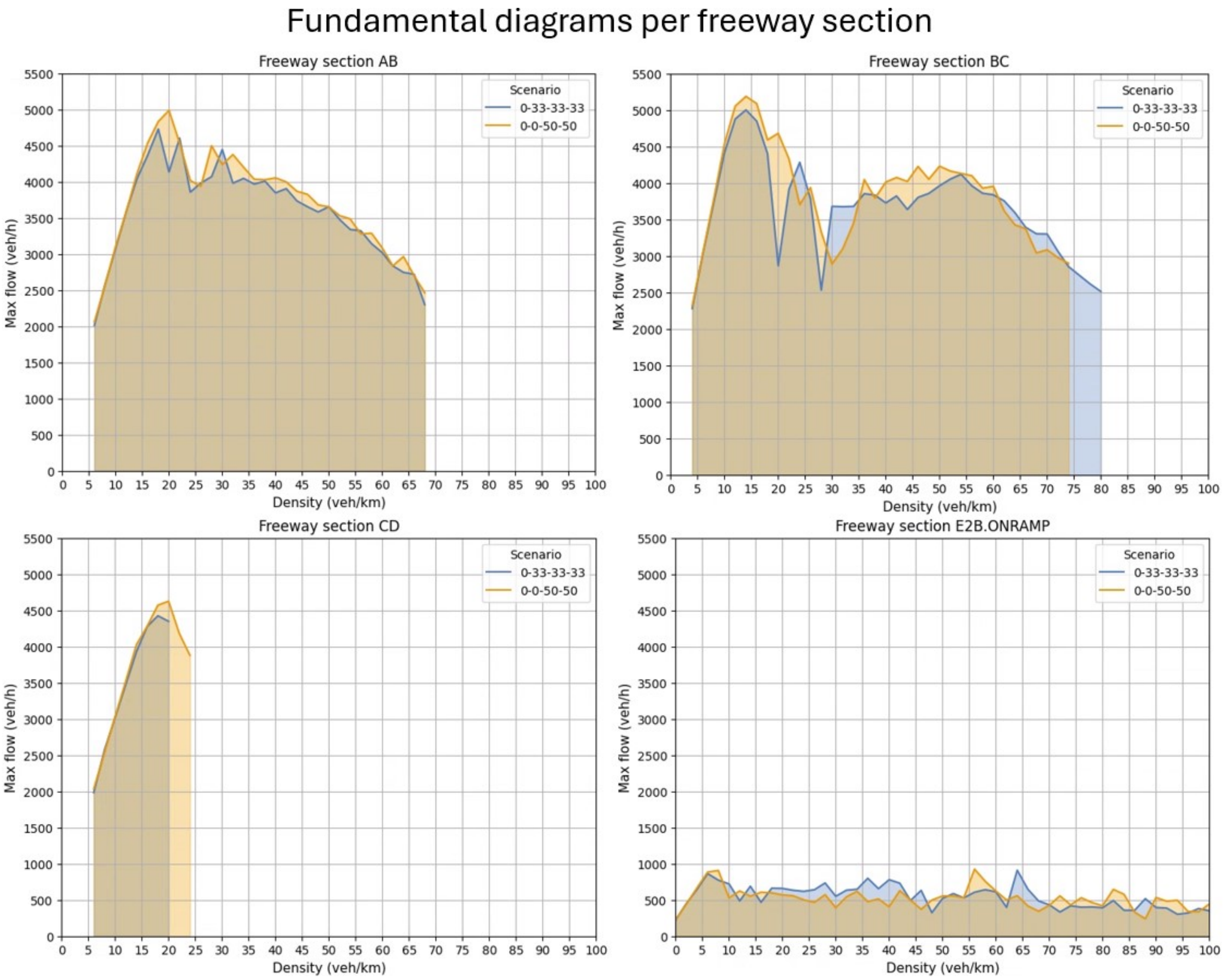


Figure 65: Fundamental diagram for freeway sections for scenario 0-0-50-50.

The mix of level 2 and level 3 vehicles is an improvement compared to the previous scenario with level 1 vehicles. The traffic flow is extended on all freeway sections which also translates to better travel times and a higher mean speed. Also, no changes regarding critical time-to-collisions were seen for this scenario.

### Scenario 0-0-20-80

More road users are able to afford level 3 vehicles and the demand for level 2 vehicles is declining. This means that the majority does have fully automated car-following and lane-changing functionality on the freeway, resulting in the following penetration rates:

- **Previous scenario:** 50% level 2, 50% level 3;
- **Current scenario:** 20% level 2, 80% level 3.

The progress of even more level 3 vehicles results in higher mean speeds for all sections on the freeway in Figure 66. Vehicles have to lower their speed less drastically and can maintain a higher speed throughout the merging area (BC). This also allows the vehicles to reach a higher speed in the post-on-ramp section (CD).

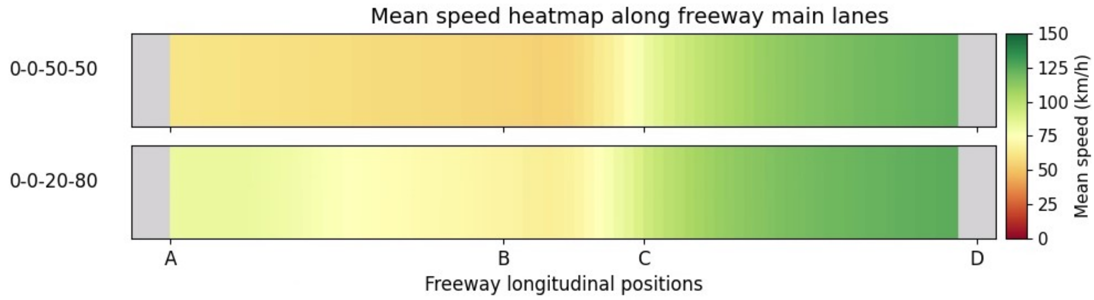


Figure 66: Speed heatmap on freeway main lanes for scenario 0-0-20-80.

The large speed improvement is also seen for travel times in boxplots from Figure 67. Travel time on the main lanes is reduced. However, an outstanding decrease in travel time for on-ramp vehicles is observed. There is still congestion but most vehicles seem to merge into the main lanes more easily.

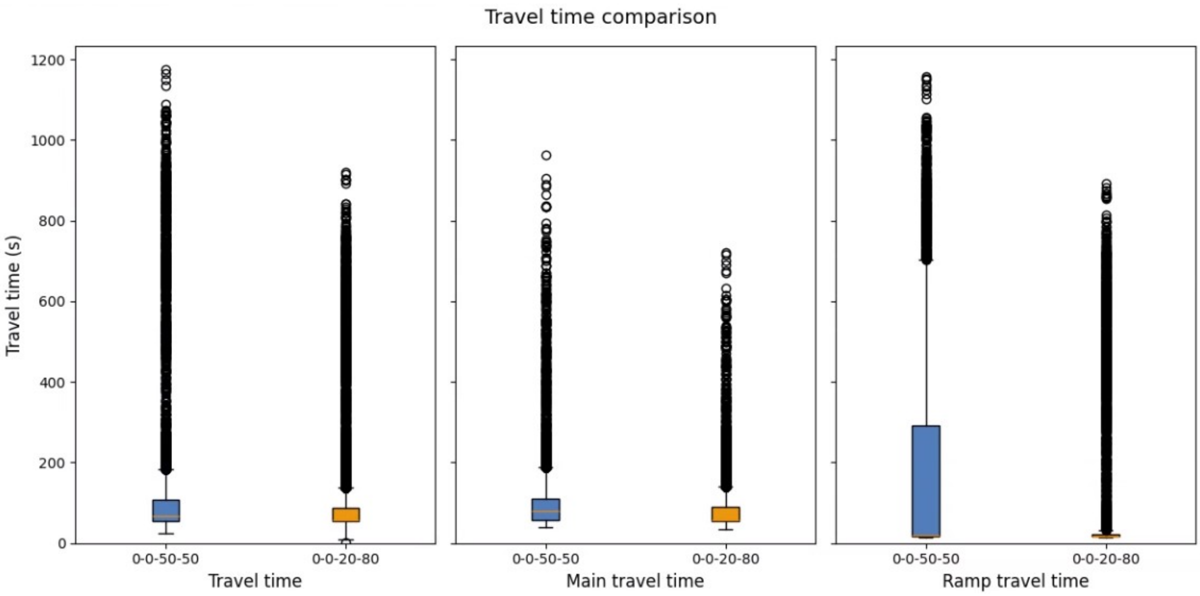


Figure 67: Travel time boxplots for scenario 0-0-20-80.

Fundamental diagrams also show improvements in traffic performance (Figure 68). The higher speed on the pre-on-ramp section (AB) results in a prolonged maximum traffic flow at saturated traffic and higher maximum flows are observed at the merging area (BC). Again the higher speed also shows higher traffic flows for the post-on-ramp section (CD) but the access road to the on-ramp (E2B.ONRAMP) does not show a large increase in flow. The travel time does indicate that vehicles merge more easily into the main lanes, but the flow of vehicles is not increased much.

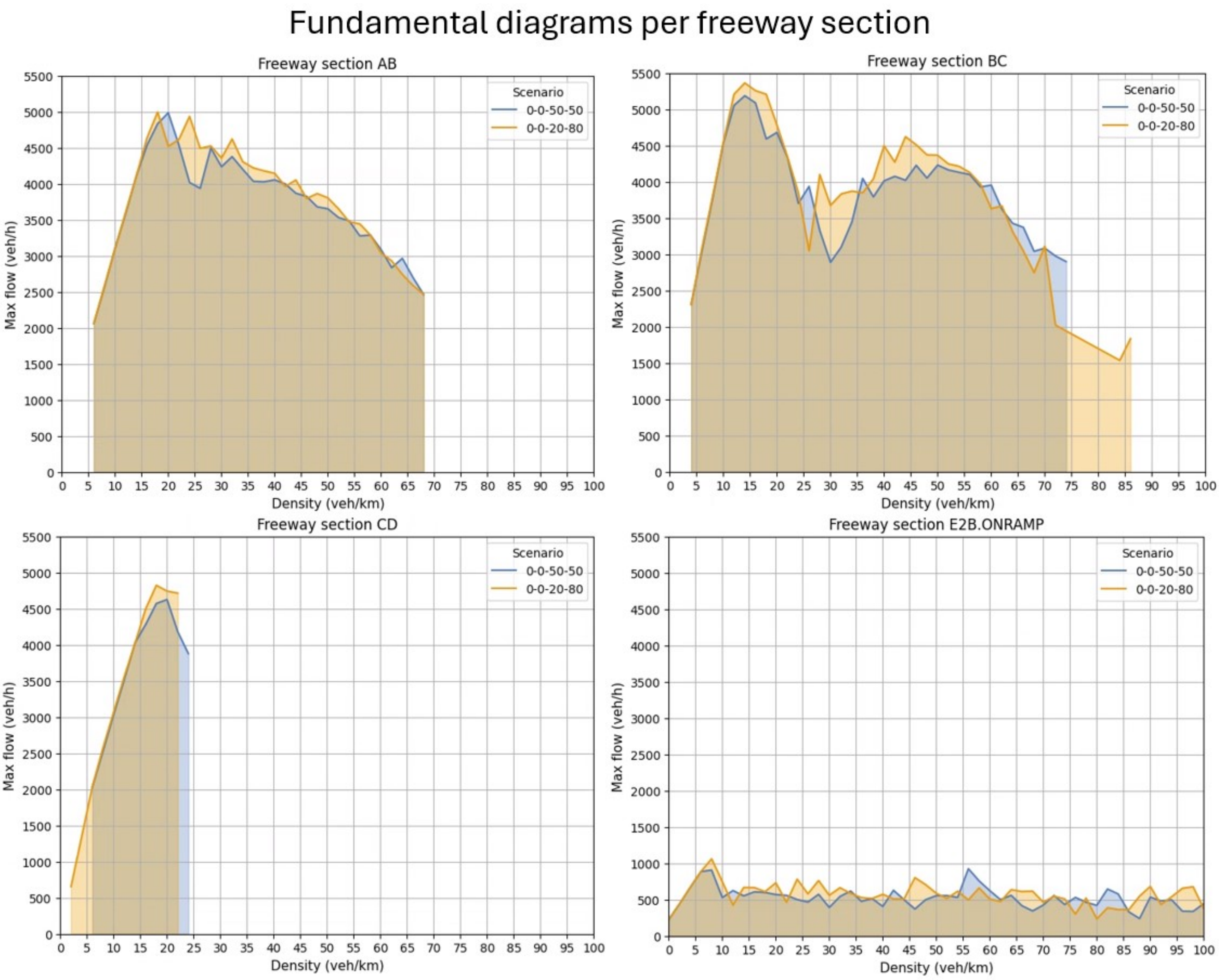


Figure 68: Fundamental diagram for freeway sections for scenario 0-0-20-80.

The previous scenario already shows improvements because of level 3 vehicles. Now for scenario 0-0-20-80, the higher penetration rate of level 3 vehicles affects the traffic performance again. Big improvements regarding speed and travel time are observed. Also, the fundamental diagram shows a higher traffic flow. No critical time-to-collisions are observed for this scenario.

**Scenario 0-0-0-100**

Previous scenarios have studied different compositions of automation levels in the vehicle fleet. However, the transition from human drivers to autonomous vehicles is finalising in this scenario where 100% of the vehicles are defined as automation level 3 vehicles.

Where previous increases in level 3 vehicles have resulted in speed improvements, the scenario of 100% level 3 vehicles shows lower speeds at the pre-on-ramp lanes (AB). Other than that, the speed distribution on the merging section (BC) is similar and an increase in mean speed is measured at the end of the post-on-ramp section (CD).

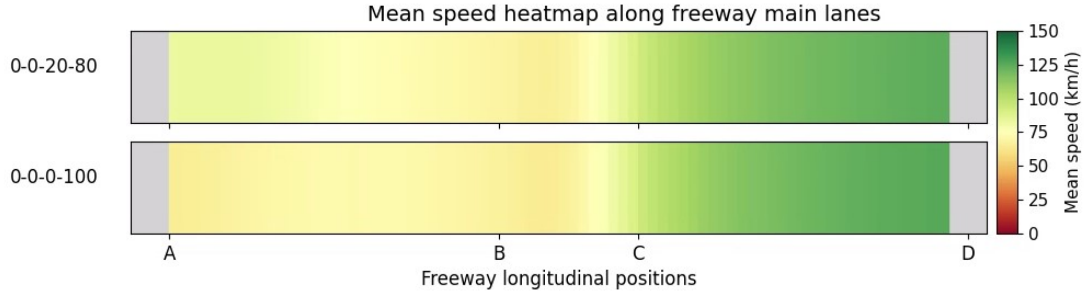


Figure 69: Speed heatmap on freeway main lanes for scenario 0-0-0-100.

Travel times in Figure 70 show that the majority of vehicles on the main lanes have similar travel times. However, the travel time on the on-ramp is increased.

The deterioration of on-ramp travel times could indicate that the low penetration rate of level 2 vehicles from the last scenario provided more merging space because of their larger headways. However, this was not observed for a combination of human drivers and level 1 vehicles, which, of course, have different dynamics than level 2 and level 3 vehicles.

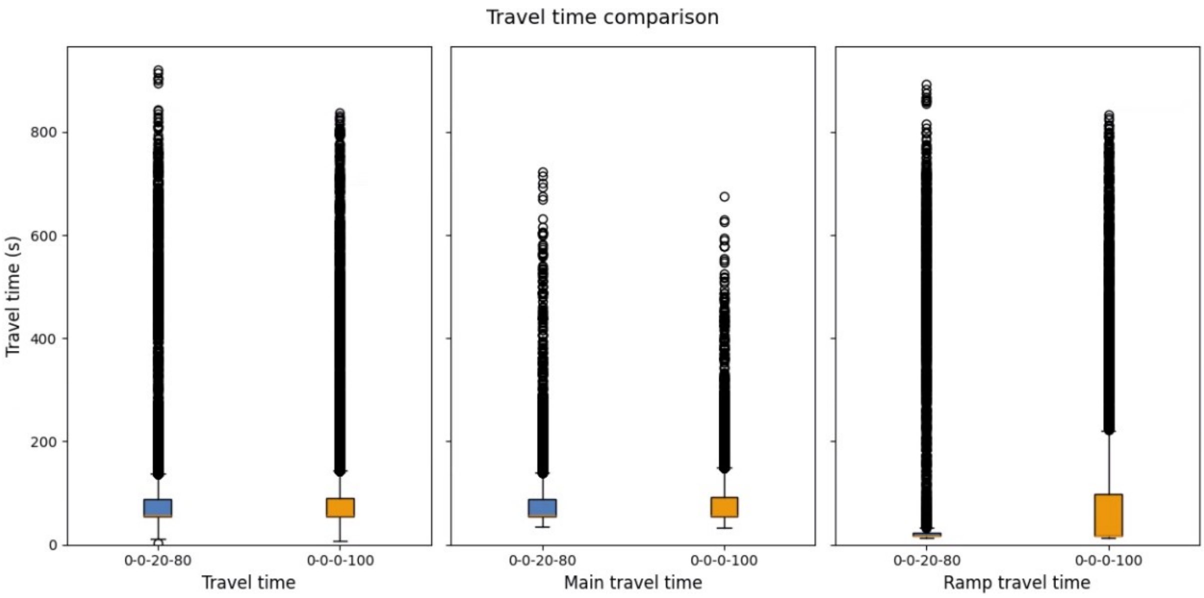


Figure 70: Travel time boxplots for scenario 0-0-0-100.

The fundamental diagrams in Figure 71 show that the fundamental diagrams are similar. However, the merging area (BC) is subject to an earlier and steeper capacity drop than before. This shows that more disruptions are present at the merge area.

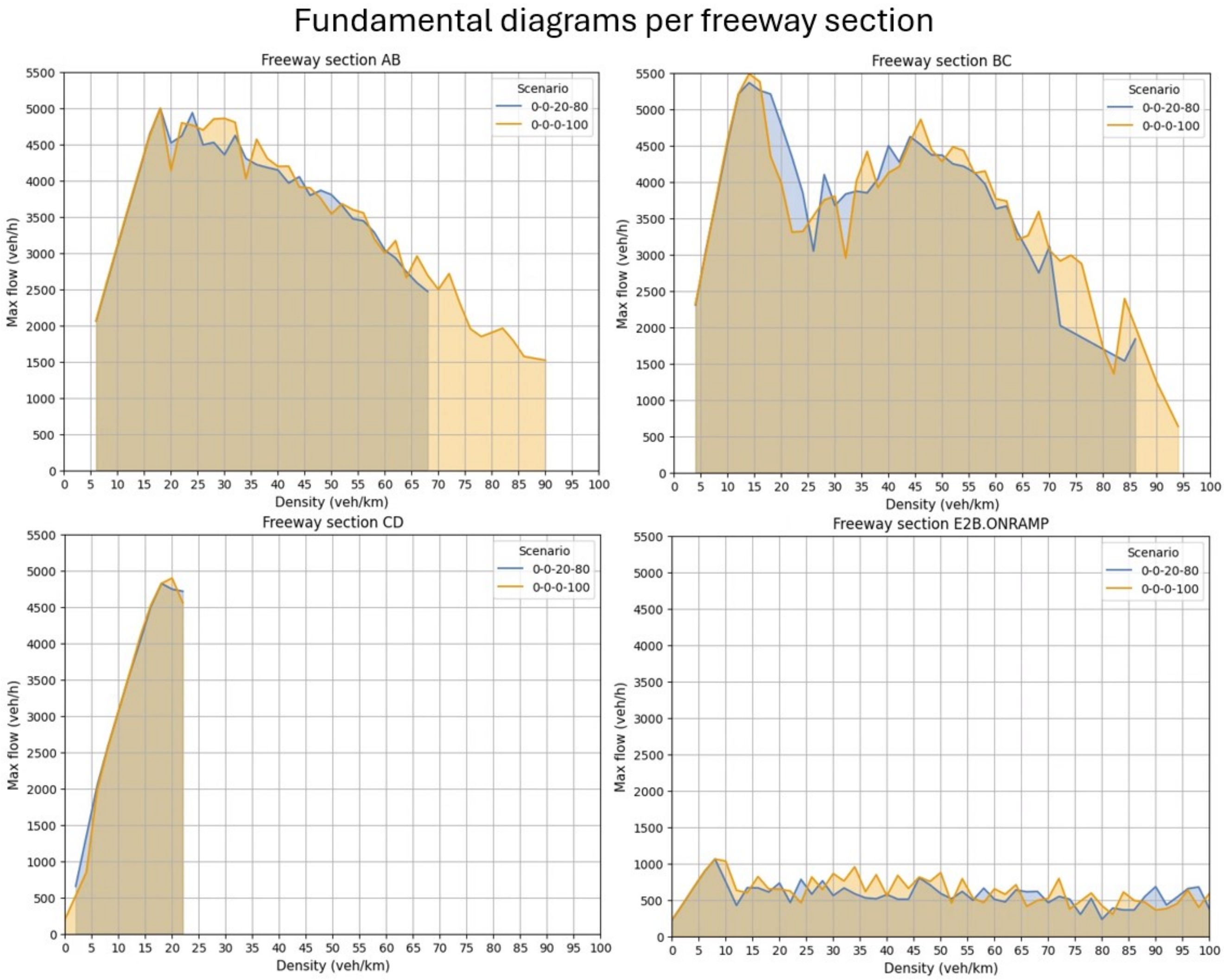


Figure 71: Fundamental diagram for freeway sections for scenario 0-0-0-100.

While the increase in level 3 vehicles has caused many improvements in earlier scenarios, this scenario shows that 100% of level 3 vehicles do not improve traffic performance much. It even worsens the mean speed at the pre-on-ramp section (AB), travel time for the on-ramp and the capacity drop at the emerging area (BC). While level 3 vehicles can maintain low headway distances, no critical time-to-collisions were observed.

**Summary of traffic performance**

The introduction of level 1 and level 2 vehicles shows that the larger time headway together with the higher lane change frequency of level 1 vehicles do enlarge the disruptions in traffic due to the on-ramp. While free-flow conditions remain similar, the capacity drop occurs at a lower density and becomes larger. Also, congestion seems to occur more often and higher densities are observed during the simulation. However, the capacity drop is damped in scenario 25-25-25-25 when all automation levels are equally present.

From there on, the introduction of more level 3 vehicles reduces the capacity drop and higher maximum flows become possible. This shows that the more human like headway parameters from the level 3 vehicles enable them to better deal with the additional traffic flow from the on-ramp. This results in higher mean speed levels on the freeway and thereby also the observed higher traffic flow. The congestion curve stays similar, so the different driving behaviour across automation levels mostly effect the free-flow and saturated traffic conditions.

### Driver distraction

The analysis of traffic performance shows that the introduction of level 1 and level 2 vehicles deteriorates traffic performance. However, level 1 and level 2 vehicles do have the advantage of supporting the driver in car-following and/or lane-changing tasks. To understand what improvement this can bring to distracted drivers, a roadside distraction is placed next to the road as described in Chapter 3.3.

**Scenario 100-0-0-0 with roadside distraction**

The roadside distraction increases the cognitive workload of the human driver. This will have other implications than the secondary driving tasks (in-vehicle distraction) since the roadside distraction affects all vehicles within a specific region. Figure 72 shows that roadside distraction increases the task saturation of the human driver.

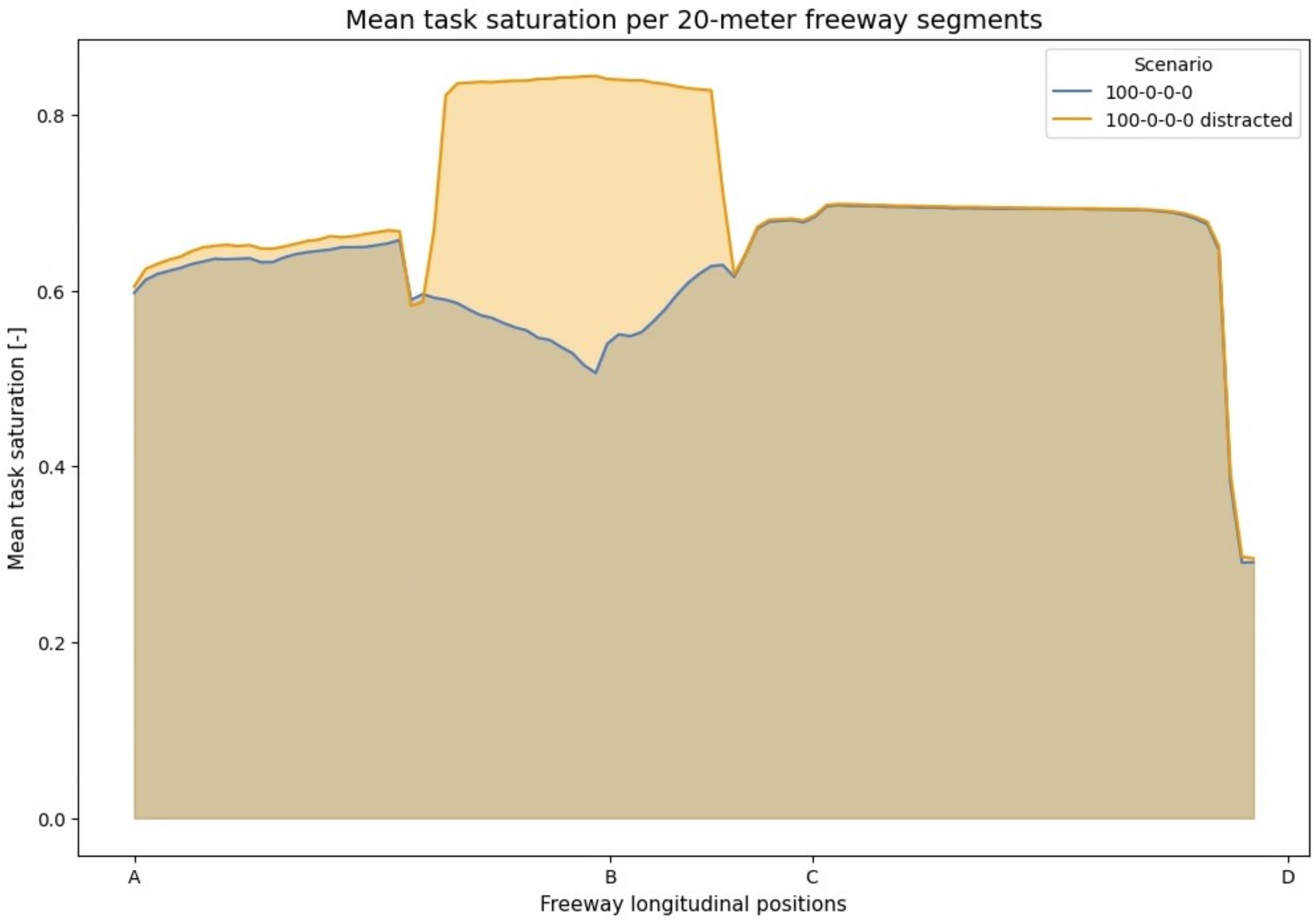


Figure 72: Mean task saturation distribution on the freeway for scenario 100-0-0-0.

Since 100% of vehicles are considered level 0 in this scenario, it is expected that the higher task saturation has significant effects on the traffic conditions. However, this effect is not seen in the mean speed heatmap of the freeway. Figure 73 shows that the reduction in speed at and before the merging area (BC), as well as the increase in speed at the post-on-ramp section (CD) are similar.

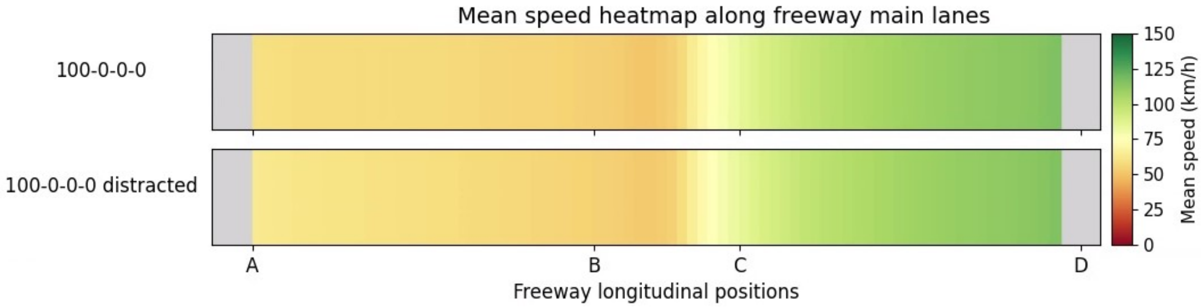


Figure 73: Speed heatmap on freeway main lanes for scenario 100-0-0-0 with roadside distraction.

The increased task load does have an effect on the travel times. Figure 74 shows that more outliers are observed for high travel times. Indicating that the simulation is subject to more severe congestion.

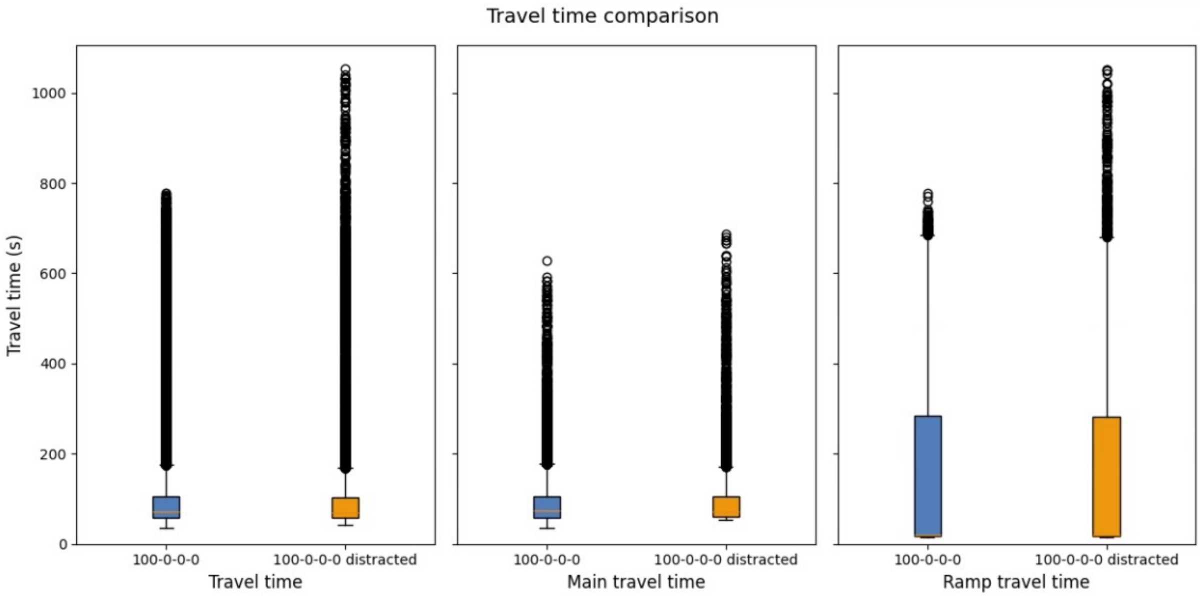


Figure 74: Travel time boxplots for scenario 100-0-0-0 with roadside distraction.

The higher workload for human drivers causes them to adapt their speed and headway to deal with the higher workload. However, this seems to positively impact the fundamental diagram for the pre-on-ramp section (AB) where the capacity drop becomes less noticeable. However, Figure 75 shows a large increase of the capacity drop at the emerging area (BC). This shows that the disruption of the additional on-ramp traffic flow has a more severe impact on traffic performance while human drivers are distracted by a roadside distraction.

Also, while distracted drivers are expected to be more prone to critical time-to-collision headway distances. Figure 76 shows that actually the number of time-to-collisions is lower when simulated with a road side distraction.

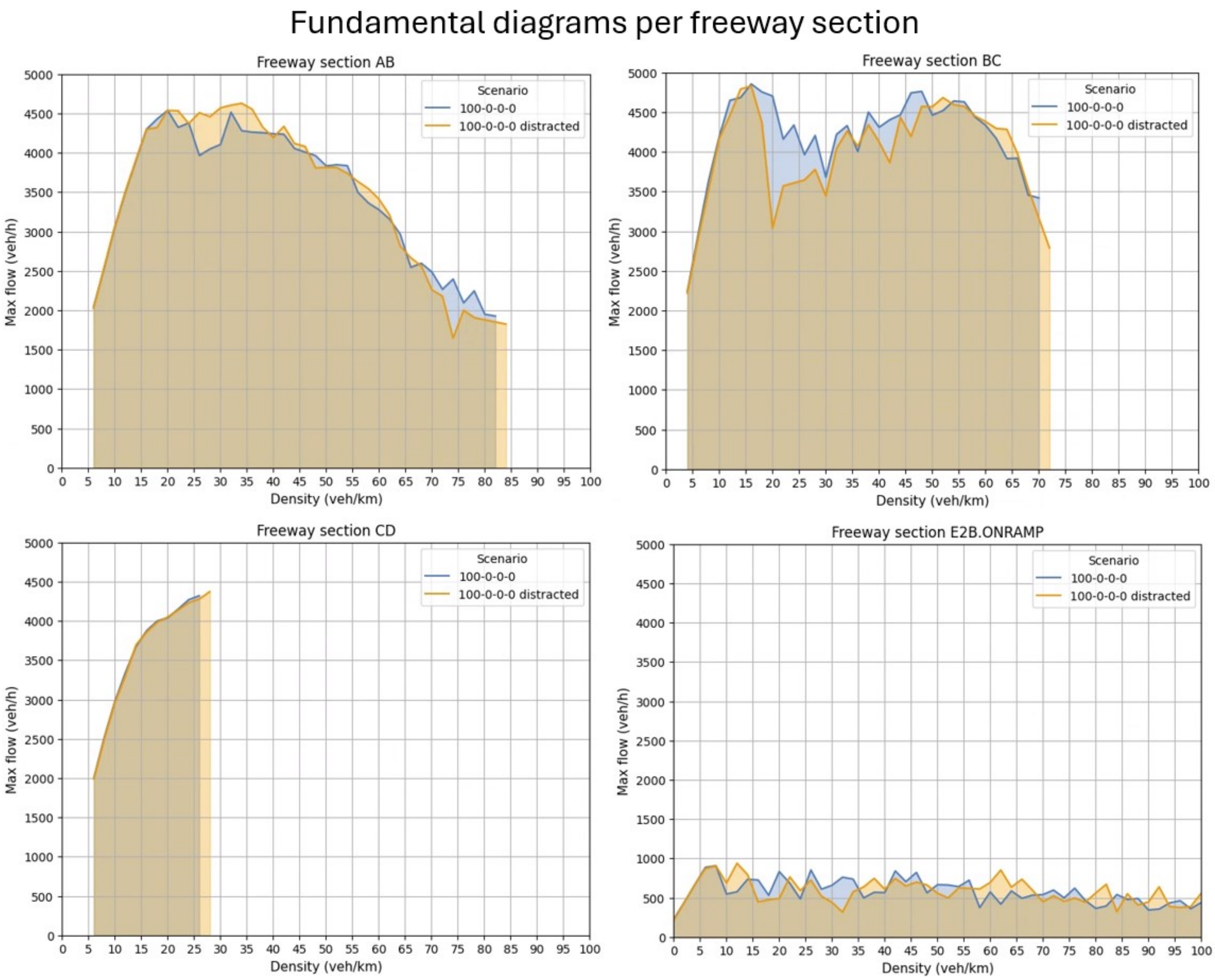


Figure 75: Fundamental diagram for freeway sections for scenario 100-0-0-0 with roadside distraction.

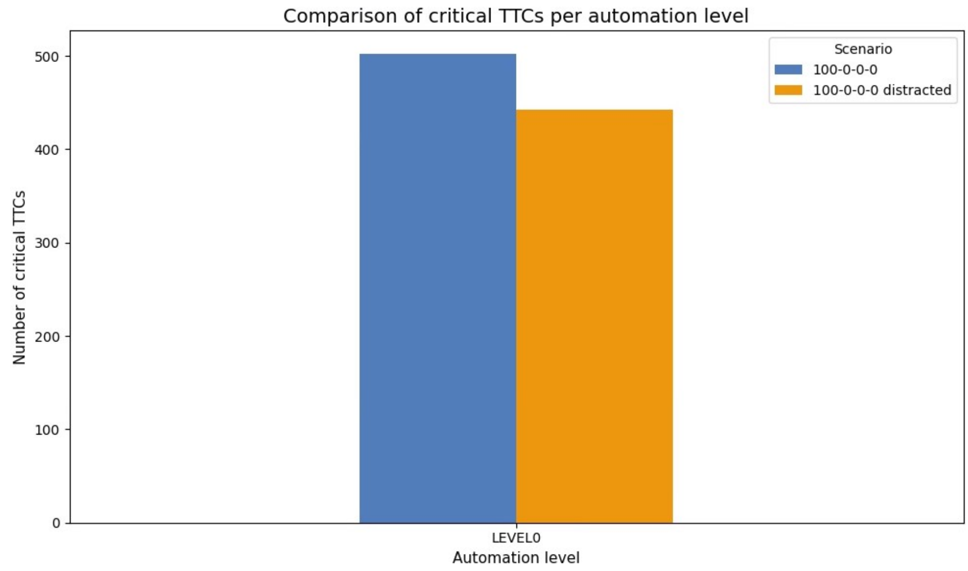


Figure 76: Number of measured critical time-to-collision headways for scenario 100-0-0-0 with roadside distraction.

**Scenario 80-20-0-0 with roadside distraction**

Now that 20% of the vehicles have supported car-following in level 1 vehicles, fewer vehicles will have a higher reaction time because of deterioration of situational awareness. Figure 77 shows that the impact of the roadside distraction in this scenario is negligible for the measured travel times.

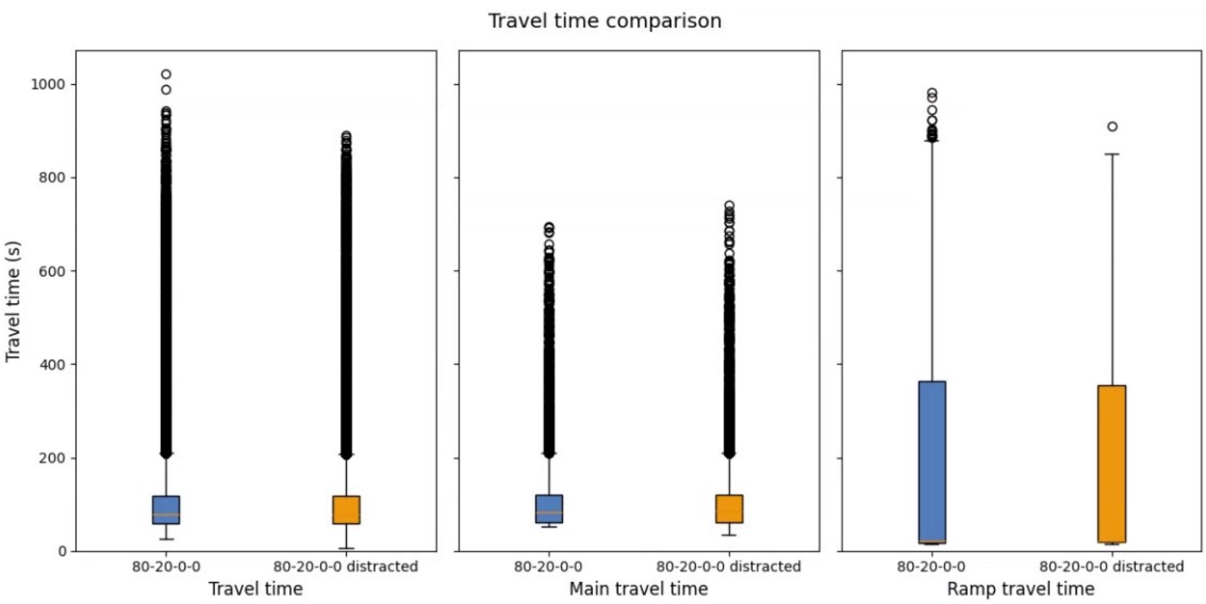


Figure 77: Travel time boxplots for scenario 80-20-0-0 with roadside distraction.

Figure 78 shows the differences for the fundamental diagrams. The differences between the scenario with and without roadside distraction become smaller but the roadside distraction does cause the capacity drop to start at a lower density. Also, the magnitude of the capacity drop is still larger. Regarding safety, a decrease in critical time-to-collisions is observed in Figure 79.

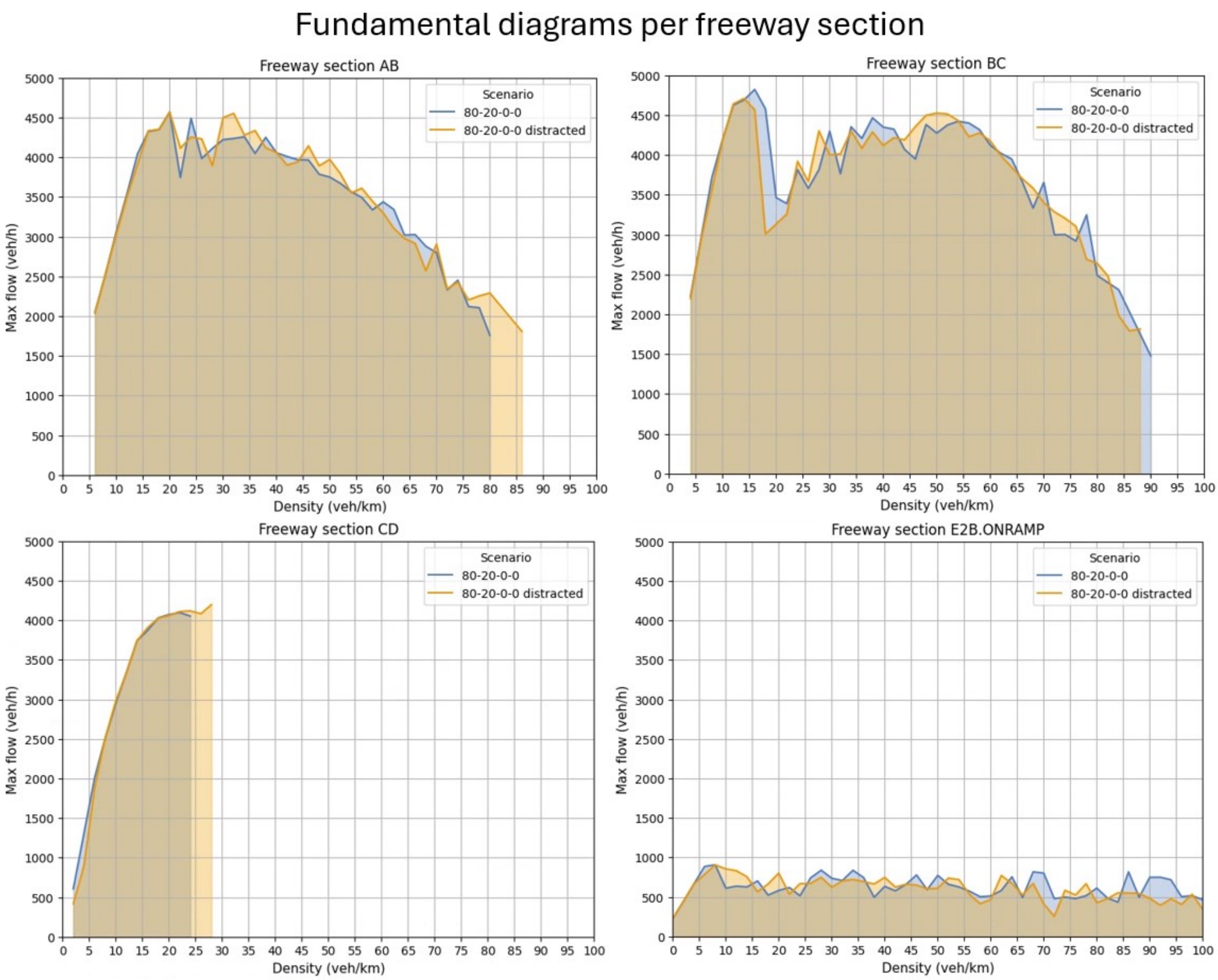


Figure 78: Fundamental diagram for freeway sections for scenario 80-20-0-0 with roadside distraction.

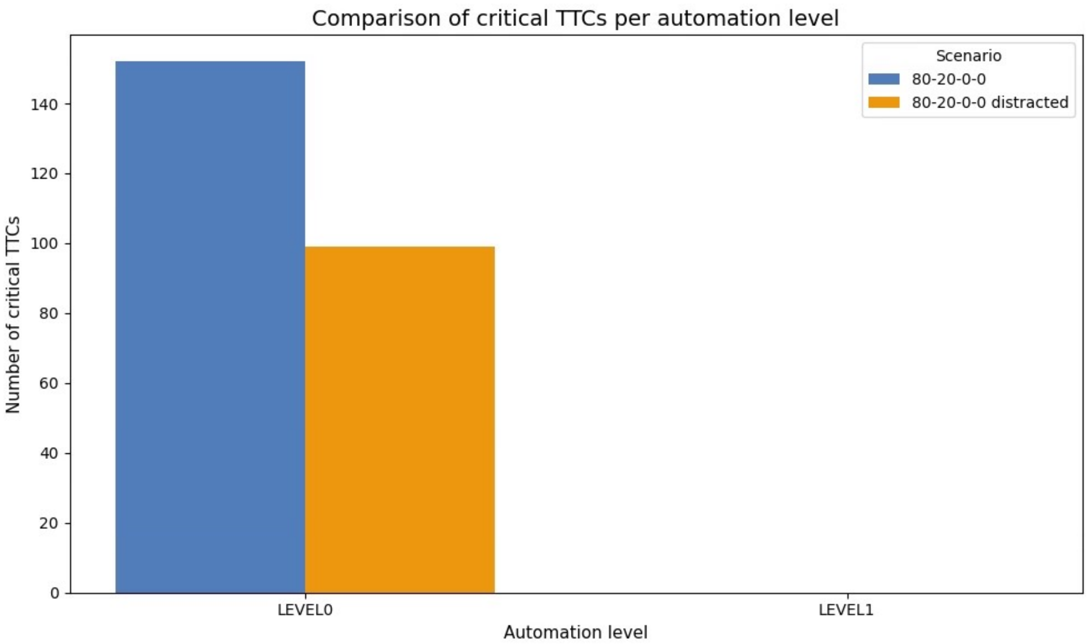


Figure 79: Number of measured critical time-to-collision headways for scenario 80-20-0-0 with roadside distraction.

By introducing automation by the means of level 1 vehicles, the impact of roadside distraction is already lower because travel times remain similar. However, the effects of the capacity drop are still relevant, causing an earlier and larger capacity drop. Also, the presence of the roadside distraction does lower critical time-to-collision counts in the simulations.

**Scenario 60-20-20-0 with roadside distraction**

The share of human drivers without ADAS support decreases even further to 60% of the vehicle fleet. This is also noticeable in the fundamental diagrams of Figure 80. The diagrams show similar maximum flow values for all sections of the freeway. A spike is observed at a density of 35 veh/km for the distracted scenario on section BC. However, this could be a rare exception during a traffic measurement interval of 30 seconds. Not only are the maximum flow values similar, also the capacity drop has become similar.

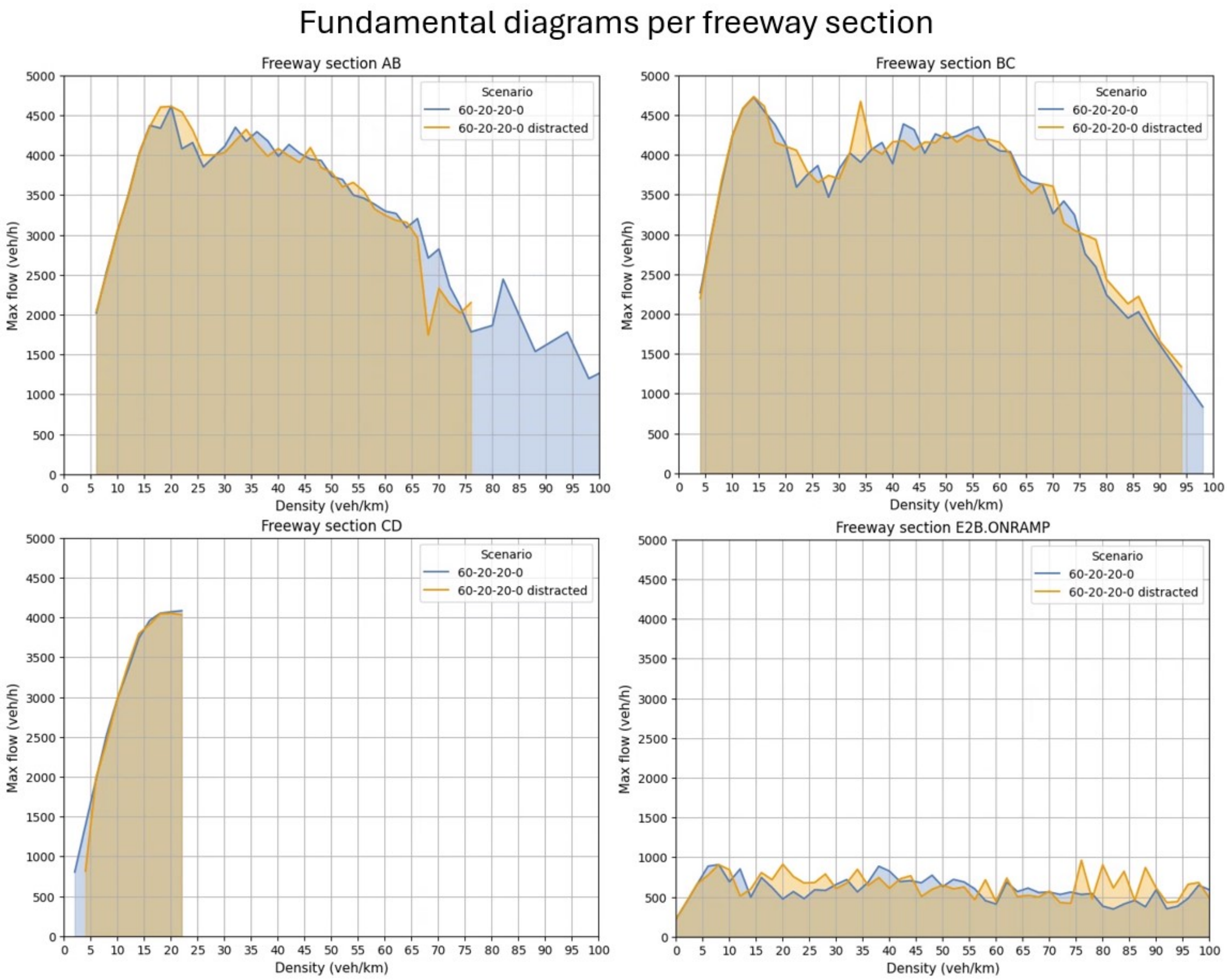


Figure 80: Fundamental diagram for freeway sections for scenario 60-20-20-0 with roadside distraction.

While previous scenarios show improvements in safety, in other words, reduce the number of critical time-to-collision occurrences for vehicles in the simulation. However, for this scenario level 0 vehicles tend to be more prone to an unsafe headway distance while distracted by a roadside distraction. The count of 39 critical time-to-collision headways increases to 51.

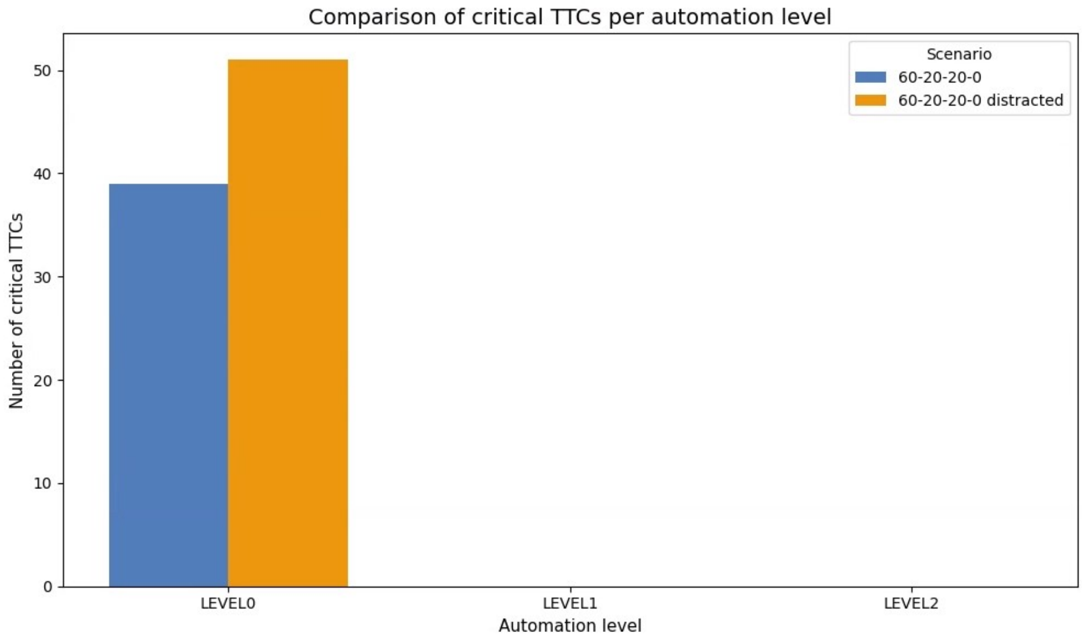


Figure 81: Number of measured critical time-to-collision headways for scenario 60-20-20-0 with roadside distraction.

This shows that the introduction of automation levels can greatly reduce the effect of roadside distractions on traffic performance. This time the roadside distraction also makes the number of critical time-to-collision increase which indicates more dangerous car-following behaviour.

**Scenario 40-20-20-20 with roadside distraction**

The effects already became minimal for a penetration rate of 60% for level 0 vehicles. For the current scenario, only 40% of the vehicles are level 1. Figure 82 shows that the fundamental diagrams for the freeway remain similar between the scenario with and without roadside distraction. However, Figure 83 shows that again more critical time-to-collisions are counted for the scenario with the roadside distraction.

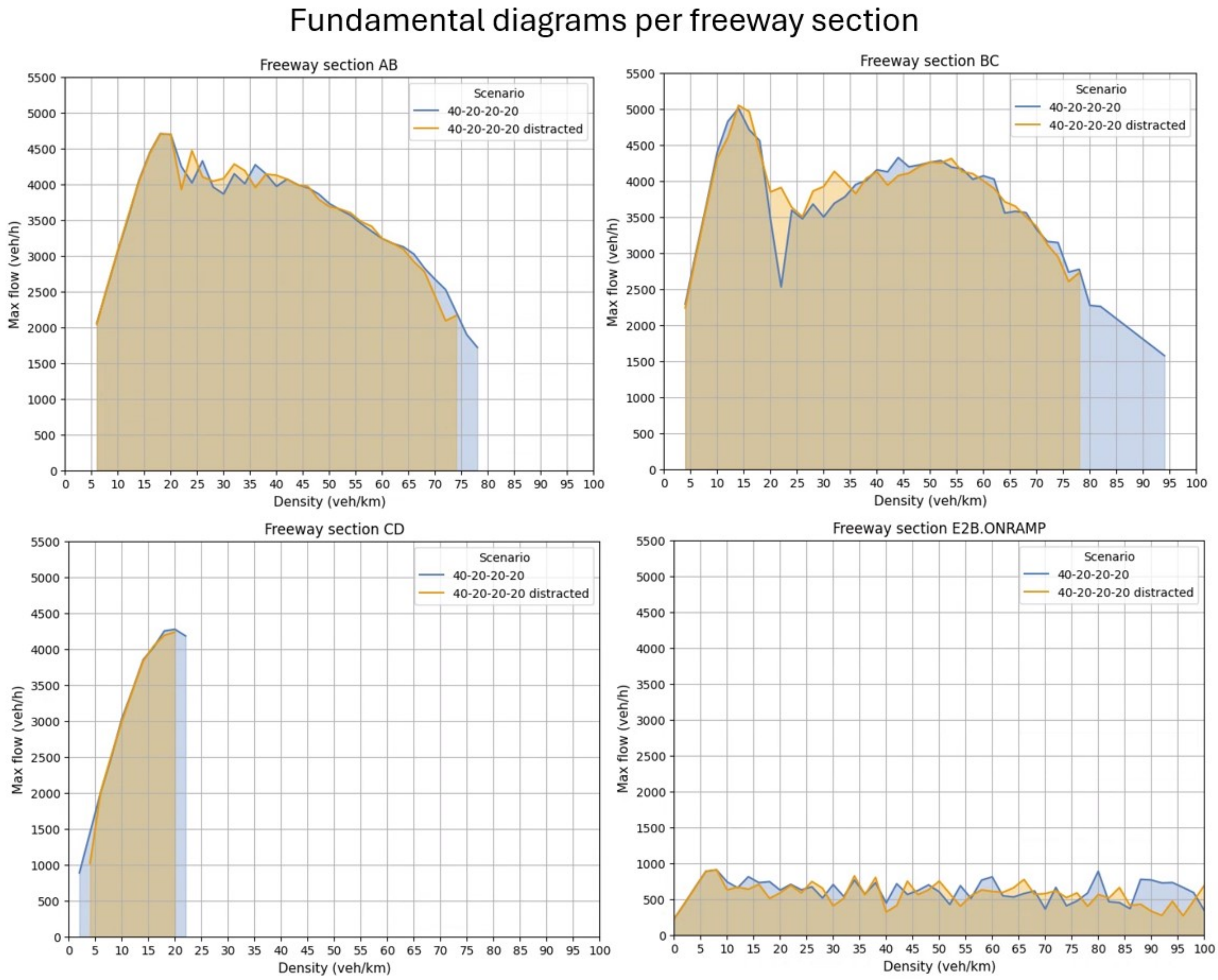


Figure 82: Fundamental diagram for freeway sections for scenario 40-20-20-20 with roadside distraction.

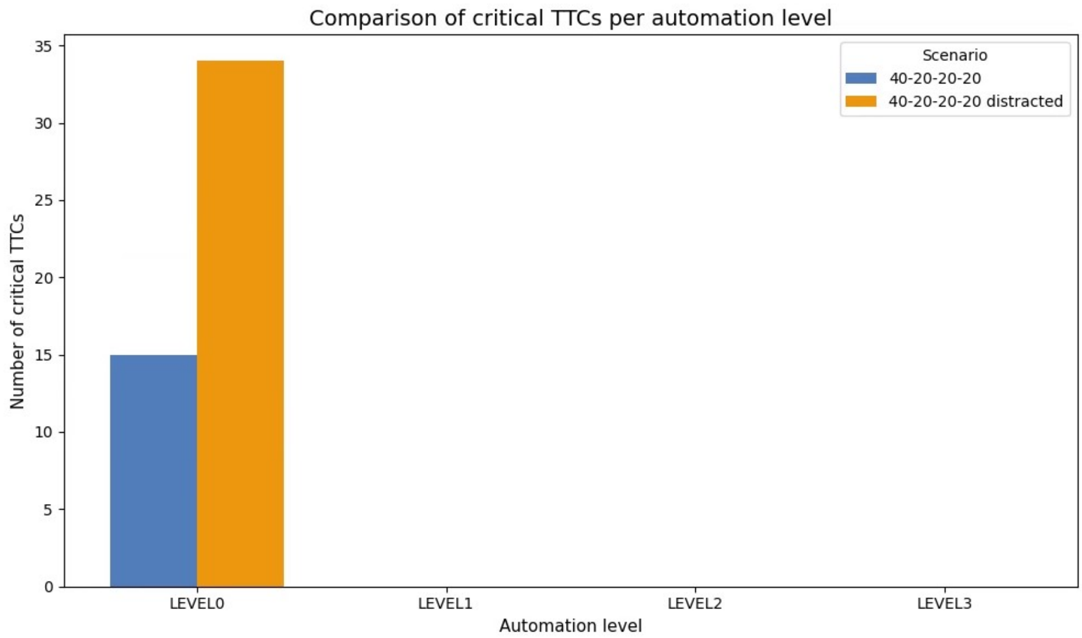


Figure 83: Number of measured critical time-to-collision headways for scenario 40-20-20-20 with roadside distraction.

### Scenario 25-25-25-25 with roadside distraction

In this scenario, only 25% of all vehicles are considered a level 0 vehicle. Previous scenarios have already shown that the negative effects of the roadside scenario are reduced by higher automation levels. Now that the penetration rate of unsupported human drivers is even lower. Again, the fundamental diagrams show similar traffic conditions (Figure 84). However, for this particular scenario, it is observed that the maximum flow values at the pre-on-ramp section (AB) are slightly lower for the scenario with the roadside distraction. Also, a downward curve starts to develop for the congestion condition in the post-on-ramp section (CD). This would indicate that some congestion is present at this section.

Additionally, while previous scenarios have shown improvements or deterioration of of safe headway distances for vehicles. Figure 85 shows that the roadside distractions make human drivers more prone to dangerous headway distances. This can be said because the occurrence of critical time-to-collisions increases slightly. Also, the critical time-to-collision headway of level 2 vehicles is not observed anymore. This cannot be caused by the roadside distraction directly since distraction is not simulated for automated driving tasks from level 2 vehicles. So, this must have changed because of changing traffic dynamics.

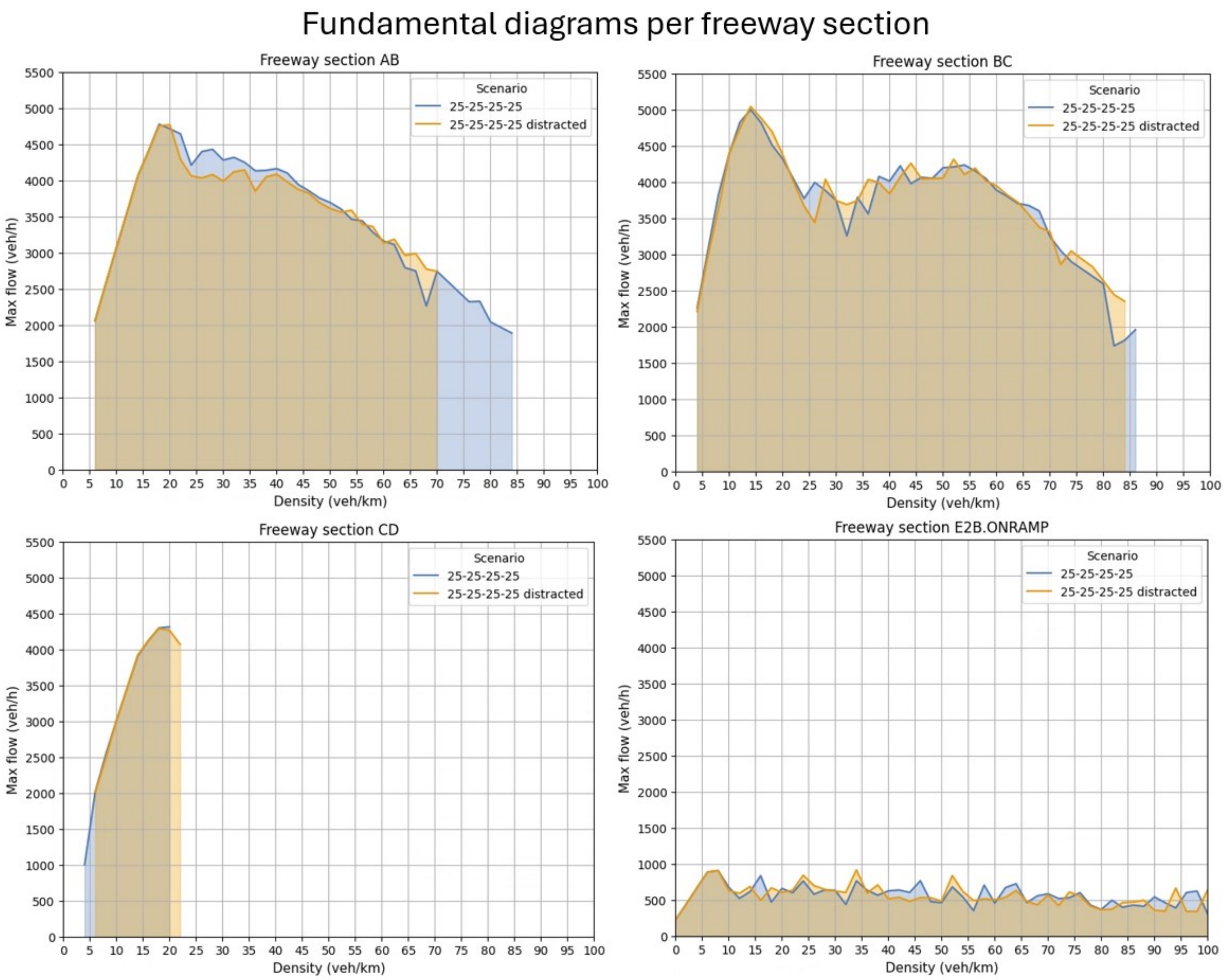


Figure 84: Fundamental diagram for freeway sections for scenario 25-25-25-25 with road-side distraction.

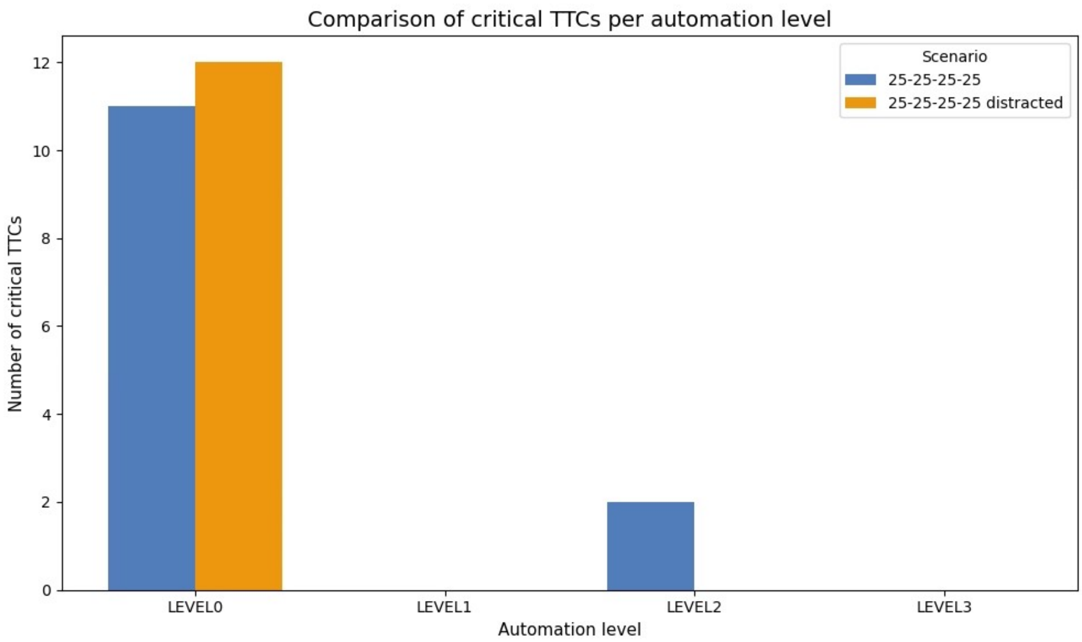


Figure 85: Number of measured critical time-to-collision headways for scenario 25-25-25-25 with roadside distraction.

### Summary of driver distraction

The effect of many distracted human drivers approaching and entering the merging area on traffic performance and safety is analysed. The roadside distraction causes higher workloads for human drivers and thus influences their driving behaviour and reaction time. The analysis shows that no significant change is observed in the mean speed on the freeway. Furthermore, the roadside distraction leads to more outliers for travel time plots. However, no large changes are observed for congestion conditions in the fundamental diagrams. However, the fundamental diagrams do show that for 100% level 0 vehicles, the capacity drop becomes larger and appears at a lower density. This means that the higher workload does result in more disruptive lane changes in the merging section of the freeway. As automation levels increase, the capacity drop becomes less significant and the fundamental diagrams become similar. This already happens at a penetration rate of 60% level 0 vehicles.

However, for high level 0 penetration rates (more than 60%) the roadside distraction lowers the number of critical time-to-collision headway distances. While no speed drops are observed, the higher reaction times associated with high cognitive workloads result in larger headway distances and thus less critical time-to-collisions. When the level 0 vehicle penetration rate becomes lower than 60%, the roadside distractions increase. This shows that the share of level 0 vehicles is important for the overall effects on traffic safety.